OPTIMAL ALLOCATION OF SOLAR PHOTOVOLTAIC UNITS IN UNBALANCED RADIAL DISTRIBUTION NETWORK USING STOCHASTIC LEARNING ALGORITHMS

Thesis submitted to

UNIVERSITY OF CALICUT

in fulfillment for the award of the degree of

DOCTOR OF PHILOSOPHY

By

Maya K. N.

Under the Guidance of

Dr. Jasmin E. A.

Department of Electrical Engineering

Government Engineering College, Thrissur-Thrissur

University of Calicut

December 2016

Department of Electrical Engineering

GOVERNMENT ENGINEERING COLLEGE

THRISSUR - 680009

Certificate

This is to certify that the thesis entitled "**Optimal Allocation of Solar Photovoltaic units in unbalanced radial distribution network using Stochastic Learning Algorithms**" is the record of bonafide research work done by **Ms. Maya K. N.** under my supervision and guidance at Department of Electrical Engineering, Govt. Engineering College, Thrissur in partial fulfillment of the requirements for the Degree of Doctor of Philosophy under the Faculty of Engineering, University of Calicut.

Thrissur-9 **Dr. JASMIN E.A.**

05.12.2016

DECLARATION

I **Maya K. N.**, hereby declare that the thesis entitled "**Optimal Allocation of Solar Photovoltaic units in unbalanced radial distribution network using Stochastic Learning Algorithms**" is based on the original work done by me under the guidance of **Dr. Jasmin E. A**, Associate Professor, Department of Electrical Engineering, Govt. Engineering College, Thrissur for the award of Ph.D programme under University of Calicut. I further declare that this work has not been included in any other thesis submitted previously for the award of any Degree, Diploma, Associateship or Fellowship or any other title for recognition.

Thrissur-9 **MAYA K. N.**

05.12.2016

ACKNOWLEDGEMENT

First and above all, I bow my head before the ***Almighty*** *Lord whose grace has been with me always throughout the research work. I have been enormously benefited from the advice, support, co-operation and encouragement given by a number of individuals during the course of this research work. I would therefore like to offer my sincere thanks to all of them.*

Creative guidance makes a scientific research, qualitative and this has been imparted to me by ***Dr. Jasmin E. A****, Associate Professor, Department of Electrical Engineering, Govt. Engineering College, Thrissur, as a helpful guide. I want to express my sincere thanks to her for the trust, the insightful discussion, offering valuable advice and for the support during the whole period of the research which made this work possible. I also acknowledge for her patience and guidance during the writing process.*

I extend my wholehearted thanks to ***Dr. Vijayakumar****, the joint director of Kerala Technical University (The Principal of GEC, Thrissur, during the period 2008-2014) for his healthy co-operation and encouragement. I am also thankful to* ***Dr. Indiradevi K.P****, Principal, Government Engineering College, Thrissur and* ***Dr. M Nandakumar****, Head of the Electrical Engi-*

neering Department, Government Engineering College, Thrissur, for providing the facilities to successfully carry out this research work.

I express my sincere gratitude to ***Dr B. Jayanand*** *, Professor, and* ***Dr Amardutt A****., Former Head, Department of Electrical Engineering, faculty and supporting staff members of Electrical Engineering for giving an opportunity to carry out my research work in the Department of Electrical Engineering, Government Engineering College Thrissur.*

I sincerely thank the external Doctoral Committee member, ***Dr. K. Santhi Swarup****, Professor, IIT Madras for providing valuable comments and suggestions at the time of interim presentations of research work. I also thank* ***Dr. T. P. Imthias Ahamed****, Professor, T. K. M. College of Engineering. Kollam, for the valuable help and suggestions extended to me for the fulfillment of this research work. I also thank* ***Mr. Manoj****, Assistant Executive Engineer, Kerala State Electricity Board for providing the data for the research work.*

I gratefully acknowledge the efforts put by my friend ***Dr. Vivek Mohan****, Assistant Professor, Amrita School of Engineering for making the numerous and timely collection of literature available to me during the entire period. I have no words to express my deep sense of gratitude to my friends at Electrical Department for making the research period a memorable one.*

I would like to place on record my gratitude to Technical Education Quality Improvement Program (TEQIP) coordinator, Government Engineering College, Thrissur, for selecting me for the research scholarship.

I am highly indebted to my ***Parents*** *for the consistent support and sharing of my responsibilities at home when I was busy with my work. I thank* *my husband **Mr. Prashant P. V.** for the consistent encouragement and absolute support to accomplish the objective. I also thank my son **Prayag P.** for patiently cooperating with me to complete the work successfully.*

Thrissur-9 **MAYA K. N.**

05.12.2016

for optimizing the size and location of DG units should be able to handle the uncertainty of DG sources. The objective is to optimally integrate solar Photovoltaic source in unbalanced radial distribution network considering the uncertainty of the PV source. The main objectives of the thesis can be enumerated as

1. Analyze various unbalanced distribution feeders for their steady state conditions before and after the integration of DG units for voltage profile, current flows, losses, etc.

2. Model the uncertainty associated with PV sources using a suitable modelling technique to represent the fluctuating power output.

3. Apply Stochastic Learning algorithms such as Learning Automata (LA) and Reinforcement Learning (RL) for optimally allocating PV units in standard unbalanced test feeders.

4. Conduct the power flow and optimally integrate the PV units in a practical distribution feeder for analyzing the impacts.

The first stage of the research work is concerned with the development of power flow algorithms for the unbalanced distribution network that can handle the DG units as PV nodes for including their representative features. Power flow methods for power distribution systems are quite different in comparison to transmission systems owing to their radial topology, unbalanced operation, and high R/X ratio. A power flow algorithm is developed by modifying the Forward- Backward sweep algorithms for incorporating the DG units modelled as PQ nodes as well as PV nodes. The algorithm is validated for balanced distribution feeder as well as two unbalanced test feeders.

The voltage profile, current flows, losses, etc. is compared for three cases, i.e. without adding DG units, by adding DG units as PQ nodes and by adding DG units as PV nodes.

The second stage of the work involves the uncertainty modelling of the solar PV generation. The solar irradiance data collected from the national solar radiation data base, are modelled using Beta Probability Distribution Function (PDF). The beta PDF is used to generate random samples that feature the behaviour of historical data that can be used to calculate the random power output produced from solar PV units. This data is used for calculating capacity factors for various types of modules which help in selecting the suitable PV module for the selected site. This power output can be treated in the power flow as a multi-state variable to analyze the hourly variation of system parameters.

In third stage, stochastic learning algorithms are used for optimally integrating PV units in the unbalanced distribution feeders. The optimal allocation is formulated as a Single Stage Decision making problem and is solved using Learning Automata. The PV units are integrated so as to minimize the power losses in the distribution feeders. The algorithm is validated for IEEE 33-bus balanced feeders and is implemented for IEEE 13-Bus and 37-bus unbalanced distribution feeders. For efficient and accurate representation of distribution system parameters the optimal integration is formulated as a Multistage Decision Problem (MDP). MDP is solved using RL for IEEE 33-bus balanced distribution feeder.

In order to check the suitability of the proposed algorithm, a 4.3 MVA practical distribution feeder is considered for a case study. The selected

feeder spans over 7.3 km with 55 buses. The optimum size of the PV units to be installed at specified locations is determined using the proposed algorithms so as to minimize the power losses in the system. The locations are selected based on the voltage profile and the type of customers. The voltage profile, energy losses, hourly variation in voltage profile, loss reduction, etc. was analyzed for the selected feeder. The results show that there is much scope for installing PV units in the selected locations for minimizing losses and improving the voltage profile.

The integration of more PV units in the distribution system is to be expected in the near future as many initiatives are taken for deployment of more energy from PV source. This requires the DG integrated system to be analyzed thoroughly with methods to find out the capacity of PV installation so that the stable operation of existing grid is not affected. The optimal sizing of PV units and the associated computation and analysis of system parameters are very important from the utility side before permitting the willing customers to connect PV units at their premises. The utility can suggest the proper sizing for the customers who are ready to connect DG sources. The customer is also benefited by the installation of PV units with proper sizing with which they can maintain the reliability and efficiency of their system. The proposed solution suggests a solution scheme for the utilities to integrate DG sources in the distribution network optimally.

Keywords: Unbalanced Distribution Network, Forward- Backward Sweep, Optimal Distributed Generation Placement, Uncertainty Modelling, Reinforcement Learning, Learning Automata

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The global power sector has witnessed a rapid growth in the penetration of Distributed Generation (DG) sources in the past few decades. This is driven by a keen interest among the countries to reduce the greenhouse gas emissions thereby mitigating global warming. Moreover, the introduction of Distributed Generation (DG) sources contribute to the diversification of energy resources, reduction of system losses, on-peak operating costs and the reduction of transmission and distribution costs. In a developing country like India, efficient and buoyant power sector with high financial robustness is the need of the hour for booming economic growth and poverty alleviation. However, in the last few years the growth of demand for electric power has exceeded the growth in the generation which leads to considerable peak energy shortages. This is hindered by the inefficiency of generation, transmission, distribution and the remarkable level of technical and commercial losses. Even though the performance of all the three sectors of the power system is equally important, the customer is mostly linked to the distribution system since the return originates at the customer end. Therefore the inadequate performance of the distribution system harms the security of the entire system.

Taking account of the above situation, the major focus of the Indian Electricity Act 2003 (Act, 2003) was towards the improvement in the performance of the distribution system and the rural electrification through distributed generation. The thrust of the act was to provide reliable supply to Rural India using the decentralized, distributed generation facility wherever the conventional electric grid was not possible. In addition to this, the Electricity Amendment bill introduced in 2014 strongly recommends the integration of renewable energy and Distributed Generation (DG) sources to the power system. This motivated Indian electric power industry to witness a marked up penetration of the local and intermittent sources of energy in the past few years. The installed capacity of renewable energy sources has reached 38.5 GW in 2015 and the growth of renewable installed capacity is drastic as compared to 18 GW in 2010.

India is blessed with immense potential for solar power owing to its geographic location within the tropic region. Most of the parts of India have 300-330 sunny days in a very year that is sufficient to meet the entire energy demand within the country. Unleashing a percentage of the available potential of 750 GW solar power is expected to provide electricity access to 300 million people who lives without electricity in Rural India. The Government has launched Jawaharlal Nehru National Solar Mission (JNNSM) which aims to achieve the installed solar capacity of 100 GW by 2022 of which 40 GW is to be contributed by the rooftop panels (mnr, 2012). The Central and

State Government have taken many initiatives as a result of which the installed capacity of the solar photovoltaic has reached 8.63 GW in 2016. The contribution of DG sources in the power generation is expected to rise in the forthcoming years, resulting in a scenario where local generation will be much cheaper than the energy supplied by the electric utilities.

There are numerous benefits that can be achieved with the integration of DG sources. Minimization of Losses, maximization of reliability, improvement in voltage profile and elimination of system upgrades are a few. But the introduction of DG sources causes problems in the power network that have not been outlined beforehand. The traditional power system operation was based on the peak load which was very much accountable and hence the generation control could be ideally performed. Further the addition of dispersed generation units cause a transformation of the distribution network to 'active' involving bi-directional power flow. Therefore, efficient analysis of the distribution system with DG is very much needed in the present situation. The decision about the DG placement is taken by the owners and the investors and in most of the cases, Distribution System Operators (DSO) have little influence over the location and size of DG units. But the impacts of the DG placement on the operation of the distribution network are critical. The improper placement of DG causes greater losses than the systems without DGs. On the other hand, optimal integration of DG resources helps to improve the performance of the distribution network in terms of voltage profile and losses. Appropriate strategies for finding out the optimal capacity and the location of the DG sources should be investigated so as to accomplish the advantages with the integration of DG sources.

There are so many factors that have to be considered in determining the optimum location and capacity of DG systems. Some of them are the penetration level of DGs, location uncertainty, varying and intermittent power output from DGs etc. This has generated interest among the researchers and engineers to study the integration issues associated with DGs, the impact of such integration on the electric power system and the pros and cons associated with DGs. Minimization of network losses is a significant aspect to be considered for the reliable and efficient operation of DG integration. There is a significant variation in the methods that are adopted for optimally integrating DG units in the distribution network. The commonly used methods can be categorized as Analytical methods, Numerical methods and Heuristic methods. The application of the first two methods is limited to small and medium systems, whereas most of the heuristic methods lack the ability to handle stochastic data that exists in practical situations. The power production from DG sources is uncertain in nature and therefore the optimization technique employed should be able to handle such uncertainty. Stochastic learning algorithms such as Reinforcement Learning (RL) and Learning Automata (LA) can be used for optimization problems in power system involving stochastic data and situations. The application of such methods in solving stochastic power system problems are a few.

The main objective of the thesis work is to analyze the unbalanced radial distribution system with PV source by optimally integrating them to the distribution network. The stochastic learning algorithms such as LA and RL are used for optimally integrating DG sources in unbalanced distribution systems by considering the random power output from DG sources. In this thesis, the integration is done after analyzing the DG integrated distribution system for impacts on voltage profile and losses and also by modelling the uncertainty associated with the solar Photovoltaic generation. The application and suitability of stochastic learning algorithms for optimal integration of DG units in the unbalanced distribution network are explored in the thesis.

For determining the optimum DG location and size, the DG integrated system should be analyzed by conducting the power flow. Also the uncertainty associated with the DG source should be modelled to represent the random variation of power output from such sources. The following section gives an insight to the preliminary analysis and modelling before integrating PV source in the distribution network. The uncertainty modelling of the solar PV source is discussed in section 1.1.2. The optimal integration is discussed in section 1.1.3. The objectives of the research work is given in Section 1.2. Then the outline of the thesis structure is given in the concluding section.

1.1 Research Focus

1.1.1 Power Flow Analysis for DG integrated Unbalanced Distribution System

Power Flow Analysis is an important and basic tool for any power system which is used in the planning, design as well as the operational stages. It helps to determine the steady state behaviour of the power system. Distribution networks are characterized by a highly radial topological structure which is different from the highly meshed structure of the transmission networks. This makes distribution systems as an ill conditioned power system. They also possess some features, which rules out the application of conventional well established power flow algorithm for distribution networks. Efficient Distribution power flow helps in realizing various applications in distribution automation and distribution management like VAR planning, switching, state estimation etc. and able to solve the load flow for distribution systems with any number of nodes, with radial or meshed topology, to which unbalanced loads and Distributed Energy Resources (DER) may be connected.

The increased penetration level of DG sources in the distribution system necessitates the development of power flow algorithms that can handle DG sources as well as the unbalance associated with the distribution network. These DG sources should be included in the power flow with their generating characteristics which requires DG units to be modelled as voltage controlled bus (PV bus). The integration of DG sources may change the topology of the radial distribution network and the power carried by the feeders are subjected to changes in direction depending upon the load and DG levels. In the distribution power flow studies DG units can be included as PQ nodes or PV nodes. The DG units modelled as PQ buses can be treated in the power flow as negative PQ loads with currents injected into the bus. But when DG units are modelled as PV nodes, modification in the power flow are necessary. Most of the research work dealing with power flow algorithms do not address the unbalance in the distribution network. Also the DG sources were included simply as PQ nodes by utilizing constant power modelling. An unbalanced power flow algorithm that can handle the DG source by modelling them as PV nodes is presented in the research work in the first stage. The algorithm is a sweep based algorithm with a capability to incorporate DG units as PV nodes. The DG units were included as PQ nodes and PV nodes to analyze the impact of modelling on the losses and voltage profile. The basic algorithm is also validated with the standard distribution analysis software openDSS.

1.1.2 Uncertainty Modelling of Solar Irradiance and Solar PV generation

The power produced from DG sources such as wind and PV generation is fluctuating in nature. Therefore the uncertainty associated with power production from such sources should be modelled appropriately. If the available data are sufficient, solar irradiance is to be modelled as as a random variable for which probabilistic distributions are used.

Several probability distribution functions were used by researchers for modelling the uncertainty associated with PV source. Weibull, Log-normal and Beta are a few. The best fitting distribution for the selected solar irradiance data should be determined. The selected PDF can be used to model the irradiance data and the corresponding power output. This is done by generating random samples that feature the behaviour of the historical data. Depending upon the characteristics there are many different types of modules, cells and arrays that are available in the market. The type of the module that is best suited for a particular site should be determined depending upon the capacity factor. This selection should be regardless of the size of the module and the power rating. The modelling of uncertainty associated with the solar irradiance and the corresponding power output helps in finding out the capacity factors and thereby helps in the selection of a particular module that yields maximum power output for the selected site.

1.1.3 Optimal Allocation of PV units

The deployment of DG sources, especially solar Photovoltaic (PV) units is one of the promising solutions to meet the rising power demand. The integration of such sources improves the overall efficiency of the distribution network by reducing the total power losses, improving the voltage profile, eliminating the need for system upgrades and thereby reducing the cost of the overall system. But these benefits can be achieved only if the DG units of optimum capacity are integrated at suitable locations in the distribution network. The problem of determination of optimal capacity and location of the installation of DG units is generally termed as Optimal Distributed Generation Placement (ODGP) problem. In ODGP problem, techniques are utilized in order to optimally allocate DG units in the distribution system so as to minimize one or more objective functions such as minimization power losses, energy losses, cost etc. subjected to various technical and operational constraints. While considering the optimal placement of intermittent DG sources such as wind and solar PV units, the optimization technique should be able to handle the uncertainty associated with the power production from such sources.

Reinforcement learning (RL) and Learning Automata (LA) are stochastic learning methods which involve learning from interactions with the environment, mapping the situations to actions so as to maximize the reward and minimize the penalties. RL and LA can handle the stochastic data and can be applied in decision making situations without the need to formulate a precise mathematical model to start with. RL have been applied to many decision making situations in power system such as unit commitment, economic dispatch and automatic generation control. The application of RL and LA for Optimal Integration of DG sources is presented in the third stage of the thesis work.

A thorough analysis of the distribution feeders is very much essential before installing PV units in the distribution system. Most of the feeders are experiencing a power deficit and poor voltage regulation during peak hours. The peak power deficit is high as 1600 MW since 80% of the load is contributed by the domestic consumers. The expansion of the transmission grid is impractical owing to the constraints on the right of way permission for laying of new lines. The ultimate solution in order to meet the peak shortage is the integration of more and more renewable energy resources into the distribution grid. The state government of Kerala has already launched a unique off-grid solar rooftop program known as the 10,000 Solar Rooftop Program with the help of the state nodal agency ANERT (Agency for Non-conventional Energy and Rural Technology) and is in the final phase. The state is now planning for the 25000 rooftop power program which would be grid connected apart from the large scale ground mounted solar power plants to be commissioned. Analysis is conducted on a practical distribution feeder in Kerala state where there is scope for installation of PV units. The impacts of the PV installation on the practical distribution feeder after the installation of PV size of optimal size at specified location are presented in the fourth and final stage of the thesis work.

1.2 Objectives

Efficient operation of the distribution system after the installation of DG units depends on the capacity of DG installation and the point of interconnection in the distribution feeder. This requires stochastic optimization algorithms for the determination of optimum capacity and location of DG installation. The optimum allocation of solar PV units so as to minimize the total power losses in the unbalanced radial distribution network using stochastic learning algorithms, namely RL and LA is the main focus of the research work. This is done by analyzing the DG integrated unbalanced distribution network by developing a suitable power flow algorithm. The uncertainty associated with the random PV power output is also considered in optimal allocation. The main objectives of the thesis can be enumerated as

1. analyze various unbalanced distribution feeders for their steady state conditions before and after the integration of DG units for voltage profile, current flows, losses etc.

2. Model the uncertainty associated with PV sources using suitable modelling technique to represent the fluctuating power output.

3. Apply Stochastic Learning algorithms such as Learning Automata (LA) and Reinforcement Learning (RL) for optimally allocating PV units in standard unbalanced test feeders.

4. Conduct the power flow and optimally integrate the PV units in a practical distribution feeder for analyzing the impacts of PV integration.

1.3 Outline of the thesis

The thesis focuses on optimal allocation of PV units in radial distribution network considering the inherent unbalanced nature of the distribution network and uncertainty associated with the PV source. As a preliminary step, the DG integrated distribution system is analyzed by a suitable power flow algorithm. The uncertainty associated with the PV units is also modelled to include them as a random variable. Different power flow algorithms and modelling techniques are reviewed in detail. The various existing solution methodologies adopted are also reviewed in detail, emphasizing their advantages and limitations.

As a first step towards integrating PV units in the distribution system, a power flow algorithm is developed for analyzing the unbalanced radial distribution feeder. The power flow algorithm is capable of handling the DG units as PV nodes for including their representative features. The power flow algorithm is developed by modifying the Forward-Backward sweep algorithm for inclusion of PV nodes. The algorithm is validated for balanced distribution feeder as well as two unbalanced test feeders. The voltage profile, current flows, losses, etc. is compared to three cases, i.e. without adding DG units, by adding DG units as PQ nodes as well as by adding DG units as PV nodes to analyze the impact of DG modelling on system parameters.

The power production from intermittent renewable energy sources are uncertain in nature and are subjected to fluctuations depending upon the weather condition. This uncertainty should be modelled by appropriate probability distribution functions. Here for representing and modelling the uncertainty associated with PV source, Beta PDF is used. Beta PDF is used to generate random samples that feature the behaviour of historical data that can be used to calculate the random power output produced from solar PV units. This data is used for calculating capacity factors for various types of modules which helps in selecting the suitable PV module for the selected site. This power output can be treated in the power flow as a multi-state variable to analyze the hourly variation of system parameters.

Optimal allocation of PV units is very important from the utility side as well as customer side for efficient operation of the PV integrated distribution system. The optimal PV integration is formulated as a single stage decision making problem and is solved using LA. The same is also modelled as multi-stage decision making problem which is solved using RL. The PV units are integrated so as to minimize the power losses in the distribution feeders. The algorithm is validated for IEEE- 33 bus balanced feeders and is implemented for IEEE 13-Bus and 37-bus unbalanced distribution feeders.

Finally a practical distribution feeder of 4.3 MVA capacity is taken as a case study. The power flow is carried out for the practical feeder and the optimum PV size to be installed at specified locations is determined by applying the stochastic learning algorithms namely, LA and RL. The locations for PV installation are selected based on the voltage profile and the type of customers. The voltage profile, energy losses, hourly variation in voltage profile, loss reduction, etc. was analyzed for the selected feeder. The results shows that there is much scope for installing PV units in the selected locations for minimizing losses and improving voltage profile.

The Chapters of the thesis are organized as follows

For stating the problem and thus developing solution approach, a thorough review has been conducted to study the various power flow algorithms for distribution network and the modelling techniques used for representing the uncertainty of DG source. A review was also conducted in order to study the various techniques that are used for optimally allocating the DG sources in the distribution network. A detailed description of all these techniques is given in *Chapter 2*.

The unique characteristics of the distribution system necessitates separate power flow algorithms for distribution networks. The power flow algorithm that is developed for unbalanced radial distribution feeder is described in *Chapter 3*. The comprehensive modelling of different distribution system components that is used in the iterative routine for power flow are also discussed. The power flow algorithm is validated for distribution feeders of varying complexity and size.

The DG units can be included in the power algorithm as PQ nodes as well as PV nodes. This modelling depends on the type of DG that is selected and the method of their interconnection to the grid. DG units to be modelled in the power flow algorithm as PV nodes for representing their features. The power flow algorithm is modified so as to include DG units as PV nodes, which is discussed in *Chapter 4*. Also the different type of DG units, their interconnection methods are also discussed.

The uncertainty associated with the PV source is modelled using Beta

PDF which is used in the output power calculation. This can be helpful in the selection of the module that is best suited for the selected site based on Capacity Factors. Modelling of solar irradiance using Beta PDF is discussed in *Chapter 5*.

RL and LA are stochastic learning algorithms that can be used to handle the stochastic data that exists in practical situations. These algorithms do not require precise model to start with the solution. The optimal allocation of PV units is solved using LA and also by RL. The application of stochastic learning algorithms for optimal allocation of PV units in various distribution feeders is discussed in *Chapter 6* which is also compared with the results from literature.

Chapter 7 discusses the application of stochastic learning algorithms for a practical distribution feeder of 4.3 MVA capacity. The optimal size of PV units to be installed at specified locations is determined using LA and RL. The locations were selected based on the voltage and the type of customers. The PV integrated system is analyzed for voltage profile, losses, energy losses etc.

The important contributions are given in the concluding chapter *Chapter 8*. The limitations and the scope for further work are also presented.

Chapter 2

Literature Review and Problem Definition

Ever mounting demand for electricity and increased concern for global warming has motivated the global power sector to transform the energy system to one that is cleaner and less dependent on coal and other fossil fuels. This resulted in the widespread use of renewable energy resources, especially Distributed Energy Resources (DERs) in the power system. The commonly used DG sources are Wind Turbines, Photovoltaic (PV) sources, Fuel cells, Internal Combustion (IC) engines, Gas turbines, micro-turbines, etc. In a developing country like India, deployment of such sources is expected to meet the growing electricity demand and rural electrification and therefore helps in booming economic growth.

The decision about the size and location of Distributed Generation (DG) is mostly taken by the owners and investors and Distribution System operators (DSOs) have little influence over this decision. But the impacts of DG integration on the distribution system operations are challenging. Proper integration of DG sources improves the efficiency of the distribution system in terms of reduction of power losses, improvement in the voltage profile, etc. Also, improper integration of DG sources may cause greater losses than the system without DG units thus reducing the performance of the system. Therefore, proper analysis of the DG integrated distribution system is very much needed to place the DG units of optimum size at the optimum locations to realize the advantages of DG integration.

The analysis of various parameters of any power system is to be done based on power flow studies. There are many power flow methods such as Newton-Raphson, Gauss Seidal etc., which are used for power flow studies. But these techniques cannot be used for distribution system because of some unique characteristics of the distribution system. Distribution networks are characterized by a highly radial topological structure which is different from the highly meshed structure of the transmission networks. Therefore, special power flow algorithms have been developed for the distribution system. Most of these methods are based on Kirchoff s Voltage Law (KVL) and Kirchoff s Current Law (KCL) leading to the power flow. The analysis of the DG integrated distribution system by conducting suitable power flow method is a prior task before planning any DG integration. Various power flow algorithms that have been used for conducting power flow of the distribution network are reviewed in Section 2.1.

The output power from the distributed energy sources such as Wind and Solar power follows the fluctuations of the primary source of energy such as wind speed and solar irradiance. This random nature of the DG sources should be modelled using suitable uncertainty model, so that the power output can be predicted in advance. The various techniques that are used for modelling the uncertainty associated with the DG sources are reviewed in Section 2.2. The power output should be considered as a time dependent variable in the power flow so that seasonal and hourly variation of the randomly varying solar and wind power output can be analyzed. This helps to plan the size of the DG unit to get the optimum power output. Therefore, uncertainty modelling also plays a vital role while planning DG integration in distribution network.

Plenty of research work has been done so as to optimally allocate the DG units in a distribution network and a state of the art of these techniques is discussed in Section 2.3. Distribution networks are inherently unbalanced in nature and DG units further add to this unbalance. Therefore the power flow algorithm should be able to handle the unbalance as well as the time dependent power output from the DG source. The optimization technique that is chosen for optimally allocating the DG sources should necessarily be a stochastic optimization technique. Most of the research works have used heuristic optimization techniques that are not so efficient in handling the stochastic data that exists in practical situations. The analysis was also carried out for balanced distribution networks without considering the unbalance and random nature of DG sources. In fact, modelling the randomness associated with the DG sources is of great importance in deciding the optimum size of DG units.

The chapter is organized as follows. Section 2.1 discusses the various power flow algorithms for distribution networks that has been developed so far. The scope of the algorithms along with their limitations are discussed. Section 2.2 describes the various techniques that have been developed to model the uncertainty associated with the PV source. Section 2.3 provides a review of the various methods used for optimal DG placement with their objective functions, advantages and disadvantages. Section 2.4 discusses various applications of reinforcement learning. The conclusion of the literature review is presented in Section 2.5.

2.1 Review of Techniques for Powerflow

Power Flow Analysis is an important and basic tool for any power system which is used in the planning, design as well as the operational stages. It helps to determine the steady state behaviour of the power system. Distribution networks are characterized by a highly radial topological structure which necessitates special power flow algorithms for their analysis. An efficient distribution power flow must be able to solve the load flow for distribution systems with any number of nodes, with radial or meshed topology, to which unbalanced loads and Distributed Energy Resources (DER) may be connected. Several methods for solving the distribution power flow were developed by various researchers. The following section summarizes the efforts made for solving distribution power flow with a critical study of each method including their special features, their advantages and limitations. These methods for solving distribution power flow can be mainly classified as Forward- Backward sweep Methods, Newton based methods and Gauss-Seidal or Fixed point algorithms.

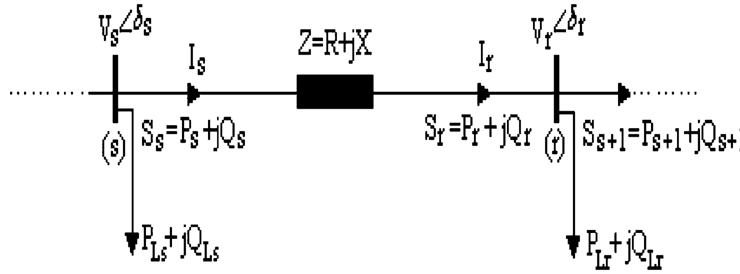


Figure 2.1: A two bus distribution network

2.1.1 Forward-Backward sweep Methods

The most popular method for solving distribution power flow falls in the category of Forward-Backward sweep method and these methods takes the advantage of the radial topology of the distribution networks. The basic steps in the method are called as forward and backward sweep. Forward sweep is used to compute the new voltage at each node starting from the substation node to the far end nodes. The currents flowing through each component are computed using Backward Sweep, starting from the far end nodes to the source node. The sweep based power flow algorithms can be classified mainly into two groups, Kirchoff's formulation and Quadratic equation based sweep algorithms. As a first step, formulation of voltage equations involved in forward-backward sweep algorithm is discussed in the next section.

2.1.2 Voltage Formulation for Distribution Network

A simple model for distribution lines is given in Fig. 2.1. The real and reactive power at the receiving end can be calculated as (Berg et al., 1967)

$$P_r = \frac{V_s V_r}{Z} cos(\theta_z - \delta_r + \delta_s) - \frac{V_r^2}{Z} cos\theta_z \tag{2.1}$$

$$Q_r = \frac{V_s V_r}{Z} sin(\theta_z - \delta_r + \delta_s) - \frac{V_r^2}{Z} sin\theta_z \tag{2.2}$$

Here V_s and V_r represents the sending end and receiving end voltages respectively. $\theta_z, \delta_r, \delta_s$ stands for the phase angles of the Line impedance and bus voltages respectively. Eq. (2.1) and (2.2) can be rewritten as

$$cos(\theta_z - \delta_r + \delta_s) = \frac{P_r Z}{V_s V_r} + \frac{V_r}{V_s} cos\theta_z \tag{2.3}$$

$$sin(\theta_z - \delta_r + \delta_s) = \frac{P_r Z}{V_s V_r} + \frac{V_r}{V_s} sin\theta_z \tag{2.4}$$

Applying the trigonometric identity,

$$cos^2(\theta_z - \delta_r + \delta_s) + sin^2(\theta_z - \delta_r + \delta_s) = 1 \tag{2.5}$$

Substituting Eq. (2.3) and (2.4) in (2.5), we get the well known bi-quadratic equation given by Eq. (2.6). The maximum real root of the equation gives the receiving end voltage magnitude. Eq. (2.7) gives line receiving end voltage in terms of sending end voltage and sending end branch powers.

$$V_r^4 + 2V_r^2(P_r R + Q_r X) - Vs^2 Vr^2 + (P_r^2 + Q_r^2) Z_2 \tag{2.6}$$

$$V_r = \sqrt{V_s^2 - 2(P_s R + Q_s X) \frac{(P_s^2 + Q_s^2) Z^2}{Vs^2}} \tag{2.7}$$

KVL equations in complex form for distribution line in Fig. 2.1 is given by

$$\overline{V_s} = \overline{V_r} + \overline{I_s Z} \tag{2.8}$$

$$\overline{V_r} = \overline{V_s} - \overline{I_s Z} \tag{2.9}$$

Equations (2.6), (2.7), (2.8) and (2.9) are widely used for calculating the sending end and receiving end voltages when forward-backward sweep algorithms are used.

a. Kirchhoffs Formulation-based Sweep Algorithms

Most of the distribution power flow methods based on forward-backward sweep employs Kirchoff's Voltage Law (KVL) and Kirchoff's Current Law (KCL) for calculating node voltages and branch currents in forward and backward sweep. The algorithm for distribution power flow using basic KVL and KCL was first proposed by Berg (Berg et al., 1967) for conducting unbalanced load flow for radial distribution systems. The concept used in developing the algorithm is that any portion of unbalanced three phase networks can be represented as a 6 element Wye-delta network and any point of electrical interest such as transformers, sectionalizing devices, changes in wire size, junctions, ends of taps etc. can be considered as nodes. But the method confined only for radial distribution networks, and considering all the nodes as PQ nodes. A similar but more efficient algorithm for solving radial distribution feeders was proposed (Kersting and Mendive, 1976) by modifying the ladder network theory. In the method, initial voltages are assumed for the far end node which is used to calculate the load currents. The backward sweep equations are used to calculate the currents in the branches. In the forward sweep, new voltages are computed by using the currents calculated from the backward sweep. The convergence is achieved if the difference in the value of the node voltages is within limits. A comprehensive model is developed for various distribution feeder components. The method can be extended for three phase networks, but can be applied only for radial distribution network.

A combination of multi port compensation technique and Kirchoff's laws were used to formulate a power flow algorithm for the balanced distribution network of either radial or weakly meshed configuration (Shirmohammadi et al., 1988). The algorithm involves the transformation of the weakly meshed network into the radial network by introducing appropriate break points and then solving the radial network using forward-backward sweep algorithm. The breaking is compensated by injecting currents at the breakpoints. But the convergence became poor as the number of breakpoints increased. This limitation had overcome in (Luo and Semlyen, 1990) by using nodal power injections instead of complex currents, i.e. Here the breaking is compensated by injecting power instead of current injections and sensitivity matrix is obtained to calculate the corrections in the breakpoint power injections by using the voltage mismatch as inputs. The PV buses are treated as breakpoints so that DG sources can be incorporated. A combination of the two methods described above is used to develop a power flow algorithm for three phase unbalanced distribution network with a capability to incorporate dispersed generators as PV buses (Cheng and Shirmohammadi, 1995a). The other issues associated with distribution systems such as Multiphase operation, unbalanced distributed loads, voltage regulators etc. are also addressed. The limitation comes only when the number of loops increases, which affects the computational efficiency of the method.

A power flow algorithm involving algebraic expressions for computing the voltage magnitudes for balanced distribution feeders was discussed in (Ghosh and Das, 1999) by modifying the forward-backward sweep algorithm. In the backward sweep, the power transferred is also calculated instead of simply applying Kirchoff's Current Law (KCL). Another robust algorithm was developed by modifying the forward-backward sweep algorithm (Thukaram et al., 1999) where KCL is applied to find out the branch currents in the backward sweep. Using these values of currents in Eq. (2.9) in the forward sweep, the new node voltages are computed. The voltage magnitude in two consequent iterations is compared for checking the convergence.

A power flow algorithm for balanced and radial feeders was proposed (Aravindhababu et al., 2001) based on a matrix named as branch to node matrix (C). The matrix is formed based on the topological characteristics of the distribution network, which is to be computed only once during the solution and therefore reduces the computational burden. This matrix along with the branch voltages are used in calculating the new node voltages. The convergence characteristics of the compensation based method were exploited in order to develop an adaptive distribution power flow for radial and weakly meshed distribution network (Zhu and Tomsovic, 2002). Along with break point compensation, PV node compensation was also proposed. Comprehensively modelling scheme is adopted for various distribution system elements and operational constraints were also included. The reactive power to be injected for maintaining voltage mismatch was found out from PV node compensation. The method was found to be reliable and fast and is checked for various radial and weakly meshed distribution system. The algorithm is also implemented for dynamic simulations.

The modified ladder theory was used in (Liu et al., 2002) with efforts to improve the convergence characteristics of the forward-backward sweep algorithm. In order to speed up the forward-backward sweep algorithm, a ratio of the node voltage to the new sending end voltage is calculated. Also the ratio of the new sending end voltage to the given value is also calculated. In the forward sweep, the new node voltage is adjusted using this ratio and hence in calculating new load currents in the backward sweep. Even though the method proved to be efficient, it was unable to handle unbalanced and meshed distribution network.

An unbalanced power flow algorithm that fully utilizes the topological structure of the distribution network was developed by (Teng et al., 2000). The method is based on two matrices namely Bus Injection to Branch Current (BIBC) and Branch Current to Bus Voltage (BCBV) matrices. The BIBC matrix represents the relation between injected bus currents and the branch currents. BCBV matrix gives the relation between bus currents and the branch voltages. Once these two matrices are developed, the power flow algorithm can be solved for any unbalanced radial distribution network. The algorithm is extended for three phase networks with DG sources in (Teng, 2003). The method was robust and efficient compared to other methods, but the application was limited, since the matrices are to be formulated using direct observation.

The compensation method proposed by (Shirmohammadi et al., 1988) was used to develop software objects for various distribution system components using Object oriented technology (Selvan and Swarup, 2004). The developed components can be used for analyzing the distribution feeder for any analysis. The algorithm is first developed for radial distribution network and is extended to the weakly meshed distribution system. This transformation was easy since the method used object oriented technology. The weakly meshed distribution network is converted to radial one by the introduction of break points which are compensated by injecting currents.

Khushalani *et.al.*, developed an unbalanced power flow algorithm(Khushalani and Schulz, 2006; Khushalani et al., 2007) by modifying the forward-backward sweep method with a capability to incorporate the DG units as PQ and PV nodes. A comprehensive modelling strategy for each and every component is developed before performing the load flow calculations. For modelling DG unit as PV node, the positive sequence voltage mismatch vector was computed and hence the reactive power injection to maintain the voltage within limits. The impact of modelling on voltage profile improvement is also analyzed. It is concluded that modelling DG units as PV nodes caused better voltage and reduced losses than the case when DG units are modelled as PQ nodes.

An improved forward and backward sweep algorithm was proposed (Chang et al., 2007) which involved backward sweep and decomposed forward sweep. Using backward sweep, the updated values of voltage are calculated using KVL and currents by KCL for each upstream bus. At the end of the backward sweep, the feeder network is decomposed into two independent resistive networks representing real and reactive component for each phase. A voltage ratio is calculated based on the maximum node voltage mismatch vector and this ratio is used to update the voltages in the forward sweep algorithm. This method showed good convergence characteristics and designed to handle unbalanced radial distribution feeders.

A loop analysis based method with modification in forward-backward sweep was proposed in (Augugliaro et al., 2008). The method involved only backward sweep where all the system quantities are determined during backward sweep with a scaling factor which is same for all the variables. The scaling factor is the ratio of the required source voltage to the calculated one. The loads are simulated as impedances in each iteration and therefore the network transforms into one containing only impedances. The voltages and currents are expressed as linear functions of a single branch current for radial system and two currents for each independent mesh in the case of a meshed system. The reactance value that is required to maintain the voltage within limits is computed in each iteration. The algorithm is compared with the Newton-Raphson method and found to have better convergence.

A simple algorithm based on KVL and KCL for solving power flow for radial distribution system also proposed by (Kumar and Selvan, 2008). Here the usual KCL and KVL are performed, but each lateral and sub lateral were treated as individual main lines. The current in any node is estimated from the neighbouring node currents and the adjacent branch currents. The current equations are formulated individually for laterals, sublaterals and main lines. This simplification causes better computational efficiency and convergence characteristics of the novel method. It is validated for IEEE-34 bus distribution system. But the inclusion of PV nodes is not addressed in the algorithm.

The algorithm in (Augugliaro et al., 2008) was improved in (Augugliaro et al., 2010) for solving distribution system with radial or meshed distribution system supplying voltage dependent loads. The transfer function method is used to express each quantity in terms of impedances and to convert meshed network into radial one, cuts are introduced and the current is injected at the cuts. The algorithm is capable of handling loads of any dependency, starting from the simple radial network to meshed network. Other benefits are in terms of computational efficiency and possible extension to transmission network with a limited number of loops. But the application of the method was limited to balanced distribution feeders.

The radial topology of the distribution network was utilized to develop a power flow algorithm known as Fast and Flexible Radial Power flow (FFRPF) for solving unbalanced distribution network (AlHajri and El-Hawary, 2010). The method involved the calculation of a single matrix known as Radial Configuration Matrix (RCM) which is a bus-bus oriented matrix that is derived from RDS configuration and consists of two submatrices, three phase section Bus matrix (SBM) and Bus section matrix (BSM) matrix. SBM is used to calculate the nodal currents in the backward sweep and BSM is used for nodal voltage calculation in the forward sweep. The algorithm is validated for balanced and unbalanced system and the results were compared with the conventional methods. The use of RCM makes the method computationally efficient with fast convergence. The method can be used only for radial distribution system and PV node incorporation is not addressed in the algorithm.

A robust power flow algorithm for solving multiphase, heavily loaded and highly meshed distribution network was developed in (Dilek et al., 2010). The method is based on the formulation of a matrix called sensitivity matrix. The independent loops are broken at certain points which are called as co-trees. The current injections and extractions are used in a correlation process and is continued until the voltage at the co-trees closely agree. The algorithm is implemented for several distribution feeders in United States of varying capacity and is compared with the conventional power flow algorithms. Another algorithm based on the decomposition of the real and reactive component was developed in (Chang et al., 2012) for analyzing weakly meshed distribution system. After decomposition of real and reactive power component of each series component, a linear proportion principle is applied to calculate the ratio of the specified to the calculated voltages. The meshed distribution network is radialized by using the concept of breakpoints. The algorithm also introduced a new bus indexing scheme for the calculation of bus voltages at the junction in the forward sweep. The algorithm is validated for various IEEE benchmark systems and compared with the conventional forward-backward sweep method for its improved computational efficiency. The inclusion of DG units is not addressed in these algorithms.

An improvement in the forward-backward sweep algorithm was made for solving, active and passive distribution network (De Oliveira-De Jesus et al., 2013). The power flow algorithm is solved using the elements of a real, quasi-symmetric matrix called TRX matrix. The TRX matrix acted as a complete database with information on the topological structure of the network, branch impedance, etc. The matrix helps to get the state of the system from the topology and branch matrix that are stored in the Distribution Management System (DMS) database. The TRX matrix constitutes only real numbers, The method is formulated for single phase and three phase unbalanced distribution network. The algorithm is validated for the IEEE 37-bus, 123-bus and also for a 8500-node distribution feeders and compared with the conventional algorithms in the literature. The method served as a scheme for the on-line and off-line study of the distribution system.

A loop analysis based continuation power flow was proposed in (Ju et al., 2014b) which involves the forward-backward sweep as the major portion and Newton's method for the correction part. The use of forward-backward sweep helped for the easy implementation of the solution for distribution systems. The corrector step involved the formation of a 2^{nd} order Jacobian matrix. The power flow algorithm is developed by making use of node-path incidence matrix. The algorithm is tailored for radial and weakly meshed systems and found to be efficient. But the algorithm did not deal with the unbalanced distribution network. The same algorithm was extended by the authors for handling PV nodes by using a Hybrid Power Flow(HPF) (Ju et al., 2014a). In the power flow procedure, the PV nodes are modelled as $V\theta$ buses and Newton's method is used to find the corrections in the voltage angle deviations. The algorithm is validated for IEEE 123-bus system and can be used in distribution systems with large scale integration of distributed Energy Resources (DERs) for achieving faster convergence. The algorithms provide a direction towards the development of power flow algorithm for unbalanced distribution networks with DG sources.

The direct forward-backward sweep algorithm was modified in (Lisboa et al., 2014) which is based on the formation of the incidence matrix that features the radial topological characteristics of the distribution networks. Based on the bus incidence matrix, linear equations are solved to get the solution instead of a matrix inversion. The solution algorithm involves linear storage complexity and therefore the computational burden is minimized. The algorithm had capability to include various load models and unbalanced operation of the distribution network. The algorithm is validated with a set of test instances varying from hundred to several thousand of nodes. Another algorithm based on forward-backward sweep algorithm was developed so as to improve the convergence characteristics for the unbalanced radial distribution system (Samal and Ganguly, 2015). Here the backward sweep equations are modified by introducing three matrices denoted as A, B, C for calculating the branch powers. A gives information on the downstream buses, B identify the end boss and C calculates the actual branch currents. The dimensions of the matrices are nXn, $1Xn$ and nXn respectively. The algorithm had better convergence characteristics compared to the normal forward-backward sweep algorithm and is validated for a 25-bus unbalanced distribution system. These algorithms are not capable to include DG sources by PV modelling.

To include the uncertainties associated with individual DG units, a Complex Affine Arithmetic Three Phase Power Flow algorithm ((CATFBS) was proposed (Wang et al., 2015). The influence of the individual DG unit is analyzed by proposing a new index denoted as Relative Influence of Uncertain Variables on Outcomes (RIUVO). The proposed power flow algorithm for including the effect of uncertainty of the multiple DG unit is validated for IEEE 13-bus and 292-bus distribution system. The algorithm showed better efficiency compared to the Monte-Carlo method for simulating the uncertainty.

One of the new algorithm in the class of forward-backward sweep algorithm was proposed by (Alinjak et al., 2016) based on a search method called as breadth-first search method. A modified Incidence Matrix (MIM) is formed using the breadth first search method. The algorithm is based on renumbering of nodes or branches which helps in a simplified procedure for detecting nodes. The search strategy helped to minimize the search for connections between nodes. The algorithm is tested for several unbalanced distribution feeders and the results were compared with the results from backward/forward sweep. The algorithm is found to be more efficient and accurate than backward-forward sweep which can be used for planning of active distribution systems.

Recently an improved load flow technique based on forward-backward sweep was proposed (Ghatak and Mukherjee, 2017) by using a single load current to bus voltage (LCBV) matrix that replaces the forward and backward sweep in a single step. Using this matrix, the bus voltages are directly determined from load current injections. The method took care of any reconfiguration problems that occurs without changing the main algorithm. The algorithm includes comprehensive modelling of various distribution system components, including voltage regulator, DG sources etc. and also takes care of weakly meshed networks. The algorithm is validated for test feeders of varying size and complexity. The results proved its robustness, efficiency and faster compared to the conventional algorithm and provided a direction in developing power flow algorithms for unbalanced distribution system with DG sources.

From the literature review, it is clear that most of the power flow methods considered distribution systems as balanced networks. The meshed configuration of the distribution network and the handling of PV nodes is not addressed in most of the algorithms. Each method has its own limitations in analyzing modern distribution systems. Efficient algorithms that can incorporate the unbalance and DG sources is very much needed in the present situation.

b. Quadratic Equation Based Sweep algorithms

The Quadratic Equation based sweep algorithms use a quadratic equation that relates the receiving end voltage to the sending end voltage and the branch power. Several power flow methods based on such equations were developed. (Cespedes, 1990) proposed a method for solving balanced/unbalanced radial distribution feeders eliminating voltage phase angles in the solution which helped to obtain exact solution for voltage magnitudes. The method used forward voltage calculation with backward power summation. The load power and branch power losses are used to calculate the branch power in the backward process. The convergence is checked by calculating the real and reactive power mismatches. Another algorithm based on quadratic equation was proposed by (Das et al., 1994) which is called as Forward Sweeping method that can be applied for balanced distribution network. Here the distribution network is solved by calculating the total real and reactive power fed through any node. The node voltages are computed using Eq. (2.6) in the forward process and the total active and reactive power for each branch are calculated in the backward process. The method proposed by (Das et al., 1994) was improved in (Ghosh and Das, 1999) by modifying the convergence criteria to improve the convergence characteristics. The first method used maximum branch active and reactive power losses mismatch as the convergence criteria, whereas in (Ghosh and Das, 1999), the total transferred active and reactive power power along with their previous values is used. The application of these classes of methods was limited for balanced radial distribution feeders.

A slight modification was done in the compensation method by making use of reduced order impedance matrix (Haque, 1996a). Here an algorithm is developed for solving power flow for distribution systems which can be either radial or meshed configuration. The process involved the conversion of meshed network into radial network with the introduction of loop break points. At the end of loop break points, power injections are calculated by means of a reduced order bus impedance matrix. The sending end branch power is used to calculate the receiving end branch power and voltage in the forward process. The same algorithm was extended for including voltage dependent load models in (Haque, 1996b). The load flow results of distribution system for various voltage dependent load models were compared. The algorithm was further extended to network with more than one feeding source in (Haque, 2000). But none of these algorithms addressed the unbalance of the distribution network.

A method that employs the Quadratic equation was given by Afsari (Afsari et al., 2002) for solving balanced radial distribution network. Here using

Eq. (2.6), the node voltage calculation is carried out separately for the laterals in the sub iterations. But instead of source voltage, the first node voltage on the lateral was considered. The difference in the actual source voltage with the calculated voltage is added to the last node voltage and backward process is repeated. This is continued until the difference in the source voltage is within the tolerance limits. The method showed good convergence characteristics because of the special procedure employed. But similar to other methods, unbalance of the distribution network is not considered in the method.

The quadratic equation was used by Ranjan and Das (Ranjan and DAS, 2003) for solving balanced radial distribution system. In the forward process, node voltages were calculated by solving Eq.(2.6) for each branch. In the backward process, the total active and reactive power transferred along with the power losses for each branch is found out by using a computerised branch and node numbering scheme. The maximum difference of the transferred active and reactive power from the source with their previous values is used as the convergence criteria. The method proved to be efficient for balanced and radial distribution network. The unbalance and weakly meshed topology of the distribution network is not addressed in the work.

Similar to the previous methods, Eminoglu *et al.* used quadratic equation for power flow analysis (Eminoglu and Hocaoglu, 2005). In the forward process Eq. (2.6) is used to compute the node voltages. But the backward process uses KVL based equations as given by Eq. (2.8) for computing new node voltages. The ratio Flow method is employed wherein the voltage ratio was used to update the value of node voltages. Voltage dependent load models are also incorporated into the quadratic equation to check the effect of load models on the convergence criteria. The maximum node voltage mismatch was used as the convergence criteria.

A forward backward sweep algorithm based on the power summation method was developed (Moghaddas-Tafreshi and Mashhour, 2009) so as to include the PQ and PV nodes more efficiently for the unbalanced distribution network. The algorithm used the real and reactive power as the flow variables and hence the required reactive power injection so as to maintain the voltage within limits can be found out directly by using positive sequence reactive matrix. The algorithm is validated for IEEE 13-bus distribution feeder and it was found that incorporating DG units as PV node gave better results compared to the other cases. The losses are minimized and the voltage is improved when DG units are incorporated as PV node.

Another algorithm for solving the power flow for radial distribution network was solved in (Singh and Ghose, 2013) based on a matrix transformation for solving branch flows in the radial distribution network. Two algorithms, namely current flow based forward-backward sweep and power flow based forward-backward sweep is used. In the current flow based algorithm, a matrix named as Load current Matrix (LCM) is formed to store the value of the load current. Each row of LCM represents the sending end node of a branch and the column represents the receiving end node. The backward sweep equations were carried out by transforming the LCM. Similarly a power flow based forward-backward sweep was also performed by forming a matrix called as Branch current matrix (BCM) which is transformed for the backward sweep. The algorithm is implemented for IEEE 34-bus distribution system and due to the elimination of network identification or renumbering, it was found to be fast and computationally efficient compared to the conventional forward-backward sweep algorithms.

The convergence characteristics of the Sweep based algorithms was studied (Eminoglu and Hocaoglu, 2008) by comparing various sweep based methods. The quadratic equation based methods proved to be faster in comparison with the KVL based algorithms. The effect of different load models such as Constant Current (CI), Constant power (CP) and Constant Impedance (CI) models was also studied. The increase in the voltage dependency of the load models created convergence difficulties for the Quadratic equation based methods due to the variation of branch power and current with voltage magnitude on each iteration. But this effect was comparatively less in the case of KVL based sweep algorithms. In Kirchoff's law based algorithms with loads modelled as Constant Current (CI) models, the number of iterations required were minimized. The technique adopted for conducting power flow should be chosen properly based on the load models, loading conditions, convergence, R/X ratio of the line etc. to obtain fast and accurate solution for the distribution system.

2.1.3 Modified Newton/Newton Like methods

Conventional Newton-Raphson methods or Newton like methods that are applied to transmission systems fails to converge when applied to the distribution system. Because of the radial nature and high R/X ratio of the distribution network, such problems may create ill condition problems for the Newton-Raphson methods. The conventional Newton-Raphson algorithms are modified so as to conduct power flow for distribution system and such methods are commonly called as Modified Newton or Newton Like methods.

One of the early work using Newton like methods was done by Baran and Wu (Baran and Wu, 1989) who proposed an iterative algorithm for solving distribution network. The solution algorithm is based on three nonlinear equations that represent real power, reactive power and voltage magnitudes which were solved iteratively. Using terminal conditions of main laterals and feeders, the number of equations was subsequently reduced, which is solved using the Newton-Raphson method. But the method showed poor convergence characteristics with increased number of loops. The Newton-Raphson method was modified by using the numerical properties of the system Jacobian in (Chiang, 1991). Three solution algorithms, namely decoupled algorithm, fast decoupled algorithm and very fast decoupled algorithms are analyzed. The algorithm assumed that the system Jacobian matrix can be considered as an identity matrix. The convergence characteristics of these algorithms were analyzed and proved to be fast and computationally efficient for network with high R/X ratio for balanced radial and weakly meshed network.

Zimmerman *et al.* (Zimmerman and Chiang, 1995) developed a novel power flow algorithm for solving three phase unbalanced radial distribution system based on the fast decoupled approach. With the current values known at one end of the feeder and the sublateral, the voltage and current for the rest of the feeder are calculated. Using the numerical characteristics of the distribution line, decoupling approximations are made in the Jacobian matrix, which is used to update unknown end voltages. These approximations make the solution of the reduced load flow equations very fast and therefore is called as fast decoupled method.

Some improvement in the convergence characteristics was achieved by using a robust and efficient modified Newton method proposed by (Zhang and Cheng, 1997). Here the approximate Jacobian matrix is represented as the product UDU^T where U is a constant triangular matrix based upon the system topology and D is a diagonal matrix which depends on the radial structure and gets updated during each iteration. The efficiency and robustness of the method were found to be comparable with that of Forward-Backward sweep method. A similar work was done (Le Nguyen, 1997) for balanced and unbalanced meshed distribution network with complex representation of the Jacobian matrix so that the solution obtained is also in complex form. The component of mismatch arising from the voltage changes is neglected here in forming the Jacobian matrix.

Most of the algorithms did not consider the unbalance associated with the distribution network. A fast algorithm was developed based on the Newton-Raphson method by Teng *et al.* (Teng and Chang, 2002). The branch voltage is used as a state variable along with the conventional bus branch data in an unbalanced radial distribution network. The advantage of the topological characteristics of the radial distribution network is taken into account in forming the Jacobian matrix. The upper triangular Jacobian matrix is decomposed into a diagonal and identity matrix and the branch voltages were obtained by solving the identity matrix by the backward substitution method. The current mismatch is used for checking convergence criterion. The method is found to be fast and robust for large distribution networks with radial topology.

Another class of Newton-like methods that were used for solving distribution systems are called as current injection methods. A current injection method was proposed by Costa et al. (da Costa et al., 1999) for solving balanced distribution network based on current injection equations. The Jacobian matrix had the same form as that of the nodal admittance matrix and for each network branch, the Jacobian matrix takes the form of a 2x2 matrix. For PV buses, a new dependent variable ΔQ is introduced with an additional constraint on zero voltage deviation. The diagonal elements of the matrix are updated in each iteration. Using the value of current injections and the transferred power, the node voltages are computed. The current mismatch which is used as the convergence criteria is also formulated in Newton form which can therefore be applied for the power flow solution of practical feeders.

The Newton method proposed by Costa et al., (da Costa et al., 1999) was extended for solving three phase power flow in (Garcia et al., 2000). In this method the PV node representation required updating of the corresponding column of the Jacobian matrix. Therefore the increment in reactive power became a state variable. But this method showed some convergence problems which reduced the computational efficiency of the algorithm. Therefore the same authors made some improvements in the PV node representation. The new PV node representation is made using an augmented linearized system of equations for representing ΔQ as the state variable by including the controlled voltage equation in the Jacobian matrix. By this new representation the convergence limitation associated with the previous method was eliminated (Garcia et al., 2004).

An effort was made to improve the convergence of the Three phase Distribution Current Injection method (TCIM) under stressed operating conditions (de Oliveira et al., 2007). An optimization factor is introduced in order to correct the voltage updates in each iteration. The performance of the algorithm under different operating conditions and taking various load models is also taken into account. A methodology for calculating multiple three phase power flow solution is also presented. But DG units were not included in the analysis. The TCIM was improved so as to include the neutral conductors and grounding (Penido et al., 2008) based on four wire current injection method. To include DG sources, an induction machine is modelled with control strategies and is integrated in the distribution network. The method is based on the currents injected at every node and in series and shunt components, which are used to formulate the power flow problem. The formulated equations are solved iteratively using the Newton-Raphson method. The algorithm is validated for IEEE 34-bud distribution system and was implemented for a large practical distribution system.

A power flow algorithm was developed on branch frame of reference to solve power flow for unbalanced radial distribution network (Chen and Yang, 2009). The method utilize graph theory, current injection technique and branch impedance matrix to solve the power flow algorithm directly and hence is called as direct Z_{BR} method. The method utilizes the radial topology of the distribution network in forming three matrices namely the element bus incidence matrix A, cut-set incidence matrix B and branch path incidence matrix K. The limitation with the method is that common elements of the distribution network can not be included since the impedance matrix should be kept constant. This limitation had overcome in (Segura et al., 2011) by developing a Generalized Single Equation load Flow (GSELF) which incorporate transformer and voltage regulator in different types of connections. The model for each and every component of the distribution feeder is expressed in terms of nodal voltages and branch currents which can be updated in the iterative process. The models for shunt capacitors, DG sources, loads of different models etc. can also be incorporated. The method found to be efficient and fast compared to the forward-backward sweep method.

A comparison between TCIM and the backward forward sweep algorithm was presented in (de Araujo et al., 2010). Even though the forward-Backward sweep algorithms showed good performance for the radial system, the effect of voltage controlled devices and meshed topology deteriorate the computational performance of the system. The number of iterations for soving such systems did not increase much for TCIM. This is because of the special structure which allows to incorporate the changes directly in the algorithm. TCIM is found to be better than Forward-Backward sweep algorithms for the networks other than the very simple radial networks. But PV node representation is not addressed in TCIM.

A power flow algorithm that used the bus incidence matrix was proposed in (Farag et al., 2011) for three phase unbalanced distribution systems with high penetration of DG sources. The bus incidence matrix give the relationship between the bus currents and branch currents. Also the unbalance of lines, loads, etc. are modelled and incorporated in the power flow. The algorithm take into account, the Static Voltage Regulators (SVR) and the inclusion of DG units. The algorithm is validated for IEEE 13-bus and 37 bus distribution feeder and compared with the direct method (Teng, 2003). The DG units are incorporated as PQ nodes as well as PV nodes. The results are analyzed without and with the incorporation of DG units and SVR. The algorithm worked efficiently for three phase unbalanced radial distribution feeders.

The Modified Augmented Nodal Analysis (MANA) was used to derive three solution algorithms for solving unbalanced distribution network (Kocar et al., 2014). The algorithms are called as Fixed-point algorithms, Newton based algorithm and Dishonest Newton's method. The fixed point algorithms use the MANA equations directly. The newton's method add the augmented section so that the constraints on the load flow can be incorporated. In the case of Newton's MANA solution, coefficient of the Jacobian matrix is updated on each iteration, but this is avoided in dishonest Newton's method. The most accurate system is found to be the Newton's MANA method in terms of accuracy and speed. The algorithm is validated for IEEE-8500 node benchmark system and was compared with other methods in the literature and found to have good performance. The only limitation was the computational burden involved in calculating the Jacobian matrix.

A new algorithm that efficiently handles the meshed network and PV nodes was developed which uses powers as flow variables in (Li et al., 2014). Here the information on the terminal power and voltage states is used to form two equations for angle difference and voltage drop. These equations along with node-branch incidence matrix is used to solve the power flow using the powers as the flow variables. The PV nodes are handled by considering the point of interconnection as break points and solving them using Thevenin's equivalent circuit. The algorithm is found to have good convergence characteristics as compared with forward-backward sweep algorithm. Another algorithm based on complex pu normalization was developed in (Tortelli et al., 2015). Here the problem of the conventional power flow algorithms for solving distribution systems with high R/X ratio was addressed by introducing complex power base and thus adopting complex pu (cpu) normalization instead of normalization. Utilizing cpu enables the application of fast decoupled power flow methods for distribution systems and therefore can be a promising solution for active distribution systems. But the unbalance is not addressed in the algorithm. But these method are intended only for balanced feeders.

The algorithm proposed in (Li et al., 2014) was improved in (Li et al., 2016) by redeveloping the calculation for the link branch powers. This is achieved by combining the link branches, slack bus and PV nodes into a single matrix. Compared to the previous method, more precision was achieved. Also a model was introduced for tap changing transformers. The multiple slacks and PV nodes were treated as loop links and is introduced in the power flow in the form of the combined matrix. The method uses only real number matrix operations which improves its solution speed. The method is validated for IEEE 69-bus distribution system. The algorithm proved to be more efficient, robust and fast compared to the conventional methods for distribution systems with high amount of dispersed generator sources.

A correction current injection method was used for power flow in unbalanced and three phase distribution networks (Sunderland et al., 2016). The power flow algorithm allowed any number of phases and neutral conductors with a flexibility to represent any kind of voltage dependency and also capable of including different types of grounding. This enable the power flow algorithm to be applied to practical distribution systems whose requirements varies. The algorithm also had the capability to include dispersed generation units by suitable modelling technique. The algorithm proved to be fast, robust and efficient for four wire distribution networks with meshed topology and high amount of dispersed generation.

The Newton like methods developed for distribution system are efficient in handling the PV node representation and weakly meshed topology of the distribution network compared to forward-backward sweep method. But the formation of the Jacobian matrix for such systems is a difficult and tedious task which limits their application.

2.1.4 Gauss-Seidal of Fixed Point type methods

One of the early algorithms for solving distribution system with Gauss-Seidal method was done based on the Implicit Gauss Z_{bus} method (Chen et al., 1991). The method used sparse bi-factored Y_{bus} matrix and equivalent current injection to solve the distribution power flow. The concept used is that the voltage at any bus arise from the specified source voltage and equivalent current injection. The loads, co generators, capacitors etc., are modelled as equivalent current injections. The solution technique is carried out by applying superposition principle, considering each source separately. The convergence characteristics of the algorithm were found to be comparable with that of the Newton method. The effect of cogenerators was also considered, but included them as constant power loads.

Teng et al., (Teng, 2002) proposed a new distribution power flow based on modified Gauss-Seidal method and Implicit Z bus method which can be used for solving radial, meshed or looped network. The method used triangular factorization of the Y_{bus} matrix and optimal ordering scheme which take the advantage of sparsity of the system equations. The three phase distribution network is decomposed into three single phase networks and the solution is done in each phase separately. The factorization of the admittance matrix is done only once during the entire procedure. The method showed good convergence properties compared to the previous method. But the method did not consider the DG source representation by modelling them as PV nodes.

The Z_{bus} Gauss method was further improved in (Vieira et al., 2004) for solving unbalanced distribution network. The technique involve the decoupling of the three phases by decomposing the various component models. The implicit factorization of sparse Y_{bus} matrix is also done separately for each phase and the problem is solved by Z_{bus}-Gauss method. The decoupling caused a substantial improvement in the performance of the conventional Z_{bus}-Gauss method when applied to unbalanced network. Parallel processing techniques can be employed and therefore the method can be used in real time operation of the large distribution system. The DG sources, inclusion is not addressed in the method.

Chen et al., proposed an unbalanced power flow algorithm based on the loop frame reference (Chen and Yang, 2010) which is based on loop impedance matrix (Stagg and El-Abiad, 1968), current injection and graph theory. The solution involved the formation of the branch path incidence matrix, K that can be calculated from the primitive impedance matrix that is obtained by direct observation. Therefore the computations on the bus admittance matrix were not necessary. The method showed good convergence characteristics and accuracy for large unbalanced radial distribution networks but not suitable to handle meshed networks. The inclusion of PV nodes and DG sources are not addressed.

A new method utilizing the Implicit Z_{Bus} method was proposed by Yang (Yang, 2016). Graph theory, sparse matrix techniques and current injection were used to improve the performance of the Gauss implicit Z_{Bus} method. The method is referred to as direct Z_{Bus} method. The complex calculations involved in power flow, such as Gaussian elimination, LU factorization and inversion are eliminated by using the loop incidence matrix for calculating the impedance matrix. Four IEEE test cases are validated with the proposed method and the performance is compared with the previous Gauss-Seidal based algorithm and found to have superior performance.

The power flow studies for distribution networks can be classified as Forward- Backward sweep algorithm, Modified Newton methods and Gauss-Seidal or Fixed point methods. The developments in all these methods were analyzed in detail. Forward-Backward sweep algorithms are the most commonly used algorithms owing to their simplicity and robustness. The DG integration and the unbalanced operation are still challenging issues as far as distribution power flow studies are concerned.

2.1.5 Distributed Generation (DG) modelling for power flow studies

The Distributed Generation (DG) had been proposed as one of the possible solutions to todays energy and environmental challenges. Accordingly the number of DG sources integrated in the power system have been increased in the past decade. These DG sources should be included in the power flow so as to retain their features which requires DG units to be modelled as voltage controlled bus (PV bus). The integration of DG sources may change the topology of the radial distribution network into meshed one and the power carried by the feeders are subjected to changes in direction depending upon the load and DG levels. In the distribution power flow studies DG units can be included as PQ nodes or PV nodes. The DG units modelled as PQ buses can be treated in the power flow as negative loads with currents injected into the bus. But when DG units are modelled as PV nodes, modification in the power flow is necessary.

There are some sweep based algorithms that incorporate the DG sources as PV nodes in the power flow for the radial balanced distribution network. Some of these algorithms handled PV nodes accurately in the balanced distribution network. One of the earlier method was proposed by (Shirmohammadi et al., 1988) which handled PV nodes considering them as break points. The current injected is calculated from the breakpoint current injection. Here the reactive power to be injected is given by Eq. (2.10)

$$Q_{pv}^{k} = \frac{Q_{pv}^{k-1} - Q_{pv}^{k-2}}{V_{pv}^{k-1} - V_{pv}^{k-2}}(V_{pv}^{k} - V_{pv}^{k-1}) + Q_{pv}^{k-1} \tag{2.10}$$

It is evident from the equation that the performance of the system heavily depends on the assumed initial conditions. If the assumed values of the initial voltage and reactive power are not proper, the convergence was slow. Therefore, some improvements were made in the algorithm in (Luo and Semlyen, 1990). This is done with the use of a linearised relation between injected power and sensitivity matrix. For this, the PV nodes were considered as PV breakpoints in contrast to the loop breakpoints by the authors in the previous work. The incremental power change is calculated with the assumption that all the voltages are close to 1.0 p.u which is calculated as

$$\overline{Z}(\overline{\Delta S})^* = \overline{\Delta V} \tag{2.11}$$

The sensitivity matrix Z is obtained from the Thevenin's equivalent circuit as seen from the breakpoints. The obtained ΔS is added to the power obtained from the last iteration.

Most of the sweep base algorithm modelled DG sources as Constant Power sources or PQ nodes. In such methods, DGs are modelled by injecting currents that are obtained using the voltage values and constant real and reactive power values. Some of the algorithms, model DG units as PV nodes as given in (Cheng and Shirmohammadi, 1995b; Zhu and Tomsovic, 2002). In the method developed in (Cheng and Shirmohammadi, 1995b), the reactive power injection required to maintain the voltage values within the limits is found using the PV node voltage and the injected current as given in Eq. (2.12).

$$[\overline{Z}][\Delta\overline{I_q}] = [\Delta\overline{V}] \tag{2.12}$$

The constant real matrix Z is computed from the real part of the sensitivity matrix obtained from Eq. (2.11). Once the required reactive power is calculated, these are modelled as PQ buses with the injected current added in the next iteration.

A similar approach was used in (Zhu and Tomsovic, 2002) where the PV node voltage mismatch obtained from Forward-backward sweep is compared with the PV node convergence criteria. If the convergence is not achieved, break point voltage mismatch and current injection required to maintain the voltage within limit to be found out. This current is to be added to the main current to obtain the total current that is to be used for voltage calculation in the next iteration. DG units were modelled as PV nodes and Eq. (2.12) is used in (Khushalani et al., 2007) for finding the reactive power needed to maintain the voltage within limits. Also the reactive power limit that can be generated by DG units is found using Eq. (2.13).

$$Q^{j}_{G,MIN} \leq Q_G \leq Q_{G,MAX} \tag{2.13}$$

A method that models the DG sources as shunt capacitors was developed in (Augugliaro et al., 2008) and here, the reactance that is needed to maintain the voltage within limits is computed in each iteration. This equation is obtained by using Thevenin's equivalent circuit as seen from the DG connected bus. The PV node representation of DG is modified so as to include the neutral connections with different types of grounding as described in (Penido et al., 2008). Here some control strategies for induction generators were also modelled so as to represent the presence of DG.

Active and reactive power were used as variables by Moghaddas *et al.*

(Moghaddas-Tafreshi and Mashhour, 2009) so that the reactive power limit to maintain the voltage within limits can be calculated easily. The voltage mismatch vector is calculated and the reactive power injection required to maintain the voltage for the unconverged node is given by

$$\overline{Z}[\Delta\overline{Q}] = [\Delta\overline{V}] \tag{2.14}$$

and the reactive power required to maintain voltage is given by

$$Q^i_{new,cal} = Q^i_{old,reg} + 3 * |Q^i| \tag{2.15}$$

Here $Q_{old,reg}$ is the regulated Q value from previous iteration.

A generalized power flow algorithm for networks with high penetration of DG units were incorporated into the power flow as PV units, but by using a dummy node and branch to maintain the voltage within limits (Farag et al., 2011; Ghatak and Mukherjee, 2017). The dummy reactive power injection is calculated as

$$Q_{spec} = |V^t_i|(\frac{V^t_{dummy,i} - |V^t_i|}{\beta_i}) \tag{2.16}$$

Here Q_{spec} is the dummy reactive power specified value, $V^t_{dummy,i}, V^t_i$ are the dummy node voltage and the PV node voltage in iteration i. The updating of dummy node voltages is given by

$$\Delta V^t_{dummy,i} = V^{spec}_i - |V^t_i| \tag{2.17}$$

$$V^{t+1}_{dummy,i} = V^t_{dummy,i} + \Delta V^t_{dummy,i} \tag{2.18}$$

In Generalized single-equation load flow method proposed by (Segura et al., 2011), the DG units were incorporated as voltage controlled buses in the power flow. The asynchronous generators used for DG interconnection were modelled as current injection in parallel with shunt admittance. The DG units which are treated as PV nodes are solved using appropriate break points (Li et al., 2014, 2016). The Solar PV units and micro wind generators were modelled and incorporated in the power flow as PV nodes (Sunderland et al., 2016) by considering the varying generation from these sources.

Even though there are plenty of methods developed to solve distribution system of radial and meshed topology, the unbalance associated with the distribution network is not addressed in many cases. The extension of balanced power flow methods may not work as far as decoupling is done properly. And also most of the methods are not designed to handle the renewable energy sources. A power flow algorithm that can include the DG units efficiently is very much needed and such a power flow algorithm is developed as described in Chapter 3 and Chapter 4.

2.2 Review of techniques for Uncertainty Modelling of Solar Photovoltaic(PV) generation

The contribution of renewable energy sources like photovoltaic, wind, etc. in the power system is increasing day by day. This situation demands improved methods to deal with the fluctuating power output. There are many techniques to handle the uncertainty associated with the various power system parameters. A review of the decision making in uncertain situations for energy systems is given in (Soroudi and Amraee, 2013). They are mainly divided into Probabilistic approach, Possibilistic approach, Hybrid Possibilistic-Probabilistic approaches, Information gap decision theory, Robust optimization and Interval analysis. But as far as renewable energy generators are concerned, they are associated inherently with aleatory uncertainties and epistemic uncertainties (Helton and Oberkampf, 2004). Aleatory uncertainties are caused due to inherent variability in the system behaviour. Imprecision due to lack of knowledge and information on the system which are referred as epistemic uncertainty (Helton and Oberkampf, 2004). In the case of PV generation, the solar irradiation falls in the category of the aleatory uncertainty and the operational parameters such as $= I_{MPP}, V_{MPP}, V_{OC}, I_{SC}, N_{ot}, Kc, T_a$ which are provided by the manufacturers and end users falls in the category of epistemic uncertainty (Li and Zio, 2012).

The PV source modelling scheme for representing the source uncertainty is mainly divided into three types which can be categorized as Time series based method, Probabilistic methods and Stochastic methods. Time series based methods use different types of models such as regression, Unobserved Component Models (UCM), Autoregressive Integrated Moving Average (ARIMA), Neural Network and transfer function using cloud cove index, etc. The suitability of these models in predicting the global horizontal irradiance (GHI) of six different sites at resolutions of 5,15,30 and 60 minutes is compared in (Reikard, 2009). It is found that, except for high resolution, ARIMA model gave better performance than other models.

Based on the results from (Reikard, 2009), Yang *et al.* used three different time-series forecasts to predict the hourly solar irradiance of various components of solar irradiance such as global horizontal irradiance (GHI), diffuse horizontal irradiance (DHI), direct normal irradiance (DNI) and cloud cover (Yang et al., 2012). In all the three forecasts, ARIMA model is used to predict the irradiance components. It was found that, considering the effect of cloud conditions gave more accurate forecasts. The Time series based methods use enormous amounts of data gathered at the location where the PV source is installed in order to predict the variation of the solar irradiance of that particular location. Therefore the modelling becomes a difficult task.

Probabilistic methods involve the generation of random numbers that features the behaviour of historical data. The most important probabilistic method is Monte-Carlo simulation. Some authors have also used Probability Density Functions (PDF) such as Beta, Weibull, Log-Normal, etc. for modelling solar irradiance. Abdelaziz *et al.* used Monte-Carlo method for modelling stochastically dependent renewable energy based distributed generators (Abdelaziz et al., 2015). Wind energy generators and PV source are considered as DG sources and the stochastic dependence between these and the system demand is modelled using Monte-Carlo method. The stochastic dependence between the random variables is expressed in terms of rank correlation coefficient. A similar approach was used in (Mohamed and Hegazy, 2015) for modelling the solar irradiance. An algorithm based on Monte-Carlo (MC) method is used in developing a model for PV based DG system. The disadvantage with the MC method was the convergence problem associated in dealing with large amount of data.

Another prominent method based on probabilistic method is the usage of appropriate probability distribution functions such as Beta PDF, Weibull PDF, etc. In (Salameh et al., 1995), three distributions, namely Weibull, Log-Normal and Beta were used to model the 30 year solar irradiance and it was found that the Beta distribution gives the best fit. Beta distribution was used to fit 5 minute-averaged solar radiation indices (Assuncao et al., 2003) and (Ettoumi et al., 2002) used Beta distribution to process the daily global radiation. It is also found that the statistical features of the solar irradiance can be best described by the Beta distribution functions. The same distribution is used by several authors to model the uncertainty associated with the solar PV generation for optimally planning the DG integration (Atwa et al., 2010; Soroudi et al., 2012). In (Atwa et al., 2010), Beta PDF was used in generating a probabilistic generation model to minimize the energy losses in the distribution system. Here the data obtained for three years is divided into seasons and used to model the solar irradiance uncertainty. Also based on capacity factors, four different types of modules were analyzed to check their suitability for the selected site. Also the seasonal variation in energy losses was also estimated so as to find the share of PV units in the hybrid DG system so as to minimize the energy losses. Soroudi *et al.* used Beta PDF to model the uncertainty of solar irradiance and an unsymmetrical two-point estimate method is used to handle this uncertainty in the planning of DG sources (Soroudi et al., 2012). Similarly Beta PDF is used to model the probabilistic nature of solar irradiance in a DG planning study (Kayal and Chanda, 2015) so as to optimally allocate DG units in the distribution system.

Stochastic methods such as Markov process, neural network and fuzzy based methods can also be used to model the power output and the uncertainty associated with PV source. A Hidden Markov model was used for modelling the daily global irradiance in (Hocaoğlu, 2011). Here the cross dependency of irradiance and temperature are considered using a dual parameter based approach. The cross dependency is accommodated with the help of an algorithm called the Viterbi decoding algorithm. In addition, stochastic methods such as neural network (Kashyap et al., 2015) and fuzzy methods (Wang et al., 2016) are also used in predicting the solar irradiance for short and long term basis.

Solar irradiation can be efficiently modelled by a probabilistic distribution (e.g. Beta distribution) when sufficient data is available. Most often, historic solar irradiation data are available from NREL (National Renewable Energy Laboratory) site, and therefore probability representation is the best suited. There are several literatures which shows that Beta distribution is the best fit for solar irradiance. Therefore Beta PDF is a simple and efficient method to model the uncertainty associated with the solar irradiance.

2.3 Review of Techniques for Optimal Distributed Generation Placement

The optimal Distributed Generation Placement (ODGP) has become increasingly important in the recent years because of the widespread integration of the DG sources into the distribution network. There are a plenty of works done in order to determine the best location for DG installation with the suitable capacity. The difference comes in the methods adopted for ODGP. The methods can be broadly classified as Analytical methods, Numerical methods and Heuristic methods. Analytic methods uses simple analytic expression to calculate the most beneficial DG size and capacity based on some rules of thumb. Numeric methods incorporates techniques likes Dynamic Programming, Non linear programming etc. in order to determine the best size and suitable location for DG installation. Heuristic methods utilizes heuristics algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc. to solve the integration of Distributed Energy Resources(DER). All these methods with the related works done are reviewed below.

2.3.1 Analytical Methods

Analytical methods use simple analytical expressions to solve the Optimal DG placement problem. One of the earlier work done in this was by making use of a technique called "2/3 rule" (Willis, 2000). It is suggested to install a DG unit of 2/3 capacity of incoming generation at 2/3 of the length of the line. The method is basically based on Zero point analysis which is the point on the feeder where power flow due to DG output is zero. This method can therefore be applied only for a distribution system with uniform loadings.

Analytical expressions for radial and meshed distribution networks were developed in order to determine the suitable location for DG installation in (Wang and Nehrir, 2004). The objective of DG integration was to minimize the power losses of the system with voltage deviation within limits. The parameters of the overhead transmission line is assumed to be uniform in this case and the simulations are carried out for DG integrated systems with loads of time invariant and time variant characteristics. The algorithm is validated using 6-bus networked system and also for IEEE 30-bus system.

Another method based on exact loss formula was developed in (Acharya et al., 2006) for optimally integrating the DG sources in the distribution network. Here analytic expressions are used to calculate the power loss in the distribution system while integrating DG sources. The sizing and placement of DG is based on the simultaneous maximum demand when the losses are maximum. The methodology is tested for three different distribution systems of varying size and complexity. The limitation of the method is that it is suitable for a distribution system with a single DG.

The micro generation in Low Voltage(LV) networks cause reduction in the network losses and the resulting avoided losses were quantified by making use of analytical expression as described in (Costa and Matos, 2009). This helped to define the economic value related to the avoided losses of the micro generators. Thus optimum location and size of single and multiple DGs in the LV distribution network are determined. Another analytical method based on loss sensitivity factor was developed (Gözel and Hocaoglu, 2009) to determine the optimum size and location of the DG units in a radial distribution system so as to minimize the power losses of the system.

Analytical methods were also used in conjunction with other well known algorithms. (Lee and Park, 2009) used analytical method in combination with Kalman Filter algorithm for determining optimal location and size for DG installation. The location of the multiple DGs are based on the distribution factor and load concentration buses so as to minimize the total losses of the system. The size of the multiple DG units are determined using Kalman Filter algorithm.

In addition to the determination of size and location of DG units, ancillary service such as reactive power, power factor, etc. can also be optimized while integrating DG sources. Analytical expressions were developed for finding out the optimal size and power factor of the DG units in a radial distribution system so as to minimize the losses in the system in (Hung et al., 2010). The power losses in the system were estimated using Exact loss formula and the DG units considered were capable of generating both real power and reactive power. The same work was improved by using an Improved Analytic method to accommodate multiple DG units (Hung and Mithulananthan, 2013).

An analytical method based on the change in real and reactive power components was used for optimal allocation of DG units in the distribution system (Naik et al., 2015). The optimal size of the DG unit is determined first which is followed by finding the optimal location for their installation so as to minimize the losses. A similar approach was used in (Viral and Khatod, 2015) where the location for DG installation is determined first followed by the estimation of optimal size of the DG unit. The analytical method is developed based on a loss saving equation developed from the losses saved due to DG integration. But these methods considered only balanced distribution feeders.

An analytical method was used so as to optimally allocate DG sources in the distribution network without the formation of bus impedance matrix in (Tah and Das, 2016). Two types of novel buses which are called as P

buses and PQV buses were considered. P buses were specified by real power and were selected based on loss reduction. The voltage at the PQV buses was controlled remotely by connecting shunt capacitors at P buses. The analytical method was derived based on a mathematical expression so as to minimize losses in IEEE 33-bus and 69 bus distribution system.

Optimal locations and sizes of multiple DG units were determined simultaneously but separately using an analytical method in (Shahzad et al., 2016). A Load Concentration Factor (LCF) was used to determine the optimal location for DG placement and exact loss formula to estimate the size of the DG unit. The operational power factor is estimated using an exhaustive method which helps in achieving more loss reduction and better voltage profile compared to the other methods. Since the process does not involve iterations, computationally the method found to be more efficient.

2.3.2 Numerical Methods

There are several numerical techniques like Gradient Search, Non-linear programming, Sequential Quadratic Programming, etc. to determine the optimal integration of DG sources into a distribution network. The optimal placement of DG sources can be formulated as a Non-linear programming method and several numeric techniques can be used to solve the same. Some of the techniques are discussed below.

a. Gradient Search Algorithm

A gradient search based generalized optimization algorithm for optimally allocating the distributed energy resources in distribution, sub transmission or transmission system at the selected nodes was proposed (Rau and Wan, 1994). Three objective functions, namely minimization of losses, minimization of Var injection and the minimization of the line loading were considered individually and optimized using a second order algorithm with the transformation of variables. The algorithm is compared for the convergence with the reduced gradient method giving a superior convergence characteristics.

b. Linear Programming

Linear Programming was also used to address the problem of optimum allocation of Distributed Energy resources (DERs). The fundamental concept was to approximate the resulting power flow as a Linear Programming Problem. This is done by using linear sensitivity factors that characterize constraints on voltage, thermal and short circuit limits which are determined from the AC power flow (Liew and Strbac, 2002). The resulting Linear Programming Problem (LPP) is solved for maximizing the capacity of DG subjected to various constraints.

Linear programming can be considered as a robust optimization method which possess a high potential for solving Optimal DG allocation problem by utilizing the AC optimal power flow as a means for formulating the LPP. Linear programming was used to maximize the energy harvested from a portion of the network with the optimal allocation of DG where non-firm DG access to the network is also considered (Keane and Malley, 2007). The work was extended in (Keane et al., 2009) by employing AC load flow sensitivities for optimizing the allocation among curtailment of adjacent wind farms.

c. Sequential Quadratic Programming

One of the earlier works using Sequential Quadratic Programming (SQP) for ODGP was proposed in (Vovos et al., 2005) for optimizing the cost function. The optimization is done by formulating the problem as optimal power flow and solving the same by SQP by taking into account the fault level constraints.

An improved SQP was used in (AlHajri et al., 2010) to optimally allocate DG units. The location of DG units was determined using all possible combination search approach. The problem of determination of the DG rating is formulated as a Non-Linear optimization problem and solved using Fast Sequential Quadratic Programming (FSQP). But the fault level constraints were not taken into account here.

The optimal allocation problem involving the minimization of cost and losses was formulated as a non linear problem, and solved using Sequential Quadratic Programming (SQP) in (Darfoun and El-Hawary, 2015). The SQP gives a pareto-set of optimal solution and the decision is taken using fuzzy decision theory. The multiple objective functions were taken using the weighted-sum method. The algorithm is tested on a 15-bus distribution system to check the effectiveness.

d. AC Optimal Power Flow and Mixed Integer Non Linear Programming

AC optimal power flow is a well known analysis technique that is often used for solving economic dispatch problem. The AC optimal power flow, which is basically a Non Linear Programming (NLP) problem can also be used for solving the problem of Optimal allocation of DG sources.

Optimal power flow was used to maximize the generation capacity in (Harrison and Wallace, 2005) by modelling fixed power factor loads as negative loads and by performing negative load shedding. The constraints on voltage limits and thermal limits were also taken into account while performing the optimal power flow.

The determination of optimal capacity at predetermined locations was done with the help of optimal power flow in (Vovos et al., 2005) taking into account the fault level constraints. The allocation of DG sources is based on their respective cost functions and the limits on fault level is taken as an additional constraint. The algorithm was improved for conducting optimal generation planning by directly incorporating the fault level constraints in OPF (Vovos and Bialek, 2005). This is done by converting the fault level constraints into non linear inequality constraints which can be directly introduced in the optimization process.

The above mentioned studies emphasis only on thermal and voltage limits without considering the other network aspects. In fact, the flexibility provided by AC OPF allows an insight into other complex aspects also. Incorporation of multiple periods to deal with the variability and the coincidence of renewable energy generation and demand, advanced control strategies such as coordinated voltage control, adaptive power factor and generation curtailment are a few. These characteristics were embedded in (Ochoa et al., 2010) to determine the maximum DG capacity that can be allotted.

The capacity of the network to accommodate new generation under security constraints was discussed in (Dent et al., 2010a). The analysis is done using OPF in order to maximize the generation capacity. The reduction in network capacity to accommodate new generation by imposing the security constraints is validated using IEEE reliability test systems with $N-1$ security constraints and can be extended to systems with any number of constraints. The algorithm was modified to include constraints on voltage step change due to DG interconnection (Dent et al., 2010b). The voltage step changes that occur while disconnecting a DG from the network are taken as constraints and are incorporated in OPF. It is found that progressively wider step changes enable greater amount of DG to be connected in the distribution network.

The time varying characteristics of the DG sources, renewable energy and its influence on energy loss minimization was investigated in (Ochoa and Harrison, 2011). Coordinated voltage control and dispatchable DG power factor were also incorporated in OPF to analyze the extra energy loss benefits. The trade off between the energy losses and generation capacity was also considered which was proven to be an efficient technique by incorporating most of the complex characteristics of the network into OPF.

The NLP formulated AC OPF do not have the capability to incorporate integer variables such as tap positions or discrete values of DG capacities. But this disadvantage can be overcome by considering a Mixed Integer Non Linear Programming approach which would restrict the size of the problem based on the solution method adopted. Such methods can also be used in DG planning situations. An integrated distribution network planning model based on MINLP was implemented by (El-Khattam et al., 2004) in hybrid electricity markets as an alternative to ODGP by using heuristic cost-benefit analysis. The heuristic cost-benefit analysis aims to obtain DG sizing and siting so as to minimize discoś investment and operating costs as well as payment toward loss compensation. In addition to the optimal site and size the DG operating hour was also determined according to the given load-curve scenario.

The nodal price and line loss sensitivity were used as economic and operational criteria so as to select zones for placing DG units in pool based electricity market (Kumar and Gao, 2010). The zone with maximum variation in the aforementioned criteria were selected for DG integration. The optimum size and number of DG units for these zones was found out using MINLP technique. The optimization is done for both pool based and hybrid electricity market. The energy cost and the losses were also analyzed for the DG integrated distribution system.

A probabilistic planning method was used in order to optimally allocate different types of DG units in a distribution network so as to minimize the energy losses of the system (Atwa et al., 2010). Here a probabilistic generation-load model was developed to simulate all possible operating conditions considering the discrete size and the allowable maximum penetration of DG units. The same approach was applied for minimizing energy losses in a wind based DG system where wind power generation is modelled using Rayleigh PDF. The Optimal DG planning problem was then formulated as a MINLP problem taking into account the uncertainty of the DG units. The algorithm was validated for rural distribution feeder for all possible combinations of DG units.

The MINLP was formulated in two stages so that multiple objectives can be taken into account (Porkar et al., 2011) for minimizing the total cost and maximizing the total system benefits. The minimization of the total cost versus investment payback is done in the first stage followed by maximization of total system benefits in the second stage. The effect of DG implementation under different distribution conditions is simulated by taking into account different DG types.

Another objective function that can be taken into account is the voltage stability margin. An attempt to determine the optimal DG location and size was done in (Al Abri et al., 2013) using voltage stability index based method. The candidate buses for DG installation are selected based on the sensitivity to voltage. The probability of load and DG units are taken into account while sizing the DG units. For optimizing the DG unit allocation, it is formulated as a MINLP so as to improve voltage stability margin considering the probabilistic nature of the renewable energy resources and load.

In (Kaur et al., 2014), the optimal DG allocation problem was divided into siting planning model and capacity planning model so as to minimize losses in the distribution system. The first phase of the allocation problem is solved by making use of sensitivity analysis and the capacity planning formulated as MINLP is solved using integrated Sequential Quadratic Programming and Branch and Bound algorithm.

A MINLP approach is used in (Kumar et al., 2016) to solve optimal allocation problem in a pool based electricity market with PV units. The solar PV units were incorporated with their uncertainty described by Beta PDF. The PV integrated system is analyzed for a 24-bus test system in a pool based electricity market. The algorithm is found to be effective for systems with limited number of buses which are of balanced nature.

e. Dynamic Programming

A novel methodology based on dynamic programming was presented in (Khalesi et al., 2011) for optimal allocation of DG sources in the distribution network so as to minimize the total losses in the system along with a view to enhance reliability and voltage profile of the system. The time varying characteristics of the loads and the prices of energy were also taken into account for the simulation to make the results more realistic. All the objectives were based on a cost-benefit form and simulated in a test network to validate the results.

f. Ordinal Optimization

Ordinal Optimization can also be used for optimally allocating the DG units in the distribution network. The ordinal optimization was used for specifying the location and capacities of the DG units such that a tradeoff between loss minimization and DG capacity maximization is achieved (Jabr and Pal, 2009). The objective function is formed using LP method and the problem was solved using optimal power flow to find out the best alternative for DG planning.

g. Exhaustive Search

In the case of ODGP problem, when a single technical issue such as voltage rise or losses to be addressed, exhaustive search would be beneficial. In the case of exhaustive search, a number of technical issues and constraints can be clubbed so that the formulated objective function includes various technical and non-technical parameters or indices. This type of methodology was adopted by various researchers. An attempt was made by Chradeja *et al.*, to quantitatively assess the technical benefits of Distributed Generation (Chiradeja and Ramakumar, 2004). Indices for voltage profile improvement, line-loss reduction, environmental impact reduction and DG benefit were proposed and the distribution network with DG was analyzed with these indices. Similarly, a multi objective performance index was developed based on various indices by providing proper weights for these indices (Ochoa et al., 2006) and the performance of the system is analyzed for IEEE 34-Bus distribution feeder.

The reliability aspect of the DG integrated distribution system is very important and can be used to develop indices (Zhu et al., 2006). The optimization of DG location and sizing was done so as to minimize the power loss and maximize the system reliability. The reliability is analyzed in terms of system average interruption duration index based on set theory. The optimization was performed considering the time varying load patterns and economic impacts.

A fault in the system is often characterized by reconfiguration of the system. The resulting network was used to analyze the effect of DG in the distribution network (Kotamarty et al., 2008). The objective of the study was to find the optimal locations for DG installation that resulted in the least voltage deviations. The changes in the voltage profile with DGs placed at different locations of varying size before and after the occurrence of the fault in an unbalanced IEEE 37-bus distribution feeder are analyzed. The results of the contingency analysis were used to determine the optimal location of

DG in order to obtain the minimum voltage deviations.

The algorithm proposed in (Ochoa et al., 2006) was improved in (Ochoa et al., 2008a) so as to include time varying characteristics of generation. The time varying characteristics of the demand and distributed generation is represented using a multi-objective performance index that takes into account the hourly variation of the load and wind power generation. This can be useful in deciding the connection points where DG is to be inserted in the distribution network without affecting the normal working condition of the network.

Recently an exhaustive search method was used by (Mohd Zin et al., 2015) to determine the size and installation location of DG units. Instead of finding the optimal size of DG units to be installed, a new method for size optimization is proposed by installing small sized DG units which are called as modules with a provision to incorporate more than one module at each bus. The optimization is done so as to minimize the losses and to improve the voltage profile. The algorithm is tested on IEEE standard test systems such as IEEE 6-bus, 14- bus and 30-bus test systems.

2.3.3 Metaheuristic Methods

Metaheuristic method is defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space. In meta heuristics, the near optimal solutions can be found by using various learning strategies which helps to structure information (Glover and Kochenberger, 2006). The meta heuristic techniques can be used to model and include various technical and non-technical issues associated with various power system optimization problems. The benefits of such methods is their ability to accommodate mixed integer problems and that they do not require the closed formulation of the different aspects as in classical optimization techniques. Such heuristic methods can be used for maximizing the efficiency of distribution system incorporating several objective functions. But they require fine and careful tuning of the optimization parameters so that convergence can be achieved with minimum computational time.

The most important disadvantage of such techniques is their inability to find the global optimum which is most often countered by performing multiple runs. They provide a reasonable solution without guaranteeing how good the solution is. In addition to a single optimum point, they provide near optimal alternatives which increases their utility in DG allocation problems. This is because the DNOś have little control over DG integration and different planning alternatives may be considered to minimize uncertainty and risks.

There are numerous metaheuristic algorithms. Genetic Algorithms (GA), Act Colony Optimization (ACO), Artificial Bee Colony Optimization (ABC), Particle Swarm Optimization (PSO), Simulated Annealing (SA) are a few. All these algorithms have been used by researchers for solving DG planning problems. These techniques are discussed below.

a. Genetic Algorithm

Optimal DG placement was solved using GA or variants of GA by several researchers. One of the early study that was done by (Kim et al., 1998) to optimally size the DG units in the distribution system for maximizing the potential benefits by the integration of any DG type using GA and improved Hereford ranch algorithm (variant of GA). The benefit is expressed as a performance index for minimizing the losses in a meshed distribution system. Also, Borges *et al.* used GA in combination with other methods to evaluate the system reliability, losses and voltage profile to optimize the size and location of DG units (Borges and Falcao, 2006). For the benefit cost relation, the benefit is calculated based on the losses and the cost is based on the investment and installation.

A similar study was carried out by (Teng et al., 2007) that use GA to find the best trade off between the cost and the benefits of DG placement. A value based method is used for allocating the DG units optimally for achieving power loss reduction, power cost reduction and reliability improvement. It is seen that, with the installation of DG types of proper size at proper locations can contribute to the improvement in service reliability and efficiency of the distribution system.

(Singh and Goswami, 2009) used a genetic algorithm based method to determine the optimal size and location of the DG units in radial as well as networked distribution system so as to minimize the power loss. Also the placement of single and multiple DGs along with different load patterns such as increased, centralized and uniform loadings is also considered. The effect of load models is taken into account and a multi objective performance index was developed so as to formulate the DG placement problem (Singh and Verma, 2009). The Integration of DG units at multiple locations was done (Shukla et al., 2010) using GA based methodology for achieving minimum loss configuration. For determining the optimal location of DG units, the loss sensitivity approach was used. The benefits from DG installation such as technical benefits and economic benefits were quantified from the utility and customer point of view respectively. The algorithm is validated using IEEE 33-bus and 69-bus distribution system.

GA can also be used to handle multiple objectives such as profit maximization, loss reduction, voltage profile improvement, etc. simultaneously. (Singh and Goswami, 2010) used a methodology based on the nodal pricing for optimally allocating distributed generation for profit, loss reduction and voltage profile improvement. The voltage rise issue associated with the integration of DG in a weak distribution network is also addressed in the algorithm. Another multiobjective optimization approach based on GA was used (Shaaban et al., 2013) to optimally allocate different type of DG units into the distribution system. The optimization is done so as to maximize the savings in investment costs, minimize the cost of energy and minimize the system interruption costs. The uncertainty associated with the load and generation is modelled by combining probability generation and Monte-Carlo simulation model.

Other heuristic approaches were also used along with GA in order to avoid premature convergence and reaching local minima. (Celli et al., 2005) used a multiobjective optimization approach based on GA and e-constrained method for optimal siting and sizing of DG sources. The various objective functions considered were, the cost of network upgrading, cost of power losses, cost of energy not supplied and the cost of energy required by the served customers. The optimization is carried out by finding non inferior solutions using GA and e-constrained method which helps to achieve optimality in the development and operation of the power system. A similar work was done in (Carpinelli et al., 2005), in which ODGP is formulated as a constrained multi objective and non differentiable optimization problem. Here a double trade off method is used where the multi objective ε-constrained method is used to find the possible solution in the first trade off. In the second trade off, the most robust solution is found out. The solution technique used here are GA and ε-constrained method i.e For optimum allocation of DG units, GA is used and ε-constrained method is used for achieving Pareto optimal solution.

In (Gandomkar et al., 2005), optimal DG siting and sizing was done with the help of the integrated use of Genetic algorithm and tabu search. The objective is to reduce the power losses and also the harmonic power losses by optimally placing the DG source. Here GA is used to optimally allocate the DG sources in the distribution system and tabu search is incorporated in GA so as to avoid the local minimum and premature convergence of GA. (Harrison et al., 2008) used a hybrid method employing GA and OPF for optimizing the location and capacity of DG sources. Here GA is utilized in searching a large range of combinations of locations and OPF was utilized in finding the available capacity for each combination. The chance of non-optimal solution due to GA and the search space limitations employing OPF alone are eliminated by employing the combined approach.

An Optimal Proposed Approach (OPA) method based on GA was presented in (El-Ela et al., 2010) to maximize the benefits of DG installation. Various objective functions including line loss reduction, voltage profile improvement, power flow reduction in critical lines, etc. are formulated as multiobjective optimization algorithm using weights with constraints using optimal proposed approach and solved using GA. Similarly, a combination of GA and Immune Algorithm was used by (Soroudi and Ehsan, 2011) for maximizing the benefits from DNO side as well as DG owners' side. The simulations are carried out by considering the load and wind power generation uncertainty associated with the system using two point estimate method. The formulated multiobjective problem is solved using Hybrid Immune Genetic Algorithm and is tested in various large distribution systems.

Most of the objectives which are crucial to the system were considered in (Singh and Goswami, 2011) by multiobjective DG placement that considered reliability, security, cost and operational aspects. Here an interactive trade off algorithm was used to obtain the optimal locations. This is based on e-constrained method and the formulated algorithm is solved using GA. The proposed method is validated for an existing rural distribution feeder with and without considering load models.

Non Dominated Sorted Genetic Algorithm (NSGA) (Deb et al., 2002) is an extension of Genetic Algorithm which is specifically intended for solving Multi Objective Optimization (MOO) problems. The main objective of NSGA is the improvement in the adaptive fit of population into paretofront regions with constraints on certain objective functions. NSGA and its variants NSGA-II have been used by several researchers in the optimal integration of DG sources. NSGA was used to find the optimal sites for distributed Wind Energy Generators in order to maximize the energy export and minimize the power losses and short circuit levels (Ochoa et al., 2008b). The variability associated with the load and the generation is also taken into account considering the voltage and thermal limits. A practical distribution feeder was considered for incorporating a single DG and multiple DG units with their optimal configuration.

NSGA-II was used for optimal allocation of DG units in the distribution network where Fuzzy numbers were used to represent the uncertainty associated with the load, electricity price and the power flow parameters (Haghifam et al., 2008). The objective is taken so as to minimize the investment and operation cost, technical risk due to uncertainty in load and economic risk due to uncertainty in electricity price. The Pareto optimal solutions were found using NSGA II. Another efficient algorithm based on Multi-objective NSGA II was used for optimizing the location of DG units in the unbalanced distribution network so as to optimize the technical as well as economic criteria in (Dehghanian et al., 2013). The loss reduction, system reliability improvement as well as minimization of cost were considered as the criteria for optimizing the location. The uncertainty associated with the stochastic generation from DG sources is modelled and incorporated using Point Estimate Method (PEM). The method thus gave a reliable solution by balancing the trade-off between the technical and economic criteria. The algorithm was validated for IEEE 37-bus distribution feeders.

The earlier versions of NSGA II were improved in (Sheng et al., 2015) by improving the mutation and crossover procedure so as to minimize losses, minimize voltage deviation and to maximize the margin for voltage stability. The decision from the Pareto set is obtained by making use of fuzzy membership function which helped in achieving the best population diversity and therefore the solution returned better solutions compared to other multi objective approaches. The algorithm is validated for several balanced distribution feeders of varying complexity.

b. Tabu Search Algorithm

One of the important disadvantages of GA is that the chances of converging into local minima is more. This can be overcome in a method called Tabu Search (TS) (Glover, 1989). It has the capability to expand its own search space and therefore prevent cycling of some solution and therefore reduces the risk of being trapped in local minima.

There are several researches in which TS was used for integrating DG sources in the distribution system. One of the earlier work was done by (Nara et al., 2001) in which Tabu Search algorithm was used for optimal placement of DG sources in distribution system with a view of reducing the power loss in the distribution system. The implementation of the Tabu Search algorithm is done using decomposition or coordination technique. The capacity and location of each DG unit are determined using separate Tabu Searches. The algorithm is validated for a distribution feeder in which industrial, commercial and domestic loads coexists.

Optimal allocation of reactive sources was also considered along with DG sources in (Golshan and Ali Arefifar, 2007), which is formulated as a combinatorial problem and solved using Tabu Search algorithm. Here the amount of DG sources and reactive power sources are computed to make up a given total of distributed generation for minimizing losses, line loadings and total required reactive power capacity. The tap positions of control variables are considered as the control variables in the optimization problem. The proposed algorithm is validated for IEEE 33- bus distribution system and also for a meshed 6-Bus system.

(Novoa and Jin, 2011) formulated ODGP as a stochastic planning model to allocate wind power generators in the distribution network to minimize the life cycle cost of the DG system satisfying the reliability criterion. The capital, environmental and operational aspects are considered under the cost. The wind power volatility and load uncertainty are modelled using probability distributions. The continuous stochastic ODGP is solved using Genetic Algorithm and a combined TS and Scatter search.

c. Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm is inspired by bird flocking or fish schooling. It is based on the movement and intelligence of the swarm. PSO is also seen to be one of the heuristic methods that is widely used in solving ODGP. PSO was used for optimal sitting and sizing of DG units in distribution systems with a view of achieving voltage profile improvement, loss reduction, and THD (Total Harmonic Distortion) reduction in distribution networks (Sedighi et al., 2010). Fitness value sensitivity of PSO algorithm was also considered while conducting load flow and THD calculation of the system.

The DG planning problem formulated as a multiobjective optimization problem is solved using PSO (El-Zonkoly, 2011) considering load models. The multi objective function is transformed into a single objective function using weight method. Various performance indices, including voltage profile index, short circuit index, MVA index, etc. were used to formulate the problem as multi objective taking into account the various technical constraints. Similarly, an improved reinitialized social structure PSO was used for solving multiple distributed generation placement in a microgrid system (Prommee and Ongsakul, 2011). The optimal sizes and locations of DG placement are determined so as to minimize the power loss of the system within real power, reactive power and voltage limits. Five different combinations of microgrid systems are considered for DG installations with real and reactive power capabilities. The algorithm is compared with basic PSO and various methods in the literature and found to have superior performance.

Hybrid heuristic methods involving PSO was also been suggested by various researchers for solving DG planning problems. A novel combined Genetic algorithm-PSO was presented for optimal location and siting of DGs in distribution system so as to minimize the losses, better voltage regulation and improve the voltage stability adhering to the system operating and security constraints in (Moradi and Abedini, 2012). Here GA is used to search the site for DG and the size is optimized by PSO. The proposed algorithm is implemented for IEEE 33-bus and 69-bus radial distribution system. The proposed algorithm found to give optimized solutions for the distribution system.

A hybrid method employing discrete PSO and OPF was proposed in (Prommee and Ongsakul, 2011) so as to optimally locate a large number of combinations of DG units. Here discrete PSO is used to optimally locate a large number of combinations of DG and OPF was used to determine the available capacity of DG so to maximize the dispatch from DG units. The proposed algorithm is validated using IEEE 30 Bus distribution system and found to have superior performance compared to other metaheuristic approaches.

(Pandi et al., 2013) used an approach based on PSO to simultaneously determine the penetration level of utility owned inverter based and synchronous based DG units, to achieve a maximum DG penetration level taking into account the standard harmonic limits and protection constraints. The proposed method is solved for IEEE 30-bus looped distribution system. The integration of inverter based DG units is limited by the constraints imposed by IEEE 519 standards on harmonic distortion and those of the synchronous generators was limited by the protection constraints. Another Hybrid PSO algorithm was proposed so as to solve the DG allocation problem to accommodate a single objective and multiple constraints (Aman et al., 2014). The objective function is considered so as to maximize the loadability at the same time minimizing the losses. The bus voltage limits and the line currents are taken as the constraints.

d. Ant Colony Optimization and Artificial Bee Colony optimization

Both ACO and ABC optimization mimics the dynamics of social insect population. The interactions are executed by observing various physical and/or chemical signs such as bee dancing in the case of ABC, level of pheromone secretion in ACO etc. This gives an insight into the behaviour of the social insect colony.

Optimal placement of DG units in radial distribution feeders was solved using population based artificial bee colony algorithm in (Abu-Mouti and El-Hawary, 2011b). The objective function is selected so as to minimize the real power loss of the system subjected to equality and inequality constraints. The proposed algorithm is tested for various test cases, including 33-bus and 69-bus radial distribution feeders to check the effectiveness of the algorithm.

Bee Colony Optimization was used for determining the optimal location, size and power factor of DG units so as to minimize losses considering various constraints on the system in (Sohi et al., 2011). The proposed algorithm is validated with a practical distribution feeder in Iran. (Wang and Singh, 2008) used Ant Colony Optimization to optimally locate the recloser or DG placement in radial distribution system so as to maximize the reliability of the system. For this purpose a composite reliability index with System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are developed. Simulations are carried out in two practical distribution feeder for validating the effectiveness of the algorithm.

A heuristic method by combining the ACO and ABC algorithm was used for optimally allocating multiple DG sources in distribution system so as to optimize several objectives such as minimization of power losses, emissions, cost and improvement in the voltage stability margin (Kefayat et al., 2015). The global search capability of ABC and the local search capability of ACO algorithms could be simultaneously achieved by combining these two algorithms. Probabilistic load flow is performed and the effect of the stochastic parameters was taken by using Point Estimate Method (PEM). The algorithm was validated for IEEE 33- bus and 69-bus distribution systems.

e. Practical Heuristic algorithms

Two different heuristic algorithms were used to optimally place DG units in a competitive electricity market (Gautam and Mithulananthan, 2007). These heuristic methods are based on Locational Marginal price (LMP) ranking and consumer payment ranking. The aim of the optimal DG placement was to simultaneously maximize the social welfare and to maximize the profit of the DG owner. LMP is used as the basis for the candidate locations for DG installation. The proposed algorithm is validated for IEEE 14- Bus system. It was observed that for DG installation at a particular node, the LMP for social welfare maximization is comparatively lesser that the LMP for profit maximization.

A heuristic iterative algorithm based on continuation power flow was used to optimally place the DG units in the distribution network (Hedayati et al., 2008). The iterative algorithm is based on the determination of network buses which are most sensitive to voltage collapse. This is based on the bifurcation theory which leads to the execution of Continuation power flow. The algorithm is tested in IEEE 34 bus distribution system for reduction of losses, improvement in voltage profile and increase of power transfer capacity and maximum loading.

A probability based approach was used in (Khodr et al., 2010) to find out the optimal location for DG installation taking into account the hourly load changes and the daily load cycle. For different hourly load scenarios, the load centers are calculated and these location points were properly weighted to calculate the best fit probability distribution function. A heuristic approach is used to calculate the regions of the higher probability for DG location.

The methodology was also applied to a real case applying different bivariate distribution functions.

In (Ghosh et al., 2010), a heuristic iterative technique based on the N-R method of load flow was used for optimally sitting and sizing DG units in the distribution system. This helps in optimizing the weighing factor of the objective function, thus maximizing the potential benefits. The objective function is selected so as to minimize both loss and the cost of the system. The optimal siting and sizing improve the voltage profile at the load buses. The proposed algorithm was validated for IEEE 6-bus, 14- bus and 30-bus distribution system.

Another heuristic algorithm was used to optimally place DG units in small distribution network (Koutroumpezis and Safigianni, 2010) by considering various technical constraints. The ODGP was solved using reconfiguration of the network structure. In cases where reconfiguration was not possible, the algorithm optimally distribute the maximum allowable penetration of the DG units in predetermined or random network buses. The DG deployment problem was approached by considering the location and size selection independently in (Abu-Mouti and El-Hawary, 2011a). In the first stage, sensitivity test was conducted for candidate location selection and a heuristic curve fitting technique is used to find out the optimal size of DG units at the preselected DG locations. The algorithm is validated for IEEE 33-bus and 69-bus distribution systems.

A heuristic method based on Continuation Power Flow (CPF) was presented in (Hemdan and Kurrat, 2011) for optimal DG placement so as to enhance the Voltage Limit Loadability (VLL). The idea was to disperse the available power from DG between recommended nodes so as to maximize the system benefits. The CPF is implemented for 85 bus system using PSAT. The results showed some recommended nodes for connecting DG units so that the increased load demand can be met.

A heuristic approach was used in (Hamedi and Gandomkar, 2012) to place a single DG based on the power loss index or the Energy Not Supplied (ENS) index. Here the reliability, power loss and power quality are evaluated in the presence of distributed generation considering load variations over time. The optimum locations for DGs are found out by optimum reliability and power loss indices. Power quality was evaluated using total harmonic distortion current (ITHD) and compared with ITHD in the case where DG is absent. ENS cost is used as the index for reliability. The test system under study was an actual distribution network with 14952 customers for increasing the system reliability and reducing the losses.

Modern heuristic methods such as bat algorithm, Imperialist competitive algorithm, Big-bang crunch optimization algorithm, Shuffled frog leaping algorithm, Bacterial foraging algorithm, etc. were also proposed by some researchers for optimal allocation of DG units. Bat algorithm is based on the behaviour of a group of bats while seeking the best location for the available food. Bat algorithm was used in (Yammani et al., 2013, 2016) for optimizing the size and location of multiple DG units so as to improve the voltage profile, minimize losses and also to maximize the capacity. The multiple DG units such as solar, fuel cell and wind turbine generators were also considered. The optimization is done under the conditions of future load enhancement and considering different load models.

Imperialist Competitive Algorithm (ICA) is an evolutionary algorithm where the initial population is defined as a country (Xing and Gao, 2014). ICA was used along with GA for optimizing the size and location of DG units and capacitor banks in the distribution system (Moradi et al., 2014). In the first step, ICA is used to find the optimal size and location of DG units and capacitors in the distribution system. Afterwards GA is used to generate a new set of colonies and search spaces of all the solutions. The algorithm is used to minimize losses, improve voltage regulation and to increase the voltage stability. The proposed algorithm is validated for IEEE 33-bus and 69-bus distribution feeders.

The Bacterial Foraging Algorithm (BFA) is an algorithm which mimics the behaviour of the bacterial foraging process of E-coli bacteria to search food so as to maximize the energy per unit time (Kowsalya et al., 2014). BFA was used for optimal allocation of DG sources so as to minimize losses, cost and voltage deviation. The optimal location for DG installation is selected based on the Loss Sensitivity Factor and BFA was used to determine the size of DG units. This algorithm was modified in (Devi and Geethanjali, 2014) by using Modified Bacterial Foraging optimization Algorithm for DG allocation. These algorithms are validated for IEEE 33-Bus and 69-bus distribution feeders without considering the unbalance of the distribution network.

Another optimization algorithm which was developed based on the food seeking behaviour a group of frogs called as Shuffled Frog Leap Algorithm (SFLA). The frogs have a tendency to leap to locations where maximum food is available. SFLA was used for DG allocation problem in (Yammani et al.,

2012) for loss reduction and cost minimization. The algorithm was validated for a 38-bus distribution system.

A comparatively newer algorithm called as Big Bang-Big Crunch algorithm is a nature inspired algorithm with excellent convergence characteristics and was used for Optimal DG allocation in (Othman et al., 2015). Here random points are generated by BB-BC in an orderly fashion and shrinks all these points to a single point. The second phase called as Big Crunch phase produces a single output called as Centre of Mass with several inputs. The algorithm is applied for balanced and unbalanced distribution feeders for power loss and energy loss minimization. Due to fast convergence the algorithm found to have better performance compared to the other meta heuristic algorithms.

There are plenty of methods that were used for optimal allocation of DG units in the distribution network. Analytical and numerical methods cannot be applied to large systems since their results are only indicative born out of assumptions. Heuristic methods are robust and therefore are premier to the analytical and numerical methods which makes it use widely. They use the entire search space to find out the optimal solutions and thereby provide the near optimal solutions. They are suitable for highly complex and large scale systems. But most of the heuristic methods are not so efficient in dealing with the uncertainty and stochastic output from the DG source. The thesis work proposes the use of stochastic learning algorithms for optimal DG placement that can effectively handle stochastic output of DG source.

2.4 Reinforcement Learning and Applications

Reinforcement Learning (RL) is a Neuro-dynamic programming that involves learning by continuous interactions with the environment (Sutton and Barto, 1998). The learning method in the case of Reinforcement learning is based on rewards and punishments. The objective of the reinforcement learning is to maximize the rewards received over time by selectively retaining the outputs. In reinforcement learning an agent continuously observes the current status of its environment which is referred to as 'state' and chooses an action from the set of possible actions. When an action is performed, the state transition occurs and the system moves to a new state and an immediate payoff or reward is obtained which depends on the previous state and the action performed. The aim is to maximize the long term sum of the reward. This is accomplished by exploiting the available information, at the same time exploring for new solutions. The balance between exploration and exploitation is an important aspect in reinforcement learning.

Reinforcement learning by combining the features of dynamic programming and supervised learning can be used to solve problems that do not have a mathematical model to start with. Reinforcement learning can be considered as an approximation to dynamic programming and can be used as an effective computational tool for building autonomous systems in various fields of control. Some of the applications of Reinforcement learning are discussed in the next section.

2.4.1 Game Playing

Temporal difference learning algorithms are widely used for game playing and its application for solving the tic-tac-toe problem is given in (Sutton and Barto, 1998). Reinforcement learning had been used to solve the game of Go by using the temporal difference learning algorithm (Silver et al., 2007). The game of Go consists of a board with black and white players and the aim is to place a single stone to an intersection on the board. The stone once played cannot be moved, but only captured. The adjacent stones with the same colour are called as blocks, and empty intersections adjacent to the block is called as liberty. The score of the player is the number of stones captured and the liberties. For solving this game, reinforcement learning with linear evaluation and large number of binary features were applied.

Reinforcement learning algorithm called as the Tabular sarsa alorithm was applied for solving First person shooter game (McPartland and Gallagher, 2011). In the first part, navigation controller is used to learn the strategy for path planning and in the second part, the combat controller was used to learn a strategy for beating the state-machine opponent. For both strategies, the reinforcement learning could be successfully applied.

2.4.2 Robotics Applications

Reinforcement learning methods were successfully applied for many robotic and autonomous applications such as autonomous helicopter control, autonomous driving control and robotic applications. The batch reinforcement learning algorithm was applied for solving a robotic soccer problem in (Riedmiller et al., 2009). The autonomously acting agents in reinforcement learning are exploited in controlling a robot for playing a robot soccer game. The batch reinforcement learning algorithm is found to have superior performance as compared to all other algorithms in solving the robot soccer game.

Mobile path planning problem was solved using the Q-learning algorithm in (Jaradat et al., 2011) in dynamic environments. In dynamic environments, the state space corresponding to the learning algorithm is infinite. The state space is redefined by limiting the number of states for solving the difficulty of convergence. By employing the algorithm the robot was able to reach the target without collision most of the time.

2.4.3 Power system Applications

The Automatic Generation Control (AGC) was modelled as a stochastic multi-stage decision making problem and is solved using reinforcement learning algorithm in (Ahamed et al., 2002). RL is capable of handling systems whose dynamics is not fully modelled and in the learning algorithm the control is evolved by observing system responses. RL algorithm with its features handled the AGC objectives more qualitatively and thus proved to be very effective in developing control strategies AGC.

The power system controllers such as Thyristor Controlled Series Capacitor (TCSC), static VAR compensators, etc. were applied in the power system network so as to improve the power system stability (Ernst et al., 2004). Such controllers require intelligent and systematic learning methods so that their decision making capability is improved which helps in the real time operation. The reinforcement learning algorithm is designed for offline mode of a dynamic brake controller and also for the online mode of TCSC so as to improve power system stability.

Reinforcement learning was applied to solve the Constrained Load Flow (CLF) problem so as to optimally control the reactive power in power system (Vlachogiannis and Hatziargyriou, 2004). The Q-learning algorithm is used to design control settings for reactive power compensating devices. The voltage magnitudes and angles were taken as the state vector, whereas the transformer tap position, shunt compensation settings were taken as the control vector. The power flows and the reactive powers of PV buses are considered as the constraint variables. The Q-learning algorithm gave better convergence characteristics compared to other CLF algorithms with optimal control settings. The algorithm is validated for IEEE 14 bus IEEE 136 bus bar system for CLF based reactive power control.

The economic dispatch problem was formulated as a multi stage decision making problem and was solved using reinforcement learning (Jasmin et al., 2011). Two RL algorithms namely, ε-greedy algorithm and pursuit algorithm are applied to distribute the power demand among various generating units so as to minimize the operating cost. An algorithm that takes into account of the transmission losses was also developed. The algorithm is validated for test systems with varying complexity and quadratic cost functions. The computational efficiency of the algorithm is found to be superior as compared to other algorithms with a capability to include stochastic real time cost data.

The RL algorithm for solving AGC was improved in (Yu et al., 2011) by using a stochastic optimal control strategy which considers NERCś Control Performance Standards (CPS). The long term delay control loop that occurs with thermal AGC plants are effectively tackled by multistep Q-learning algorithm. The RL based control strategies found to be effective in AGC by enhancing the robustness and performance at the same time ensuring CPS compliances. The relaxed control technique is also implemented by online tuning relaxation factors for controlling the degree of compliance and relaxation.

The real time measurements were processed and used to design a controller for power system stabilizers which is called as real-time close-loop wide-area decentralized power system stabilizers (WD-PSSs) (Hadidi and Jeyasurya, 2013). RL based PSS do not need any mathematical model or complete information of the system. The WD-PSSs were found to be effective in stabilizing the system after severe faults without tripping any generator or load area. Thus stability margin was increased, which enhanced the damping of oscillations. This framework is implemented on a sample power system which gave better results compared to other controllers.

An intelligent Maximum Power Point Tracking (MPPT) algorithm was developed for variable speed wind energy conversion systems based on reinforcement learning (Wei et al., 2015). The model free Q-learning algorithm is used to update the action-value pairs which helps in online learning of the controller. The optimum speed-power curve is then obtained which aids in fast real time MPPT control of WECS without knowledge of wind turbine parameters or wind speed information. The algorithm is validated by simulation as well as experimentation for a 1.5 MW DFIG and 200 W PMSG wind turbine.

2.5 Conclusion

A detailed review of various power flow algorithms for distribution network is discussed in Section 2.1. Most of the power flow algorithms neglect the unbalance of the distribution feeders and the handling of DG units in the distribution system which necessitates an efficient power flow algorithm that can incorporate DG sources in an unbalanced distribution network. The varying power output from DG sources such as PV source should also be taken into account by suitable uncertainty modelling. A review of various techniques used for uncertainty modelling of solar PV generation is discussed in Section 2.2. When sufficient data are available, probability representation is best suited for representing the uncertainty of the PV source. Numerous methods have been used by researchers for optimally allocating DG sources in the distribution network, which are discussed in Section 2.3. Each method has its own limitation in handling the optimal DG placement, but most of the methods lack the ability to handle stochastic data that exist in practical systems. Therefore, development of an efficient method that can handle stochastic data of DG sources and unbalance of the distribution network is still relevant. Reinforcement learning is a Neuro-dynamic programming that is efficient in handling stochastic data and are can be used to solve decision making problems. Various applications of Reinforcement learning are discussed in Section 2.4. The application of reinforcement learning algorithms for optimal allocation of DG units is to be investigated in the thesis. As a first step, the power flow algorithm for unbalanced distribution network is discussed in the next chapter.

Chapter 3

Power Flow Studies for Unbalanced Distribution System

3.1 Introduction

The efficient and reliable power system operation necessitates the knowledge of the steady state condition of the power system for varying load demand. The power flow study is an important and basic tool for any power system that gives an insight into the steady state behaviour and are used in the planning, design and operational stages. In the last few decades, there were considerable development in the solution algorithms and were successfully implemented for various systems. The major solution algorithms are Newton-Raphson method, Gauss-Seidal method and fast decoupled methods. These algorithms have been developed for the power transmission systems, but there are limitations in applying these algorithms for distribution systems. Under steady state conditions, transmission systems assumed to have balanced operation. In contrast distribution systems that are characterized by high R/X ratio and unbalanced operation. Such systems pose ill conditioned problems to Newton-Raphson algorithms whereas Gauss-Seidal method fails to converge for such systems. Therefore, robust and efficient solution algorithms for distribution systems is very much necessary.

An efficient and robust power flow algorithm for distribution systems should be capable of solving systems with any number of nodes which may be radial or weakly meshed in nature in which fluctuating DG sources or any number of unbalanced loads may be connected. There are plenty of algorithms that were developed in order to handle distribution systems which are thoroughly reviewed in Chapter 2. But most of the algorithms work on the assumption that the distribution network is balanced and is fed only at one point. Distribution networks are inherently unbalanced due to the unbalanced loads and the presence of DG sources. This requires a power flow algorithm that can handle unbalance in the distribution system and the DG sources if present. The algorithm should also be capable of handling the fluctuating power output from the DG sources without affecting the efficiency of the algorithm. The Forward-Backward sweep algorithm proposed by W.H Kersting is one of the algorithm that is used by several researchers with modifications due to its simplicity and robustness. The limitation of the method is that the algorithm is not designed to handle the DG sources by considering them as PV nodes. Hence an efficient and general power flow algorithm suitable for a DG integrated system is very needed for ensuring better steady state operation of the distribution system.

The contributions in the impact of DG sources in unbalanced distribution system are very less. Initial discussion on the handling of PV nodes in the unbalanced distribution system was given by several authors. To ensure better steady state operation of the distribution network, an efficient power flow technique with DG handling capability is very much essential. The chapter describes the proposed power flow algorithm which is able to handle PV nodes. For developing the power flow algorithm, it is necessary to model each and every component in the distribution network which is also described in the chapter. The proposed power flow algorithm uses the sweep algorithm using basic Kirchoff's laws with modification so that PV nodes can also be included in the algorithm.

3.2 Component Modelling of Distribution System

The modelling of various components of distribution feeder is a critical step in the analysis of the distribution system. The components of a distribution feeder may be either series or shunt. The shunt components include spot static loads, spot induction machines and capacitor banks. The modelling of overhead and underground line segments is important for the computation of impedance and admittance matrix. The final voltage transformation to customers load is provided by transformer banks, which make it important to model the various three phase transformer connections correctly. The maximum demand on the distribution feeder is determined by the loads connected

Figure 3.1: General Feeder Component

to it. Thus the models developed for the components is to be used in the iterative routine for power flow.

The sweep algorithm for solving distribution networks comprises two steps known as forward sweep and backward sweep. Forward sweep equations use KVL and helps in computing the new voltage at each bus as given by Eq. (3.1). Using KCL, the new updated currents through each branch is computed in backward sweep as per Eq. (3.2).

$$[VLN_{abc}]_m = [A] \cdot [VLN_{abc}]_n - [B] \cdot [I_{abc}]_n \tag{3.1}$$

The backward sweep equation gives

$$[I_{abc}]_m = [c] \cdot [VLN_{abc}]_n + [d] \cdot [I_{abc}]_n \tag{3.2}$$

where $[VLN_{abc}]_m, [VLN_{abc}]_n$ represents the value of voltage for nodes m and n respectively and $[I_{abc}]_m, [I_{abc}]_m$ represents the corresponding currents. The matrices A, B, c, d are the generalised matrices.

For conducting the power flow algorithm, the initial node currents are assumed as zero. Thus, using the forward-sweep, the no load voltages for all the nodes can be calculated. The backward sweep is carried out for

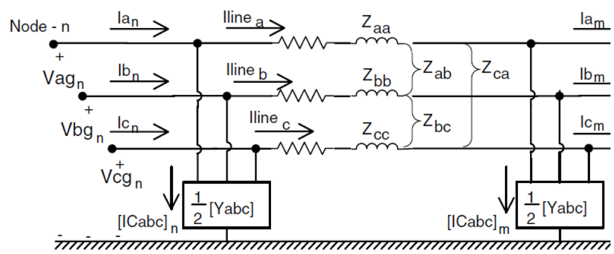


Figure 3.2: Three Phase Line Segment Model

calculating the currents at the end nodes and further progressing towards the source node by summing up the branch currents. The updated value of the currents is used in the next Forward sweep iteration for calculating the new value of voltages. This procedure is repeated until the difference in the voltages in two consequent iterations are within tolerance limits. The generalized matrices of A, B, c and d matrices should be modelled for all the series and shunt components using the appropriate equations (Kersting, 2012).

1. Three phase line segment model: The representation of a three phase line segment is shown in Fig. 3.2. This model holds good for three phase, two phase as well as single phase line by making the corresponding admittance values as equal to zero. From this exact model, the following equations can be written.

$$[VLG_{abc}]_n = [VLG_{abc}]_m + [Z_{abc}] \cdot [Iline_{abc}]_n \tag{3.3}$$

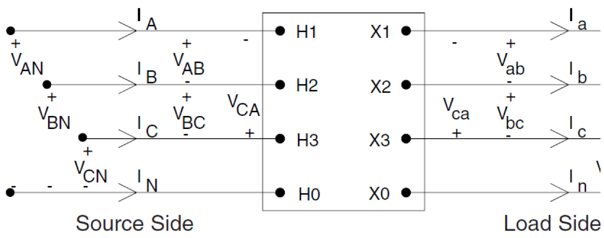


Figure 3.3: General Three Phase Transformer Bank

where $[I_{abc}]_n$ in (3.3) is given by (3.4)

$$[Iline_{abc}]_n = [Iline_{abc}]_m + \frac{1}{2}[Y_{abc}] \cdot [VLG_{abc}]_m \tag{3.4}$$

Equations (3.3) and (3.4) can be used form the generalized constant matrices A, B, c and d for the line segment.

2. Three Phase transformer models: The generalised transformer bank model is shown in Fig. 3.3. Here the upper case letters represent the source side, whereas the lower case letters denotes the load side. The forward and backward sweep equation for the transformer can be written as

$$[VLN_{ABC}] = [a_t] \cdot [VLN_{abc}] + [b_t] \cdot [I_{abc}] \tag{3.5}$$

$$[I_{ABC}] = [c_t] \cdot [VLN_{abc}] + [d_t] \cdot [I_{abc}] \tag{3.6}$$

where the matrices $[a_t], [b_t], [c_t], [d_t]$ in Equations (3.5) and (3.6) are functions of the winding turns ratio n_t which depends on the configuration of the transformer.

3. Capacitor Model: Capacitor banks either wye or delta are connected in the distribution system to help in achieving proper voltage regulation and for reactive power support. Capacitors can be modelled as constant susceptance whose values are given by

$$B = \frac{KVAR}{kV^2 \cdot 1000} Siemens \tag{3.7}$$

The susceptance can be used to find the currents injected which is given by

$$IC = jB \cdot V \tag{3.8}$$

In Wye connection IC and V denotes line currents and phase voltage whereas in Delta connection they represent delta currents and line voltages.

4. Load Model: The usual load models used for distribution system studies are constant impedance, constant current or constant power models that can be either in Wye or Delta. Sometimes hybrid models are also used. If complex power $[S_{abc}]$ and phase voltage $[VLN_{abc}]$ are given, then current due to constant complex power is

$$I_{pqi} = \left(\frac{S_i}{VLN_i} \right)^* \tag{3.9}$$

The constant load impedance is given by

$$Z_i = \frac{VLN_i^2}{S_i^* \cdot 1000} \tag{3.10}$$

Which can be used to compute the corresponding current due to constant impedance

$$I_{zi} = \frac{VLN_i^2}{Z_i} \tag{3.11}$$

The constant current load results in a current whose magnitude given by

$$I_{pqi} = \left| \left(\frac{S_i}{VLN_i} \right)^* \right| \tag{3.12}$$

This magnitude of current is kept constant throughout the iteration and the angle is found out using Eq. (3.10) which changes during each iteration.

3.3 Iterative Routine for Power Flow

The first step in the Power flow algorithm for the unbalanced distribution system is a forward process. Using the value of the substation voltage, the initial voltage for all the other nodes is calculated assuming the initial branch current as equal to zero. This step returns the no load voltages which can be used as the initial condition for the far end nodes to start the backward process. The backward process starts by the computation of load currents if present for the end nodes according the type of load model. The load can be either Wye or Delta and may be modelled as constant impedance, constant power or constant current according to the load model used. The equations describing the same are given by Eq. (3.9)-(3.12). To this, capacitor current if present should be added where capacitor current is given by Eq. (3.8). The resulting value returns the total injected current at a particular bus.

Initially, this computation is carried out for the end nodes. In the subsequent stages, the current of the branches connected to the end nodes to be calculated and the total current that is injected at any node is given by Eq. (3.13)

$$I_{n\phi} = \sum I_{m\phi} + I_{Cn\phi} + I_{loadn\phi} \qquad \phi = [a, b, c] \tag{3.13}$$

Where $\sum I_{m\phi}$ represents the sum of all branch currents of all the nodes connected to node n and $I_{Cn\phi}$ and $I_{loadn\phi}$ represents the currents injected by the capacitor and the loads connected to node n. This is carried out starting from the far end nodes to the source node. The equation for the backward process is given by Eq. (3.2).

Using the updated values of currents, the forward process is to be carried out to find out the updated voltages starting from the source node till far end nodes. This is done by assuming the nominal voltage at the source bus and using Eq. (3.1).

The voltage mismatch of the nodes in the subsequent iteration is used as the convergence criteria which is given in Eq. (3.14). If this value is within the defined tolerance limits, the convergence has been achieved. Otherwise, the backward process is to be carried out using updated values of node voltages obtained in the forward process.

$$\Delta V_{\phi}^{n(k)} = \left| V_{\phi}^{n(k)} \right| - \left| V_{\phi}^{n(k-1)} \right| \tag{3.14}$$

Once the power flow has been converged the power loss should be found out. The power loss is given by (Hung and Mithulananthan, 2013)

$$P_{loss} = \sum_{m} \sum_{n} A_{mn}(P_m P_n + Q_m Q_n) + B_{mn}(Q_m P_n + P_m Q_n) \tag{3.15}$$

where

$$A_{mn} = \frac{R_{mn} cos(\delta_m - \delta_n)}{V_m V_n} \tag{3.16}$$

$$B_{mn} = \frac{R_{mn} sin(\delta_m - \delta_n)}{V_m V_n} \tag{3.17}$$

Fig. 3.4 summarizes the described power flow algorithm.

3.4 Results and Discussion

The proposed power flow algorithm is validated using three different test systems of varying complexity. Three IEEE standard distribution feeders are considered, of which one is the balanced test feeder and the others are unbalanced. IEEE 33-bus balanced distribution feeder is considered so that the application of the power flow algorithm for balanced test feeder can be verified. The other feeders considered are IEEE 13-bus and 37-bus unbalanced distribution feeders. The details of the test system are given in the following sections. The results of the power flow algorithm are validated using results obtained from the standard distribution analysis software openDSS (Dugan, 2012). The distribution analysis softwares even though give accurate results, the representation of PV nodes and simulation under stochastic environments is not possible with them.

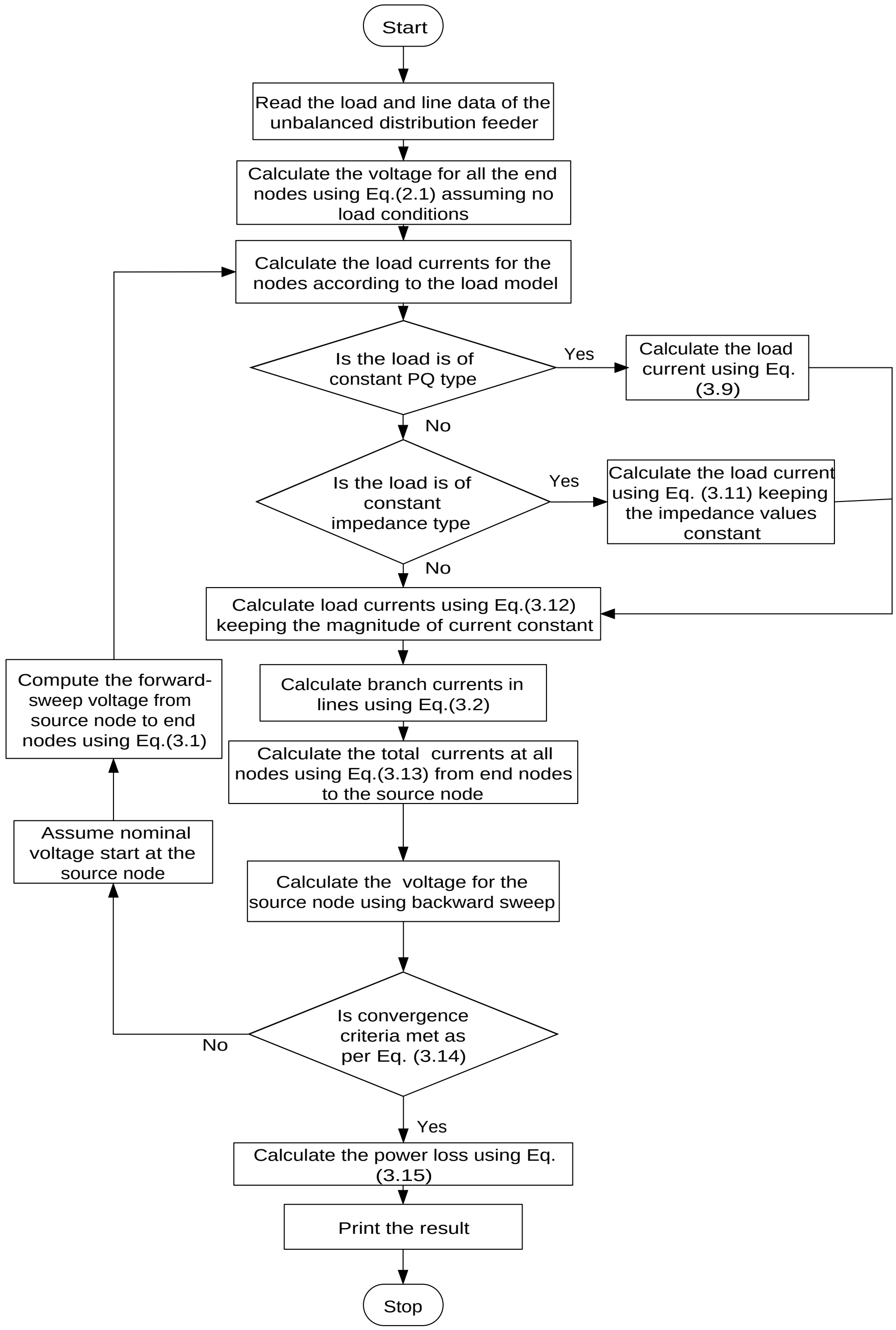


Figure 3.4: Flowchart for power flow of unbalanced distribution system

3.4.1 IEEE 33-bus Balanced Distribution feeder

IEEE 33-Bus test system is a three phase balanced distribution system with a reference voltage level of 12.66 kV. The single line diagram of the system is given in Fig. 3.5. It consists of a single supply point with 33 buses, 3 laterals, 37 branches and 5 loops or tie switches that are kept open during normal conditions. These tie switches (branches 33-37) are usually closed during fault conditions so that continuity of supply is maintained. Another use of these tie switches these can be closed to change the resistance of the circuit to reduce losses. The real and reactive power for the system are 3715 kW, and 2300 $kVAR$. The results for the power flow are given in Table.

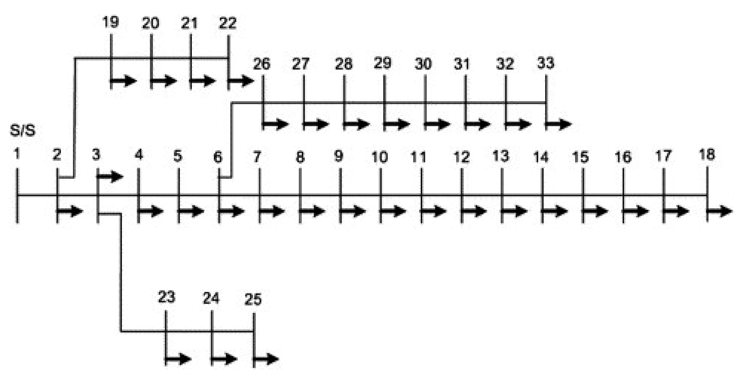


Figure 3.5: Single Line Diagram of IEEE 33-Bus distribution feeder

3.1. The real power losses obtained is 211.38 kW. The minimum voltage on the system was found to be 0.9140 p.u. It took only two iterations for the power flow to converge. The results are validated with that obtained using OpenDSS (Dugan, 2012).

Table 3.1: Voltage magnitude and angles for IEEE-33 Bus balanced test feeder

Bus Number	Voltage Magnitude(p.u)	Voltage Angle(degrees)
1	1.0000	0.0000
2	0.9970	0.0148
3	0.9830	0.0985
4	0.9755	0.1658
5	0.9682	0.2341
6	0.9498	0.1446
7	0.9463	-0.0872
8	0.9415	-0.0539
9	0.9352	-0.1312
10	0.9294	-0.1980
11	0.9286	-0.1914
12	0.9271	-0.1812
13	0.9210	-0.2778
14	0.9187	-0.3585
15	0.9173	-0.3976
16	0.9160	-0.4223
17	0.9140	-0.5017
18	0.9134	-0.5120
19	0.9965	0.0039
20	0.9929	-0.0636
21	0.9922	-0.0831
22	0.9916	-0.1036
23	0.9794	0.0673
24	0.9727	-0.0220
25	0.9694	-0.0662
26	0.9479	0.1858
27	0.9453	0.2443
28	0.9339	0.3386
29	0.9257	0.4249
30	0.9222	0.5338
31	0.9180	0.4534
32	0.9171	0.4312
33	0.9168	0.4237

3.4.2 IEEE 13-bus Unbalanced Distribution Feeder

The IEEE 13-bus test feeder is taken to evaluate the effectiveness the proposed power flow algorithm. The feeder consists of two transformers 115/4.16kV of Delta/GY configuration at the main substation and 4.16/0.48 kV of GY/GY configuration in one of the lines. The feeder is characterized by both spot and distributed loads, which are balanced, unbalanced, single phase, three phase, delta and wye connected with all combinations of load models. There are overhead lines and underground cables with different spacing of phases. Three phase and single phase capacitors are utilized in the feeder topology. The single line diagram of the distribution feeder is shown in Fig. 3.6 and its data (Kersting, 2001) is given in Appendix. The voltage profile and cur-

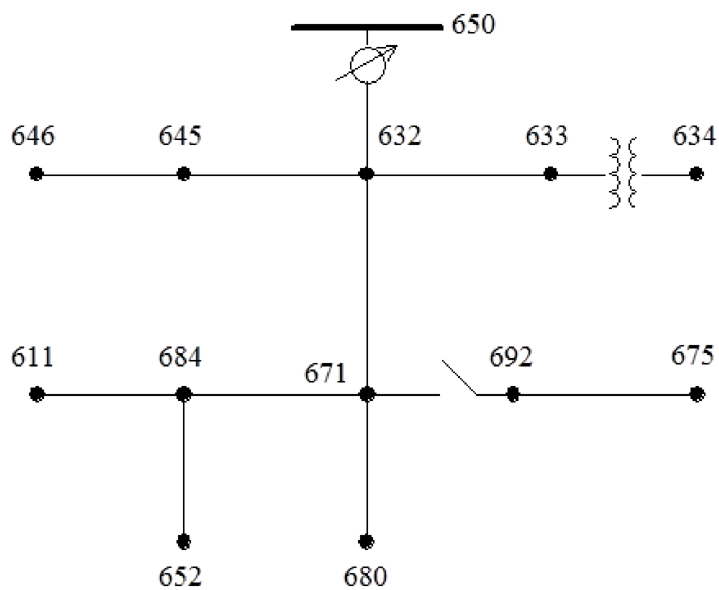


Figure 3.6: Single Line Diagram of IEEE 13-Bus Distribution System

rent flows for the three phases are given in Table. 3.2 and 3.3 respectively.

The real power losses obtained for the three phases are 90.8, 71.61 and 183.5 kW respectively. The minimum voltages for the three phases are 0.917 p.u, 0.9697 and 0.8970 p.u for the three phases. The results are validated with that obtained using OpenDSS (Dugan, 2012).

Table 3.2: Voltage profile IEEE 13-bus feeder

Node ID	Van	∠ Van	Vbn	∠ Vbn	Vcn	∠ Vcn
650	1	0	1	-120	1	120
632	0.9576	-2.78	-0.9899	-121.77	0.9443	117.78
633	0.9543	-2.9	0.9877	-121.91	0.9425	117.56
634	0.9287	-3.44	0.9697	-122.5	0.9226	117.04
671	0.9240	-5.9	1.0013	-122.51	0.8985	115.7
692	0.9240	-5.9	1.0013	-122.51	0.8985	115.7
675	0.9170	-6.21	1.003	-122.8	0.898	115.72
680	0.9240	-5.9	1.0013	-122.51	0.8985	115.7
645	-	-	0.982	-122.15	0.9430	117.65
646	-	-	0.978	-122.21	0.9409	117.61
684	0.922	-5.93	-	-	0.8992	115.56
652	0.918	-5.87	-	-	-	-
611	-	-	-	-	0.8970	115.56

3.4.3 IEEE-37 bus Unbalanced Distribution Feeder

The IEEE 37-Bus distribution feeder is a real feeder in California. The single line diagram for the distribution feeder is given in Fig. 3.7. The feeder consists of different types of loads such as spot loads, single phase and three phase loads which may be balanced or unbalanced, Delta or Wye connected that may be characterized by constant Z, constant kW, kVAR or constant current type of modelling. The feeder also consists of both underground and

Table 3.3: Current values of IEEE 13-bus feeder

Node ID	Ia (A)	∠ Ia	Ib (A)	∠ Ib	Ic (A)	∠ Ic
650-632	592.7	-28.7	438.4	-140.1	627.2	90.75
632-633	87.2	-39.2	63.5	-158.9	67.8	80.3
632-645	-	-	147.8	-143.5	65.36	58.26
632-671	506.8	-27.8	230.1	-137.8	508.9	97.43
645-646	-	-	62.25	-122.5	60.25	57.89
633-634	750.2	-38.3	559.3	-160.2	588.4	81.2
671-692	248.7	-20.67	67.1	-59.2	192.1	106.32
671-684	58.7	-38.63	0	0	71.9	118.51
671-680	0	0	0	0	0	0
692-675	218.7	-8.9	67.1	-59.2	137.2	106.7
684-611	-	-	-	-	71.9	118.51
684-652	58.7	-38.63	-	-	-	-

overhead lines with different spacing between phases. The substation and inline transformers are of delta-delta type. The voltage profile for the feeder is shown in Table. 3.4. The real power losses obtained for the three phases are 49.17, 27.97 and 72.56 kW respectively. The minimum voltages for the three phases are 0.956 p.u, 0.973 and o.954 p.u for the three phases.

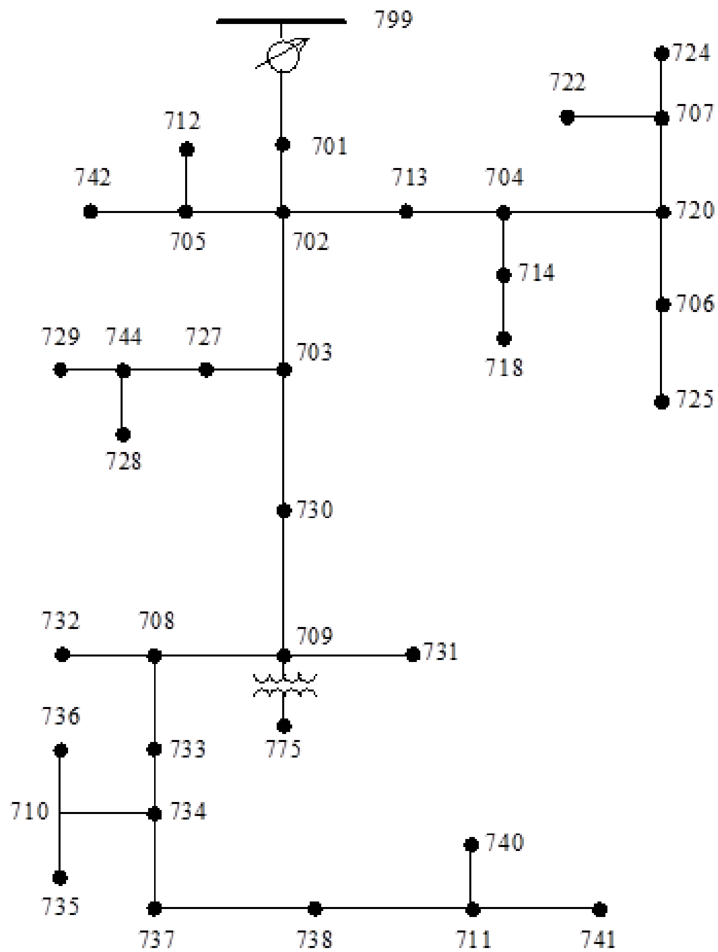


Figure 3.7: Single line diagram of IEEE 37-Bus Distribution System

Table 3.4: Voltage Magnitude and angle of IEEE 37-bus feeder

Node ID	Van	∠ Van	Vbn	∠ Vbn	Vcn	∠ Vcn
790	1.000	0	1	-120.00	1.000	120.00
701	0.989	-0.091	0.989	-120.45	0.984	119.59
702	0.982	-0.147	0.984	-120.66	0.972	119.35
713	0.981	-0.159	0.982	-120.63	0.974	119.53
704	0.980	-0.167	0.981	-120.67	0.973	119.56
720	0.977	-0.209	0.977	-120.68	0.969	119.60
707	0.977	-0.298	0.975	-120.66	0.968	119.74
724	0.976	-0.3287	0.971	-120.64	0.969	119.76
722	0.976	-0.324	0.972	-120.66	0.969	119.73
706	0.977	-0.234	0.977	-120.69	0.975	119.64
725	0.978	-0.239	0.977	-120.69	0.973	119.62
714	0.979	-0.165	0.982	-120.62	0.974	119.53
718	0.978	-0.155	0.982	-120.58	0.97	119.50
705	0.982	-0.125	0.985	-120.60	0.977	119.53
742	0.982	-0.145	0.984	-120.60	0.977	119.55
712	0.982	-0.105	0.985	-120.62	0.976	119.54
703	0.976	-0.175	0.983	-120.71	0.972	119.25
727	0.975	-0.155	0.982	-120.70	0.971	119.25
744	0.974	-0.155	0.981	-120.69	0.970	119.23
729	0.974	-0.145	0.981	-120.68	0.970	119.22
728	0.973	-0.145	0.981	-120.69	0.970	119.23
730	0.971	-0.115	0.980	-120.74	0.966	119.16
709	0.969	-0.105	0.979	-120.75	0.965	119.12
775	0.969	-0.105	0.979	-120.75	0.965	119.12
731	0.969	-0.125	0.978	-120.75	0.965	119.15
708	0.966	-0.075	0.978	-120.75	0.963	119.06
732	0.966	-0.055	0.978	-120.76	0.962	119.06
733	0.964	-0.055	0.977	-120.74	0.961	119.00
734	0.961	-0.005	0.975	-120.75	0.958	118.92
710	0.960	0.035	0.974	-120.78	0.956	118.94
736	0.960	-0.015	0.973	-120.76	0.956	118.99
735	0.960	0.045	0.974	-120.79	0.956	118.95
737	0.957	0.035	0.974	-120.72	0.956	118.82
738	0.956	0.055	0.974	-120.72	0.954	118.79
711	0.956	0.085	0.974	-120.75	0.954	118.78
740	0.956	0.095	0.974	-120.76	0.953	118.79
741	0.956	0.085	0.974	-120.76	0.953	118.78

3.5 Conclusion

The inherent unbalance and presence of DG sources necessitates a generalized power flow algorithm that is well suited to handle the unbalance associated with the distribution system. The chapter describes a modified general power flow algorithm for analyzing unbalanced distribution feeders. The algorithm is tested for three test feeders of varying size and complexity. The results are compared with those obtained from the standard distribution analysis package openDSS which demonstrates the efficiency and accuracy of the algorithm. OpenDSS even though provide accurate results, it is not designed to include generator (PV) nodes. The exact generation characteristics can be included for renewable energy sources only if they are included as PV nodes in the power flow algorithm. Also the simulation of stochastic environments inherent in renewable energy generators are not possible in OpenDSS. The power flow algorithm developed is able to handle the DG units as both PQ and PV nodes with slight modification in the algorithm which is described in Chapter 4.

Chapter 4

Integration of Distributed Generation in Unbalanced Distribution System

4.1 Modelling of Distributed Generation(DG) system

Distributed generation (or DG) include small-scale electric power generators that produce electricity close to the point of consumption (Ackermann et al., 2001). The various DG units that are connected at distribution system are given below.

1. Wind Turbines: The grid connected wind turbines can be classified as fixed type and variable type. The fixed type of wind turbine requires a gear box where the rotor of the squirrel cage induction generator is

directly connected to the grid and the rotor is rotated using a propeller through the grid. Variable speed wind turbine consists of a doubly fed induction generator or a synchronous generator. Modern turbines uses permanent magnets instead of the conventional generator. The output of these generators are converted into grid compatible AC power by using a rectifier and inverter.

2. Fuel cells: Fuel cells convert the stored chemical energy in the fuel into electrical energy and thermal energy by using an electrochemical process without the help of any electrical machines. Inverter is used to convert the DC output power into AC power which is compatible with the grid properties.

3. Photovoltaic (PV) systems: The PV systems produce DC power output and are connected to the grid using inverter which converts the DC power to grid compatible AC power.

4. Internal combustion (IC) engines: The IC engines use the principle of conversion of chemical energy stored in gas or liquid fuels into mechanical one. Similar to the wind turbines, these are directly connected to the grid with the help of synchronous or induction generators.

5. Gas turbines: Gas turbines involve two stage conversion process. The first stage involves the conversion of chemical energy into heat where the chemical energy is derived from the potential energy stored in the fossil fuels. In the second stage, the heat is converted into mechanical energy and is used to rotate a synchronous generator which is directly connected to the grid.

6. Micro-turbines: The working of micro-turbines is similar to that of gas turbines, but it uses a high speed permanent magnet synchronous generator instead of the synchronous generator which is connected to the grid using power electronic converters.

It is clear that depending upon the type of DG used, the modelling also differs. The DG units can be connected to the grid by three ways, by using a synchronous or asynchronous generator to connect directly to the grid, by using electric machine and power electronic interfaces or by using only power electronic converter as in the case of photovoltaic and fuel cells. The operation of the machine determines the model of the DG for the power flow studies where it is directly connected to the grid. When power electronic interface is used, the controller circuitry determines the model of the DG. The various modelling schemes are determined from the characteristics of the machines as described below:

1. Induction generator model: In an induction generator, both active and reactive powers can be represented as functions of slip (Naka et al., 2001).

$$\begin{aligned} P &= f(V, s) \\ Q &= g(V, s) \end{aligned} \tag{4.1}$$

   where P and Q are produced active and reactive power, respectively, s is the slip of induction generator speed and V is the bus voltage. For the squirrel cage induction generator, P can be assumed as constant and reactive power can be taken independent of slip. Thus Eq. (4.1) can be written as

$$P = Ps = constant \tag{4.2}$$

$$Q = g(V) \tag{4.3}$$

At steady state the voltage magnitude is close to one p.u in squirrel cage induction generators which make it possible to model it as PQ node.

2. Synchronous Generator model: In accordance with the excitation system, the synchronous generator can have Fixed excitation system and regulating excitation system (Losi and Russo, 2005), (Chen et al., 2006). In the second category, the machine can work either in voltage control mode (constant terminal voltage) and power factor control mode (fixed power factor) which can be modeled as PV node and PQ node respectively for power flow studies with DGs. The round rotor synchronous generator modelled as fixed excitation induction generator may inject reactive power to the grid and can be modelled by Eq. (4.4) with Q as positive.

$$Q = \sqrt{(\frac{E_q}{X_d})^2 - P^2} - \frac{V^2}{X_d} \tag{4.4}$$

where P and Q are the active and reactive power of the DG, E_q and V are no load voltage and the generator terminal voltage respectively and X_d represents the synchronous reactance. Under the assumption of constant P,

$$P = Ps = constant \tag{4.5}$$

$$Q = g(V) \tag{4.6}$$

Here the value of Q is always positive, i,e. Synchronous generator without excitation can be used to inject reactive power to the grid.

3. Power Electronic Interfaces are used for grid connection of several DG units like PV systems, Fuel cells etc. (Nehrir et al., 2006). In such cases DG model for power flow studies depends on the control method used for the converter (Chen et al., 2006). When the control method employed to control P and V independently, PV model is used and when it controls P and Q independently PQ model is used.

4.2 Integration of Dispersed Generation units in the power flow solution

As mentioned in the previous section, the inverter connected DG sources are modelled according to the controller circuitry used for inverter. Therefore DG sources can be modelled as either PQ nodes or PV nodes in the distribution power flow. A review of the various modelling techniques for DG integration for power flow are reviewed in Section. 2.1.5 of Chapter 2. The DG units are considered as negative loads with currents injected into the bus when PQ modelling technique is used. In order to include the representative features of DG units, they should be modelled as PV nodes in the power flow solution which requires slight modification in the power flow algorithm.

The positive sequence voltage and the real power for the PV node are specified initially. The initial value of the reactive power is assumed to be zero. With these values, the power flow algorithm is carried out till convergence. The positive voltage mismatch vector is computed to check if the value is within tolerance limits according to Eq. (4.7).

$$\Delta V_1^k = \left|V_{1spec}^k\right| - \left|V_{1calc}^k\right| < \varepsilon \tag{4.7}$$

where k is a PV node. The PV node voltage is converged if the computed value of the voltage mismatch vector are within limits. If the value exceeds the tolerance limits, the voltage values should be maintained within limits by injecting reactive power. This is obtained by calculating positive sequence sensitivity impedance matrix which is given by Eq. (4.8)

$$\Delta I_Q^k = inv(Z_1^k) * \Delta V_1^k \tag{4.8}$$

Matrix Z_1^k is a square matrix of the order n_{pvt} where n_{pvt} is the total number of PV nodes (Khushalani et al., 2007). The sign of the reactive power injection is given by the sign of ΔV_1^k returns the sign of reactive power, whether reactive power is injected or drawn from the grid . For positive ΔV_1^k, reactive power is produced and injected into the grid and for negative values of ΔV_1^k, the reactive power is absorbed from the grid. The following equations are used to calculate the reactive power to be injected so as to maintain the voltage to the specified limits.

$$\Delta I^k_{Q,\phi} = \Delta I^k_Q * e^{sign(\Delta V^k_1)*90^o+\delta V^k_\phi} \qquad \phi = a, b, c \tag{4.9}$$

where δV^k_ϕ are the angles of the converged voltages in the three phases at the k^{th} node which results in reactive power injection given by

$$Q^{new}_G = imag(V^k_\phi * I^{k*}_\phi) \tag{4.10}$$

Summing the reactive power injection to the previous value, the total reactive power for a PV bus can be calculated using Eq. (4.11).

$$Q^{total}_G = Q^{previous}_G + Q^{new}_G \tag{4.11}$$

If the injected reactive power at any bus exceeds the limits, the reactive power is fixed at the limiting value. Now the corresponding bus can be converted into PQ node. The limiting current is given by Eq.(4.12)

$$\Delta I^k_{Q,limit} = \frac{\frac{Q^k_{limit}}{3}}{mag\left(V^k_1\right)} \tag{4.12}$$

The total current is given by summing up this injected current to the load current.

$$I^k_{Q,\Phi} = I^k_\Phi + \Delta I^k_{Q,\Phi} \quad \Phi = a, b, c \tag{4.13}$$

To check the convergence criteria for the voltage mismatch vector, the load flow is executed again. The procedure is repeated until the voltage mismatch vector for all the PV buses are within limits. Fig. 4.1 summarises the steps of the algorithm.

4.3 Results and Discussions

4.3.1 Results for IEEE-13 bus distribution system

For IEEE 13-bus distribution feeder, the DG unit was modelled using PQ node and PV node. The voltage profile and current magnitudes of the distribution feeder without connecting DG units are given in Chapter 3.

1. A delta connected load of P=630 kW and Q=305 kW are connected at node number 671. The power factor of the load was assumed to be constant at 0.9. The DG unit was modelled as PQ node. The results for voltage magnitudes and currents are given in Table. 4.1 and 4.2 respectively. The results are compared with the results obtained from openDSS. The corresponding power loss for the distribution feeder are 32.6 kW, 8.2 kW and 60.5 kW for phase A, B and C respectively.

2. The DG unit is modelled as PV node in the second case. The specified voltage at PV node is kept at 1.0 p.u. The reactive power to be injected at the specified bus to maintain voltages within limits is computed as 1.51 MW. The results for the voltage profile and current magnitude are given in Table. 4.3 ans 4.4 respectively. It can be seen that the voltage is again improved when DG unit is modelled as PV node. The corresponding power loss for the distribution feeder are 30.7 kW, 7.2 kW and 55.3 kW for phase A, B and C respectively.

The voltage profile for the three cases is plotted in Fig. 4.3. It can be

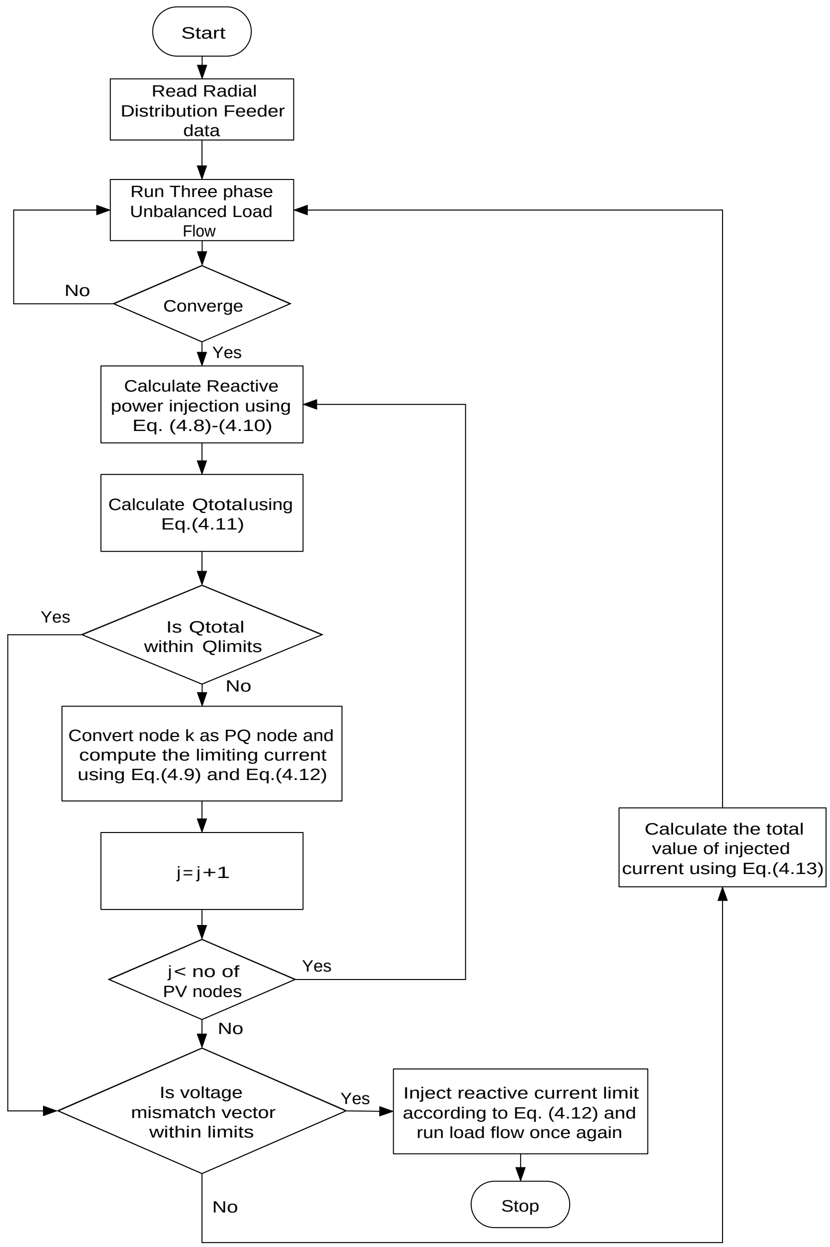


Figure 4.1: Flowchart for power flow with DG units

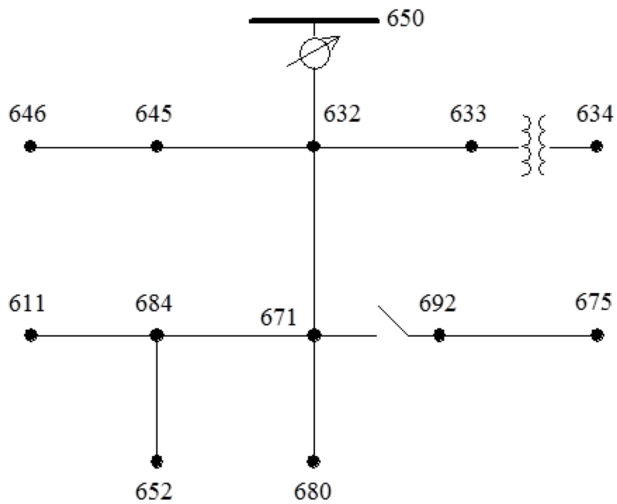


Figure 4.2: Single Line Diagram of IEEE 13-Bus Distribution System

Table 4.1: Voltage profile IEEE 13-bus feeder with DG unit as PQ node

Node ID	Van	∠ Van	Vbn	∠ Vbn	Vcn	∠ Vcn
650	1	0	1	-120	1	120
632	0.9821	-1.71	1.007	-120.45	0.9705	118.83
645	-	-	0.9986	-120.63	0.9688	118.86
646	-	-	0.9986	-120.74	0.9665	118.91
633	0.9775	-1.75	1.005	-120.53	0.968	118.82
634	0.9543	-2.51	0.986	-121.03	0.9484	118.32
671	0.9732	-3.53	1.034	-119.7	0.9532	118.22
692	0.9734	-3.53	1.034	-119.7	0.9532	118.22
675	0.9671	-3.76	1.037	-119.8	0.9503	118.24
684	0.971	-3.52	0	0	0.9503	118.12
611	-	-	-	-	0.9482	117.97
652	0.9645	-3.48	-	-	-	-
680	0.9733	-3.53	1.034	-119.7	0.9532	118.22

Table 4.2: Current values of IEEE 13-bus feeder with DG unit as PQ node

Node ID	Ia (A)	∠ Ia	Ib (A)	∠ Ib	Ic (A)	∠ Ic
650-632	270.8	-26.5	138.04	-124.5	306.8	96.78
632-633	85.67	-36.96	63.4	-156.74	65.67	80.23
632-645	-	-	146.5	-141.8	64.53	58.78
632-671	190.34	-20.9	97.45	-0.65	200.03	114.52
645-646	-	-	63.72	-121.8	62.82	58.63
633-634	730.78	-36.97	547.3	-158.9	572.3	80.98
671-692	232.85	-16.77	67.91	-54.23	183.2	110.34
671-684	61.87	-36.7	-	-	70.45	121.94
671-680	0	0	0	0	0	0
692-675	210.12	-4.17	-	-	127.45	112.34
684-611	-	-	67.91	-54.23	70.45	121.94
684-652	61.87	-36.7	-	-	-	-

Table 4.3: Voltage profile IEEE 13-bus feeder with DG unit as PV node

Node ID	Van	∠ Van	Vbn	∠ Vbn	Vcn	∠ Vcn
650	1	0	1	-120	1	120
632	0.9889	-1.82	1.0137	-120.54	0.9786	118.73
645	-	-	1.0045	-120.74	0.978	118.76
646	-	- 1.0026	-120.82	0.974	118.81	
633	0.9861	-1.87	1.012	-120.61	0.9763	118.75
634	0.9607	-2.62	0.9927	-121.8	0.9567	118.23
671	0.9871	-3.78	1.045	-119.8	0.9684	118.02
692	0.9871	-3.78	1.045	-119.8	0.9684	118.02
675	0.9808	-4.06	1.0485	-120.13	0.9667	118.05
684	0.9852	-3.83	-	-	0.9665	117.91
611	-	-	-	-	0.9642	117.76
652	0.9787	-3.76	-	-	-	-
680	0.9871	-3.78	1.047	-119.8	0.9684	118.02

Table 4.4: Current values of IEEE 13-bus feeder with DG unit as PV node

Node ID	Ia (A)	∠ Ia	Ib (A)	∠ Ib	Ic (A)	∠ Ic
650-632	250.4	-9.45	154.7	-97.89	274.34	111.32
632-633	84.23	-37.34	62.81	-157.2	64.33	81.24
632-645	-	-	143.78	-143	64.33	58.67
632-671	178.98	3.54	155.84	-14.34	195.67	136.8
645-646	-	-	62.4	-121.21	62.14	58.79
633-634	728.9	-37.12	545.2	-157.89	564.8	81.42
671-692	230.03	-16.8	68.89	-53.18	178.9	110.86
671-684	62.78	-37.64	-	-	71.2	123.2
671-680	0	0	0	0	0	0
692-675	205.81	-3.76	68.89	-53.18	125.3	113.07
684-611	-	-	-	-	71.2	123.2
684-652	62.78	-37.64	-	-	-	-

Table 4.5: Comparison of Voltage Magnitudes in the three cases

Node ID	Without adding DG unit			Adding DG unit as PQ node			Adding DG unit as PV node		
	Va(p.u)	Vb(p.u)	Vc(p.u)	Va(p.u)	Vb(p.u)	Vc(p.u)	Va(p.u)	Vb(p.u)	Vc(p.u)
650	1	1	1	1	1	1	1	1	1
632	0.9576	0.9899	0.9443	0.9821	1.007	0.9705	0.9889	1.0137	0.9786
645	-	0.982	0.943	-	0.9986	0.9688	-	1.0045	0.978
646	-	0.978	0.9409	-	0.9986	0.9665	-	1.0026	0.974
633	0.9543	0.9877	0.9425	0.9775	1.005	0.968	0.9861	1.012	0.9763
634	0.9287	0.9697	0.9226	0.9543	0.986	0.9484	0.9607	0.9927	0.9567
671	0.924	1.0013	0.8985	0.9732	1.034	0.9532	0.9871	1.045	0.9684
692	0.924	1.0013	0.8985	0.9734	1.034	0.9532	0.9871	1.045	0.9684
675	0.917	1.003	0.898	0.9671	1.037	0.9503	0.9808	1.0485	0.9667
684	0.922	-	0.8992	0.971	-	0.9503	0.9852		0.9665
611	-	-	0.897	-	-	0.9482	-	-	0.9642
652	0.918	-	-	0.9645	-	-	0.9787	-	-
680	0.924	1.0013	0.8985	0.9733	1.034	0.9532	0.9871	1.047	0.9684

seen that DG unit modelled as PQ node improves the voltage at all the nodes whereas the voltage is again improved when DG unit is modelled as PV node. This is due to the fact that PV nodes are ideal for representing DG units. Also in the case of phase B, the voltage sometimes goes above 1.p.u which causes the voltage rise issue. The voltage on phase B before DG installation was near to 1 p.u. Random installation of DG unit without optimal size and location caused this issue of voltage rise.

Table 4.6: Comparison of Current Magnitudes in the three cases

Branches	Without adding DG unit			Adding DG unit as PQ node			Adding DG unit as PV node		
	Ia(A)	Ib(A)	Ic(A)	Ia(A)	Ib(A)	Ic(A)	Ia(A)	Ib(A)	Ic(A)
650-632	592.7	438.4	627.2	270.8	138.04	306.8	250.4	154.7	274.34
632-633	87.2	63.5	67.8	85.67	63.4	65.67	84.23	62.81	64.33
632-645	-	147.8	65.36	-	146.5	64.53	-	143.78	64.33
632-671	506.8	230.1	508.9	190.34	97.45	200.03	178.98	155.84	195.67
645-646	-	62.25	60.25	-	63.72	62.82	-	62.4	62.14
633-634	750.2	559.3	588.4	730.78	547.3	572.3	728.9	545.2	564.8
671-692	248.7	67.1	192.1	232.85	67.91	183.2	230.03	68.89	178.9
671-684	58.7	-	71.9	61.87	-	70.45	62.78		71.2
671-680	0	0	0	0	0	0	0	0	0
692-675	218.7	67.1	137.2	210.12	67.91	127.45	205.81	68.89	125.3
684-611	-	-	71.9	-	-	70.45	-		71.2
684-652	58.7	-	-	61.87	-	-	62.78	-	-

The DG installation caused significant changes in the current values only in the branches that serves as the path towards the substation node from node selected for DG installation. In those lines, the current value has been decreased due to injected current in the reverse direction. In the other branches, the change in the current values are not significant.

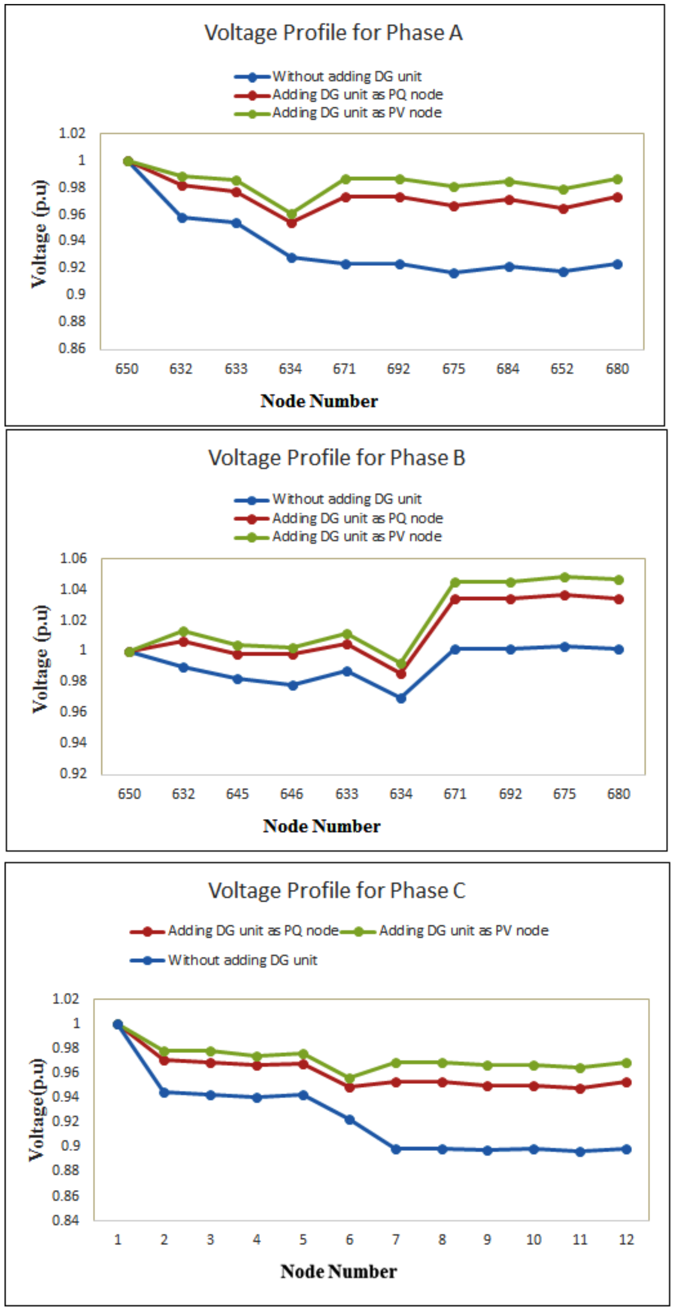


Figure 4.3: Voltage profile for the three phase

a. Impact of Modelling on the Losses

To analyze the impact of PQ and PV modelling on the losses of the system, the losses are compared in the three cases, i.e without the addition of DG unit, adding DG unit as PQ node and adding DG unit as PV node. It can be observed that the losses are minimized from case 1 to case 3 which shows that representing DG unit as PV node is more accurate than PQ node. A comparison of power losses with the modelling scheme adopted is given in Fig. 4.4.

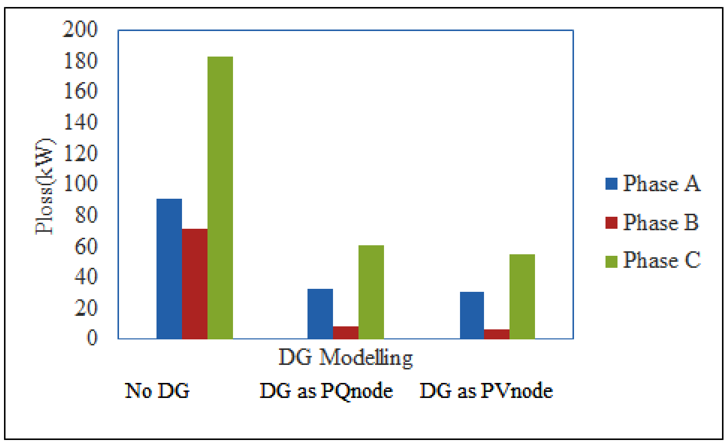


Figure 4.4: Impact of Modelling on the total Losses

4.3.2 Results for IEEE 37-Bus distribution feeder

1. A delta connected load of P=550 kW and Q=267 kVAR are connected at node number 706, as shown in Fig. 3.7. The power factor of the load was assumed to be constant at 0.9. The DG unit was modelled as PQ node. It took three iterations for the load flow to converge. The results for voltage magnitudes are given in Table. 4.7. The results are

compared with the results obtained from openDSS. The corresponding power loss for the distribution feeder are 24.5 kW, 13.1 kW and 60.7 kW for phase A, B and C respectively .

2. The DG unit is modelled as a PV node in the second case. The specified voltage at PV node is kept at 1.0 p.u. Similar to the previous case, the load flow converged in three iterations. The results for the voltage profile are given in Table. 4.8. It can be seen that the voltage is again improved when the DG unit is modelled as PV node. The corresponding power loss of the distribution feeder are 20.4 kW, 10.2 kW and 53.3 kW for phase A, B and C respectively.

Table 4.7: Voltage profile for IEEE-37 Bus feeder adding DG sources as PQ node

Node ID	Va(p.u)	∠Va	Vb(p.u)	∠Vb	Vc(p.u)	∠Vc
790	1	0	1.0000	-120	1.0000	120
701	0.9953	-0.065	0.9955	-120.360	0.9905	119.670
702	0.9923	-0.138	0.9946	-120.570	0.9823	119.430
713	0.9908	-0.15	0.9923	-120.540	0.9843	119.610
704	0.9902	-0.158	0.9911	-120.580	0.9834	119.640
720	0.9832	-0.2	0.9834	-120.590	0.9756	119.680
707	0.9832	-0.289	0.9816	-120.570	0.9746	119.820
724	0.9829	-0.3197	0.9779	-120.550	0.9760	119.840
722	0.9823	-0.315	0.9783	-120.570	0.9758	119.810
706	0.9843	-0.225	0.9834	-120.600	0.9819	119.720
725	0.9845	-0.23	0.9840	-120.600	0.9800	119.700
714	0.986	-0.156	0.9890	-120.528	0.9810	119.614
718	0.9877	-0.146	0.9917	-120.488	0.9837	119.584
705	0.9903	-0.116	0.9933	-120.508	0.9853	119.614
742	0.9903	-0.136	0.9923	-120.508	0.9853	119.634
712	0.9903	-0.096	0.9933	-120.528	0.9843	119.624
703	0.987	-0.166	0.9940	-120.618	0.9830	119.334
727	0.986	-0.146	0.9930	-120.608	0.9820	119.334
744	0.9851	-0.146	0.9921	-120.598	0.9811	119.314
729	0.9851	-0.136	0.9921	-120.588	0.9811	119.304
728	0.9841	-0.136	0.9921	-120.598	0.9811	119.314
730	0.982	-0.106	0.9910	-120.648	0.9770	119.244
709	0.9798	-0.096	0.9898	-120.658	0.9758	119.204
775	0.9798	-0.096	0.9898	-120.658	0.9758	119.204
731	0.9798	-0.116	0.9888	-120.658	0.9758	119.234
708	0.977	-0.066	0.9890	-120.658	0.9740	119.144
732	0.977	-0.046	0.9890	-120.668	0.9730	119.144
733	0.9832	-0.046	0.9962	-120.648	0.9802	119.084
734	0.9822	0.004	0.9962	-120.658	0.9792	119.004
710	0.9819	0.029	0.9959	-120.688	0.9779	119.024
736	0.9819	-0.006	0.9949	-120.668	0.9779	119.074
735	0.9819	0.036	0.9959	-120.698	0.9779	119.034
737	0.9723	0.026	0.9893	-120.628	0.9713	118.904
738	0.9713	0.046	0.9893	-120.628	0.9693	118.874
711	0.9713	0.076	0.9893	-120.658	0.9693	118.864
740	0.9713	0.086	0.9893	-120.668	0.9683	118.874
741	0.9713	0.076	0.9893	-120.668	0.9683	118.864

Table 4.8: Voltage profile for IEEE-37 Bus feeder adding DG sources as PV node

Node ID	Va(p.u)	∠Va	Vb(p.u)	∠ Vb	Vc(p.u)	∠Vc
790	1	0	1	-120	1	120
701	0.9962	-0.082	0.9964	-120.390	0.9914	119.65
702	0.9931	-0.141	0.9954	-120.600	0.9832	119.41
713	0.9912	-0.153	0.9927	-120.570	0.9847	119.59
704	0.9909	-0.161	0.9918	-120.610	0.9838	119.62
720	0.9839	-0.203	0.9841	-120.620	0.9763	119.66
707	0.9841	-0.292	0.9825	-120.600	0.9753	119.80
724	0.9837	-0.3227	0.9787	-120.580	0.9768	119.82
722	0.9834	-0.318	0.9794	-120.600	0.9766	119.79
706	0.9851	-0.228	0.9842	-120.630	0.9827	119.70
725	0.985	-0.233	0.9845	-120.630	0.9808	119.68
714	0.9868	-0.159	0.9898	-120.558	0.9818	119.59
718	0.9902	-0.149	0.9942	-120.518	0.9845	119.56
705	0.9912	-0.119	0.9942	-120.538	0.9862	119.59
742	0.9913	-0.139	0.9933	-120.538	0.9862	119.61
712	0.9913	-0.099	0.9943	-120.558	0.9853	119.60
703	0.9902	-0.169	0.9972	-120.648	0.9840	119.31
727	0.9889	-0.149	0.9959	-120.638	0.9849	119.31
744	0.9871	-0.149	0.9941	-120.628	0.9840	119.29
729	0.9871	-0.139	0.9941	-120.618	0.9831	119.28
728	0.9864	-0.139	0.9944	-120.628	0.9831	119.29
730	0.9843	-0.109	0.9933	-120.678	0.9793	119.22
709	0.9821	-0.099	0.9921	-120.688	0.9781	119.18
775	0.9821	-0.099	0.9921	-120.688	0.9781	119.18
731	0.9821	-0.119	0.9911	-120.688	0.9781	119.21
708	0.9803	-0.069	0.9923	-120.688	0.9773	119.12
732	0.9803	-0.049	0.9923	-120.698	0.9763	119.12
733	0.9841	-0.049	0.9971	-120.678	0.9811	119.06
734	0.9831	0.001	0.9971	-120.688	0.9801	118.98
710	0.983	0.041	0.9970	-120.718	0.9790	119.00
736	0.983	-0.009	0.9960	-120.698	0.9790	119.05
735	0.983	0.051	0.9970	-120.728	0.9790	119.01
737	0.973	0.029	0.9900	-120.658	0.9724	118.88
738	0.9725	0.049	0.9905	-120.658	0.9705	118.85
711	0.9725	0.079	0.9905	-120.688	0.9705	118.84
740	0.9725	0.089	0.9905	-120.698	0.9695	118.85
741	0.9725	0.079	0.9905	-120.698	0.9695	118.84

4.4 Conclusion

The chapter discusses various modelling schemes that can be adopted for integrating DG units in the distribution system. Depending upon the interconnection method to the grid and the type used, the modelling for DG units differs. The DG units can be modelled in the power flow algorithm as PQ nodes and PV nodes. Modelling DG units as PQ nodes do not cause any alterations in the power flow. But the power flow algorithm to be modified for integrating DG unit as PV node. A power flow algorithm is developed which can handle DG units by PV modelling using the positive sequence impedance matrix. The developed algorithm is validated for IEEE 13-bus and 37-bus distribution feeder. The results show that modelling the DG unit as PV node causes improvement in voltage profile and also a greater reduction in losses than when the DG unit is modelled as PQ node. Therefore representing DG unit as PV node is more accurate for power flow studies. In addition to the PV modelling, the uncertainty associated with the fluctuating power output from the DG sources should also be modelled which is discussed in the next chapter.

Chapter 5

Uncertainty Modelling of Solar Photovoltaic(PV) Generation Systems

5.1 Introduction

The penetration level of intermittent renewable sources of energy has marked up a rapid increase in the last decade. The integration of such renewable energy resources helps in reducing the total power losses and improvement of voltage profile. In addition, they produce clean energy which helps in meeting the rising power demand with minimum environmental challenges. But the power produced from such intermittent sources is subjected to uncertainties. This is due to the fluctuating nature of primary solar energy from which the power output is derived. The uncertainty associated with such renewable energy sources can be categorized as aleatory uncertainties and epistemic uncertainties. Aleatory uncertainties are due to the inherent variability in the system behaviour. In the case of Photovoltaic (PV) generators, solar irradiation falls in the category of aleatory uncertainty. The operational parameters that are specified by the manufacturers and end users falls in the category of epistemic uncertainties. When the information is available, it is reasonable to ignore such uncertainties. If the available data are sufficient, solar irradiance is to be modelled as a random variable for which probabilistic distributions are used.

There are several literatures that models solar irradiance using probability distributions. In (Salameh et al., 1995), three distributions, namely Weibull, Log-Normal and Beta were used to model the solar irradiance and it is found that Beta distribution gives the best fit. (Assuncao et al., 2003) used the Beta distribution to fit 5 minutes-averaged solar radiation indexes. The same distribution is used by several authors to model the uncertainty associated with the solar PV generation for optimally planning the DG integration (Atwa et al., 2010). In this study, the historic solar irradiance of the selected site is taken from National Renewable Energy Laboratory (NREL) solar radiation database. The Probability Distribution Function (PDF) that is best suited for the data is found out and the solar irradiance is modelled to represent the uncertainty.

There are so many different types of modules, cells and PV arrays depending upon the characteristics and plenty are available in the market. The type of module that is best suited for a particular site should be found out. The selection of PV module can be regardless of the size of the module and can be based on capacity factors calculated for each type of module. The probability distribution modelling is also used to calculate the capacity factors for selection of the most suited module for the selected site. The chapter discusses the uncertainty modelling of Solar PV units by a suitable PDF which helps in estimating the random power output from the PV source and selecting the optimum PV module suited for the selected site from four different PV modules based on capacity factors. This would serve as a methodology while designing solar PV systems which will help to model the uncertainty and thereby increasing the efficiency of the distribution system with PV units.

5.2 Modelling of Solar irradiance from Historical Data

The site selected for the study lies at 10.52^oN 76.21^o E that experiences a tropical monsoon climate. The irradiance data for one year, which is taken as the study period is collected from National Solar Radiation Database (Sengupta et al., 2014). The total study period is divided into four seasons and a typical day is used to represent a particular season. Each day representing a season is segmented into 24 hours representing the hourly variation of any season. This would result in 96 time segments for one year and 90 data points for each of the 96 segments with 30 days in a month and 3 months per season.

For simulating solar irradiance data using PDF, the frequency distribution corresponding to a typical hour in a season is generated. After obtaining the time series of the solar irradiance level, a histogram is plotted for the same hour. The data of the same hour found to be unimodal, except few cases where the data is bimodal in nature. There are several probability distributions that are used to model the solar irradiance, the most commonly used distributions are Beta, Log-normal and Weibull distributions. The frequency histograms are tested with the predicted distribution functions and Chi Square test is used to test the goodness of fit for the predicted distribution. A brief description of the three probability distributions used here is given below.

1. Beta Probability Density Function is described by

$$f_b(s) = \frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)} * (s)^{\alpha-1} * (1-s)^{\beta-1}$$
$$\text{for} 0 \leq s \leq 1, \alpha, \beta \geq 0 \qquad 0 \quad \text{otherwise} \tag{5.1}$$

The mean(μ) and standard deviation (σ) of the random variable s is used to calculate the parameters of the Beta Distribution Function.

$$\beta = (1-\mu) * \left(\frac{\mu * (1+\mu)}{\sigma^2} - 1\right) \tag{5.2}$$

$$\alpha = \frac{\mu * \beta}{1-\mu} \tag{5.3}$$

2. Weibull Distribution Function is given by

$$f(x;\lambda,k) = \begin{cases} (\frac{k}{\lambda})(\frac{x}{\lambda})^{k-1}, & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{5.4}$$

Here $k > 0$ and $\lambda > 0$ are called shape factor and scale factor respectively.

3. Log-normal probability density function is described by

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma x} \exp(-\frac{(\ln x - \mu)^2}{2\sigma^2}) \tag{5.5}$$

where μ and σ represents the mean and standard deviation.

The three distributions are tested for fitting the solar irradiance data corresponding to a typical hour. For the winter season, at 12 a.m, the plot of the histograms and probability density functions is shown in Fig. 5.1. It can be observed that, the irradiance data is best fitted for Beta and Log-normal distributions. The same plot for 3 p.m in the summer season is shown in Fig. 5.2 and is best fitted for Weibull and Beta distributions. This is repeated for different hours in various seasons. In most of the cases, Beta PDF was found to give the best fit to the solar irradiance data. The Chi-Square test was also conducted to check for the goodness of fit of Beta PDF for modelling irradiance.

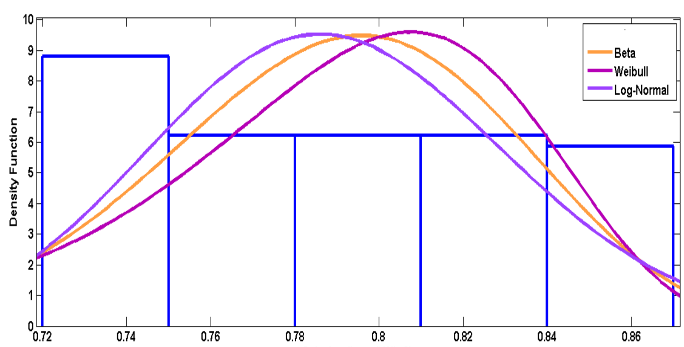


Figure 5.1: Histogram versus Irradiance level plotted for 12 p.m in the winter season

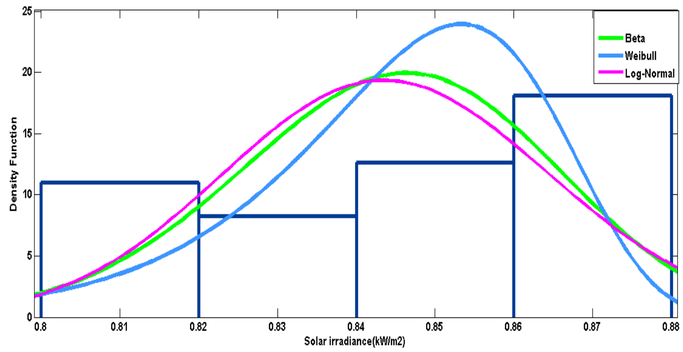


Figure 5.2: Histogram versus Irradiance level plotted for 12 p.m in the summer season

5.3 Modelling Solar Irradiance using Beta PDF and Output Power Calculation

Beta PDF is used to model the randomness related to the hourly solar irradiation data using the following equations (Atwa et al., 2010). For generating the Beta PDF, mean and standard deviation of each hour data is estimated (Maya and Jasmin, 2015).

$$
\begin{aligned}
f_b(s) = \frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)} * (s)^{\alpha-1} * (1-s)^{\beta-1} \\
\text{for} \quad 0 \le s \le 1, \alpha, \beta \ge 0 \\
= 0 \qquad\qquad \text{otherwise}
\end{aligned} \tag{5.6}
$$

Where

s	solar irradiance in kW/m^2
$f_b(s)$	Beta distribution function of s
α, β	parameters of Beta distribution function

The mean (μ) and standard deviation (σ) of the random variable s are used to calculate the parameters of the Beta Distribution Function.

$$\beta = (1 - \mu) * \left(\frac{\mu * (1 + \mu)}{\sigma^2} - 1 \right) \tag{5.7}$$

$$\alpha = \frac{\mu * \beta}{1 - \mu} \tag{5.8}$$

In order to represent the generated power from PV source as a multi-state variable in the power flow, the Beta PDF which is continuous is divided into a number of states. The states are selected such that in each state, the solar irradiation is within limits, i.e between 0 and 1 kW/m^2. For each of these states, the probability of solar irradiation is estimated using Eq. (5.9)(Maya and Jasmin, 2015).

$$P_s\{G_y\} = \int_{s_{y1}}^{s_{y2}} f_b(v)dv \tag{5.9}$$

Where

$P_s\{G_y\}$	Probability of the solar irradiance being in state y
s_{y1} and s_{y2}	solar irradiance limits of state y

The generated power from the PV source depends on ambient temperature, solar irradiance and the characteristics of the module itself. For each time segment, the output power can be calculated during different states using the following equations (5.10)-(5.14).

$$Tc_y = T_A + s_{ay}\left(\frac{N_{OT} - 20}{0.8}\right) \tag{5.10}$$

$$I_y = s_{ay}[I_{sc} + K_i(Tc - 25)] \tag{5.11}$$

$$V_y = V_{oc} - K_v * Tc_y \tag{5.12}$$

$$P_{Sy}(s_{ay}) = N * FF * V_y * I_y \tag{5.13}$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{oc} * I_{sc}} \tag{5.14}$$

where

Tc_y	Cell Temperature in ^{0} C during state y
T_A	Ambient Temperature in ^{0} C
K_v	Voltage Temperature coefficient V/^{0} C
K_i	Current Temperature coefficient I/^{0} C
N_{OT}	Nominal operating temperature of cell in ^{0} C
FF	Fill Factor
I_{sc}	Short circuit current in A
V_{oc}	Open-circuit voltage in V
I_{MPP}	Current at maximum power point in A
V_{MPP}	Voltage at maximum power point in B
P_{Sy}	Output power of the PV module during state y
s_{ay}	Average solar irradiance of state y

When the power output is obtained for each of the states, the power flow is carried out for each state to obtain the variation of the power flow parameters with solar irradiation and the PV module characteristics.

The generated Beta PDF is used to synthetically generate hourly solar irradiance data that will help in planning the DG integration. This is accomplished by generating some random samples from the Beta PDF that features the behaviour of the historical data and thus helps in the modelling of randomness associated with the solar irradiance. The four seasons in Kerala can be divided as winter, summer, southwest monsoon and retreating monsoon, whose hourly average solar radiation are 240.07 W/m^2, 265.38 W/m^2, 184.61 W/m^2 and 223.3 W/m^2 respectively according to the satellite data. From the Beta PDF, the random samples that feature the behaviour of the historical data is generated. The estimated solar irradiance for each season is plotted in Fig. 5.3. The value of the samples generated are validated by selecting 3

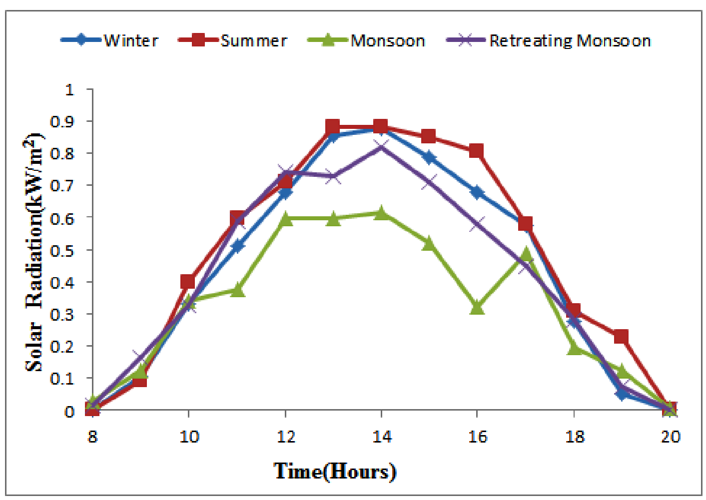


Figure 5.3: Forecasted Hourly Solar Irradiance for various Seasons

days in the season randomly and checking the value of the irradiance against the generated value. A plot of the same for summer season is given in Fig.5.4. It can be observed that, both the plots are similar which proves the accuracy of the modelling technique.

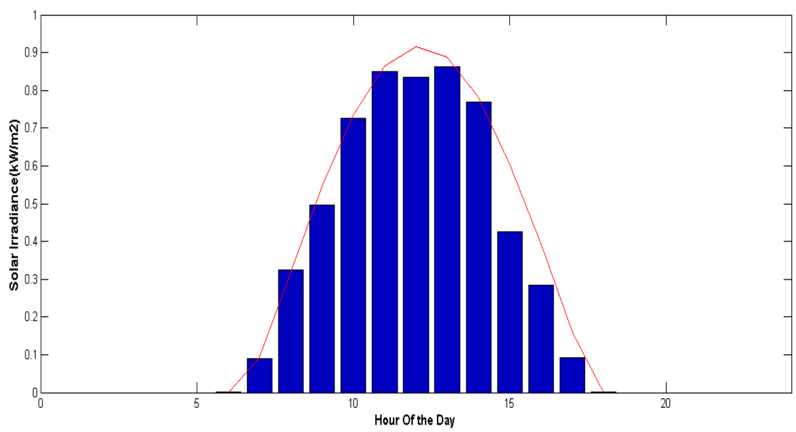


Figure 5.4: Comparison of generated and actual value of irradiance

5.4 Selection of the Module type for the selected site

The output of the PV module is dependent on the solar irradiance, ambient temperature and the characteristics of the module itself. Therefore PV power output should be considered as a multi state variable so that the various parameters can be analyzed with respect to the solar irradiance. For this purpose the solar irradiance is modelled using Beta PDF and the power output for different types of modules is calculated. The characteristics of the modules are given in Table. 5.1 (Atwa et al., 2010). The simulated power output for Type D module using Equations (5.10)-(5.14) is given in Table 5.2.

For selecting a particular module type for a particular site, the capacity

Table 5.1: Characteristics of the Module types

Module Characteristics	**Module Type**			
	A	**B**	**C**	**D**
Watt peak(W)	50.00	53.00	60.00	75.00
Open circuit voltage(V)	55.50	21.70	21.10	21.98
Short circuit current (A)	1.80	3.40	3.80	5.32
Voltage at maximum power(V)	38.00	17.40	17.10	17.32
Current at maximum power(V)	1.32	3.05	3.50	4.76
Voltage temperature coefficient(mV/^{0}C)	194.00	88.00	75.00	14.40
Current temperature coefficient(mA/^{0}C)	1.40	1.50	3.10	1.22
Nominal cell operating temperature(^{0}C)	43.00	43.00	43.00	43.00

factor of various types of the PV modules should be calculated. The Capacity Factor (CF) can be defined as the ratio between the average power output and the rated power (Atwa et al., 2010). The hourly average power output of a PV module is the summation of the power produced at all possible states for this hour multiplied by the corresponding probability of each state. Thus the average power output of each time segment is calculated, and then the average power output of a typical day in each season and hence the annual average output power can be estimated. A comparison of the CF of the different modules is given in Fig. 5.5.

From Fig. 5.5 it is clear that module D is best suited for the selected site as its capacity factor is more compared to all other modules. This is very much independent on the power value of the module and there is a critical role for the value of the parameters that are specified by the manufacturer in deciding the module types that is best suited for a particular site.

Table 5.2: Simulated Power output of PV module in Watts

Time (Hours)	Simulated Power Output from PV module(Watts)			
	Winter	Summer	Monsoon	R. Monsoon
12 a.m	0	0	0	0
1 a.m	0	0	0	0
2 a.m	0	0	0	0
3 a.m	0	0	0	0
4 a.m	0	0	0	0
5 a.m	0	0	0	0
6 a.m	0	0	0	0
7 a.m	0.0	0.299088	2.318076	1.130763
8 a.m	8.36854	7.379193	10.0398	13.40828
9 a.m	26.77009	32.23827	27.62869	26.32975
10 a.m	41.27643	48.23487	30.31874	47.28848
11 a.m	54.69465	57.08257	48.13533	59.67413
12 p.m	68.68222	70.58908	47.9654	58.36318
1.p.m	70.44084	70.71372	49.37414	65.69778
2 p.m	63.06829	68.35341	41.85735	57.03526
3 p.m	54.48318	64.68629	26.11653	46.75175
4 p.m	46.37736	46.65187	39.35413	36.02033
5 p.m	22.33481	24.97351	15.84026	22.87475
6 p.m	4.115785	18.39568	9.919551	5.875181
7 p.m	0.002215	0.191043	0.593094	0.0
8 p.m	0	0	0	0
9 p.m	0	0	0	0
10 p.m	0	0	0	0
11 p.m	0	0	0	0

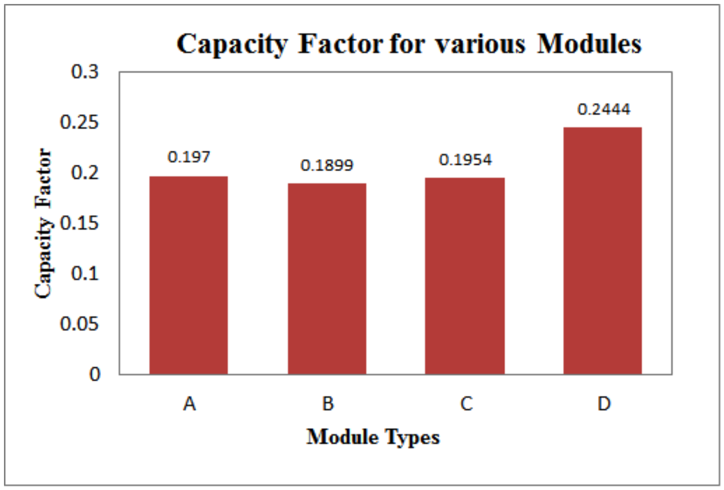


Figure 5.5: CF of PV modules

5.5 Conclusion

The uncertainty modelling of the Solar PV generator by using the probability density function has been analyzed. The solar irradiance data is tested for fitness using Beta, Weibull and Log-normal distributions and Beta PDF was found to be the suitable distribution by fitting the solar irradiance data. Beta PDF is used to generate random samples that feature the behaviour of the historical data and the generated PDF is used to find out the random power output for different types of modules. The capacity factors of four different types of modules for the selected site are calculated. Thus the optimum PV module that is best suited for the selected site is determined. This information can be used to design the PV units of optimal capacity, which are to be found out using appropriate optimization techniques. In the next chapter, the stochastic learning algorithm used for optimal allocation of PV units is explained.

Chapter 6

Optimal Allocation of PV units using Learning Automata and Reinforcement Learning

6.1 Introduction

The substantial growth of distributed generation in the deregulated power market is driven by various technical, commercial, economic as well as environmental factors which surround the electric power industry (Lopes et al., 2007). These may include reduction in power loss and on-peak operating costs, improvement in voltage profile and load factors, elimination of system upgrades and thereby improving the system integrity, reliability, efficiency, etc. The integration of DG sources into the distribution network change the overall scenario of the present distribution network from passive to active which alter the normal operation of the distribution network. Therefore, in addition to the benefits, the distribution network is subjected to a number of challenges such as voltage rise effect, power quality issues, stability and protection issues. There is an absence of clear-cut policy in determining the market mechanism in connection with the overall cost of electricity generated from the DG integrated system. Therefore, strategic placement of the DG units is very essential for maximising the benefits and limiting the challenges by the addition of DG units into the distribution networks.

The optimal integration of the DG units into the distribution network has been addressed by several researchers in different ways. Minimization of network losses is the significant aspect to be considered for the reliable and efficient operation of DG integration. The significant variation in the approaches to the optimal allocation of DG units comes through the methods used for the optimization process. The methods can be broadly classified as analytical method, numeric method and the heuristic method. A thorough review of these methods for optimal DG placement is given in Chapter 2.

In most of the research works, the test feeders considered for validating the analysis are of balanced nature. Unbalance is an inherent characteristic of the distribution feeder. The unbalanced loading at the nodes and the unbalanced multi phase operation are the reasons behind distribution system unbalance. In practical situations, balanced loading at the distribution feeders is unrealistic and therefore carrying out balanced studies for optimal integration of DG sources is not relevant. The uncertainty associated with the DGs is also not considered in most of the cases. The power output from the DGs such as wind and solar Photovoltaics cannot be predicted in advance and hence are uncertain. This uncertainty should also be taken into account while planning DGs in the distribution network along with the randomly varying power output from such sources. This requires the optimization to be run on a stochastic basis or stochastic optimization need to be done to handle such uncertainties. Even though there are many heuristic methods that are used in optimal DG placement, most of the methods are not so efficient in handling the stochastic data that exist in practical system. The power output from the PV source is random in nature which depends on many parameters such as solar irradiance, ambient temperature and characteristics of module etc.

The focus of the chapter is the optimal sizing of the PV units in order to achieve power loss reduction and voltage profile improvement in a radial distribution network of unbalanced nature. The method employed here is stochastic learning algorithms, namely Learning Automata (LA) and Reinforcement Learning (RL) which are learning methods capable of handling the stochastic data in practical system. The optimal sizing of PV units and the associated computation and analysis of system parameters are very important from the utility side before permitting the customers who are willing to connect PV units on their premises. The utility can suggest the proper sizing for the customers. The customer is also benefited by the installation of PV units with proper sizing with which they can maintain the reliability and efficiency of their system. This necessitates a robust and efficient power flow algorithm and optimization technique which can handle the uncertainty.

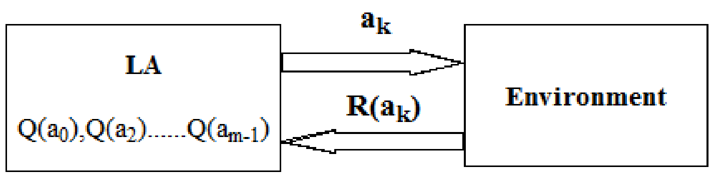


Figure 6.1: Process of Learning Automata

6.2 Learning Automata Algorithm for Single Stage Decision Making Problem

Learning automata (Thathachar and Sastry, 2011) is a simple model for adaptive decision making in uncertain environments. It can be defined as an automaton which selects one of its actions related to its past experiences and rewards or punishments from the environment. This is similar to the way by which an organism learns from the environment. In the simplest way, the learning automata can be represented as shown in Fig. 6.1. LA algorithm is explained with the help of N-arm bandit problem.

The n-arm bandit problem, consists of a slot machine with n arms. The player is allowed to play on any of the arm a but has to pay a fee say 1 unit. When played on any arm, the player is given with a random reward which is represented by $R(a)$. Assuming fixed probability distribution for each arm, each arm is expected to return a random variable with uniform probability distribution, which the player is unaware of. As an example, by playing on arm 3, a random variable whose value lies between 0.5 and 0.8 is returned by the machine, whose mean value $Q(3)$= 0.75. Similarly, by playing on arm 4, a random variable whose value lies between 0.6 and 0.8 is returned by the machine, whose mean value $Q(4)$= 0.7 and so on.

The player in the n-arm bandit problem has to find the arm that returns maximum mean with minimum number of trials. For achieving the goal, the LA algorithms continuously interact with the random environment by performing sufficient number of actions which helps in obtaining the best decision. Here the decision to be taken is the arm number on which the player has to play to get maximum reward. One method is to make large number of trials on each arm and find the mean returned by the machine for each arm. Let $R^i(a)$ denotes the reward obtained for playing an arm a in the i^{th} trial, then the mean value corresponding to each arm in a total of n trials can be estimated as

$$Q^n(a) = \frac{\sum_{i=1}^{n} R^i(a)}{n}$$

Once the value of Q^n is obtained for arm a, the best arm, which is denoted as "greedy arm" (a_g) can be found out as

$$Q^n(a_g) = max_{a \in A} Q^n(a) \tag{6.1}$$

The corresponding action which gives the maximum is given by

$$Q^n(a_g) = \max_{a \in A} Q^n(a) \Rightarrow a_g = \arg\,\max_{a \in A} Q^n(a) \tag{6.2}$$

The method described above is direct and simple but not efficient. Suppose the machine has $m = 1000$ arms and the number of trials, n =1000. Then to find out the best arm, the player has to play $1000 * 1000 = 10^6$ times which is not efficient. To solve the problem more efficiently, LA algorithm uses an iterative technique and also chooses the actions that have the highest probability of being the best action. The iterative algorithm is based on the recursive formulae derived below which helps to find out the updated value of the performance index (Sutton and Barto, 1998).

$$Q^{n+1}(a) \begin{cases} = \dfrac{\sum_{i=1}^{n} R^i(a) + R^{n+1}(a)}{n+1} \\ = \dfrac{nQ^n(a) + R^{n+1}(a) + Q^n(a) - Q^n(a)}{n+1} \\ = Q^n(a) + \dfrac{1}{n+1}(R^{n+1}(a) - Q^n(a)) \end{cases} \tag{6.3}$$

Starting from an initial estimate $Q^0(a) = 0$, the equation helps in finding the estimates of the expected value. In n-arm bandit problem, $Q(a)$ is the expected value of reward corresponding to arm a. Similarly $Q^n(a)$ is the expectation of $Q(a)$ over n trials or observations.

The recursive equation can be used to estimate the expected value of $R(a)$ when the observations are selected independently.

$$Q^{n+1}(a) = Q^n(a) + \alpha_n[R(a) - Q^n(a)] \tag{6.4}$$

Here α is called the update factor whose value helps in the convergence of the algorithm.

One distinct feature of LA algorithms is the balance between *exploration* and *exploitation*. It explores the environment to gather information to build a policy. The balance is possible by using the acquired knowledge to make better decisions, but without leaving the unexplored areas. An agent can follow certain actions to obtain more rewards, but the only way to choose the best action is the exploration of the environment. The strategy for exploration mainly depends on the time the agent and the environment are in interaction. In the case of n-armed bandit problem, consider the situation where the player thinks that a particular arm has the highest probability of giving maximum reward. The dilemma lies, whether he has to select that particular arm all the time or choose another arm with minimum information.

In the initial stages of the algorithm, the action a_g may not be the best action since the calculated mean $Q^n(a)$ is far from the true value. But as the algorithm proceeds and the number of trials n increases, the possibility of a_g being the best action increases. Therefore, in the initial phases of the algorithm the requirement is to acquire maximum information by *exploring* the unknown environment. As the number of trials increases, it is better to *exploit* the available information. For balancing this trade off between the exploration and exploitation, exploration strategies are used. The exploration strategy used here is the ε-greedy method which is explained in Section 6.3.5.

6.3 Multi Stage Decision Problem (MDP) and Reinforcement Learning

6.3.1 Introduction to Reinforcement Learning

Reinforcement Learning (RL) is a machine learning approach which has the features of both supervised and unsupervised learning. The main difference of reinforcement learning from other methods is that the emphasis is given for learning by the individual by directly interacting with the environment without depending on supervision or adequate models of the environment. In reinforcement learning, an agent follows the trial and error process to interact with the environment and to learn the optimal actions to be taken in each state in order to maximize the reward signal. By exploration of an unknown system, the sufficient experience is gained which helps such algorithms to act in an optimal way.

Reinforcement Learning combines two disciplines to solve the problems successfully which cannot be addressed individually by the two disciplines which are dynamic programming and supervised learning. Dynamic programming is a traditional method in the field of mathematics that has been used to solve many optimization problems. But the application of dynamic programming is limited to, problems which involves small and simple systems. Supervised learning on the other hand, requires various sets of input-output pairs for training network. Reinforcement learning by combining the features of these disciplines can be used to solve problems, to build into powerful machine learning systems. In reinforcement learning the goal to be achieved is defined.

The agent, otherwise the learner or decision maker continuously interacts with the environment to achieve the defined goal. The agent performs sufficient number of actions and the environment responds to each of these actions in the form of rewards. The ultimate aim is to maximize the reward over time. At each time step, $t = 0, 1, 2, 3, ...$, the agent interacts with the environment and some representation of the environment's state $s_t \in S$ is

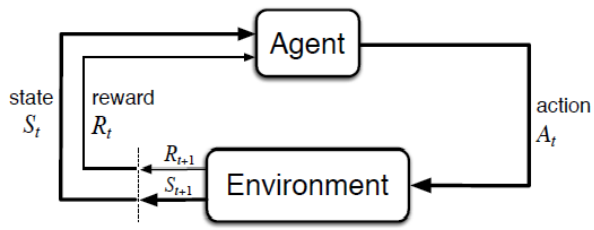


Figure 6.2: Interaction between Agent and Environment in reinforcement learning

obtained. Here S is the set of all possible state. Corresponding to each state, an action $a_t \in A(s_t)$ is performed, where $A(s_t)$ is the set of actions for state s_t. When an action is performed, the environment returns a numerical reward $r_{t+1} \in R$ and finds itself in a new state s_{t+1}. The interaction between the agent and environment is shown in Fig. 6.2.

The main elements of a reinforcement learning system are state space, action space, policy, reward function and a model of the environment (Sutton and Barto, 1998) which are described in the following subsection with the help of the grid-world problem.

6.3.2 Elements of Reinforcement Learning

The various elements of Reinforcement learning are explained with the example of the canonical grid world problem for finding the shortest path given in Fig. 6.3.

The grid considered here has 25 cells arranged in 5 rows and 5 columns. At any instant, the agent can be placed in any one of the 25 cells. The agent has to reach the goal state T by travelling through the cells. The crossed cells have some obstacles and there is a cost incurred when agent moves from one

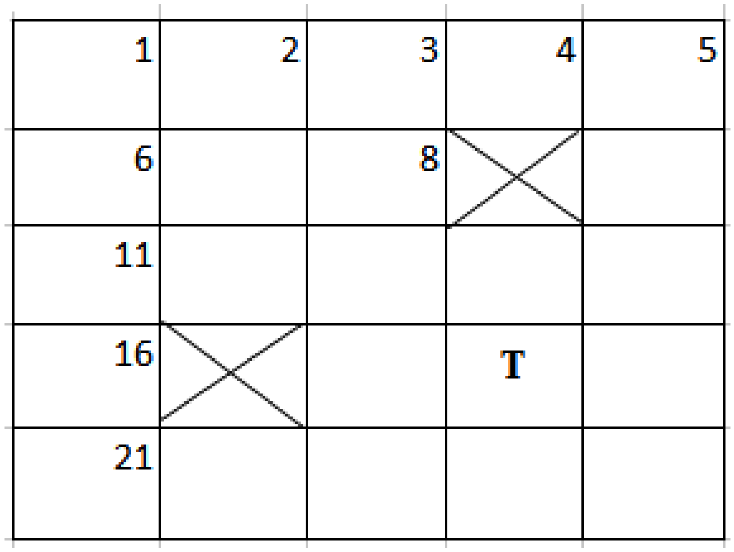


Figure 6.3: Grid World problem

cell to another. The cost is high when the agent moves through the crossed cells. The aim of the problem is to reach the goal state with minimum cost. There are different paths that the agent can follow for reaching the goal and depending upon the path the cost also varies. The optimum path that is to be followed is the aim of the grid world problem. With respect to the same, the various elements of reinforcement learning are described below.

1. State Space: The state is described by the cell number in which the agent is placed or the current position of the agent. This cell number is the subset of the entire 25 cells. This cell space is referred to as state space which is the set of all possible states at any instant of time that the agent can occupy. At any instant, the position or state of the agent is denoted as $x_k \in X$ where X represents the state space. From the initial state x_0, the agent performs a series cell transitions or actions

$a_o, a_1, a_2.....a_{N-1}$.

2. Action Space: The agent can perform any action $a_k \in A_k$ at any instant of time, where A_k represents the set of possible actions that can be taken at any instant. The action space depends upon the current state x_k. For example, if the agent is placed in cell number 8 i.e $x_k = 8$, move to the right is not permitted since it represents an obstacle. The permissible set of actions that can be performed at any instant k constitutes the action space.

3. System Model: In Reinforcement learning, the agent interacts with the environment to obtain a solution. In some cases, this would not be possible, which necessitate a mathematical or simulation model of the system. In the shortest path problem considered here, the next position or state of the agent depends on the current state and the action that is taken.

   For the grid mentioned in Fig. 6.3, if $x_k = 8, a_k = down$ then $x_{k+1} = 13$, and if $x_k = 8, a_k = left$ then $x_{k+1} = 7$. For such simple systems, by direct observation the next state can be obtained, but for large systems, simulation model is required to study the environment in which agent moves so that x_{k+1} can be obtained.

4. Policy: A policy in reinforcement learning can be defined as any mapping from states of the environment to the actions that are taken in that state. The next state is a function of the present state and the action that is to be taken in the present state. In the example considered here, if the current state of the system is $x_k = 21$, there are many paths

it can follow to reach the goal state. Each path can be considered as a policy represented by π_1, π_2, etc. The ultimate aim is to find out the optimum policy π^* which returns minimum cost.

5. Reinforcement Function: Reinforcement function can be defined as the goal that is to be achieved otherwise, should reflect the goal of the agent. Reinforcement function maps the states into a reward or reinforcement which indicates the desirability of that particular state. When an action is performed in a given state, a reward in the form of a scalar value is returned by the environment. The ultimate goal of RL is to maximize the sum of reinforcements received. In the case of shortest path problem, each normal cell movement results in a cost of 2 unit. But moving to the cell with obstacle results in penalties or more cost. The reinforcement function received by performing an action a_k, moving from x_k to x_{k+1} is represented as $g(x_k, a_k, x_{k+1})$. The reward r_k is the immediate reinforcement or the reinforcement function returned by the RL environment at each time step.

6.3.3 Multi Stage Decision Problem(MDP)

Reinforcement learning can be applied successfully for problems in which sequence of decisions to be taken and such problems are called as Multistage Decision Problems (MDP). The rewards returned in each stage of decision making can be stochastic in nature. The application of reinforcement learning for solving MDP is described below.

If $x \in X$ is the current state of the system and if system, moves to a new state y, by taking an action $a \in A$, and if the probability of such transition is described by P_{xy} and can be calculated as

$$P_{xy} > 0 \quad \forall x, y \in X, a \in A \tag{6.5}$$

$$\sum_{y \in X} P_{xy} = 1 \quad \forall x \in X, a \in A \tag{6.6}$$

An immediate reward $g(x_k, x_{k+1}, a)$ is obtained corresponding to each state and actions taken in that state. The goal is to find an optimal policy which determines the actions to be taken in each state of the environment such that the cumulative measure of reward obtained is optimum.

Suppose, we start from an initial state x_0 and selects an action $a_0 \in A$. Depending upon the selected action, a new state x_1 is obtained. The new state is randomly chosen according to a probability $P_{x_0 x_1}$. Now an action a_1 is chosen and the system moves to another state x_2. Then an action a_2 is chosen and so on. This can be pictorially represented as

$$x_0 \overset{a_0}{\rightarrow} x_1 \overset{a_1}{\rightarrow} x_2 \overset{a_2}{\rightarrow} x_3 .... \tag{6.7}$$

When these sequence of states, $x_0, x_1....$ are encountered with actions $a_0, a_1...$, the total reward or pay off is obtained as

$$g(x_0, a_0) + \gamma g(x_1, a_1) + \gamma^2 g(x_2, a_2) + ... \tag{6.8}$$

In terms of states, this can be written as

$$g(x_0) + \gamma g(x_1) + \gamma^2 g(x_2) + ... \tag{6.9}$$

The ultimate aim of the reinforcement learning is to select actions over time, so as to maximize the expected value of the reward.

$$E[g(x_0) + \gamma g(x_1) + \gamma^2 g(x_2) + ...] \tag{6.10}$$

Here γ is called the discount factor and the reward at stage k is discounted by γ^k. Therefore, positive values of rewards should be acquired in the initial stages so as to maximize the expected value.

A policy as described in the previous section can be defined as a mapping from a state to an action. We can say a policy π is followed, if an action $a = \pi(x)$ is performed in a state x. Therefore, the value function can be defined as

$$V^{\pi}(x) = E[g(x_0) + \gamma g(x_1) + \gamma^2 g(x_2) + ...|s_0 = s, \pi] \tag{6.11}$$

For a fixed policy π, according to Bellman's equation,

$$V^{\pi}(x) = g(x) + \gamma \sum_{x' \in X} P_{x,\pi(x)}(x')V^{\pi}(x') \tag{6.12}$$

From the equation, it is clear that the value function corresponding to a policy π consists of two terms, the first term $g(x)$ is the immediate reward obtained in state x and the second term is the expected sum of future discounted rewards for state x', where x' is the state obtained by following a policy $\pi(x)$. For a finite stage MDP, such an equation for $V^{\pi}(x)$ can be developed for each state and which can be solved for finding $V^{\pi}(x)$ for each state x.

The optimal value function can thus be defines as

$$V^*(x) = \underset{\pi}{max} V^\pi(x) \tag{6.13}$$

The optimal value function can also be defined as "best possible expected sum of discounted rewards that can be attained using any policy" (Sutton and Barto, 1998). Using Bellman's equation, the optimal value function can be written as

$$V^*(x) = g(x) + \gamma \underset{a \in A}{max} \sum_{x' \in X} P_{x,a}(x') V^*(x') \tag{6.14}$$

The first term of the equation represents the immediate reward of the state x. The second term corresponds to the maximum of future discounted rewards over all action a.

Accordingly the policy that corresponds to the optimal value function for a maximization problem is given by

$$\pi^*(x) = g(x) + \underset{a \in A}{argmax} \sum_{x' \in X} P_{x,a}(x') V^*(x') \tag{6.15}$$

Here $\pi^*(x)$ returns an action a that corresponds to the maximum of "max" in Eq. (6.12).

For each state x and policy π, there exists an optimal value function given by

$$V^*(x) = V^{\pi^*}(x) \geq V^\pi(x) \tag{6.16}$$

Corresponding to the optimal policy π^*, there exists an optimal value function V^*, such that the value of π^* is greater than any other policy. The policy π^* it is the optimal policy for all the states $x \in X$, independent of the initial state.

Thus the MDP is formulated mathematically. Also procedure to be followed to reach optimal policy and optimum function is obtained. The next section describes the solution approach for reaching the optimal policy which is described as Q-learning.

6.3.4 Q Learning Algorithm

The solution approach that is used here to find an optimal policy is the Q-learning algorithm which finds the optimal policy by learning the values of function $Q(x, a)$. The value of the Q function is the value of taking an action in a state under policy π. The Q-value corresponding to a policy π is defined as

$$Q^\pi(x) = g(x) + \gamma \sum_{x' \in X} P_{x,\pi(x)}(x') V^\pi(x') \tag{6.17}$$

Comparing Eq. (6.17) with Eq. (6.12),

$$Q^\pi(x, \pi(x)) = V^\pi(x), \quad \forall x \in X \tag{6.18}$$

For optimal policy π^*, the above equations can be written as $Q^{\pi^*}(x, \pi^*(x)) = V^{\pi^*}(x) = V^*(x), \forall x \in X$ which returns optimum value of Q for the state action pair (x, π^*). For a maximization problem, the optimal Q-value can be defined as

$$Q^*(x,a) = \max_{\pi} Q^{\pi}(x,a) \tag{6.19}$$

which implies

$$Q^*(x,a) = Q^{\pi^*}(x,a) \quad \forall x \in X, \forall a \in A \tag{6.20}$$

The optimal policy then can be defined as

$$\pi^*(x) = argmax_{a \in A} Q^*(x,a) \tag{6.21}$$

The Q-learning method can be employed by generating a sequence of samples which can be used to update the value of Q. An action corresponding to state x is taken by the agent using some strategies to reach the next state x' which corresponds to an immediate reward given by $g(x,a,x')$ that is used to update the value of Q iteratively

$$Q^{n+1}(x,a) = Q^n(x,a) + \alpha[g(x,a,x') + \gamma \max_{a \in A} Q^n(x',a) - Q^n(x,a)] \\ \forall x \in X, \forall a \in A \tag{6.22}$$

With small values of α, Q^n converges to Q^* and therefore for large values of n, $Q^*(x,a)$ can be approximated as $Q^n(x,a)$. The discount factor $\gamma \in$(0,1) and the learning parameter $\alpha \in (0,1)$ should be chosen based on trial and error method. The Q-learning algorithm for a MDP with N stages can be summarised as follows

For all states $x \in X$ *and* $a \in A$

Initialize the value of $Q^0(x,a) = 0$

For $i = 1 : max\_iter$

Observe the current state x_0

For k=1:N

Pick an action a_k *using action selection strategy*

Perform action a_k *and reach state* x_{k+1}

Obtain the immediate reward $g(x_k, a_k, x_{k+1})$

Update the value of $Q_(x_k, a_k)$

Update the state from x_k *to* x_{k+1}

End

End

End

When every action is performed sufficient of times in each state, estimated Q-values would converge to true Q-values. To select an action from the action set various action selection strategies are used and most commonly used method is the ϵ-greedy algorithm which is described in Section 6.3.5.

6.3.5 Action Selection based on ε-greedy method

The action that corresponds to the optimum values of Q is called as greedy action. At any discrete step, there will be one action whose estimated performance index upto that moment is best. That can be regarded as greedy which is based on the current estimate of the performance index. But the current estimate may be wrong. There may be better action. Therefore the solution strategy should explore the goodness achieved for the greedy action at the same time exploring other possibilities. i.e Exploitation is the process of extending the knowledge of the model by trying out so that more profitable actions can be found out. At the same time, it has to exploit the knowledge to achieve the maximum returns. This is achieved using exploration strategy known as ε-greedy algorithm.

In the initial stages of the algorithm, the action a_g may not be the best action since the estimated mean $Q^n(a)$ is far from the true value. But as the algorithm proceeds and the number of trials n increases, the possibility of a_g being the best action increases. Therefore, in the initial phases of the algorithm the requirement is to acquire maximum information by exploring the unknown environment. As the number of trials increases it is better to exploit the available information. The ε-greedy algorithm maintains the balance between exploration and exploitation by choosing the greedy action a_g with a probability of $(1 - \varepsilon)$. The probability of selecting any random action a is assigned as ε. Initially, the value of ε is selected as close to 1. As the algorithm proceeds, the value of ε is decreased so that the probability of choosing the greedy action a_g increases. This is done because in the initial phases of the algorithm, the deviation of the estimated mean $Q^n(a)$ from the true value will be maximum.

6.4 Formulating Optimal Sizing of PV Units as Learning Automata

The future distribution systems would be occupied with more number of DG units which will change the entire scenario of the distribution network. This transformation requires proper analysis for the integration of DG units. Optimal allocation of the DG units helps to exploit the benefits of DG units by minimizing the challenges. Photovoltaic source is the most abundant DG source as far as tropic regions are concerned. It is also the type of DG unit that can be installed by the consumers easily compared to any of DG units. When the DG units have to be installed in any distribution network, the two important aspects to be considered are the size of the DG unit and the location of installation without affecting the normal operation of the network. Each node of the distribution network is associated with an optimal size of the PV unit and this size can be considered while permitting the willing customers to install PV unit at their premises. Here the methodology utilizes the learning automata approach for finding out the optimal size of the PV unit at each node of the distribution network. For achieving this the optimal sizing should be formulated as learning automata.

The solar irradiance data of California, which is the location for the IEEE 37-bus distribution feeder is studied. The suitability of the Beta PDF for fitting the solar irradiance data is checked by conducting Chi-Square test. The uncertainty is modelled using Beta PDF by generating random samples that feature the behaviour of historical data. The data is divided into four seasons and each season is represented by a typical day as explained in Chapter 5. After finding the mean and standard deviation, Beta PDF is generated for each hour corresponding to each season. The generated PDF is analyzed so as to study the uncertainty. So if we select a particular hour, say 12 p.m. in Season 3, the value of the irradiance varies randomly. Selection of the number of modules to obtain a specific PV output is done based on the av-

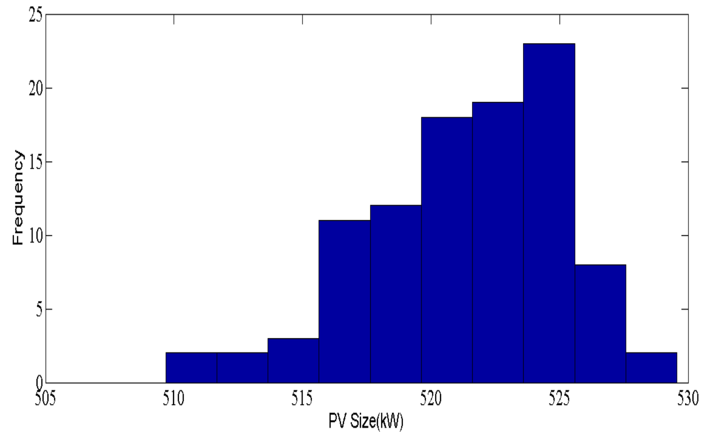


Figure 6.4: Random Variation of Power output

erage solar irradiance for that hour which is simulated using Beta PDF. So by fixing the number of modules, the output power of the PV unit varies randomly. The variation of the power output by choosing a PV size of 520 kW in season 2 at 11 noon for phase A in the case of IEEE 37-bus system is shown in Fig. 6.4 for 100 trials. The frequency plot indicates that, there is variation of power from 509 kW to 529 kW even though the power output is chosen to be 520 kW. This random nature of the PV power output needs an optimization method which is well capable of handling stochastic data. This makes the application of stochastic learning algorithms very much suitable here.

The objective function selected is the minimization of the total power loss, i.e. Our problem is essentially a *minimization* problem. In the present case, the learner (dispatcher) is to get a solution to find the optimum size of the PV unit to be installed at a specific node satisfying the operating constraints such as voltage and power limits so as to minimize the total power loss which is selected as the objective function in this study. Here the total network loss corresponding to a_k, $Loss(a_k)$ where Loss is given by (Hung and Mithulananthan, 2013).

$$P_{loss} = \sum_i \sum_j A_{ij}(P_i P_j + Q_i Q_j) + B_{ij}(Q_i P_j + P_i Q_j) \tag{6.23}$$

where

$$A_{ij} = \frac{R_{ij} cos(\delta_i - \delta_j)}{V_i V j} \tag{6.24}$$

$$B_{ij} = \frac{R_{ij} sin(\delta_i - \delta_j)}{V_i V j} \tag{6.25}$$

subjected to the constraints given below

$$\begin{gathered} |V_i^{min}| \leq |V_i| \leq |V_i^{max}| \\ |P_{DG,i}^{min}| \leq |P_{DG,i}| \leq |P_{DG,i}^{max}| \\ |Q_{DG,i}^{min}| \leq |Q_{DG,i}| \leq |Q_{DG,i}^{max}| \end{gathered} \tag{6.26}$$

Here the action set consists of the possible values of the PV unit. The range of the PV size is assumed to vary from 250 kW to total load plus losses in step size of 50 kW according to the size of the system in the case of IEEE 33-bus distribution system. The number of modules of PV unit that is required to generate the PV output power also vary accordingly. One of these actions can be selected and applied. If the IEEE-33 bus distribution system is considered, the action set can be written as $A = [250, 300, 350, ..., 4000]$ kW of PV unit and the size of action set is 76.

On applying an action a_k, the environment (the distribution network) returns a numerical value equal to the total power loss in the system corresponding to action a_k or a specific PV size. For example, In the case of IEEE-33 bus RDS suppose we choose a specific action, i.e PV size of 2600 kW at bus number 6. Therefore, the number of PV units/modules so as to yield the required power should be determined based on Eq. (6.27).

$$No\_modules = PVsize/av\_power \tag{6.27}$$

Here $PVsize$ is the selected value of size of PV unit and av_power is the average power output from the solar panel for the hour considered. But the value of PV output power varies randomly which is modelled using Beta PDF as explained in with respect to Fig. 6.4. To find out the actual power the following equation is used.

$$PVout = No\_modules * PV\_rand \tag{6.28}$$

Here PV_rand is the random output power that is obtained by modelling the uncertainty of PV power using BetaPDF.

With this value of power from PV unit, the power flow algorithm is run again by including PV power as explained in Chapter 3. After running the load flow, in the n^{th} trial, this action will return a reward which is the total network losses. For this specific action, the total power loss in kW is 107.04. This numerical value can be used to update the performance index in learning automata $Q^{n+1}(a_k)$ corresponding to the PV size of 2600 kW at bus number 6.

The input to the learning system is the specific point of installation of PV unit and the range of PV size. The Learning Automata system learns by taking up continuous actions and updating the corresponding performance index. The values of the performance index are first initialized as zero. One of the action a_k, a particular PV size will be selected from the 76 possible actions in the action set, using ϵ-greedy strategy, i.e the action with minimum value of the performance index (greedy action), a_g is selected with a probability of (1-ϵ) and one of the other actions in random with a probability of ϵ as explained in Section 6.3.5. The loss value obtained by selecting a particular action a_k is denoted as $Loss(a_k)$ which acts as the numerical return provided by the environment. It is then used to update the value of the performance index as given by Eq. (6.29).

$$Q^{n+1}(a_k) = Q^n(a_k) + \alpha \left[Loss(a_k) - Q^n(a_k)\right] \tag{6.29}$$

here α is called the learning parameter whose value lies between 0 and 1.

The learning parameter influences the convergence and correctness of the optimum value of the performance index. A large value of α will make the algorithm oscillatory and a very small value will slow down the convergence. Here it is chosen as 0.1 by trial and error method. Various permissible values of PV size are selected and loss corresponding to each value of PV size is estimated from the power flow algorithm. The losses are used to update the performance index. The action selection and updating performance index are repeated sufficient number of times so that the value of the performance index will be converging and afterwards the PV size that corresponds to the minimum loss value will be chosen with highest probability. After the convergence of the learning algorithm, the optimum size (action a_k) corresponding to minimum power loss is found as $a* = \text{argmin} Q(a_k)$. The complete algorithm is given below.

Read the system parameters such as line data, load data etc

Initialize ε*=0.5 and* α*=0.1*

Choose suitable discretization step, 50 kW

Identify the max. no: of PV size installation 'm'

Generate the possible actions,$a_0 ... a_{m-1}$

Initialize $Q^0(a_k) = 0$, $0 < k < m - 1$

For ($n = 0$ *to max_iteration)*

Begin

> *Select a PV size,* a_k *using* ε *greedy algorithm,using the current values of the performance index.*
>
> *Calculate the number of PV modules corresponding to the selected PV size by using Eq. (6.27).*
>
> *Calculate the random power generated by PV unit using Eq. (6.28)).*
>
> *Calculate* $Loss(a_k)$ *using Eq. (6.23) by running the Load Flow using modified sweep algorithm.*
>
> *Update* $Q^n(a_k)$ *to* $Q^{n+1}(a_k)$ *using Eq. (6.29).*

End

Find the greedy action from the updated values of $Q(a_k), 0 < k < m - 1$

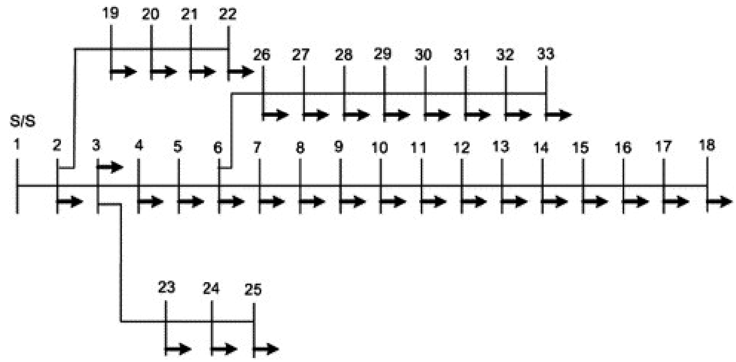


Figure 6.5: Line diagram of IEEE 33-bus RDS

6.5 Results and Discussions

6.5.1 IEEE 33 bus balanced RDS

In order to validate the effectiveness of the developed algorithm by comparing with the results obtained in the literature, IEEE 33 bus distribution system is considered. The line diagram of IEEE 33-bus distribution feeder is shown in Fig. 6.5. The size of the DG units assumed to vary from 250 kW to 3250 kW resulting in total number of actions equal to 60 with a discrete interval of 50 kW. The maximum power loss reduction with the installation of PV units achieved was 49.19 %. The results are tabulated in Table. 6.1 and found to be comparable with the results obtained from using the Improved Analytical Method (IA), and Exhaustive Load Flow method (ELF) as given in(Hung and Mithulananthan, 2013). The optimum size for the installation of DG units for each bus is given in Fig. 6.6 and the real power loss associated with the optimum size of PV units is shown in Fig. 6.7. The minimum voltage on the system is also improved as a result of the addition of the PV unit from 0.9134 to 0.9525 as shown in Fig. 6.8.

Table 6.1: Optimum size, Location, Power loss a for and Minimum Voltage for IEEE-33 bus RDS

Methodology	Installed DG Location	DG(kW)	PLoss(kW)	Loss Reduction(%)	Min Voltage(pu)
No DG	-	-	211.38	-	0.9134
IA	6	2601	111.10	47.39	0.9425
ELF	6	2601	111.10	47.39	0.9425
Proposed LA method	6	2600	107.4	49.19	0.9525

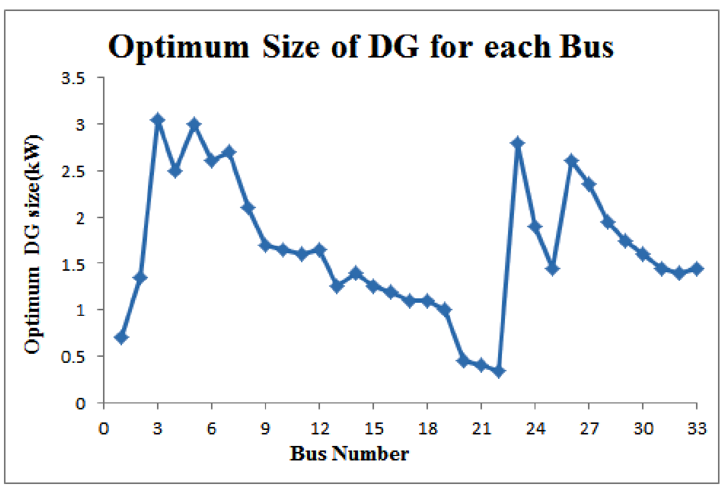


Figure 6.6: Optimum Size of PV units for each Bus

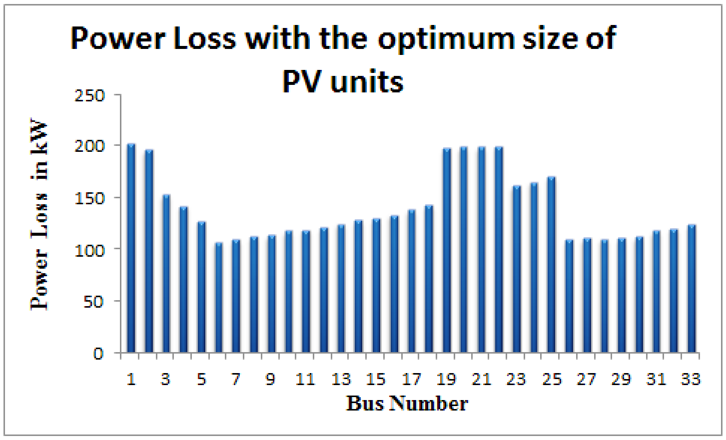


Figure 6.7: Power Loss with Optimum size of PV units for each Bus

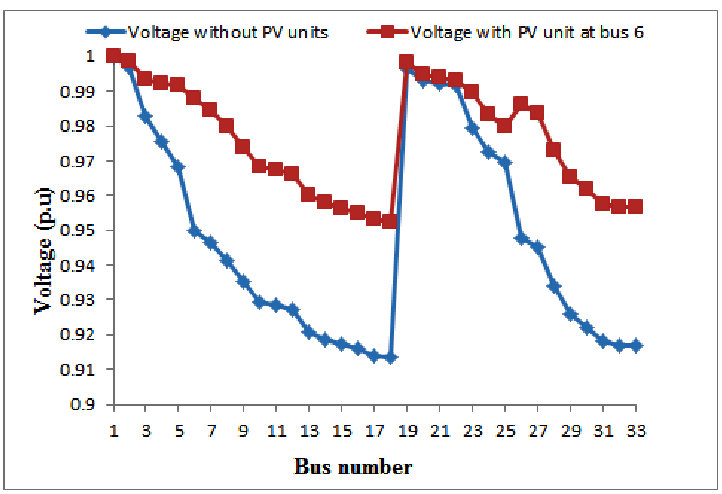


Figure 6.8: Voltage Profile variation with PV units for each Bus

6.5.2 IEEE 13 bus unbalanced RDS

IEEE 13 bus RDS is a very unbalanced feeder which has unequal loading on all the three phases. The feeder consists of two transformers 115/4.16kV of Delta/GY configuration at the main substation and 4.16/0.48 kV of GY/GY configuration in one of the lines. The feeder is characterized by both spot and distributed loads, which are balanced, unbalanced, single phase, three phase, delta and wye connected with all combinations of load models. There are overhead lines and underground cables with different spacing of phases. Three phase and single phase capacitors are utilized in the feeder topology. A detailed description of the system is given in (Kersting, 2001) and the line diagram is given in Fig. 6.9. The Size of the DG units in the case of this feeder assumed to vary from 50 kW to 1500 kW. The optimum size of the PV unit for each phase in shown in Fig. 6.10. The power loss with the addition of the PV unit is shown for each phase in Fig. 6.11.

It can be seen that for Phase A, the minimum power loss obtained is 17.27 kW with the addition of PV unit of size 1300 kW at Bus no 692. For Phase B, the minimum power loss achieved is 17.3 kW with the addition of PV unit of size 1150 kW at Bus No 632. For Phase C, the minimum power loss achieved is 25.9 kW with the addition of PV unit of size 1500 kW at Bus No 633. For the three phases altogether, the minimum power loss obtained is 23.08 kW with the PV unit installed at Bus No 692 with the optimum size of PV unit as 1300, 850 and 1500 kW for Phase A, B, C respectively. For each case, the voltage profile is within allowable limit. The power loss reduction achieved for each phase along with the average power loss reduction is plotted for each node in Fig.6.12. For phases A, B,

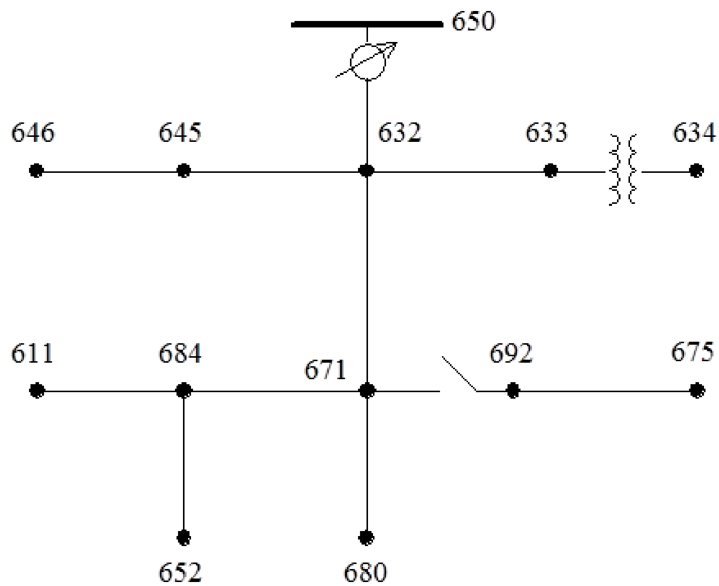


Figure 6.9: Line diagram of IEEE 13-bus RDS

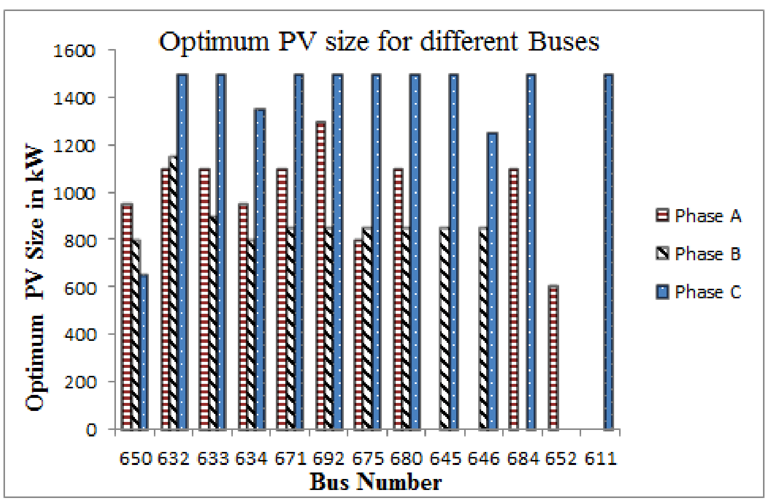


Figure 6.10: Optimum Size of the PV units for each node for 13-Bus RDS

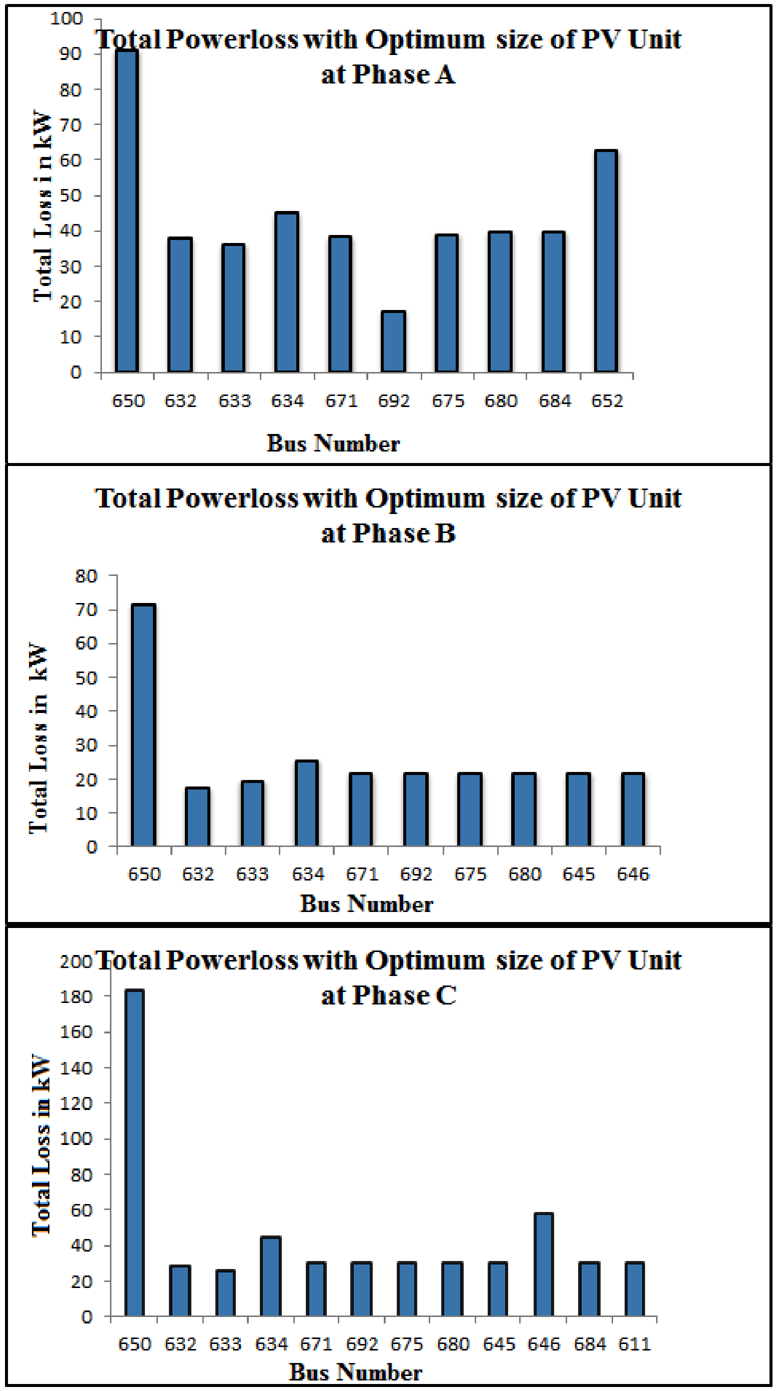


Figure 6.11: Total Loss in kW with Optimum PV size at each node for 13 bus RDS

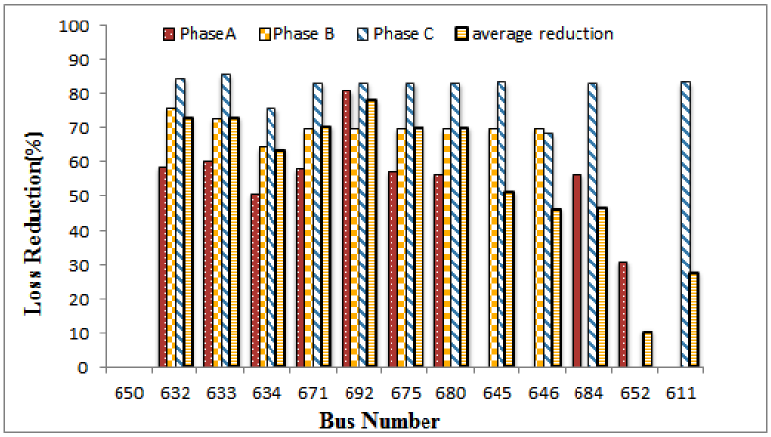


Figure 6.12: Loss Reduction in Percentage with Optimum PV size installed at each bus

C the maximum power loss reduction achieved in percentage are 80.9,75.3 and 85.87 respectively. On an average, the maximum power loss reduction is achieved is 78.08 for node number 692 with the installation of PV unit of size 1300,850 and 1500 kW for phases A, B and C respectively. The results are summarised in Table. 6.2. It is also seen that for buses with missing phases, the loss reduction is comparatively less compared to the other buses where all the phases are present.

6.5.3 IEEE 37 bus Unbalanced RDS

To check the effectiveness of the proposed methodology for application to larger systems, IEEE 37 bus unbalanced RDS is considered. The feeder consists of two transformers 230 kV/4.8 kV of Delta/Delta configuration at the main substation and 4.8/0.48 kV of Delta/Delta configuration in one of the lines. The Total real loading on the system are 727 kW, 639 kW and

Table 6.2: Optimum size, Location and power loss for IEEE 13 bus RDS

	Phase	Installed PV Location	PV size (kW)	Total power loss(kW)	Loss minimization(%)
Without PV unit	A	-	-	90.87	-
	B	-	-	71.63	-
	C	-	-	183.5	-
With PV Unit	A	692	1300	17.27	80.9
	B	632	1150	17.3	75.3
	C	633	1500	25.9	85.87

1091 kW on phases A, B, C respectively. The Total reactive loading on the system are 357 kVAr, 314 kVAr and 530 kVAr on phases A, B, C respectively. A detailed description of the system is given in (Kersting, 2001) and line diagram is given in Fig. 6.13. Due to the significant unbalance in the total loading on the three phases, the DG size on the three phases assumed to vary. For phase A, the DG size is assumed to vary from 26 kW to 780 kW. For phase B, the DG size is assumed to vary between 21 kW to 630 kW and for phase C, the DG size is assumed to vary between 30 kW to 1200 kW. The optimal size of the PV unit at various buses are shown in Fig. 6.14. By installing the PV unit of the optimum size, the total power loss incurred in the system is shown in Fig. 6.15. The corresponding power loss reduction achieved with the installation of PV unit is shown in Fig. 6.16. It can be seen that the minimum loss achieved on the system is 8.9 kW for phase A with the installation of PV unit of size 520 kW at bus number 734. For phase B, the minimum loss achieved is 2.88 kW with the installation of PV

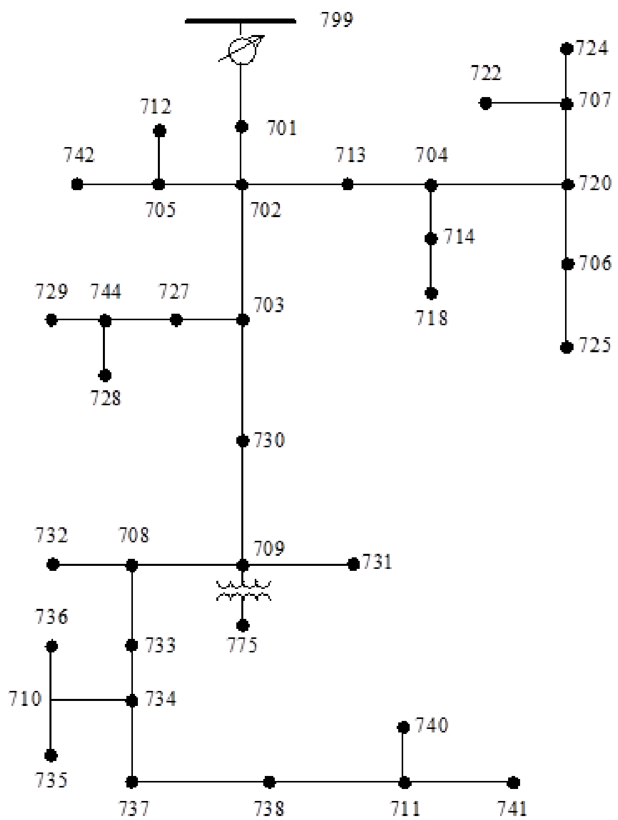


Figure 6.13: Line diagram of IEEE 37-bus RDS

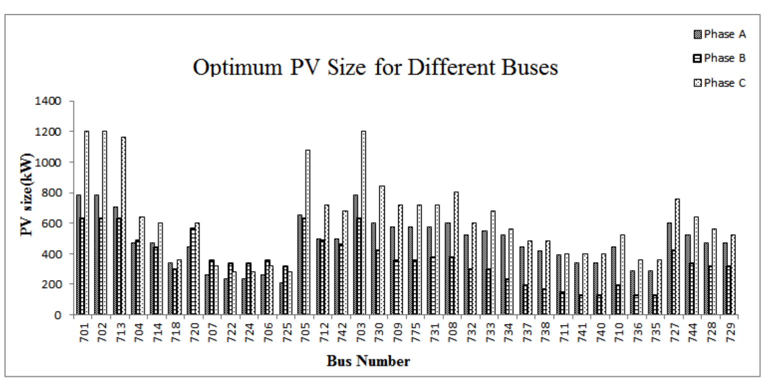


Figure 6.14: Optimum Size of the PV units for each node for 37-Bus RDS

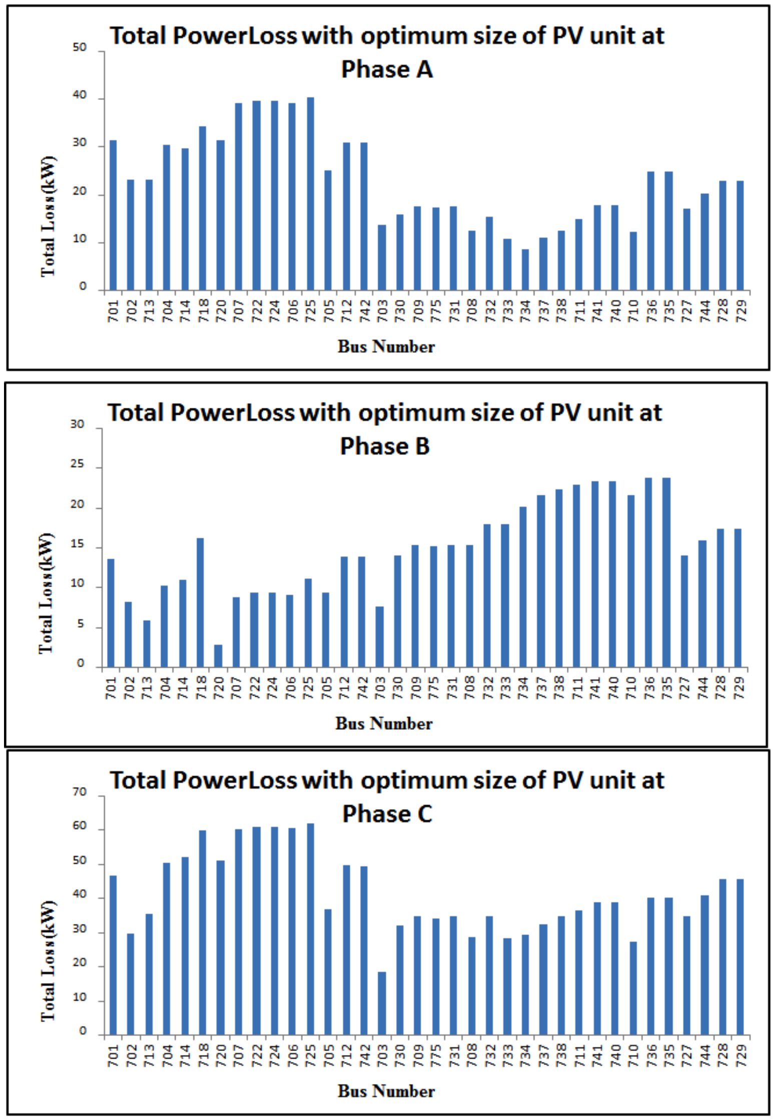


Figure 6.15: Total Loss in kW with Optimum PV size at each node for 37 bus RDS

unit of size 567 kW at bus number 720. For phase C, the minimum loss achieved is 18.63 kW with the installation of PV unit of size 1200 kW at bus number 703. The minimum power loss on an average is 13.31 kW with the installation of 780, 630 and 1200 kW at bus number 703 in phases A, B and C respectively. For all the cases, the voltage profile is within limits. The maximum loss reduction achieved are 82.31%, 89.67% and 74.32% at the optimized location. The maximum power loss reduction achieved on an average is 73.05 % with the installation of 780, 630 and 1200 kW at bus number 703 in phases A, B and C respectively. A plot of the percentage loss reduction is given in Fig. 6.16. The results for the IEEE 37 bus feeder is summarised in Table 6.3.

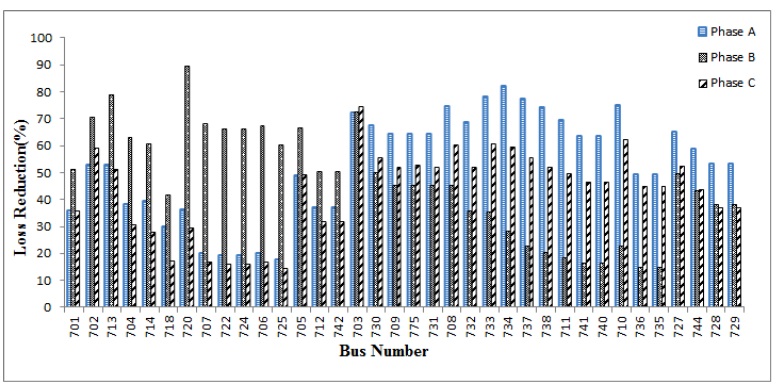


Figure 6.16: Loss Reduction in Percentage with Optimum PV size installed at each bus for 37 bus RDS

Table 6.3: Optimum size, Location and power loss for IEEE 37 bus RDS

	Phase	Installed PV Location	PV size (kW)	Total power loss(kW)	Loss minimization(%)
Without PV unit	A	-	-	49.17	-
	B	-	-	27.97	-
	C	-	-	72.56	-
With PV Unit	A	734	520	8.9	82.31
	B	720	567	2.88	89.67
	C	703	1200	18.63	74.32

6.6 Optimal Distributed Generation Placement as a Multistage Decision Problem(MDP)

Reinforcement Learning (RL) is a machine learning approach which has the features of both supervised and unsupervised learning. The main objective of Reinforcement Learning (RL) is to find an optimal policy that maximizes the reward. Here an agent follows a systematic process to interact with the environment and to learn the optimal actions to be taken in each state in order to maximize the reward signal. By the exploration of an unknown system, sufficient experience is gained which helps such algorithms to act in an optimal way. The basic elements of the RL paradigm comprise mainly of the elements which are policy, state space, action space reinforcement function and value function which are explained in Section 6.3.1.

The Optimal DG placement problems deal with the determination of the best location and the most beneficial capacity for DG installation. In most of the research work done earlier, the optimal DG placement problem is formulated as a single stage decision making problem which are solved by heuristics or Heuristic methods like Genetic Algorithm (GA), Particle Swarm optimization (PSO) etc. The ODGP problem can be better represented as a multi-stage decision making problem which helps to observe the current system state and select the sequence of actions accordingly. This will allow us to integrate the DG units more efficiently specifying the objectives.

In this view, the DG integrated Distribution system can be abstracted as follows. At each instant k, k= 1,2,3....., the system observes the current $'state'$ of the system x_k, and takes an $'action'$, a_k. In the case of Optimal integration of DG sources, the voltage of the system, voltage angles, line flows, etc. can be considered as state vector whose values are available after the power flow. Here in this study, the voltage magnitude is taken as the state vector since the voltage profile is a major factor of concern in DG placement. The state vector at the instant k, x_k can be the filtered or averaged values of the quantity over the time interval $k-1$ to k. This helps in discretising the chosen quantity to transform into the state vector. The set of all possible states X is assumed to be finite. For the IEEE 33-bus system, the state space can be represented as $X = [V_1, V_2....V_n]$ where V represents the voltage vector for the buses.

The possible actions for Optimal DG integration are the various values of $\triangle P$, where $\triangle P$ represents the change in the value of the dispatched power from DG from the previous state. The value of $\triangle P$ can be either positive or negative depending upon the value of the state vector, i.e. the voltage magnitude. The finite action set is denoted by A. The action set can be represented as $A = [50, 100, ...4000]$ kW of PV unit.

The objective of the DG placement problem considered here is the minimization of the power losses subjected to maximum and minimum power limits. Depending upon the objective function, the reinforcement function can be defined. The total power loss incurred should be the cumulative reward over k stages. Therefore the reinforcement function in k^{th} stage can be defined as the power loss corresponding to an action a_k.

$$P_{loss} = \sum_i \sum_j A_{ij}(P_iP_j + Q_iQ_j) + B_{ij}(Q_iP_j + P_iQ_j) \tag{6.30}$$

where

$$\begin{aligned} A_{ij} &= \frac{R_{ij}cos(\delta_i - \delta_j)}{V_iVj} \\ B_{ij} &= \frac{R_{ij}sin(\delta_i - \delta_j)}{V_iVj} \end{aligned} \tag{6.31}$$

subjected to the constraints given below

$$\begin{aligned} |V_i^{min}| \leq |V_i| \leq |V_i^{max}| \\ |P_{DG,i}^{min}| \leq |P_{DG,i}| \leq |P_{DG,i}^{max}| \\ |Q_{DG,i}^{min}| \leq |Q_{DG,i}| \leq |Q_{DG,i}^{max}| \end{aligned} \tag{6.32}$$

Now the Optimal DG placement problem has been formulated as a Multistage Decision Problem (MDP) which passes through N stages. At each stage k, a PV size is selected using some exploration strategy from one of the state of voltage. This results in a new value of voltage and this transition results in a reward corresponding to the size of PV units installed. So the problem can be simply defined as to be finding an optimal action a_k corresponding to state x_k in each stage k. Now the formulated MDP can be solved using Q-learning algorithm.

6.6.1 Q-learning algorithm for Optimal DG Placement

In the previous section, the optimal DG placement problem is modelled as a multi-stage problem. In this section Q-learning algorithm to solve the MDP is explained. At any stage k, the voltage values are considered as the state vector. For representing the state vector x_k in discrete form, the continuous voltage values are divided into a number states depending upon their values and the minimum and maximum voltages. For example, if the voltage value is between 0.9 $p.u$ and 0.91 $p.u$, then the state of the voltage is 1 and if it is between 0.93 $p.u$ and 0.94 $p.u$, then the state of the voltage is 4 and so on. Here 10 states are considered depending upon the variation in the voltage values.

Now an action a_k is taken which is the change in value of the PV power ΔP whose value can be positive or negative. The increment or decrement in PV power is selected based on ε-greedy algorithm. Here the size of the PV unit is assumed to vary from 250 kW to a value which corresponds to the sum of load and losses.

By performing this action, the system is moved to next state x_{k+1}. The next state or the new values of voltage are obtained after conducting the load flow which also returns a reward. Since the power loss is taken as the reward in the study, the reward function corresponding to action a_k is given by Eq. (6.30). Now Q-learning algorithm as described in Section 6.3.4can be used to find the solution for this problem. The Q-values, $Q(x, a)$ can be estimated for each state action pair which gets updated during each step of the learning phase. Thus the Q-values can be updated using Eq.(6.33)

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha[g(x_k, a_k, x_{k+1}) + \gamma \min_{a' \in A_{k+1}} Q^n(x_{k+1}, a') - Q^n(x, a)] \quad \forall x \in X, \forall a \in A \tag{6.33}$$

Here α is called the learning parameter and γ is called as the discount factor which is assumed as 1. In the last stage of the algorithm, Eq. (6.33) can be written as

$$Q^{n+1}(a_k, x_k) = Q^n(a_k, x_k) + \alpha \left[g(x_k, a_k, x_{k+1}) - Q^n(a_k, x_k)\right] \tag{6.34}$$

During the initial phases of learning, the calculated Q-values, $Q^n(a_k, x_k$ will be much deviated from the optimal value Q^*. As the learning proceeds, the estimated Q-values approach optimal value Q^*. With small values of α and sufficient number of state-action pairs, the value of Q^n will be converging to the optimal value Q^*.

The value of ε is very important in deciding the balance between the exploration and exploitation. Value of ε is usually chosen as close to 1 in the initial stages and as the learning proceeds, the value of ε reduced by 10 % and the greedy action ultimately turns to be the best action. The learning algorithm for optimal DG placement using MDP approach is explained in Section 6.6.2.

6.6.2 Learning Algorithm for Optimal Integration of DG Sources

Read the system parameters such as line data, load data etc.

Identify the feasible state space X and action space A

Read the initial status of state vector x_0. i.e voltage for all the nodes

Initialise $Q(x, a) = 0 \; \forall x \in X$ *and* $\forall a \in A$.

Initialise $k = 0$

Initialize $\varepsilon = 0.5$ *and* $\alpha = 0.1$ *and* $\gamma = 1$

For $n = 0 : max\_iter$

For $k = 0$ *to* $N - 1$

Do

Choose a PV unit to be installed using ε-greedy algorithm

Calculate the number of PV modules corresponding to the selected PV size by using Eq. (6.27).

Calculate the random power generated by PV unit using Eq. (6.28)) and run the power flow algorithm

Find the value of the state vector x_{k+1}

Calculate loss using Eq. (6.30)

If $(k < N - 1)$, *update* Q^n *to* Q^{n+1} *using Eq. (6.33)*

Else update Q^n *to* Q^{n+1} *using Eq. (6.34)*

End Do

Update the value of ε

End

Update Q-values

6.7 Results and Discussions

6.7.1 IEEE-33 Bus Balanced Distribution System

The proposed algorithm is validated for IEEE 33- Bus balanced distribution system. The voltages of the various buses are discretised and grouped into various states which are predefined earlier. Using the Reinforcement learning approach, the optimum location and size of the PV unit to be installed is determined. The size of the DG units assumed to vary from 250 kW to 3250 kW, resulting in total number of actions equal to 60 with a discrete interval of 50 kW. The maximum power loss reduction with the installation of PV units achieved was 49.19 %. The results are tabulated in Table. 6.4 and found to be comparable with the results obtained from using the Improved Analytical Method (IA), and Exhaustive Load Flow method (ELF) as given in (Hung and Mithulananthan, 2013). The voltage profile of the system with the installation of PV Units of optimum location and size is given in Fig. 6.17. The minimum voltage on the system is also improved as a result of the addition of the PV unit from 0.9134 to 0.9525.

Table 6.4: Optimum size, Location, Power loss and Minimum Voltage for IEEE-33 bus RDS

Methodology	Installed DG Location	DG size (kW)	PLoss (kW)	Loss Reduction(%)	Min Voltage(pu)
No DG	-	-	211.38	-	0.9134
IA	6	2601	111.10	47.39	0.9425
ELF	6	2601	111.10	47.39	0.9425
RL algorithm	6	2600	107.4	49.19	0.9525

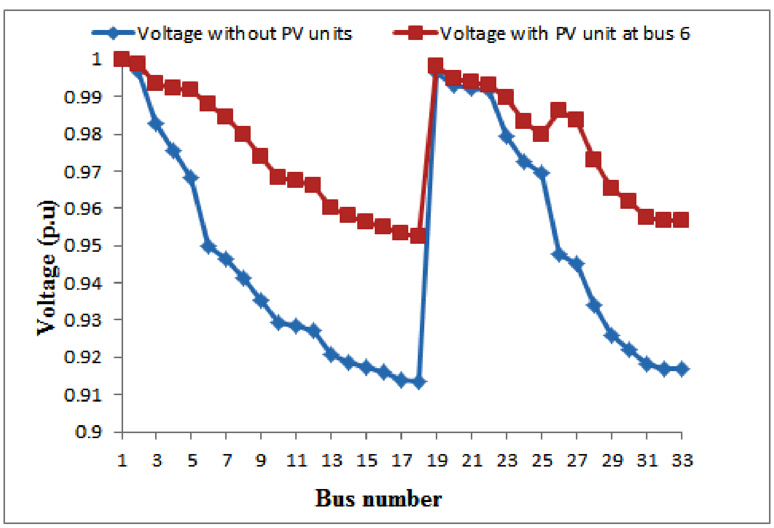


Figure 6.17: Voltage Profile variation with PV units for each Bus

6.8 Conclusion

The optimal integration of DG sources in the unbalanced distribution network is a challenging issue in the planning of the distribution system. The Photovoltaic type of DG is becoming popular because of its abundance. Here the optimal sizing of the PV units in the unbalanced distribution network is formulated as a Single Stage Decision making Process (SSDMP) using Learning Automata (LA) algorithm. An effort is also made to model the optimal DG placement problem as a MDP using Reinforcement Learning. The size of the PV unit is optimized so as to minimize the total network losses of the system subjected to various operating constraints. The uncertainty associated with the solar PV source is modelled using Beta PDF. The LA algorithm was validated and compared with the results in the literature for the balanced IEEE-33 bus distribution system and applied for the IEEE 13-bus RDS and IEEE 37-bus RDS. The effectiveness of the RL algorithm for optimal DG placement is validated using IEEE 33-bus distribution system. The proposed algorithms can therefore be used to estimate the optimal PV size to be installed in the distribution system with a capability to include the uncertainty associated with the PV source.

Chapter 7

Case Study of PV Integration in Practical Distribution System

7.1 Introduction

The very mounting demand for the electricity supply and the rising concern about global warming and climate change has motivated the electricity sector to adopt renewable and local sources of energy. In a developing country like India, efficient and buoyant power sector with high financial robustness is the need of the hour for booming economic growth and poverty alleviation. India is blessed with immense potential for solar power owing to its geographic location within the tropic region. Most of the parts of India have 300-330 sunny days in a very year that is sufficient to meet the entire energy demand within the country. The Indian Government have taken many initiatives for developing the renewable sources of energy for improving the rural electrification and energy security exploiting the solar energy. The Government has launched Jawaharlal Nehru National Solar Mission (JNNSM) which aims to achieve the installed solar capacity of 100 GW by 2022 of which 40 GW is to be contributed by the rooftop panels (mnr, 2012). The Central and State Government has taken many initiatives as a result of which the installed capacity of the solar photovoltaic has reached 5 GW in 2015. The contribution of DG sources in the power generation is expected to rise in the forthcoming years, resulting in a scenario where local generation will be much cheaper than the energy supplied by the electric utilities.

The conventional power system was designed to have centralized generation which is being supplied to the ultimate consumers using the extensive transmission and distribution network resulting in a unidirectional power flow. Introduction of DG sources, therefore causes problems in the power network that have not been outlined beforehand. The traditional power system operation was based on the peak load which was very much accountable hence the generation control could be ideally performed. Further the addition of dispersed generation units cause a transformation of the distribution network to active involving bi-directional power flow. Therefore, efficient analysis of the distribution system with DG is very much needed in the present situation. Appropriate strategies for finding out the optimal capacity and the location of the DG sources should be investigated so as to accomplish the advantages with the integration of DG sources.

As far as distribution systems in India, especially the state of Kerala is considered, most of them are operating at their maximum capacity, which leads to overloading and under voltage situation during peak hours. The state is suffering from a peak power deficit, which is as much as 1600 MW since 80% of the demand comes from the domestic sector. The expansion of the transmission grid is impractical owing to the constraints on the right of way permission for laying of new lines. The ultimate solution in order to meet the peak shortage is the integration of more and more renewable energy resources into the distribution grid. The state has already launched a unique off-grid solar rooftop programme known as the 10,000 Solar Rooftop Programme with the help of the state nodal agency ANERT (Agency for Non-conventional Energy and Rural technology) and is in the final phase. The state is now planning for the 25000 rooftop power programme which would be grid connected apart from the large scale ground mounted solar power plants to be commissioned. Therefore a study of the effects of the DG integrated distribution system is the need of the hour in the present scenario.

The focus of the chapter is to analyze a real-life 4.3 MVA distribution feeder in Kerala state, India which is unbalanced in nature. The aim is to optimally size the PV units so as to attain power loss reduction and voltage profile improvement in the radial distribution network. The selected area has significant solar radiation with 4-5 sunny hours. The method employed here is Learning Automata (LA) and Reinforcement Learning (RL) which are capable of handling the stochastic data in practical system and is already validated for standard radial distribution feeders in Chapter 6. Here the randomness of the Photovoltaic sources is considered using Beta PDF. The randomness associated with the solar irradiance is modelled using beta

PDF and this random power output is taken as the output power of DG. The integrated system was analyzed for voltage profile and power loss reduction. The optimal sizing of PV units and the associated computation and analysis of system parameters are very important from the utility side before permitting the willing customers to connect PV units at their premises. The utility can suggest the proper sizing for the willing customers. The customer is also benefited by the installation of PV units with Proper sizing with which they can maintain the reliability and efficiency of their system. The chapter discusses in detail, the application of stochastic learning algorithms namely LA and RL for finding the optimal capacity of PV units to be installed at selected locations in 4.3 MVA practical distribution feeder and the effect of this integration on voltage profile and loss reduction.

7.2 Problem Formulation for the selected system

The study has been conducted on a 4.3 MVA radial distribution network in Kerala state, India which is spanning over a length of 7.2 km with 55 buses. This network is indented to supply power to both single phase and three phase loads. The details of the connected load for the distribution network is shown in Table. 7.1 and the line diagram of the feeder is shown in Fig. 7.1. The nearest generating station is about 150 km away from the site considered and therefore the voltage drop in the peak hours is not within the desirable limits. It is expected that the integration of the DG sources contributes to the improvement in voltage profile, where the support from the grid is not

Table 7.1: Details of Connected Load

Connected Transformer Capacity	No, of transformers connected	Load Connected to each transformer	Total Load(kVA)
100	23	84	1932
160	7	134	938
250	1	210	210
400	1	336	336
500	2	420	840
Total	34	-	4256

possible.

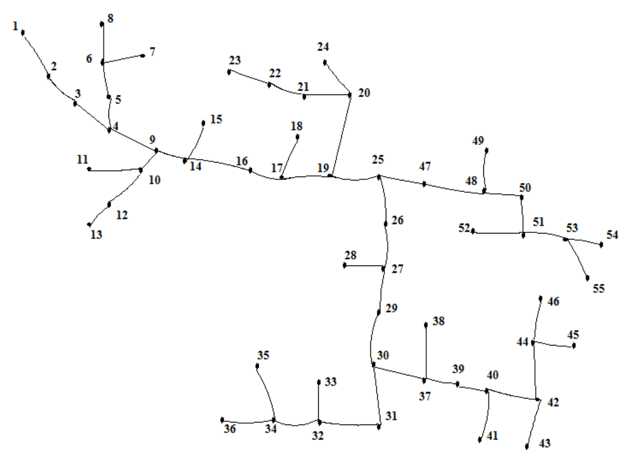


Figure 7.1: Single Line Diagram of the 55-Bus Radial Distribution Feeder

The analysis of the existing power distribution network indicates that the main problem faced by the consumers in the selected site is the poor voltage during the peak hours. On the other hand, high level of transmission and distribution losses is the main challenge faced by the electric utility. The chapter evaluates the performance of a real-life distribution feeder in terms of voltage profile and the network losses before and after the installation of the PV units. There are many power flow methods that can be applied to distribution systems which are reviewed in Chapter 2. The detailed power flow algorithm employed here for the unbalanced distribution network is given in Chapter 3.

From the results of the load flow studies, it can be seen that the voltage profile for the system is not within the acceptable limits. The minimum voltage on the system is 0.85 p.u which is far below the desirable limit of 10% and the voltage unbalance is above the allowable limit of 4%. Therefore, with the introduction of PV units at the buses where the voltage profile is not within limits there is a scope for improvement and since percentage unbalance in different phases is high, carrying out balanced studies is not recommended. The variation in voltage with the distance from the substation for phase A is shown in Fig. 7.2 for the three phases.

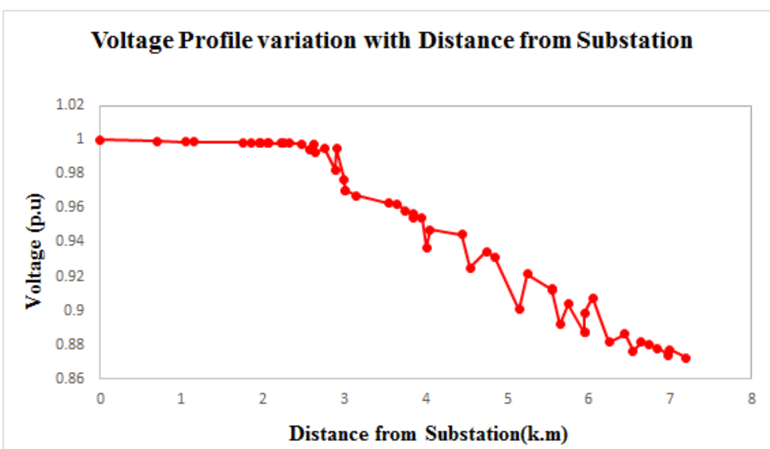


Figure 7.2: Voltage Profile variation with distance from substation for phase A

7.3 Optimal size of PV unit for 4.3 MVA Real-life Unbalanced RDS

Estimating the optimal size of the PV units has been modelled as a single stage decision making problem and is solved using learning automata. The concept of learning automata and the formulation of the optimal sizing problem as learning automata is explained in detail in Chapter 6. Minimization of power loss is considered as the objective function. Here the penetration level of the PV units in the distribution transformer assumed to vary between 20 % and 80 %. Therefore the action set considered here composed of the PV units with rating varying between 20 kW and 80 kW in discrete step size of 4 kW for distribution transformers with 100 kVA rating. The complete algorithm for optimal sizing using learning automata is given in Section 6.4 in Chapter 6.

For the real life feeder, two cases have been considered. In the first case, four nodes with minimum voltage were selected for DG installation. In the second case, large consumers on the system are selected so that there is a scope for the utility to install rooftop panels on the system. The voltage profile improvement and the loss reduction with the installation of PV unit is additionally analyzed. The sections of the radial distribution feeder with minimum voltage are highlighted in the line diagram. A minimum of a node from all these sections is taken into account for the installation of the PV unit. The details of the two cases are given in the next sections.

7.3.1 Case I- Installation of PV units in under voltage sections

It is evident from Fig. 7.2 that as the distance from the substation increases, there is a drop in the voltage which makes the voltage goes below the nominal values. The Fig. 7.3 shows the sections in the distribution feeder where the voltage is below the nominal value and where there is a scope for the installation of PV unit.

At least one node belonging to each highlighted section is considered

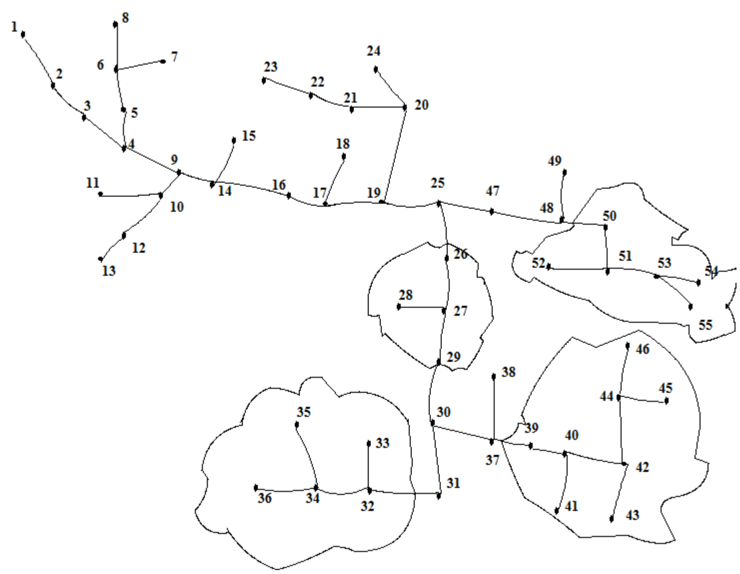


Figure 7.3: Single Line Diagram of the 55-Bus RDS Under voltage Sections Highlighted

for PV integration. The nodes selected are 28, 36, 41, 43, 46 and 55. For finding out the optimum size of the PV unit at each of these nodes, learning Automata (LA) algorithm is used. Most of the transformers used are rated 100 kVA and maximum PV penetration is restricted to 80%. The results for the optimum size of the PV unit size required so as to minimize the power losses and improve the voltage profile is tabulated in Table. 7.2.

The installation of PV units of the specified size causes improvement in

Table 7.2: Optimum PV Size for the selected Nodes

Node Number	Optimum Size(kW)		
	Phase A	Phase B	Phase C
28	40	60	20
36	56	24	28
41	40	24	24
43	40	64	32
46	40	24	40
55	64	24	52

voltage profile and loss reduction in the distribution feeder. The improvement in the voltage profile of the three phases with the installation of the PV unit is shown in Fig. 7.4.

It can be seen that by installing the PV unit at the selected locations, there is a slight drop in voltage at the near end of the substation, but within limits. But at the nodes where the voltage was sub nominal, there is a significant improvement in the voltage profile. The minimum voltage on the system is improved to 0.9093 p.u, 0.9182 p.u, 0.92 p.u from 0.8314 p.u, 0.8337 p.u and 0.8383 p.u for phases A, B and C respectively which are within acceptable limits of $\pm$ 10%. There is also a significant reduction in the power loss in ranges of 33%-40%. The results of the optimization algorithm for optimal PV sizing is summarised in Table. 7.3.

With the installation of PV units of optimal size, the energy losses are also minimized. The annual energy losses have been calculated by considering

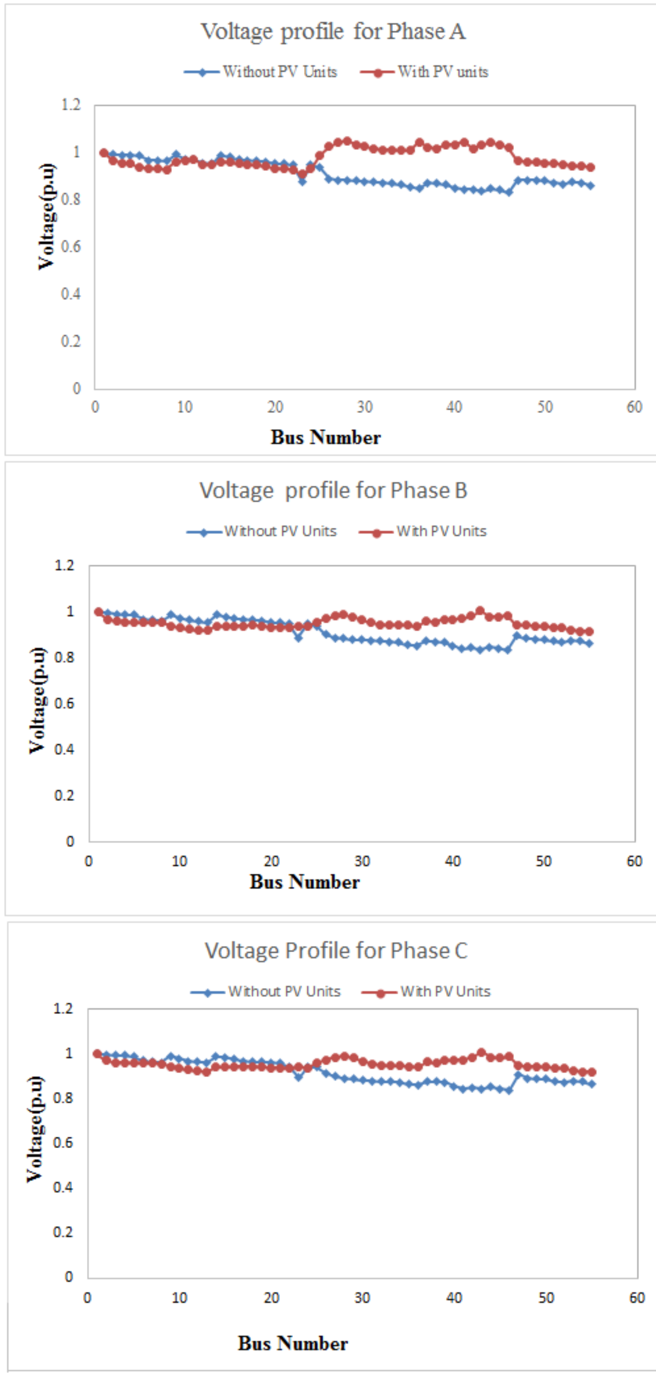


Figure 7.4: Voltage Profile for the three phases without and with PV units

Table 7.3: Voltage profile and Power Loss without and With the addition of PV Units

	Without PV Units		With PV Units		
Phase	Minimum Voltage (p.u)	Loss (kW)	Minimum Voltage (p.u)	Loss (kW)	Loss Reduction (%)
A	0.8314	95.62	0.9093	59.05	38.24
B	0.8337	84.40	0.9182	56.069	33.56
C	0.8383	87.94	0.92	57.84	34.22

the hourly power output for each season. For this calculation, the solar irradiance data of the site are taken from national solar irradiation database and Beta PDF is used to model the uncertainty. The equation for calculating the energy losses in a typical day representing a season is given by (Hung et al., 2013).

$$E_{loss,day} = \sum_{t=1}^{24} P_{loss}^{t} \Delta t, \tag{7.1}$$

Here Δt represents the time duration which is taken as one hour. The Energy loss for a particular season can be calculated as

$$E_{loss,season} = No\_days \times E_{loss,day}, \tag{7.2}$$

Here No_days represents the total number of days in a season and $E_{loss,day}$ is given by Eq. (7.1). Adding the value of energy loss for each season gives the annual energy loss. The annual energy losses as a percentage of the total real power for the three phases are shown in Fig. 7.5. The reduction in energy losses is less compared to the power losses because of the hourly and seasonal variation in Solar power output. This uncertainty associated with the solar power output is modelled using Beta PDF and power output is estimated by randomly generating samples which is discussed in Chapter 5.

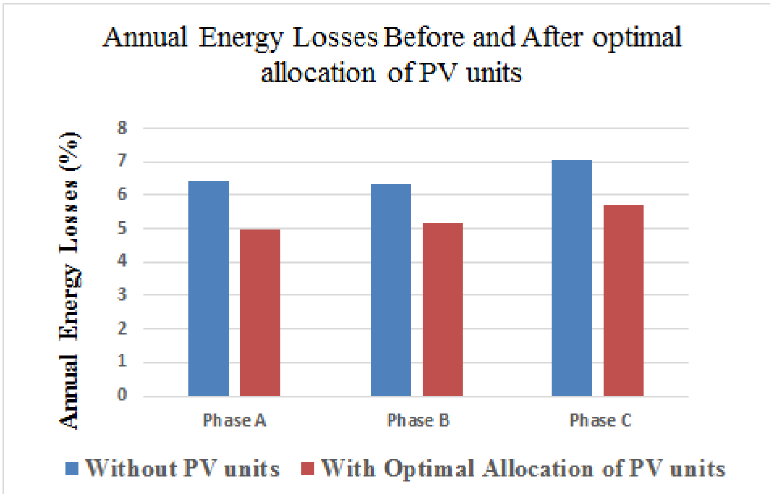


Figure 7.5: Annual Energy losses before and after the installation of PV units

7.3.2 Case II-Installation of PV Units on the High Tension(HT) consumers

The selected distribution feeder is having a number of HT consumers, including academic institutions, Government and Non-Governmental Organisations where there is a scope for the utility to install rooftop PV panels. The selected HT consumer is a Police Training Academy which is spread around 348 Acres. Three HT transformers were chosen from the selected organisation in which one transformer is of 250 kVA capacity and two others are of 500 kVA capacity. The load of the selected site is found to vary from 30 kVA to 84 kVA. Maximum 80% penetration of PV units is allowed for each transformer. The selected nodes are highlighted in the Single line Diagram of the distribution feeder in Fig. 7.6. The optimum size of the PV panels required to minimize the losses and improve the voltage profile are shown in Table. 7.4.

With the installation of the PV units of the optimum size, the power

Table 7.4: Optimum PV Size for the selected Nodes

Node Number	Optimum Size(kW)		
	Phase A	Phase B	Phase C
18	70	50	100
22	260	400	380
24	360	400	380

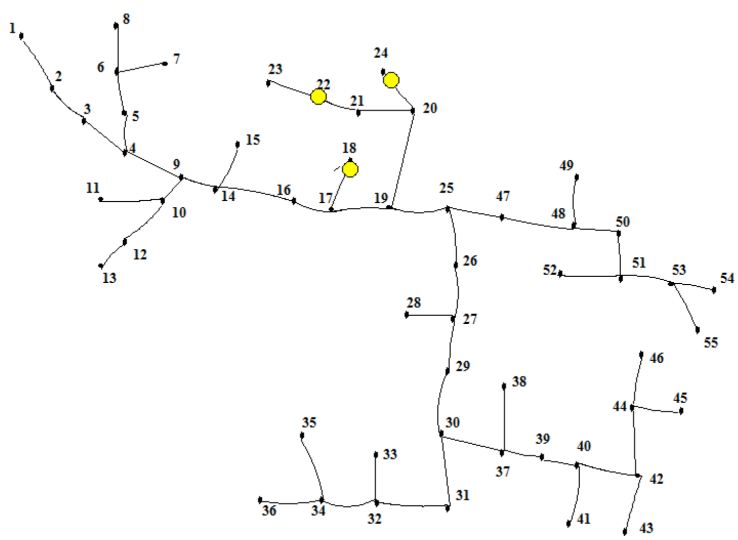


Figure 7.6: Single Line Diagram of the 55-Bus RDS under voltage Sections Highlighted

losses are reduced and there is a significant improvement in the voltage profile on all the three phases. The voltage profile without and with the installation of the PV units is shown in Fig. 7.7.

Table 7.5: Voltage profile and Power Loss without and With the addition of PV Units

	Without PV Units		With PV Units		
Phase	Minimum Voltage (p.u)	Loss (kW)	Minimum Voltage (p.u)	Loss (kW)	Loss Reduction (%)
A	0.8314	95.62	0.9285	64.77	32.26
B	0.8337	84.40	0.9187	61.89	26.67
C	0.8383	87.94	0.9163	64.78	26.33

It can be seen that the voltage improvement is more significant as compared to the previous case where the PV units were installed based on the voltage. The minimum voltage on the system is improved to 0.9285 p.u, 0.9197 p.u, 0.9163 p.u from 0.8314 p.u, 0.8337 p.u and 0.8383 p.u for phases A, B and C respectively which are within acceptable limits of ± 10%. The maximum voltage on the system are 1.009, 1.015 and 1.06 p.u for phases A, B and C respectively. There is also a significant reduction in the power loss about 30-40 %. The results of the optimization algorithm for optimal PV sizing at the HT terminals are summarised in Table. 7.5.

7.3.3 Study of Power Loss variation with Seasonal changes in Solar Irradiance- Uncertainty Modelling using Beta PDF

The output of the PV module is dependent on the solar irradiance, ambient temperature and the characteristics of the module itself. Therefore PV power

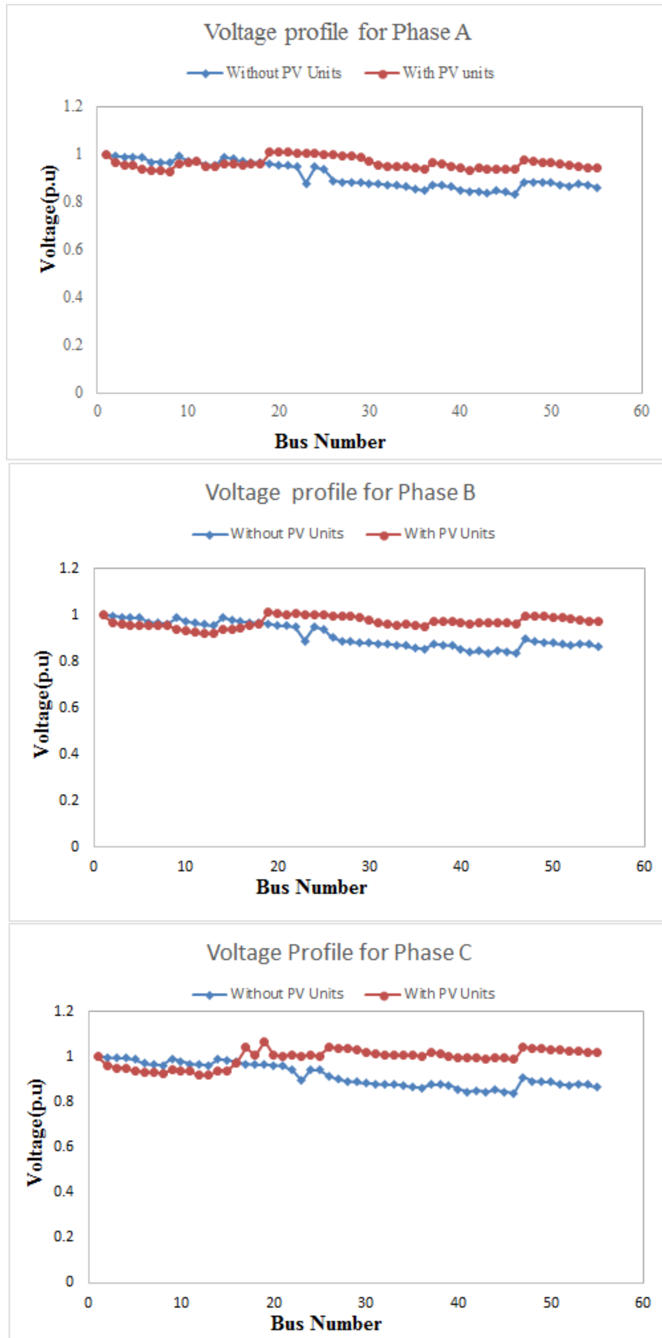


Figure 7.7: Voltage Profile for the three phases without and with the addition of PV units

output should be considered as a multi- state variable so that the seasonal variations in the power loss can be related to the solar irradiance. For this purpose the solar irradiance is modelled using Beta PDF as mentioned before. Each season is represented by a typical day. The four seasons in Kerala can be divided as winter, summer, south west monsoon and retreating monsoon whose hourly average solar radiation are 240.07 W/m^2, 265.38 W/m^2, 184.61 W/m^2 and 223.3 W/m^2 respectively according to the satellite data. The data of the selected location is for one year is taken and the hourly irradiance for each season is predicted using Beta PDF. The predicted power output for each season is plotted in Fig. 7.8.

To incorporate this uncertainty in the solar irradiance and the resulting

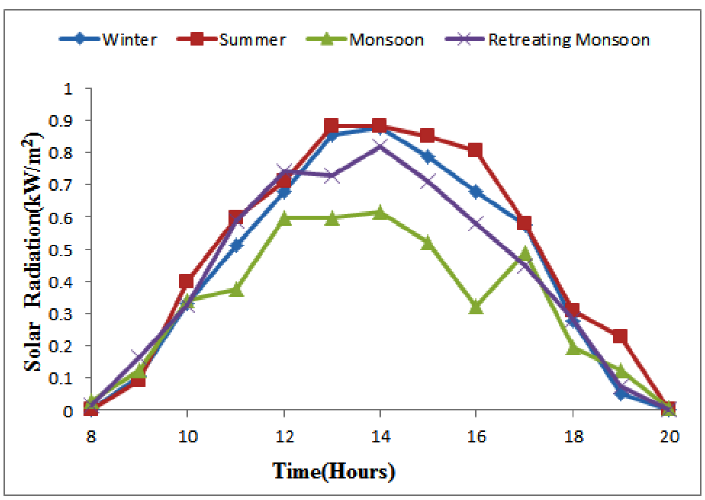


Figure 7.8: Forecasted Hourly Solar Irradiance for various Seasons

power output in the power flow, the solar power output should be considered as multi-state variable in the power flow. As an example, the power output of the bus number 28 for phase A is taken as a multi state variable whose power output is the output power of the solar panel. The number of modules of the solar panel is selected in order to provide the optimal capacity of the PV unit provided the solar irradiance is at its peak. The resulting hourly power loss reduction for each season is plotted in Fig. 7.9. The main observations on hourly and seasonal variations of power loss drawn from the plot are described below.

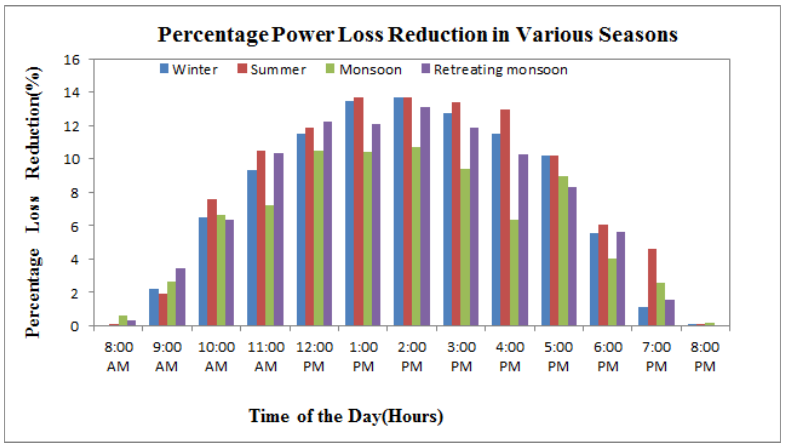


Figure 7.9: Hourly power Loss Reduction for various Seasons

- The hourly variations illustrate that the loss reduction is marginal in the mornings and evenings, but there is a significant reduction in the power loss at noon hours when the solar radiation is at its peak.
- analyzing the seasonal variations, it can be observed that the power loss reduction is minimum for the monsoons, indicating less number of sunny hours and low intensity of the solar irradiance in the season.
- Also the seasonal variations in the power loss is marginal in the morning and evening hours compared to the noon, which is the result of the equitable climate and solar irradiance throughout the year.

7.3.4 Estimation of Optimum PV size and Voltage profile on Hourly Basis

As explained in Chapter 6, learning automata system makes decisions by continuous interactions with the environment. In the case of optimal PV sizing problem, the action a_k to be taken is the selection of a PV size. When a PV size is selected based on ε-greedy strategy, the random power output from the installed PV unit should be found out. This is done based on the modelling of uncertainty using Beta PDF. The number of PV units/modules so as to yield the required power should be determined based on Eq. (7.3).

$$No\_modules = PVsize/av\_power \tag{7.3}$$

Here $PVsize$ is the selected value of size of PV unit and av_power is the average power output from the solar panel for the hour considered. But the value of PV output power varies randomly which is modelled using Beta PDF as explained in Section 6.1 with respect to Fig.6.4. To find out the actual power Eq. (7.4) is used.

$$PVout = No\_modules * PV\_rand \tag{7.4}$$

Here PV_rand is the random output power that is obtained by modelling the uncertainty of PV power using Beta PDF.

With the power from the PV unit, the load flow is run again and the loss corresponding to the selected action is obtained. Here the objective function considered is the minimization of power loss where loss is given by

$$P_{loss} = \sum_{i} \sum_{j} A_{ij}(P_iP_j + Q_iQ_j) + B_{ij}(Q_iP_j + P_iQ_j) \tag{7.5}$$

where

$$A_{ij} = \frac{R_{ij}cos(\delta_i - \delta_j)}{V_iVj} \tag{7.6}$$

$$B_{ij} = \frac{R_{ij}sin(\delta_i - \delta_j)}{V_iVj} \tag{7.7}$$

subjected to the constraints given below

$$\begin{aligned} |V_i^{min}| \le |V_i| \le |V_i^{max}| \\ |P_{DG,i}^{min}| \le |P_{DG,i}| \le |P_{DG,i}^{max}| \\ |Q_{DG,i}^{min}| \le |Q_{DG,i}| \le |Q_{DG,i}^{max}| \end{aligned} \tag{7.8}$$

The loss value is used to update the value of the performance index, which is given by Eq. (7.9).

$$Q^{n+1}(a_k) = Q^n(a_k) + \alpha \left[Loss(a_k) - Q^n(a_k)\right] \tag{7.9}$$

Sufficient number of actions are taken and the performance index is updated till the value of Q^n reaches the optimum value Q^*.

Now the Learning Automata (LA) algorithm is modified to determine the optimum PV size for different hours of a day. The optimum size of PV units to be installed at Bus Number 41 of the real bus RDS for different hours of a typical day representing winter season from 8 a.m. to 8 p.m. for all the three phases are plotted in Fig. 7.10. This can be repeated for all the seasons. The algorithm for analyzing the variation of optimum PV size on a daily basis is given below.

Read the system parameters such as line data, load data, etc.

Identify the number of hours for with non zero value of PV output power as No_PV

Initialize ε*=0.5 and* α*=0.1*

Choose suitable discretization step, 50 kW

Identify the max. no: of PV size installation 'm'

Generate the possible actions,$a_0 ... a_{m-1}$

Initialize $Q^0(a_k) = 0$, $0 < k < m-1$

For (no_hours $= 1$ *to No_PV)*

For ($n = 0$ *to max_iteration)*

Begin

> *Select a PV size,* a_k *using* ε *greedy algorithm,using the current values of the performance index.*
>
> *Calculate the number of PV modules corresponding to the selected PV size by using Eq. (7.3).*
>
> *Calculate the random power generated by PV unit using Eq. (7.4)).*
>
> *Calculate* $Loss(a_k)$ *using Eq. (7.5) by running the Load Flow using modified sweep algorithm.*

Update $Q^n(a_k)$ *to* $Q^{n+1}(a_k)$ *using eqn 7.9.*

End

Find the greedy action from the updated values of $Q(a_k), 0 < k < m-1$

End

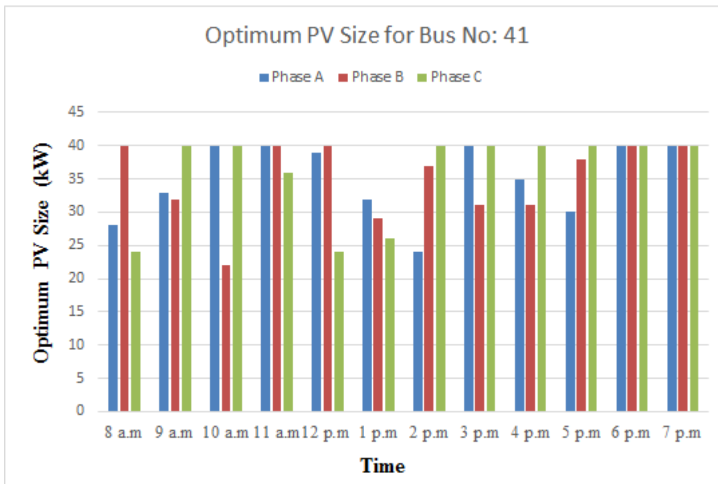


Figure 7.10: Optimum PV size for Bus No:41 for different hours

Similarly an analysis was also conducted in order to study the variation of the voltage profile during different hours of the day. It can be seen that there is a variation in the voltage profile at different times of the day, which depends purely on the intensity of solar irradiation and the power output. For the hours when the sun is at its peak, the voltage profile is near to 1 p.u and when the intensity is lower, there is not much improvement in the voltage profile as compared to the case when PV units are not installed. The voltage profile at Bus No: 41 for a typical day representing winter season is shown in Fig. 7.11. The graph represents the variation of the voltage profile by installing PV unit of size 39 kW installed on phase A. The major interpretation that can be made from the graph is that the voltage profile has significant improvement during peak sunny hours.

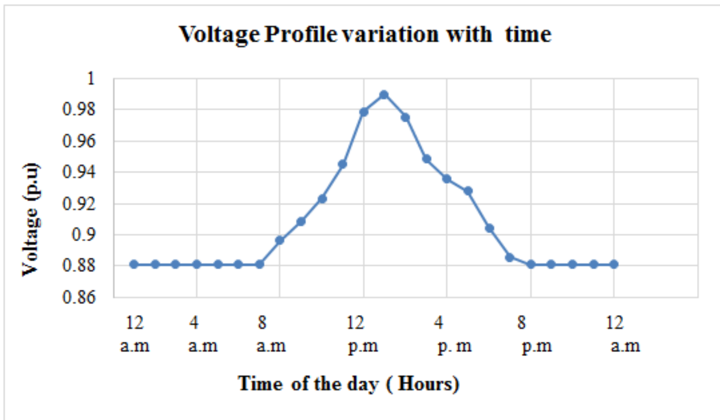


Figure 7.11: Voltage Profile Variation for Bus No:41 for different hours

7.4 Multi-stage modelling of Optimal PV unit sizing for 4.3 MVA practical distribution system

The modelling the Optimal PV sizing problem as multi-stage problem using RL is described in detail in Chapter 6 in Section 6.6. Q-learning algorithm is used for updating the performance index and solving the MDP. The complete algorithm is also given in Section 6.6 of Chapter 6.

At least one node belonging to each highlighted section is considered for PV integration. The nodes selected are 28,36,41,43,46 and 55. For finding out the optimum size of the PV unit at each of these nodes, Reinforcement

Learning algorithm is used. All these nodes are 100 kVA transformers and maximum permissible PV penetration is taken as 80%. The results for the optimum size of the PV unit size required so as to minimize the power losses and improve the voltage profile is tabulated in Table. 7.6.

The installation of PV unit of the specified size causes improvement

Table 7.6: Optimum PV Size for the selected Nodes

Node Number	Optimum Size(kW)		
	Phase A	Phase B	Phase C
28	68	44	64
36	68	68	64
41	68	44	64
43	68	40	64
46	80	80	80
55	80	80	80

in the voltage profile and loss reduction in the distribution feeder. The improvement in voltage profile of the three phases with the installation of the PV unit is shown in Fig. 7.12.

It can be seen that by installing the PV unit at the specified locations, there is a slight drop in voltage at the near end of the substation, but within limits. But at the nodes where the voltage was sub nominal, there is a significant improvement in the voltage profile. The minimum voltage on the system is improved to 0.9093 p.u, 0.9108 p.u, 0.9018 p.u from 0.8314 p.u, 0.8337 p.u and 0.8383 p.u for phases A, B and C respectively which are within acceptable limits of ± 10%. There is also a significant reduction in the power loss about 27 %-32%. The results of the optimization algorithm for optimal PV sizing are summarised in Table. 7.7.

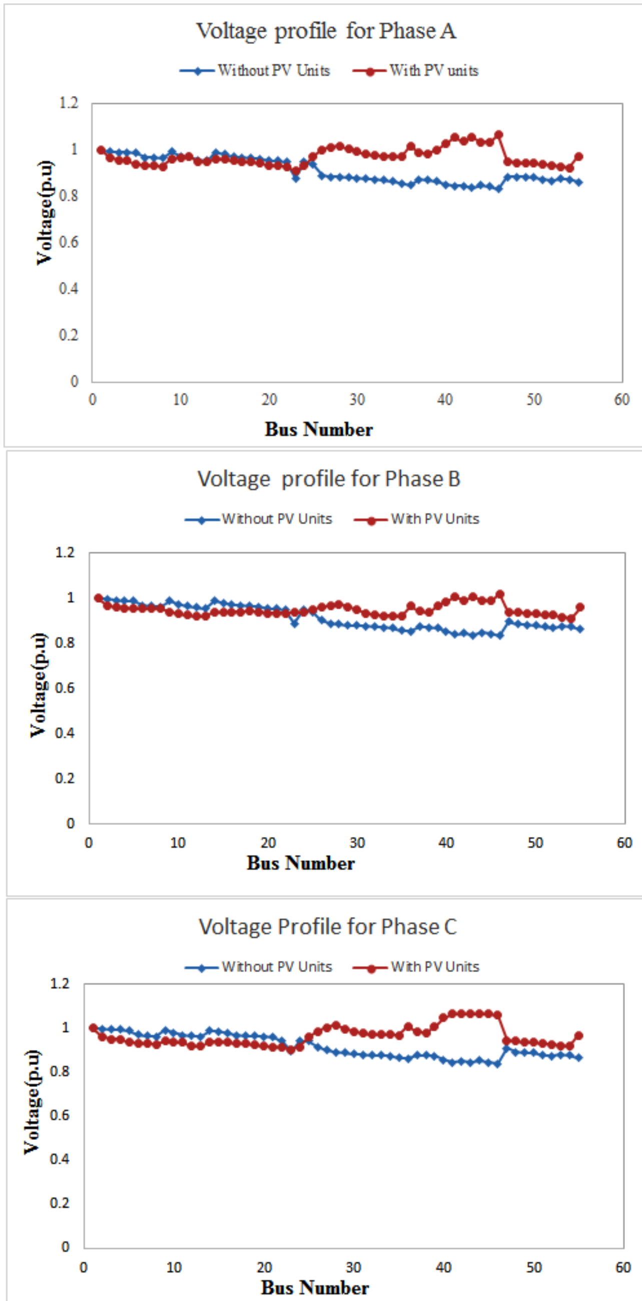


Figure 7.12: Voltage Profile for the three phases without and with PV units

Table 7.7: Voltage profile and Power Loss without and With the addition of PV Units

	Without PV Units		With PV Units		
Phase	Minimum Voltage(p.u)	Loss(kW)	Minimum Voltage(p.u)	Loss(kW)	Loss Reduction(%)
A	0.8314	95.62	0.9093	69.79	27.01
B	0.8337	84.40	0.9182	58.12	31.13
C	0.8383	87.94	0.92	63.08	28.26

7.5 Conclusion

The effect of integration of Photovoltaic (PV) unit on a real-life 4.3 MVA distribution feeder for improvement in voltage profile and loss reduction is analyzed. The size of the PV unit is optimized so as to minimize the total network losses of the system subjected to various operating constraints. The system parameters were analyzed by incorporating optimal size of the PV units at the specified locations. Here the optimal sizing of the PV units in the unbalanced distribution network is formulated as a Single Stage Decision making Process using Learning Automata algorithm and multistage decision making process using Reinforcement Learning. The locations for the PV unit installation were chosen based on the voltage quality and type of customers. The uncertainty associated with the Photovoltaic source is modelled using Beta PDF. The LA and RL algorithm with their capability to incorporate the uncertainty associated with the PV source found to be effective for optimizing the size of the PV units. With the introduction of PV units, there is a significant improvement in the voltage profile along with a reduction in the network losses. This suggests a solution for utilities for the planning of the

DG integrated distribution system.

Chapter 8

Conclusions and Future Work

8.1 Introduction

The increased penetration of Distributed Generation (DG) sources in the distribution system contributes to the diversification of energy resources, reduction of system losses, on-peak operating costs and the reduction of transmission and distribution costs. But at the same time, the integration of such sources changes the overall characteristics of the distribution network posing several challenges to the power system operation unless integrated properly. This necessitates an efficient analysis of the DG integrated system with accurate power flow algorithms that can handle the DG sources and unbalance associated with distribution network. Moreover, the DG sources of optimal capacity are to be installed at optimal locations to ensure that benefits are maximized with the integration of DG sources. There are so many factors that have to be considered in determining the optimum location and capacity of DG systems. Some of them are the penetration level of DGs, location uncertainty, varying and intermittent power output from DGs etc. Minimization of network losses is a significant aspect to be considered for the reliable and efficient operation of DG integration.

Review of various methods that are adopted for optimal DG placement is carried out. These methods can be categorized as analytical, numerical and heuristic methods. The analytical and numerical methods can be applied only for small distribution feeders. Most of the heuristic methods discussed in the review lack the ability to handle stochastic data existing in practical systems. Also the test feeders considered in most of the cases are of balanced nature. The Unbalance is an inherent characteristic of the distribution system which is not addressed in most of the work. The application of stochastic learning algorithms namely, learning automata and reinforcement learning for optimal allocation of PV units in unbalanced distribution network are investigated in the thesis work. This is accomplished with the help of the developed power flow algorithm that can handle the DG source as PV nodes with their representative features. Also the uncertainty associated with the PV power output is modelled using Beta PDF so that the variation in system parameters with respect to the fluctuating power output is also analyzed. The objective of the research work is to introduce the stochastic learning algorithms for optimal integration of PV sources in the unbalanced distribution system.

8.2 Summary and Major findings

The review of existing methods for optimal allocation of DG sources led to the scope of introducing efficient algorithms for optimally integrating DG sources with the capability to handle stochastic data existing in practical situations. Stochastic learning algorithms such as reinforcement learning and learning automata are promising methods that can be used for solving optimization problems. In this research work, application of stochastic learning algorithms such as RL and LA is proposed for optimal integration of PV sources in unbalanced distribution feeders.

8.2.1 Power Flow algorithm for DG integrated distribution system

A power flow algorithm is developed by modifying the Forward-Backward sweep algorithm for the unbalanced radial distribution feeders. The power flow is carried out by modelling each and every component of the distribution feeder such as transformers, lines, loads, etc. The loads were modelled by constant current, constant power and constant impedance models. The power flow algorithm is modified so as to include the DG sources by modelling them as PQ nodes as well as PV nodes. The inclusion of DG sources as PQ nodes does not cause any change in the power flow algorithm since they are treated as negative loads. When DG units are modelled as PV nodes, modifications need to be done. The positive voltage mismatch vector is estimated and if it is within limits, the power flow is converged. Otherwise the reactive power injection required to maintain the voltage values within the limits is calculated using Positive sequence impedance sensitive matrix. This is repeated until convergence is achieved.

The developed power flow algorithm is validated for IEEE 33-bus balanced feeder and also for IEEE 13-bus and 37-bus unbalanced distribution feeders. The voltage profile, current flows and the losses are analyzed in the three cases, i.e. without DG units, including DG units as PQ nodes as well as including DG unit as PV nodes. It is observed that the voltage profile is more improved and losses are minimal when the DG units are modelled as PV nodes. The power flow algorithm was first validated using openDSS and extended to accommodate DG sources. The power flow algorithm developed can be used for analyzing the DG integrated unbalanced distribution system.

8.2.2 Uncertainty Modelling of Solar Irradiance using Beta PDF

The fluctuating power output from PV source is considered as a random variable by modelling the uncertainty associated with the solar irradiance. The solar irradiance data of a selected site are collected from the National solar radiation database. The solar radiation data for one year is collected which is divided into four seasons with an assumption that each year is represented by a typical day in that season. The data are checked for its fitness against Weibull, Log-Normal and Beta PDF which were used in the literature. For the selected site, Beta PDF was found to be the best fitting distribution. The beta PDF is used to generate random samples that feature the behaviour of the historical data. The Beta PDF is generated for each season with 90 data points corresponding to 90 days in each season. This data is used to estimate the power output from the PV source.

A methodology to find out the PV module that is best suited for a particular site is also presented. The selection is done based on the Capacity factors for various types of modules. Four different types of modules were considered for analysis based on the module characteristics. The module that gives the highest capacity factor is the best module for the selected site. Here Module B with a watt-peak rating of 75 W is found to give the highest capacity factor of 0.2444. The fluctuating power output is also treated as a multi-state variable in the power flow to analyze the variation in system parameters with respect to the fluctuating solar irradiance. The hourly variation in voltage profile, losses, energy etc. was analyzed for a practical distribution feeder.

8.2.3 Optimal Integration of PV source in the Unbalanced Distribution Network

The benefits of the DG integration is possible only if the DG units of optimal capacity are installed at optimal locations. The ODGP problem is solved using several analytical, numerical and heuristic methods in previous literatures and most of the methods ignored the unbalance associated with the feeders. Also the uncertainty associated with the intermittent DG sources is not considered in most of the cases. Here stochastic learning algorithms namely, Learning Automata (LA) and Reinforcement Learning (RL) is introduced for optimal integration of PV source in the unbalanced distribution network. The ODGP problem is formulated as a Single Stage Decision

Making Problem and is solved using LA so as to minimize losses in the distribution network. The LA system continuously interacts with the environment and perform sufficient number of actions. Depending upon the value of the reward, the performance index is updated in each iteration. Here PV size to be installed is the action and the corresponding value of loss is the reward. The best action is selected using the value of updated performance index and is termed as the greedy action. Here the ε-greedy algorithm is used as an exploration strategy to choose the best action. The LA algorithm is validated for IEEE 33-bus balanced distribution feeder. It is also implemented for IEEE 13-bus and 37-bus distribution feeder for loss minimization. The results proved that the losses are minimized and the voltage profile is improved with the installation of PV unit of optimal capacity.

The ODGP problem is modelled as Multi Stage Decision Making Problem (MSDMP) using RL so as to incorporate the effect of voltage values which is also a major factor of concern. The ultimate goal is to maximize the reward over time. For achieving this, at each time step the agent interacts with the environment and some representation of the environment's state $x_k \in X$ is obtained. Here X is the set of all possible states. Corresponding to each state, an action $a_k \in A$ is performed, where A is the set of actions. When an action is performed, the environment returns a numerical reward $r_k \in R$ and finds itself in a new state x_{k+1}. Here the voltage values of the nodes are included as state variables and depending upon the value of the node voltages, the PV size changed and the corresponding losses are obtained which is used to update Q-value. The new state variables are observed and the action is changed accordingly. The Q-learning algorithm is applied for optimal PV integration and the losses and the voltage profile are analyzed for IEEE-33 bus distribution feeder.

The stochastic learning algorithms proposed for optimal PV integration is implemented for a 4.3 MVA practical distribution feeder. The distribution feeder consists of 55 buses spanning over a length of 7.3 km. The PV units were installed depending upon the voltage level and type of customers. In the first case PV units were installed in the under voltage sections at six different locations. In the second case, the PV unit is installed in a high voltage customer side. The voltage profile, power losses and energy losses were analyzed for the two cases. The variation in the power loss and voltage profile with the fluctuating solar irradiance is also analyzed. The randomly varying power output from the PV unit was treated as a multi-state variable in the power flow. The results for loss reduction and voltage profile shows that there is a scope for installation of PV units in the distribution system to meet the rising power demand and to improve the voltage profile.

8.3 Major Research Contributions

The research work analyzes the effects of optimal integration of solar PV units in unbalanced distribution network in terms of voltage profile and losses. Here stochastic learning algorithms namely, LA and RL are developed for solving the problem of optimal integration of PV units in the unbalanced distribution network. As a preliminary step, a power flow algorithm is developed that has the capability to include DG units as PV nodes with their representative features. The uncertainty associated with the DG units is also modelled using Beta PDF and using the same the PV module that is best suited for the selected site is determined by making use of capacity factors. The developed stochastic algorithm is compared for power loss and voltage profile with the Improved Analytical method and Exhaustive load flow method in literature. The main contributions of the thesis can be summarized as

- A power flow algorithm for solving unbalanced distribution system is developed which has the capability to include DG units as PV nodes and is validated for several unbalanced distribution feeders.

- The uncertainty associated with the solar irradiance is modelled using Beta PDF and is utilized to estimate capacity factors and hence in choosing the optimum PV module that is best suited for the selected site.

- Stochastic learning algorithms namely, LA and RL are used in solving the problem of optimal allocation of PV units in the unbalanced distribution network so as to minimize the power losses in the system.

- LA and RL are used in determining the optimum size of the PV units to be installed at specified locations in the 4.3 MVA practical distribution feeder. The loss minimization and voltage profile improvement with PV integration is analyzed. Also the variation of system parameters with respect to the fluctuating PV power output is also investigated.

The proposed algorithm can be used to find out the optimum size of PV units to be installed at each node in the distribution system before permitting the willing customers to connect PV units at their premises. The utility can suggest the proper sizing for the willing customers. Therefore, this suggests a solution for utilities for the planning of the DG integrated distribution system.

8.4 Limitation and Future Work

The thesis work concentrates only on the optimal allocation of PV units. The other DG sources such as fuel cell, micro-turbines, diesel generators can also be considered to optimally allocate a hybrid DG system. Also the storage can also be considered by making use of batteries which need to be modelled appropriately. The optimization of a battery connected hybrid DG system will help in designing a reliable DG system that can be used to provide electric supply for a small community grid.

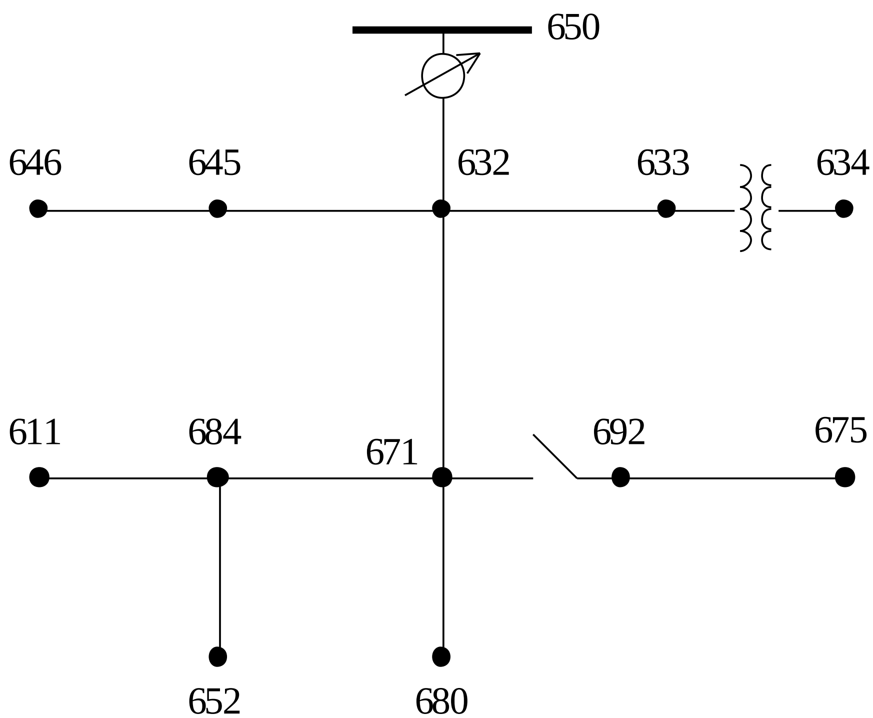
In the thesis work, the objective of the algorithm considered is limited to the operational aspect of the system, i.e., the minimization of losses. The algorithm can be extended to a multi-objective optimization by proper economic analysis. The economic considerations are also equally important from the customer side which necessitate the minimization of cost also to be considered for optimal integration.

As a future work, the optimization can be carried out for a hybrid DG system with multiple DG units along with the battery. Minimization of cost of the DG system can also be considered to transform the algorithm into a multi-objective optimization.

Appendix A

Appendix

IEEE 13 Node Test Feeder



Overhead Line Configuration Data:

Config.	Phasing	Phase	Neutral	Spacing
		ACSR	ACSR	ID
601	B A C N	556,500 26/7	4/0 6/1	500
602	C A B N	4/0 6/1	4/0 6/1	500
603	C B N	1/0	1/0	505
604	A C N	1/0	1/0	505
605	C N	1/0	1/0	510

Underground Line Configuration Data:

Config.	Phasing	Cable	Neutral	Space ID
606	A B C N	250,000 AA, CN	None	515
607	A N	1/0 AA, TS	1/0 Cu	520

Line Segment Data:

Node A	Node B	Length(ft.)	Config.
632	645	500	603
632	633	500	602
633	634	0	XFM-1
645	646	300	603
650	632	2000	601
684	652	800	607
632	671	2000	601
671	684	300	604
671	680	1000	601
671	692	0	Switch
684	611	300	605
692	675	500	606

Transformer Data:

	kVA	kV-high	kV-low	R - %	X - %
Substation:	5,000	115 - D	4.16 Gr. Y	1	8
XFM -1	500	4.16 – Gr.W	0.48 – Gr.W	1.1	2

Capacitor Data:

Node	Ph-A	Ph-B	Ph-C
	kVAr	kVAr	kVAr
675	200	200	200
611			100
Total	200	200	300

Regulator Data:

Regulator ID:	1		
Line Segment:	650 - 632		
Location:	50		
Phases:	A - B -C		
Connection:	3-Ph,LG		
Monitoring Phase:	A-B-C		
Bandwidth:	2.0 volts		
PT Ratio:	20		
Primary CT Rating:	700		
Compensator Settings:	Ph-A	Ph-B	Ph-C
R - Setting:	3	3	3
X - Setting:	9	9	9
Volltage Level:	122	122	122

Spot Load Data:

Node	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kW	kVAr
634	Y-PQ	160	110	120	90	120	90
645	Y-PQ	0	0	170	125	0	0
646	D-Z	0	0	230	132	0	0
652	Y-Z	128	86	0	0	0	0
671	D-PQ	385	220	385	220	385	220
675	Y-PQ	485	190	68	60	290	212
692	D-I	0	0	0	0	170	151
611	Y-I	0	0	0	0	170	80
	TOTAL	1158	606	973	627	1135	753

Distributed Load Data:

Node A	Node B	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
		Model	kW	kVAr	kW	kVAr	kW	kVAr
632	671	Y-PQ	17	10	66	38	117	68

IEEE 13 NODE TEST FEEDER

Impedances

Configuration 601:

```
          Z (R +jX) in ohms per mile
 0.3465  1.0179   0.1560  0.5017   0.1580  0.4236
                  0.3375  1.0478   0.1535  0.3849
                                   0.3414  1.0348
         B in micro Siemens per mile
           6.2998   -1.9958   -1.2595
                     5.9597   -0.7417
                               5.6386
```

Configuration 602:

```
          Z (R +jX) in ohms per mile
0.7526  1.1814   0.1580  0.4236   0.1560  0.5017
                 0.7475  1.1983   0.1535  0.3849
                                  0.7436  1.2112
         B in micro Siemens per mile
           5.6990   -1.0817   -1.6905
                     5.1795   -0.6588
                               5.4246
```

Configuration 603:

```
          Z (R +jX) in ohms per mile
 0.0000  0.0000   0.0000  0.0000   0.0000  0.0000
                  1.3294  1.3471   0.2066  0.4591
                                   1.3238  1.3569
         B in micro Siemens per mile
           0.0000    0.0000    0.0000
                     4.7097   -0.8999
                               4.6658
```

Configuration 604:

```
          Z (R +jX) in ohms per mile
 1.3238  1.3569   0.0000  0.0000   0.2066  0.4591
                  0.0000  0.0000   0.0000  0.0000
                                   1.3294  1.3471
         B in micro Siemens per mile
           4.6658    0.0000   -0.8999
                     0.0000    0.0000
                               4.7097
```

Configuration 605:

```
          Z (R +jX) in ohms per mile
 0.0000  0.0000   0.0000  0.0000   0.0000  0.0000
                  0.0000  0.0000   0.0000  0.0000
                                   1.3292  1.3475
         B in micro Siemens per mile
           0.0000    0.0000    0.0000
                     0.0000    0.0000
                               4.5193
```

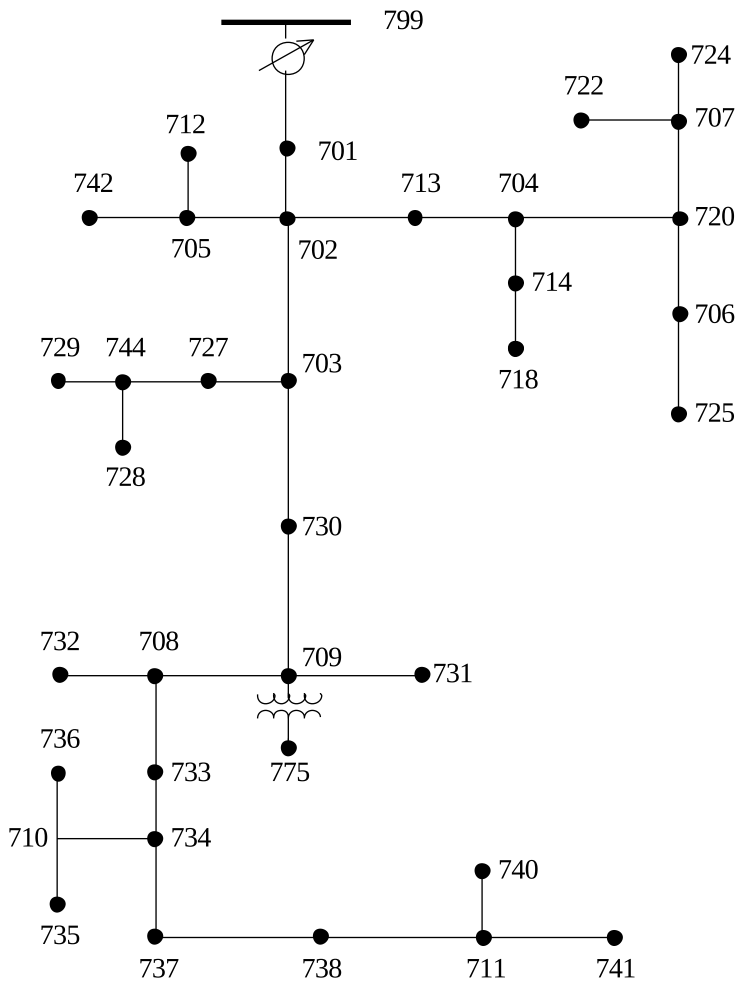
Configuration 606:

```
          Z (R +jX) in ohms per mile
0.7982  0.4463   0.3192  0.0328   0.2849 -0.0143
                 0.7891  0.4041   0.3192  0.0328
                                  0.7982  0.4463
         B in micro Siemens per mile
          96.8897    0.0000    0.0000
                    96.8897    0.0000
                              96.8897
```

Configuration 607:

```
          Z (R +jX) in ohms per mile
 1.3425  0.5124   0.0000  0.0000   0.0000  0.0000
                  0.0000  0.0000   0.0000  0.0000
                                   0.0000  0.0000
         B in micro Siemens per mile
          88.9912    0.0000    0.0000
                     0.0000    0.0000
                               0.0000
```

IEEE 37 Node Test Feeder



Segment Data

Node A	Node B	Length(ft.)	Config.
701	702	960	722
702	705	400	724
702	713	360	723
702	703	1320	722
703	727	240	724
703	730	600	723
704	714	80	724
704	720	800	723
705	742	320	724
705	712	240	724
706	725	280	724
707	724	760	724
707	722	120	724
708	733	320	723
708	732	320	724
709	731	600	723
709	708	320	723
710	735	200	724
710	736	1280	724
711	741	400	723
711	740	200	724
713	704	520	723
714	718	520	724
720	707	920	724
720	706	600	723
727	744	280	723
730	709	200	723
733	734	560	723
734	737	640	723
734	710	520	724
737	738	400	723
738	711	400	723
744	728	200	724
744	729	280	724
775	709	0	XFM-1
799	701	1850	721

Underground Cable Configurations (Config.)

Config.	Phasing	Cable	Spacing ID
721	A B C	1,000,000 AA, CN	515
722	A B C	500,000 AA, CN	515
723	A B C	2/0 AA, CN	515
724	A B C	#2 AA, CN	515

Regulator Data

Regulator ID:	1	
Line Segment:	799 -701	
Location:	799	
Phases:	A - B -C	
Connection:	AB - CB	
Monitoring Phase:	AB & CB	
Bandwidth:	2.0 volts	
PT Ratio:	40	
Primary CT Rating:	350	
Compensator Settings:	Ph-AB	Ph-CB
R - Setting:	1.5	1.5
X - Setting:	3	3
Voltage Level:	122	122

Transformer Data

	kVA	kV-high	kV-low	R - %	X - %
Substation:	2,500	230 D	4.8 D	2	8
XFM -1	500	4.8 D	.480 D	0.09	1.81

Spot Loads

Node	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-4 kVAr
701	D-PQ	140	70	140	70	350	175
712	D-PQ	0	0	0	0	85	40
713	D-PQ	0	0	0	0	85	40
714	D-I	17	8	21	10	0	0
718	D-Z	85	40	0	0	0	0
720	D-PQ	0	0	0	0	85	40
722	D-I	0	0	140	70	21	10
724	D-Z	0	0	42	21	0	0
725	D-PQ	0	0	42	21	0	0
727	D-PQ	0	0	0	0	42	21
728	D-PQ	42	21	42	21	42	21
729	D-I	42	21	0	0	0	0
730	D-Z	0	0	0	0	85	40
731	D-Z	0	0	85	40	0	0
732	D-PQ	0	0	0	0	42	21
733	D-I	85	40	0	0	0	0
734	D-PQ	0	0	0	0	42	21
735	D-PQ	0	0	0	0	85	40
736	D-Z	0	0	42	21	0	0
737	D-I	140	70	0	0	0	0
738	D-PQ	126	62	0	0	0	0
740	D-PQ	0	0	0	0	85	40
741	D-I	0	0	0	0	42	21
742	D-Z	8	4	85	40	0	0
744	D-PQ	42	21	0	0	0	0
Total		727	357	639	314	1091	530

IEEE 37 NODE TEST FEEDER
Phase Impedance and Admittance Matrices

Configuration 721

```
          Z (R +jX) in ohms per mile
 0.2926  0.1973   0.0673 -0.0368   0.0337 -0.0417
                  0.2646  0.1900   0.0673 -0.0368
                                   0.2926  0.1973
         B in micro Siemens per mile
         159.7919    0.0000    0.0000
                   159.7919    0.0000
                             159.7919
```

Configuration 722

```
          Z (R +jX) in ohms per mile
 0.4751  0.2973   0.1629 -0.0326   0.1234 -0.0607
                  0.4488  0.2678   0.1629 -0.0326
                                   0.4751  0.2973
         B in micro Siemens per mile
         127.8306    0.0000    0.0000
                   127.8306    0.0000
                             127.8306
```

Configuration 723

```
          Z (R +jX) in ohms per mile
 1.2936  0.6713   0.4871  0.2111   0.4585  0.1521
                  1.3022  0.6326   0.4871  0.2111
                                   1.2936  0.6713
         B in micro Siemens per mile
          74.8405    0.0000    0.0000
                    74.8405    0.0000
                              74.8405
```

Configuration 724

```
          Z (R +jX) in ohms per mile
 2.0952  0.7758   0.5204  0.2738   0.4926  0.2123
                  2.1068  0.7398   0.5204  0.2738
                                   2.0952  0.7758
         B in micro Siemens per mile
          60.2483    0.0000    0.0000
                    60.2483    0.0000
                              60.2483
```

Table A.1: Load details of 4.3 MVA distribution feeder

Node No	Node name	Loadings in kVA Phase A	Phase B	Phase C	distance in km from s/s
1	substation	0	0	0	0.00001
2	100 kva fireforce	57	31	53	0.7
3	160 kva pallimoola	74	85	88	1.05
4	junction	0	0	0	1.15
5	AR camp	20	25	13	1.95
6	IMA	38	40	36	2.23
7	AIR HT	54	40	38	2.33
8	BECH HT	60	50	48	2.63
9	junction	0	0	0	1.75
10	junction	0	0	0	2.05
11	100 kva manakulam	25	20	78	2.25
12	100kva royal street	85	71	68	2.75
13	100kva mannumkadu67	67	71	60	2.9
14	junction	0	0	0	1.85
15	100 kva policestation	69	70	65	1.97
16	100kva KAP duty office	28	48	8	2.065
17	junction	0	0	0	2.465
18	250kva KAP first	54	40	27	2.565
19	junction	0	0	0	2.645
20	junction	0	0	0	2.885
21	Academic canteen	10	3.4	6.2	2.995
22	Academy main	78	84	80	3.005
23	100kva LH	53	47	24	4.005
24	500 kva T and G	52.4	32	30	3.005
25	junction	0	0	0	3.145
26	100 kva upasana road	63	27	77	3.545
27	junction	0	0	0	3.745
28	100kva nest	60	56	54	3.845
29	100kva sangeertanam	71	76	42	3.945
30	junction	0	0	0	4.545

Table A.2: Load details of 4.3 MVA distribution feeder

Node No		Loadings in kVA			
	Node name	Phase A	Phase B	Phase C	distance in km from s/s
31	100kva manavazhy	48	50	47	5.145
32	junction	0	0	0	5.645
33	100kva adiyara	53	56	61	5.945
34	junction	0	0	0	5.945
35	100 kva idea	45	51	48	6.245
36	100 kva jv	54	58	60	6.545
37	junction	0	0	0	5.545
38	400kva madhavam	75	78	64	5.745
39	100 kva indiranagar	105	57	54	5.945
40	junction	0	0	0	6.445
41	100 kva vrindavan	56	61	58	6.975
42	junction	0	0	0	6.645
43	100 kva pahipalam	55	44	82	6.995
44	junction	0	0	0	6.745
45	100 kva sandeepani	80	81	86	6.845
46	100 kva kuttumukku	55	44	66	7.195
47	100kva pulinchuvadu	60	96	64	3.645
48	junction	0	0	0	3.845
49	100 kva kangapadam	107	85	82	4.045
50	junction	0	0	0	4.445
51	junction	0	0	0	4.745
52	160 kva kangapadam ht	92	84	85	4.845
53	junction	0	0	0	5.245
54	Milma Ht	78	85	88	5.545
55	100kva health centre	52	60	58	6.045

Bibliography

(2012). Jawaharlal Nehru National Solar Mission Phase II Policy Document. http://http://mnre.gov.in/file-manager/UserFiles/draft-jnnsmpd-2.pdf/. [Online; accessed December-2015].

Abdelaziz, A., Hegazy, Y., El-Khattam, W., and Othman, M. (2015). Optimal allocation of stochastically dependent renewable energy based distributed generators in unbalanced distribution networks. *Electric Power Systems Research*, 119:34–44.

Abu-Mouti, F. and El-Hawary, M. (2011a). Heuristic curve-fitted technique for distributed generation optimisation in radial distribution feeder systems. *Generation, Transmission & Distribution, IET*, 5(2):172–180.

Abu-Mouti, F. S. and El-Hawary, M. (2011b). Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. *Power Delivery, IEEE Transactions on*, 26(4):2090–2101.

Acharya, N., Mahat, P., and Mithulananthan, N. (2006). An analytical approach for dg allocation in primary distribution network. *International Journal of Electrical Power & Energy Systems*, 28(10):669–678.

Ackermann, T., Andersson, G., and Söder, L. (2001). Distributed generation: a definition. *Electric power systems research*, 57(3):195–204.

Act, I. E. (2003). Indian electricity act.

Afsari, M., Singh, S., Raju, G., and Rao, G. (2002). A fast power flow solution of radial distribution networks. *Electric Power Components and Systems*, 30(10):1065–1074.

Ahamed, T. I., Rao, P. N., and Sastry, P. (2002). A reinforcement learning approach to automatic generation control. *Electric power systems research*, 63(1):9–26.

Al Abri, R., El-Saadany, E. F., and Atwa, Y. M. (2013). Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. *Power Systems, IEEE Transactions on*, 28(1):326–334.

AlHajri, M., AlRashidi, M., and El-Hawary, M. (2010). Improved sequential quadratic programming approach for optimal distribution generation deployments via stability and sensitivity analyses. *Electric Power Components and Systems*, 38(14):1595–1614.

AlHajri, M. and El-Hawary, M. (2010). Exploiting the radial distribution structure in developing a fast and flexible radial power flow for unbalanced three-phase networks. *IEEE transactions on Power Delivery*, 25(1):378–389.

Alinjak, T., Pavić, I., and Stojkov, M. (2016). Improvement of backward/forward sweep power flow method by using modified breadth-first search strategy. *IET Generation, Transmission & Distribution*.

Aman, M., Jasmon, G., Bakar, A., and Mokhlis, H. (2014). A new approach for optimum simultaneous multi-dg distributed generation units placement and sizing based on maximization of system loadability using hpso (hybrid particle swarm optimization) algorithm. *Energy*, 66:202–215.

Aravindhababu, P., Ganapathy, S., and Nayar, K. (2001). A novel technique for the analysis of radial distribution systems. *International journal of electrical power & energy systems*, 23(3):167–171.

Assuncao, H., Escobedo, J., and Oliveira, A. (2003). Modelling frequency distributions of 5 minute-averaged solar radiation indexes using beta probability functions. *Theoretical and Applied Climatology*, 75(3-4):213–224.

Atwa, Y., El-Saadany, E., Salama, M., and Seethapathy, R. (2010). Optimal renewable resources mix for distribution system energy loss minimization. *Power Systems, IEEE Transactions on*, 25(1):360–370.

Augugliaro, A., Dusonchet, L., Favuzza, S., Ippolito, M., and Sanseverino, E. R. (2008). A new backward/forward method for solving radial distribution networks with pv nodes. *Electric Power Systems Research*, 78(3):330–336.

Augugliaro, A., Dusonchet, L., Favuzza, S., Ippolito, M. G., and Sanseverino, E. R. (2010). A backward sweep method for power flow solution in distribution networks. *International journal of electrical power & energy systems*, 32(4):271–280.

Baran, M. E. and Wu, F. F. (1989). "optimal sizing of capacitors placed on a radial distribution system". *Power Delivery, IEEE Transactions on*, 4(1):735–743.

Berg, R., Hawkins, E., and Pleines, W. (1967). Mechanized calculation of unbalanced load flow on radial distribution circuits. *Power Apparatus and Systems, IEEE Transactions on*, (4):415–421.

Borges, C. L. and Falcao, D. M. (2006). Optimal distributed generation allocation for reliability, losses, and voltage improvement. *International Journal of Electrical Power & Energy Systems*, 28(6):413–420.

Carpinelli, G., Celli, G., Mocci, S., Pilo, F., and Russo, A. (2005). Optimisation of embedded generation sizing and siting by using a double trade-off method. In *Generation, Transmission and Distribution, IEE Proceedings-*, volume 152, pages 503–513. IET.

Celli, G., Ghiani, E., Mocci, S., and Pilo, F. (2005). A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. *Power Systems, IEEE Transactions on*, 20(2):750–757.

Cespedes, R. (1990). "new method for the analysis of distribution networks". *Power Delivery, IEEE Transactions on*, 5(1):391–396.

Chang, G., Chu, S., and Wang, H. (2007). An improved backward/forward sweep load flow algorithm for radial distribution systems. *Power Systems, IEEE Transactions on*, 22(2):882–884.

Chang, G., Chu, S.-Y., Hsu, M.-F., Chuang, C.-S., and Wang, H.-L. (2012). An efficient power flow algorithm for weakly meshed distribution systems. *Electric Power Systems Research*, 84(1):90–99.

Chen, H., Chen, J., Shi, D., and Duan, X. (2006). Power flow study and voltage stability analysis for distribution systems with distributed generation. In *Power Engineering Society General Meeting, 2006. IEEE*, pages 8–pp. IEEE.

Chen, T.-H., Chen, M.-S., Hwang, K.-J., Kotas, P., and Chebli, E. A. (1991). Distribution system power flow analysis-a rigid approach. *Power Delivery, IEEE Transactions on*, 6(3):1146–1152.

Chen, T.-H. and Yang, N.-C. (2009). Three-phase power-flow by direct z br method for unbalanced radial distribution systems. *IET generation, transmission & distribution*, 3(10):903–910.

Chen, T.-H. and Yang, N.-C. (2010). Loop frame of reference based three-phase power flow for unbalanced radial distribution systems. *Electric power systems research*, 80(7):799–806.

Cheng, C. S. and Shirmohammadi, D. (1995a). "a three-phase power flow method for real-time distribution system analysis". *Power Systems, IEEE Transactions on*, 10(2).

Cheng, C. S. and Shirmohammadi, D. (1995b). A three-phase power flow method for real-time distribution system analysis. *IEEE Transactions on Power Systems*, 10(2):671–679.

Chiang, H.-D. (1991). A decoupled load flow method for distribution power networks: algorithms, analysis and convergence study. *International Journal of Electrical Power & Energy Systems*, 13(3):130–138.

Chiradeja, P. and Ramakumar, R. (2004). An approach to quantify the technical benefits of distributed generation. *Energy Conversion, IEEE Transactions on*, 19(4):764–773.

Costa, P. M. and Matos, M. A. (2009). Avoided losses on lv networks as a result of microgeneration. *Electric Power Systems Research*, 79(4):629–634.

da Costa, V. M., Martins, N., and Pereira, J. L. R. (1999). Developments in the newton raphson power flow formulation based on current injections. *IEEE Transactions on power systems*, 14(4):1320–1326.

Darfoun, M. A. and El-Hawary, M. E. (2015). Multi-objective optimization approach for optimal distributed generation sizing and placement. *Electric Power Components and Systems*, 43(7):828–836.

Das, D., Nagi, H., and Kothari, D. (1994). Novel method for solving radial distribution networks. *IEE Proceedings-Generation, Transmission and Distribution*, 141(4):291–298.

de Araujo, L. R., Penido, D. R. R., Júnior, S. C., Pereira, J. L. R., and Garcia, P. A. N. (2010). Comparisons between the three-phase current injection method and the forward/backward sweep method. *International Journal of Electrical Power & Energy Systems*, 32(7):825–833.

de Oliveira, M. L., Guedes, M. R., et al. (2007). Developments in the analysis of unbalanced three-phase power flow solutions. *International Journal of Electrical Power & Energy Systems*, 29(2):175–182.

De Oliveira-De Jesus, P., Alvarez, M., and Yusta, J. (2013). Distribution power flow method based on a real quasi-symmetric matrix. *Electric Power Systems Research*, 95:148–159.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: Nsga-ii. *Evolutionary Computation, IEEE Transactions on*, 6(2):182–197.

Dehghanian, P., Hosseini, S. H., Moeini-Aghtaie, M., and Arabali, A. (2013). Optimal siting of dg units in power systems from a probabilistic multi-objective optimization perspective. *International Journal of Electrical Power & Energy Systems*, 51:14–26.

Dent, C. J., Ochoa, L. F., and Harrison, G. P. (2010a). Network distributed generation capacity analysis using opf with voltage step constraints. *Power Systems, IEEE Transactions on*, 25(1):296–304.

Dent, C. J., Ochoa, L. F., Harrison, G. P., and Bialek, J. W. (2010b). Efficient secure ac opf for network generation capacity assessment. *Power Systems, IEEE Transactions on*, 25(1):575–583.

Devi, S. and Geethanjali, M. (2014). Application of modified bacterial foraging optimization algorithm for optimal placement and sizing of distributed generation. *Expert Systems with Applications*, 41(6):2772–2781.

Dilek, M., De Leon, F., Broadwater, R., and Lee, S. (2010). A robust multiphase power flow for general distribution networks. *IEEE Transactions on Power Systems*, 25(2):760–768.

Dugan, R. C. (2012). Reference guide: The open distribution system simulator (opendss). *Electric Power Research Institute, Inc.*

El-Ela, A. A., Allam, S. M., and Shatla, M. (2010). Maximal optimal benefits of distributed generation using genetic algorithms. *Electric Power Systems Research*, 80(7):869–877.

El-Khattam, W., Bhattacharya, K., Hegazy, Y., and Salama, M. (2004). Optimal investment planning for distributed generation in a competitive electricity market. *Power Systems, IEEE Transactions on*, 19(3):1674–1684.

El-Zonkoly, A. (2011). Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation. *Generation, Transmission & Distribution, IET*, 5(7):760–771.

Eminoglu, U. and Hocaoglu, M. H. (2005). A new power flow method for radial distribution systems including voltage dependent load models. *Electric power systems research*, 76(1):106–114.

Eminoglu, U. and Hocaoglu, M. H. (2008). Distribution systems forward/backward sweep-based power flow algorithms: a review and comparison study. *Electric Power Components and Systems*, 37(1):91–110.

Ernst, D., Glavic, M., and Wehenkel, L. (2004). Power systems stability control: reinforcement learning framework. *IEEE transactions on power systems*, 19(1):427–435.

Ettoumi, F. Y., Mefti, A., Adane, A., and Bouroubi, M. (2002). Statistical analysis of solar measurements in algeria using beta distributions. *Renewable Energy*, 26(1):47–67.

Farag, H. E., El-Saadany, E., El Shatshat, R., and Zidan, A. (2011). A generalized power flow analysis for distribution systems with high penetration of distributed generation. *Electric Power Systems Research*, 81(7):1499–1506.

Gandomkar, M., Vakilian, M., and Ehsan, M. (2005). A genetic–based tabu search algorithm for optimal dg allocation in distribution networks. *Electric Power Components and Systems*, 33(12):1351–1362.

Garcia, P. A., Pereira, J., Carneiro, S., Vinagre, M. P., and Gomes, F. V. (2004). Improvements in the representation of pv buses on three-phase distribution power flow. *IEEE Transactions on Power Delivery*, 19(2):894–896.

Garcia, P. A., Pereira, J. L. R., Carneiro Jr, S., da Costa, V. M., and Martins, N. (2000). Three-phase power flow calculations using the current injection method. *Power Systems, IEEE Transactions on*, 15(2):508–514.

Gautam, D. and Mithulananthan, N. (2007). Optimal dg placement in deregulated electricity market. *Electric Power Systems Research*, 77(12):1627–1636.

Ghatak, U. and Mukherjee, V. (2017). An improved load flow technique based on load current injection for modern distribution system. *International Journal of Electrical Power & Energy Systems*, 84:168–181.

Ghosh, S. and Das, D. (1999). Method for load-flow solution of radial distribution networks. *IEE Proceedings-Generation, Transmission and Distribution*, 146(6):641–648.

Ghosh, S., Ghoshal, S. P., and Ghosh, S. (2010). Optimal sizing and placement of distributed generation in a network system. *International Journal of Electrical Power & Energy Systems*, 32(8):849–856.

Glover, F. (1989). Tabu search-part i. *ORSA Journal on computing*, 1(3):190–206.

Glover, F. W. and Kochenberger, G. A. (2006). *Handbook of metaheuristics*, volume 57. Springer Science & Business Media.

Golshan, M. E. H. and Ali Arefifar, S. (2007). Optimal allocation of distributed generation and reactive sources considering tap positions of voltage regulators as control variables. *European transactions on electrical power*, 17(3):219–239.

Gözel, T. and Hocaoglu, M. H. (2009). An analytical method for the sizing and siting of distributed generators in radial systems. *Electric Power Systems Research*, 79(6):912–918.

Hadidi, R. and Jeyasurya, B. (2013). Reinforcement learning based real-time wide-area stabilizing control agents to enhance power system stability. *IEEE Transactions on Smart Grid*, 4(1):489–497.

Haghifam, M., Falaghi, H., and Malik, O. (2008). Risk-based distributed generation placement. *IET Generation Transmission and Distribution*, 2(2):252–260.

Hamedi, H. and Gandomkar, M. (2012). A straightforward approach to minimizing unsupplied energy and power loss through dg placement and evaluating power quality in relation to load variations over time. *International Journal of Electrical Power & Energy Systems*, 35(1):93–96.

Haque, M. (1996a). Efficient load flow method for distribution systems with radial or mesh configuration. *IEE Proceedings-Generation, Transmission and Distribution*, 143(1):33–38.

Haque, M. (1996b). Load flow solution of distribution systems with voltage dependent load models. *Electric Power Systems Research*, 36(3):151–156.

Haque, M. (2000). A general load flow method for distribution systems. *Electric Power Systems Research*, 54(1):47–54.

Harrison, G. and Wallace, A. (2005). Optimal power flow evaluation of distribution network capacity for the connection of distributed generation. In *Generation, Transmission and Distribution, IEE Proceedings-*, volume 152, pages 115–122. IET.

Harrison, G. P., Piccolo, A., Siano, P., and Wallace, A. R. (2008). Hybrid ga and opf evaluation of network capacity for distributed generation connections. *Electric Power Systems Research*, 78(3):392–398.

Hedayati, H., Nabaviniaki, S. A., and Akbarimajd, A. (2008). A method for placement of dg units in distribution networks. *Power Delivery, IEEE Transactions on*, 23(3):1620–1628.

Helton, J. C. and Oberkampf, W. (2004). Alternative representations of epistemic uncertainty. *Reliability Engineering & System Safety*, 85(1):1–10.

Hemdan, N. G. and Kurrat, M. (2011). Efficient integration of distributed generation for meeting the increased load demand. *International Journal of Electrical Power & Energy Systems*, 33(9):1572–1583.

Hocaoğlu, F. O. (2011). Stochastic approach for daily solar radiation modeling. *Solar Energy*, 85(2):278–287.

Hung, D. Q. and Mithulananthan, N. (2013). Multiple distributed generator placement in primary distribution networks for loss reduction. *Industrial Electronics, IEEE Transactions on*, 60(4):1700–1708.

Hung, D. Q., Mithulananthan, N., and Bansal, R. (2010). Analytical expressions for dg allocation in primary distribution networks. *Energy Conversion, IEEE Transactions on*, 25(3):814–820.

Hung, D. Q., Mithulananthan, N., and Bansal, R. (2013). Analytical strategies for renewable distributed generation integration considering energy loss minimization. *Applied Energy*, 105:75–85.

Jabr, R. A. and Pal, B. (2009). Ordinal optimisation approach for locating and sizing of distributed generation. *Generation, Transmission & Distribution, IET*, 3(8):713–723.

Jaradat, M. A. K., Al-Rousan, M., and Quadan, L. (2011). Reinforcement based mobile robot navigation in dynamic environment. *Robotics and Computer-Integrated Manufacturing*, 27(1):135–149.

Jasmin, E., Ahamed, T. I., and Raj, V. J. (2011). Reinforcement learning approaches to economic dispatch problem. *International Journal of Electrical Power & Energy Systems*, 33(4):836–845.

Ju, Y., Wu, W., Zhang, B., and Sun, H. (2014a). An extension of fbs three-phase power flow for handling pv nodes in active distribution networks. *IEEE Transactions on Smart Grid*, 5(4):1547–1555.

Ju, Y., Wu, W., Zhang, B., and Sun, H. (2014b). Loop-analysis-based continuation power flow algorithm for distribution networks. *IET Generation, Transmission & Distribution*, 8(7):1284–1292.

Kashyap, Y., Bansal, A., and Sao, A. K. (2015). Solar radiation forecasting with multiple parameters neural networks. *Renewable and Sustainable Energy Reviews*, 49:825–835.

Kaur, S., Kumbhar, G., and Sharma, J. (2014). A minlp technique for optimal placement of multiple dg units in distribution systems. *International Journal of Electrical Power & Energy Systems*, 63:609–617.

Kayal, P. and Chanda, C. (2015). Optimal mix of solar and wind distributed generations considering performance improvement of electrical distribution network. *Renewable Energy*, 75:173–186.

Keane, A. and Malley, M. O. (2007). Optimal utilization of distribution networks for energy harvesting. *Power Systems, IEEE Transactions on*, 22(1):467–475.

Keane, A., Zhou, Q., Bialek, J. W., and O'Malley, M. (2009). Planning and operating non-firm distributed generation. *Renewable Power Generation, IET*, 3(4):455–464.

Kefayat, M., Ara, A. L., and Niaki, S. N. (2015). A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources. *Energy Conversion and Management*, 92:149–161.

Kersting, W. and Mendive, D. (1976). "an application of ladder network theory to the solution of threephase radial load-flow problems". In *IEEE Conference Paper presented at the IEEE Winter Power Meeting, New York*.

Kersting, W. H. (2001). Radial distribution test feeders. In *Power Engineering Society Winter Meeting, 2001. IEEE*, volume 2, pages 908–912. IEEE.

Kersting, W. H. (2012). *Distribution system modeling and analysis*. CRC press.

Khalesi, N., Rezaei, N., and Haghifam, M.-R. (2011). Dg allocation with application of dynamic programming for loss reduction and reliability improvement. *International Journal of Electrical Power & Energy Systems*, 33(2):288–295.

Khodr, H., Silva, M. R., Vale, Z., and Ramos, C. (2010). A probabilistic methodology for distributed generation location in isolated electrical service area. *Electric Power Systems Research*, 80(4):390–399.

Khushalani, S. and Schulz, N. (2006). Unbalanced distribution power flow with distributed generation. In *Transmission and Distribution Conference and Exhibition, 2005/2006 IEEE PES*, pages 301–306. IEEE.

Khushalani, S., Solanki, J. M., and Schulz, N. N. (2007). Development of three-phase unbalanced power flow using pv and pq models for distributed generation and study of the impact of dg models. *Power Systems, IEEE Transactions on*, 22(3):1019–1025.

Kim, J., Nam, S., Park, S., and Singh, C. (1998). Dispersed generation planning using improved hereford ranch algorithm. *Electric Power Systems Research*, 47(1):47–55.

Kocar, I., Mahseredjian, J., Karaagac, U., Soykan, G., and Saad, O. (2014). Multiphase load-flow solution for large-scale distribution systems using mana. *IEEE Transactions on Power Delivery*, 29(2):908–915.

Kotamarty, S., Khushalani, S., and Schulz, N. (2008). Impact of distributed generation on distribution contingency analysis. *Electric Power Systems Research*, 78(9):1537–1545.

Koutroumpezis, G. and Safigianni, A. (2010). Optimum allocation of the maximum possible distributed generation penetration in a distribution network. *Electric Power Systems Research*, 80(12):1421–1427.

Kowsalya, M. et al. (2014). Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization. *Swarm and Evolutionary Computation*, 15:58–65.

Kumar, A. and Gao, W. (2010). Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets. *IET generation, transmission & distribution*, 4(2):281–298.

Kumar, K. V. and Selvan, M. (2008). A simplified approach for load flow analysis of radial distribution network. *International Journal of Computer, Information and Systems Science, and Engineering*, 2(4):271–282.

Kumar, M., Kumar, A., and Sandhu, K. (2016). Pv-based distributed generation location using mixed integer non-linear programming in deregulated electricity market. In *Advanced Computing and Communication Technologies*, pages 535–547. Springer.

Le Nguyen, H. (1997). Newton-raphson method in complex form [power system load flow analysis]. *Power Systems, IEEE Transactions on*, 12(3):1355–1359.

Lee, S.-H. and Park, J.-W. (2009). Selection of optimal location and size of multiple distributed generations by using kalman filter algorithm. *Power Systems, IEEE Transactions on*, 24(3):1393–1400.

Li, H., Jin, Y., Zhang, A., Shen, X., Li, C., and Kong, B. (2016). An improved hybrid load flow calculation algorithm for weakly-meshed power distribution system. *International Journal of Electrical Power & Energy Systems*, 74:437–445.

Li, H., Zhang, A., Shen, X., and Xu, J. (2014). A load flow method for weakly meshed distribution networks using powers as flow variables. *International Journal of Electrical Power & Energy Systems*, 58:291–299.

Li, Y. and Zio, E. (2012). Uncertainty analysis of the adequacy assessment model of a distributed generation system. *Renewable Energy*, 41:235–244.

Liew, S. and Strbac, G. (2002). Maximising penetration of wind generation in existing distribution networks. In *Generation, Transmission and Distribution, IEE Proceedings-*, volume 149, pages 256–262. IET.

Lisboa, A., Guedes, L., Vieira, D., and Saldanha, R. (2014). A fast power flow method for radial networks with linear storage and no matrix inversions. *International Journal of Electrical Power & Energy Systems*, 63:901–907.

Liu, J., Salama, M., and Mansour, R. (2002). An efficient power flow algorithm for distribution systems with polynomial load. *International Journal of Electrical Engineering Education*, 39(4):371–386.

Lopes, J., Hatziargyriou, N., Mutale, J., Djapic, P., and Jenkins, N. (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric Power Systems Research*, 77(9):1189–1203.

Losi, A. and Russo, M. (2005). Dispersed generation modeling for object-oriented distribution load flow. *Power Delivery, IEEE Transactions on*, 20(2):1532–1540.

Luo, G.-X. and Semlyen, A. (1990). Efficient load flow for large weakly meshed networks. *IEEE Transactions on Power Systems*, 5(4):1309–1316.

Maya, K. and Jasmin, E. (2015). A generalised three phase power flow algorithm incorporating the uncertainty of photo voltaic (pv) source for unbalanced distribution network. In *Advancements in Power and Energy (TAP Energy), 2015 International Conference on*, pages 29–34. IEEE.

McPartland, M. and Gallagher, M. (2011). Reinforcement learning in first person shooter games. *IEEE Transactions on Computational Intelligence and AI in Games*, 3(1):43–56.

Moghaddas-Tafreshi, S. and Mashhour, E. (2009). Distributed generation modeling for power flow studies and a three-phase unbalanced power flow solution for radial distribution systems considering distributed generation. *Electric Power Systems Research*, 79(4):680–686.

Mohamed, E. A. and Hegazy, Y. G. (2015). A novel probablistic strategy for modeling photovoltaic based distributed generators. *World Academy of Science, Engineering and Technology, International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering*, 9(8):864–867.

Mohd Zin, A. A. B., Khairuddin, A. B., and Shariati, O. (2015). Optimal sizing and siting of distributed generators by exhaustive search. *Distributed Generation & Alternative Energy Journal*, 30(3):29–56.

Moradi, M. H. and Abedini, M. (2012). A combination of genetic algorithm and particle swarm optimization for optimal dg location and sizing in distribution systems. *International Journal of Electrical Power & Energy Systems*, 34(1):66–74.

Moradi, M. H., Zeinalzadeh, A., Mohammadi, Y., and Abedini, M. (2014). An efficient hybrid method for solving the optimal sitting and sizing problem of dg and shunt capacitor banks simultaneously based on imperialist competitive algorithm and genetic algorithm. *International Journal of Electrical Power & Energy Systems*, 54:101–111.

Naik, S. N. G., Khatod, D. K., and Sharma, M. P. (2015). Analytical approach for optimal siting and sizing of distributed generation in radial distribution networks. *IET Generation, Transmission & Distribution*, 9(3):209–220.

Naka, S., Genji, T., and Fukuyama, Y. (2001). Practical equipment models for fast distribution power flow considering interconnection of distributed generators. In *Power Engineering Society Summer Meeting, 2001*, volume 2, pages 1007–1012. IEEE.

Nara, K., Hayashi, Y., Ikeda, K., and Ashizawa, T. (2001). Application of tabu search to optimal placement of distributed generators. In *Power Engineering Society Winter Meeting, 2001. IEEE*, volume 2, pages 918–923. IEEE.

Nehrir, M. H., Wang, C., and Shaw, S. R. (2006). Fuel cells: promising devices for distributed generation. *Power and Energy Magazine, IEEE*, 4(1):47–53.

Novoa, C. and Jin, T. (2011). Reliability centered planning for distributed generation considering wind power volatility. *Electric Power Systems Research*, 81(8):1654–1661.

Ochoa, L. F., Dent, C. J., and Harrison, G. P. (2010). Distribution network capacity assessment: Variable dg and active networks. *Power Systems, IEEE Transactions on*, 25(1):87–95.

Ochoa, L. F. and Harrison, G. P. (2011). Minimizing energy losses: Optimal accommodation and smart operation of renewable distributed generation. *Power Systems, IEEE Transactions on*, 26(1):198–205.

Ochoa, L. F., Padilha-Feltrin, A., and Harrison, G. P. (2006). Evaluating distributed generation impacts with a multiobjective index. *Power Delivery, IEEE Transactions on*, 21(3):1452–1458.

Ochoa, L. F., Padilha-Feltrin, A., and Harrison, G. P. (2008a). Evaluating distributed time-varying generation through a multiobjective index. *Power Delivery, IEEE Transactions on*, 23(2):1132–1138.

Ochoa, L. F., Padilha-Feltrin, A., and Harrison, G. P. (2008b). Time-series-based maximization of distributed wind power generation integration. *Energy Conversion, IEEE Transactions on*, 23(3):968–974.

Othman, M., El-Khattam, W., Hegazy, Y. G., and Abdelaziz, A. Y. (2015). Optimal placement and sizing of distributed generators in unbalanced distribution systems using supervised big bang-big crunch method. *IEEE Transactions on Power Systems*, 30(2):911–919.

Pandi, V. R., Zeineldin, H., and Xiao, W. (2013). Determining optimal location and size of distributed generation resources considering harmonic and protection coordination limits. *Power Systems, IEEE Transactions on*, 28(2):1245–1254.

Penido, D. R. R., de Araujo, L. R., Carneiro, S., Pereira, J. L. R., and Garcia, P. A. N. (2008). Three-phase power flow based on four-conductor current injection method for unbalanced distribution networks. *IEEE Transactions on Power Systems*, 23(2):494–503.

Porkar, S., Poure, P., Abbaspour-Tehrani-fard, A., and Saadate, S. (2011). Optimal allocation of distributed generation using a two-stage multi-objective mixed-integer-nonlinear programming. *European Transactions on Electrical Power*, 21(1):1072–1087.

Prommee, W. and Ongsakul, W. (2011). Optimal multiple distributed generation placement in microgrid system by improved reinitialized social structures particle swarm optimization. *European Transactions on Electrical Power*, 21(1):489–504.

Ranjan, R. and DAS (2003). Simple and efficient computer algorithm to solve radial distribution networks. *Electric power components and systems*, 31(1):95–107.

Rau, N. S. and Wan, Y.-h. (1994). Optimum location of resources in distributed planning. *Power Systems, IEEE Transactions on*, 9(4):2014–2020.

Reikard, G. (2009). Predicting solar radiation at high resolutions: A comparison of time series forecasts. *Solar Energy*, 83(3):342–349.

Riedmiller, M., Gabel, T., Hafner, R., and Lange, S. (2009). Reinforcement learning for robot soccer. *Autonomous Robots*, 27(1):55–73.

Salameh, Z. M., Borowy, B. S., and Amin, A. R. (1995). Photovoltaic module-site matching based on the capacity factors. *Energy Conversion, IEEE Transactions on*, 10(2):326–332.

Samal, P. and Ganguly, S. (2015). A modified forward backward sweep load flow algorithm for unbalanced radial distribution systems. In *2015 IEEE Power & Energy Society General Meeting*, pages 1–5. IEEE.

Sedighi, M., Igderi, A., and Parastar, A. (2010). Sitting and sizing of distributed generation in distribution network to improve of several parameters by pso algorithm. In *IPEC, 2010 Conference Proceedings*, pages 1083–1087. IEEE.

Segura, S., Da Silva, L., and Romero, R. (2011). Generalised single-equation load flow method for unbalanced distribution systems. *IET generation, transmission & distribution*, 5(3):347–355.

Selvan, M. and Swarup, K. (2004). Distribution system load flow using object-oriented methodology. In *Power System Technology, 2004. PowerCon 2004. 2004 International Conference on*, volume 2, pages 1168–1173. IEEE.

Sengupta, M., Perez, R., Gueymard, C., Anderberg, M., and Gotseff, P. (2014). Satellite-based solar resource data sets for india 2002–2012. Technical report, National Renewable Energy Laboratory (NREL), Golden, CO.

Shaaban, M. F., Atwa, Y. M., and El-Saadany, E. F. (2013). Dg allocation for benefit maximization in distribution networks. *Power Systems, IEEE Transactions on*, 28(2):639–649.

Shahzad, M., Ahmad, I., Gawlik, W., and Palensky, P. (2016). Load concentration factor based analytical method for optimal placement of multiple distribution generators for loss minimization and voltage profile improvement. *Energies*, 9(4):287.

Sheng, W., Liu, K.-Y., Liu, Y., Meng, X., and Li, Y. (2015). Optimal placement and sizing of distributed generation via an improved nondominated sorting genetic algorithm ii. *IEEE Transactions on Power Delivery*, 30(2):569–578.

Shirmohammadi, D., Hong, H., Semlyen, A., and Luo, G. (1988). A compensation-based power flow method for weakly meshed distribution and transmission networks. *Power Systems, IEEE Transactions on*, 3(2):753–762.

Shukla, T., Singh, S., Srinivasarao, V., and Naik, K. (2010). Optimal sizing of distributed generation placed on radial distribution systems. *Electric power components and systems*, 38(3):260–274.

Silver, D., Sutton, R. S., and Müller, M. (2007). Reinforcement learning of local shape in the game of go. In *IJCAI*, volume 7, pages 1053–1058.

Singh, D. and Verma, K. (2009). Multiobjective optimization for dg planning with load models. *Power Systems, IEEE Transactions on*, 24(1):427–436.

Singh, R. and Goswami, S. (2009). Optimum siting and sizing of distributed generations in radial and networked systems. *Electric Power Components and Systems*, 37(2):127–145.

Singh, R. K. and Goswami, S. (2010). Optimum allocation of distributed generations based on nodal pricing for profit, loss reduction, and voltage improvement including voltage rise issue. *International Journal of Electrical Power & Energy Systems*, 32(6):637–644.

Singh, R. K. and Goswami, S. (2011). Multi-objective optimization of distributed generation planning using impact indices and trade-off technique. *Electric Power Components and Systems*, 39(11):1175–1190.

Singh, S. and Ghose, T. (2013). Improved radial load flow method. *International Journal of Electrical Power & Energy Systems*, 44(1):721–727.

Sohi, M. F., Shirdel, M., and Javidaneh, A. (2011). Applying bco algorithm to solve the optimal dg placement and sizing problem. In *Power Engineering and Optimization Conference (PEOCO), 2011 5th International*, pages 71–76. IEEE.

Soroudi, A., Aien, M., and Ehsan, M. (2012). A probabilistic modeling of photo voltaic modules and wind power generation impact on distribution networks. *IEEE Systems Journal*, 6(2):254–259.

Soroudi, A. and Amraee, T. (2013). Decision making under uncertainty in energy systems: state of the art. *Renewable and Sustainable Energy Reviews*, 28:376–384.

Soroudi, A. and Ehsan, M. (2011). Efficient immune-ga method for dnos in sizing and placement of distributed generation units. *European Transactions on Electrical Power*, 21(3):1361–1375.

Stagg, G. W. and El-Abiad, A. H. (1968). *Computer methods in power system analysis*. McGraw-Hill.

Sunderland, K., Coppo, M., Conlon, M., and Turri, R. (2016). A correction current injection method for power flow analysis of unbalanced multiple-grounded 4-wire distribution networks. *Electric Power Systems Research*, 132:30–38.

Sutton, R. S. and Barto, A. G. (1998). *Reinforcement learning: An introduction*. MIT press.

Tah, A. and Das, D. (2016). Novel analytical method for the placement and sizing of distributed generation unit on distribution networks with and without considering p and pqv buses. *International Journal of Electrical Power & Energy Systems*, 78:401–413.

Teng, J.-H. (2002). A modified gauss–seidel algorithm of three-phase power flow analysis in distribution networks. *International journal of electrical power & energy systems*, 24(2):97–102.

Teng, J.-H. (2003). A direct approach for distribution system load flow solutions. *Power Delivery, IEEE Transactions on*, 18(3):882–887.

Teng, J.-H. and Chang, C.-Y. (2002). A novel and fast three-phase load flow for unbalanced radial distribution systems. *Power Systems, IEEE Transactions on*, 17(4):1238–1244.

Teng, J.-H. et al. (2000). A network-topology-based three-phase load flow for distribution system. *Source: Proceedings of the National Science Council, Republic of China, Part A: Physical Science and Engineering*, 24(4):259–264.

Teng, J.-H., Liu, Y.-H., Chen, C.-Y., and Chen, C.-F. (2007). Value-based distributed generator placements for service quality improvements. *International Journal of Electrical Power & Energy Systems*, 29(3):268–274.

Thathachar, M. A. and Sastry, P. S. (2011). *Networks of learning automata: Techniques for online stochastic optimization*. Springer Science & Business Media.

Thukaram, D., Banda, H. W., and Jerome, J. (1999). A robust three phase power flow algorithm for radial distribution systems. *Electric Power Systems Research*, 50(3):227–236.

Tortelli, O. L., Lourenço, E. M., Garcia, A. V., and Pal, B. C. (2015). Fast decoupled power flow to emerging distribution systems via complex pu normalization. *IEEE Transactions on Power Systems*, 30(3):1351–1358.

Vieira, J., Freitas, W., and Morelato, A. (2004). Phase-decoupled method for three-phase power-flow analysis of unbalanced distribution systems. *IEE Proceedings-Generation, Transmission and Distribution*, 151(5):568–574.

Viral, R. and Khatod, D. (2015). An analytical approach for sizing and siting of dgs in balanced radial distribution networks for loss minimization. *International Journal of Electrical Power & Energy Systems*, 67:191–201.

Vlachogiannis, J. G. and Hatziargyriou, N. D. (2004). Reinforcement learning for reactive power control. *IEEE transactions on power systems*, 19(3):1317–1325.

Vovos, P. N. and Bialek, J. W. (2005). Direct incorporation of fault level constraints in optimal power flow as a tool for network capacity analysis. *Power Systems, IEEE Transactions on*, 20(4):2125–2134.

Vovos, P. N., Harrison, G. P., Wallace, A. R., and Bialek, J. W. (2005). Optimal power flow as a tool for fault level-constrained network capacity analysis. *Power Systems, IEEE Transactions on*, 20(2):734–741.

Wang, C. and Nehrir, M. H. (2004). Analytical approaches for optimal placement of distributed generation sources in power systems. *Power Systems, IEEE Transactions on*, 19(4):2068–2076.

Wang, L., Kisi, O., Zounemat-Kermani, M., Zhu, Z., Gong, W., Niu, Z., Liu, H., and Liu, Z. (2016). Prediction of solar radiation in china using different adaptive neuro-fuzzy methods and m5 model tree. *International Journal of Climatology*.

Wang, L. and Singh, C. (2008). Reliability-constrained optimum placement of reclosers and distributed generators in distribution networks using an ant colony system algorithm. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 38(6):757–764.

Wang, S., Han, L., and Wu, L. (2015). Uncertainty tracing of distributed generations via complex affine arithmetic based unbalanced three-phase power flow. *IEEE Transactions on Power Systems*, 30(6):3053–3062.

Wei, C., Zhang, Z., Qiao, W., and Qu, L. (2015). Reinforcement-learning-based intelligent maximum power point tracking control for wind energy conversion systems. *IEEE Transactions on Industrial Electronics*, 62(10):6360–6370.

Willis, H. L. (2000). Analytical methods and rules of thumb for modeling dg-distribution interaction. In *Power Engineering Society Summer Meeting, 2000. IEEE*, volume 3, pages 1643–1644. IEEE.

Xing, B. and Gao, W.-J. (2014). Imperialist competitive algorithm. In *Innovative Computational Intelligence: A Rough Guide to 134 Clever Algorithms*, pages 203–209. Springer.

Yammani, C., Maheswarapu, S., and Matam, S. (2012). Multiobjective optimization for optimal placement and size of dg using shuffled frog leaping algorithm. *Energy Procedia*, 14:990–995.

Yammani, C., Maheswarapu, S., and Matam, S. K. (2013). Optimal placement and sizing of der's with load models using bat algorithm. In *Circuits, Power and Computing Technologies (ICCPCT), 2013 International Conference on*, pages 394–399. IEEE.

Yammani, C., Maheswarapu, S., and Matam, S. K. (2016). Optimal placement and sizing of distributed generations using shuffled bat algorithm with future load enhancement. *International Transactions on Electrical Energy Systems*, 26(2):274–292.

Yang, D., Jirutitijaroen, P., and Walsh, W. M. (2012). Hourly solar irradiance time series forecasting using cloud cover index. *Solar Energy*, 86(12):3531–3543.

Yang, N.-C. (2016). Three-phase power flow calculations using direct z bus method for large-scale unbalanced distribution networks. *IET Generation, Transmission & Distribution*, 10(4):1048–1055.

Yu, T., Zhou, B., Chan, K. W., Chen, L., and Yang, B. (2011). Stochastic optimal relaxed automatic generation control in non-markov environment based on multi-step learning. *IEEE Transactions on Power Systems*, 26(3):1272–1282.

Zhang, F. and Cheng, C. S. (1997). A modified newton method for radial distribution system power flow analysis. *Power Systems, IEEE Transactions on*, 12(1):389–397.

Zhu, D., Broadwater, R. P., Tam, K.-S., Seguin, R., and Asgeirsson, H. (2006). Impact of dg placement on reliability and efficiency with time-varying loads. *Power Systems, IEEE Transactions on*, 21(1):419–427.

Zhu, Y. and Tomsovic, K. (2002). Adaptive power flow method for distribution systems with dispersed generation. *Power Delivery, IEEE Transactions on*, 17(3):822–827.

Zimmerman, R. D. and Chiang, H.-D. (1995). Fast decoupled power flow for unbalanced radial distribution systems. *Power Systems, IEEE Transactions on*, 10(4):2045–2052.

List of Publications

Journal Publications

1. Maya K N, Jasmin E. A. "Optimal integration of distributed generation (DG) resources in unbalanced distribution system considering uncertainty modelling." International Transactions on Electrical Energy Systems (2016)., Impact Factor:1.084 .

2. Maya K. Narayanan, Jasmin E. Abdu, and TP Imthias Ahamed. "Loss minimization using optimal allocation of photovoltaic units in unbalanced radial distribution feeders: A case study." Journal of Renewable and Sustainable Energy 8.5 (2016): 055503., Impact Factor: 0.961 .

3. Maya K N, Jasmin E. A., "Optimal Operation of Photo Voltaic (PV) units using Learning Automata Algorithm in Unbalanced Distribution Network. " International Journal of Control Theory and Applications, 8(3), 2015, pp. 907-913.

Conference Publications

1. Maya, K. N., and E. A. Jasmin. ”Radial Power Flow For a Distribution System with Distributed Energy Resources.” proceedings of International Conference on Emerging Trends in Electrical Engineering (ICETREE-2014), available at www.elsevierst.com, Chapter 31.

2. Maya, K. N., and E. A. Jasmin. ”A generalised three phase power flow algorithm incorporating the uncertainty of Photo Voltaic (PV) source for unbalanced distribution network.” Advancements in Power and Energy (TAP Energy), 2015 International Conference on. IEEE, 2015.

3. Maya, K. N., and E. A. Jasmin. ”A Three Phase Power Flow Algorithm for Distribution Network Incorporating the Impact of Distributed Generation Models.” Procedia Technology 21 (2015): 326-331.

4. Maya, K. N., and E. A. Jasmin. ”Optimal Operation of Photo Voltaic (PV) units using Learning Automata algorithm in Unbalanced Distribution Network” at Control and Instrumentation System Conference (CISCON) 2015,at Manipal Institute of Technology.

5. Maya, K. N., and E. A. Jasmin. ”Optimal integration of photo voltaic sources in unbalanced distribution system using Reinforcement Learning.” 2015 International Conference on Power, Instrumentation, Control and Computing (PICC). IEEE, 2015.

6. Maya, K. N., and E. A. Jasmin. ”Multi-stage formulation of Optimal Distributed Generation Placement using Reinforcement Learning.” ac-

cepted for presentation at IEEE International Conference on Power Electronics, Drives And Energy Systems, December 2016.

ABOUT THE AUTHOR

Maya K. N. was born at Wadakkanchery in Thrissur district in 1988. She had her B.Tech in Electrical and Elctronics Engineering from L.B.S. College of Engineering, Kasaragod, Kerala in the year 2009 and took M.Tech in Power Systems from Government Engineering College, Thrissur in 2011. She had good academic record and is being actively involved in the various academic activities. She worked as Lecturer in Electrical and Electronics Engineering at Nitte Meenakshi Institute of Technology, Bangalore from August 2011 to April 2013. She joined as a full time research scholar under TEQIP fellowship in the Dept. of Electrical Engineering, Govt. Engineering College, Thrissur in August 2013. She had presented several papers in National and International conferences. Major Area of interest includes Power System Analysis, Distribution system Modelling and Analysis, Optimization, Distributed Generation, etc.

Permanent Address: Thekkedath Mana,
Puduruthy P.O,
Wadakkanchery Via,
Thrissur, Kerala, India
Pin: 680623