DISTRIBUTED GENERATION PLANNING USING HYBRID OPTIMIZATION APPROACHES

Ph.D. THESIS

by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **"DISTRIBUTED GENERATION PLANNING USING HYBRID OPTIMIZATION APPROACHES"** in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Electrical Engineering of the Indian Institute of Technology Roorkee is an authentic record of my own work carried out during a period from July, 2011 to January, 2014 under the supervision of (Late) Dr. Jaydev Sharma, Professor and Dr. Ganesh Balu Kumbhar, Assistant Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee and from February, 2014 to August, 2015 under the supervision of Dr. Ganesh Balu Kumbhar, Assistant professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee. The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

(Sandeep Kaur)

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

(Ganesh Balu Kumbhar)
Supervisor

Dated:

ABSTRACT

Objective of power system operation is to meet the energy demand economically and reliably. In the present environment, the justification for the large central-station plants is weakening because of economic, technical, and environmental concerns. In coming years, Distributed Generation (DG), a term commonly used for small-scale generation, will meet a large portion of electrical energy demand. As the penetration of distributed generation is increasing in the distribution network, it is no more passive in nature. Therefore, it is in the best interest of all the players involved to allocate them in an optimal way such that it could reduce system losses, improve the voltage profile, increase reliability, and reduce overall cost. Hence, the basic aim of this thesis is to develop efficient, economic and environment friendly methodologies for DG planning. Moreover, the thesis intends to propose hybrid optimization algorithms to solve these problems faster, accurate and efficient manner.

Distribution utilities always strive to reduce power loss in their systems. Therefore, distribution loss reduction has always been one of the important objectives of DG planning. In view of this, the first contribution of this thesis is an integrated MINLP based approach for optimal placement of single and multiple DG units for loss minimization. To reduce the computational burden, two-tier model is proposed. Firstly, in Siting Planning Model (SPM), prospective candidate buses are shortlisted based on Combined Loss Sensitivity (CLS). This short-list of potential candidate buses is then passed to Capacity Planning Model (CPM). In CPM, the optimal locations and DG sizes are computed using MINLP based formulation. In this formulation, Sequential Quadratic Programming (SQP) and Branch and Bound (BAB) algorithms are integrated to handle discrete and continuous variables. This approach gives improved computational performance, strong convergence property, less solution time. It is observed that the proposed algorithm based on MINLP gives optimal solution due to its property of simultaneous placement of multiple DG units.

The literature published in the last one decade has suggested many heuristic algorithms to solve the optimization problems of DG placement. These techniques are derivative free and simple to implement. However, they need several iterations to ensure converged solution and become computationally intensive. Convergence also depends on proper selection of tuning parameters. To

overcome these difficulties, a hybrid optimization technique integrating Improved Harmony Search (IHS) and Optimal Power Flow (OPF) is presented for DG placement to minimize losses. The proposed formulation with few controlling parameters and embedded OPF shows strong convergence property and improved computational performance.

The published literature reveals that environmental regulations, national policy of incentive and penalty for harmful emission plays a significant role in optimal DG planning. In India, National Action Plan on Climatic Change has set an ambitious target of 15% by 2020 for Renewable Purchase Obligation (RPO). To encourage renewable power generation as well as to meet RPO targets, a novel methodology to minimize annual cost, with Emission Offset Incentive (EOI), Generation Based Incentive (GBI) and penalty for carbon emission, is presented. The annual cost comprises DG capital, operation, maintenance, energy loss, grid energy and emission cost. Optimal solutions for different incentive schemes in terms of size, location, and types of DG are obtained. It is concluded that the appropriate incentive scheme can make cost intensive DGs such as SPV and wind viable. Furthermore, to solve the proposed formulation efficiently, a hybrid optimization approach is proposed by integrating Improved Harmony Search (IHS), and Teaching and Learning Based Optimization (TLBO).

In DG planning with dispatchable DGs, peak load planning might lead to overestimation of DG size. Long term DG planning with multiple load levels may affect the optimal size, location, and time of adding new DG units at potential locations. Therefore, a novel formulation is proposed considering multi load levels to ensure system constraints within limits for all load conditions. It also considers simultaneous placement of DG and capacitor. It not only provides the optimal DG capacity, but also computes the optimal size for each load level and planning year.

The increased DG penetration with proper planning methodology and efficient optimization algorithm would result in huge financial saving for utilities. This thesis has presented few such methodologies and hybrid optimization algorithms demonstrating their applications and usefulness.

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(SANDEEP KAUR)

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation/Symbol		**Stands for**
DG	:	Distributed Generation,
GA	:	Genetic Algorithm,
NSGA	:	Non- dominated sorting genetic algorithm,
NR	:	Newton-Raphson,
GHG	:	Greenhouse gases,
EA	:	Evolutionary algorithm,
PSO	:	Particle swarm optimization,
OPF	:	Optimal power flow,
LP	:	Linear programming,
NLP	:	Nonlinear programming,
MINLP	:	Mixed integer nonlinear programming,
SQP	:	Sequential quadratic programming,
BAB	:	Branch and bound,
HS	:	Harmony search,
HMCR	:	Harmony memory consideration rate,
HMS	:	Harmony memory,
PAR	:	Parity adjustment rate,
bw	:	Bandwidth,
IHS	:	Improved harmony search,
HSTL	:	Harmony search teaching-learning,
TLBO	:	Teaching-learning based optimization,
IA	:	Improved Analytical,
DISCO/DISCOM	:	Distribution company,
DNO	:	Distribution network operator,
ODGP	:	Optimal DG planning,
RPO	:	Renewable Purchase Obligation,
EOI	:	Emission Offset Incentive,
GBI	:	Generation Based Incentive,

LF	:	Load factor,
LLF	:	Loss load factor,
PV	:	Photovoltaic,
SPV	:	Solar photovoltaic,
CHP	:	Combined heat and power,
WECS	:	Wind energy conversion system,
NDG	:	Number of DG,
SPM	:	Siting planning model,
CPM	:	Capacity planning model,
O&M	:	Operation and maintenance,
ABC	:	Ant bee colony,
CIGRE	:	International Council on Large Electric Systems,
ANSI	:	American National Standards Institute,
R_{ij}	:	Resistance of the line between bus *i* and bus *j*,
X_{ij}	:	Reactance of the line between bus *i* and bus *j*,
$\lvert V_i \rvert$	:	Voltage magnitude at bus *i*,
$V_{\min}$	:	Minimum voltage magnitude of system buses,
$V_{\max}$	:	Maximum voltage magnitude of system buses,
$\lvert V_j \rvert$	:	Voltage magnitude at bus *j*,
δ_i	:	Voltage angle at bus *i*,
δ_j	:	Voltage angle at bus *j*,
N_B	:	Number of buses,
NB	:	Number of branches,
P_i	:	Active power injections at bus *i*,
Q_i	:	Reactive power injections at bus *i*,
P_j	:	Active power injections at bus *j*,
Q_j	:	Reactive power injections at bus *j*,
$P_{G(\max)}$	:	Maximum real power generation at slack bus,
$Q_{G(\min)}$	:	Minimum reactive power generation at slack bus,
$Q_{G(\max)}$	:	Maximum reactive power generation at slack bus,
G_{ij}	:	Conductance of the line between bus *i* and bus *j*,
B_{ij}	:	Susceptance of the line between bus *i* and bus *j*,

P_G^i	:	Active power generation of generator at bus *i*,
Q_G^i	:	Reactive power generation of generator at bus *i*,
P_D^i	:	Active power demand at bus *i*,
Q_D^i	:	Reactive power demand at bus *i*,
P_{DG}^i	:	Real power injection from DG placed at node *i*,
Q_{DG}^i	:	Reactive power injection from DG placed at node *i*,
P_{loss}	:	Real power loss,
Q_{loss}	:	Reactive power loss,
$(P_{DG})_{\min}$	:	Minimum real power injection by DG,
$(P_{DG})_{\max}$	:	Maximum real power injection by DG,
$(Q_{DG})_{\min}$	:	Minimum reative power injection by DG,
$(Q_{DG})_{\max}$	:	Maximum reative power injection by DG,
NDG	:	Number of DG units on candidate buses,
N_{DG}^{max}	:	Maximum number of DG on candidate buses,
$S_{ij(\max)}$	:	Power flow (MVA) limit of feeder section between i^{th} and j^{th} bus,
S_{ij}	:	Power flow (MVA) in feeder section between i^{th} and j^{th} bus,
C_{tc}	:	Total annual cost of generation,
C_{en}^{SS}	:	Annual cost of energy drawn from the substation,
C_{Loss}	:	Annual cost of energy losses,
C_{emi}	:	Annual cost of GHG emissions,
C_{pen}	:	Annual penalty cost,
C_{cpt}^{DG}	:	Capital cost of DG,
C_{op}^{DG}	:	Operational cost of DG,
$C_{o\&m}^{DG}$	:	Maintenance cost of DG,
$C_{inc\_emi}^{DG}$	:	Incentive cost of DG for emission reduction,
Cf	:	Capacity factor,
c_{fl}^{bmg}	:	Fuel cost of biomass DG,
S_n^{DG}	:	Installed capacity of DG at bus *n*,
E_n^{DG}	:	Annual energy produced by DG,
c_{en}^{ss}	:	Cost factor ($/MWh) for grid energy,
e_i	:	Emission factor,
CV_{pen}	:	Penalty Cost of voltage limit violation,

CS_{pen}		Penalty cost of thermal limit violation
α	:	Load growth for every year,
$CDGB$	:	List of candidate DG buses,
LL	:	Number of load levels,
C_{DG}^{inst}	:	Installation cost of DG,
r	:	Discount rate,
T	:	Planning period in years,
$H_{d,t}$	:	Duration of load level *d* in year *t*,
S_{rated}^{SS}	:	Substation rated capacity,
I_l	:	Line Current of feeder *i*,
x^{new}	:	New harmony vector,
x	:	Set of decision variables,
x_i^{Lower}, x_i^{Upper}	:	Lower and upper limits of decision variables,
N	:	Number of decision variables,
$M_{k,i}$	:	Mean of kth subject in ith iteration,
TF	:	Teaching factor,
NI	:	Number of improvizations,
$NI_{\max}$	:	Maximum number of improvizations,

CHAPTER 1
INTRODUCTION

1.1 Distributed Generation (DG)

Small-scale generation connected to the distribution grid is commonly referred as Distributed Generation (DG). It is also referred as 'Embedded Generation' or 'Disperse Generation'. CIGRE define DG as the generating plant with a maximum capacity less than 100MW, which is usually connected to the distribution networks and are neither centrally planned nor dispatched **[**1**].** In the literature, there exist many definitions of DG depending on the technologies and applications. Ackermann et al. **[**2**]** have given the most recent definition of DG as,

"*DG is an electric power generation source connected directly to the distribution network or on the customer side of the meter.*"

Following is the classification of DG based on ratings [2]:

- Micro DG: ranging from 1 W to 5 kW,
- Small DG: ranging from 5 kW to 5 MW,
- Medium DG: ranging from 5 MW to 50 MW,
- Large DG: ranging from 50 MW to 300 MW,

DG units are based on conventional as well as renewable energy resources. Technologies such as IC engines, reciprocating engines, gas turbines, micro-turbines, etc. are associated with conventional energy sources. The renewable energy technologies are solar PV, wind, small hydro, biomass, solar-thermal, and geothermal systems, etc.[2-4].

1.2 DG Technologies

A brief description of Major DG technologies is as follows.

- ***Combustion Engines*****:** Combustion engines, which are commonly used as DG, are gas turbine. Gas turbines are smaller than any other rotating power source and provide higher reliability than reciprocating engines. They accept a wide variety of fuels such as biomass gas, flare gas, natural gas, etc. They also have superior response to load variations and excellent steady state frequency regulation as compared to steam turbines or reciprocating engines. In addition, gas turbines require lower maintenance and produce lower emissions than reciprocating engines. It is the most common configuration for standby and utility grid support applications. Because of compact design and low emissions, they are convenient and environmental friendly sources for standby power and peak shaving requirement. Micro-turbine is a simple form of gas turbine consisting radial compressor and turbine rotor. Electrical efficiency of micro-turbine is more than the traditional gas turbine.

- ***Fuel cell*****:** A fuel cell is a device based on electrochemical process. Since it produces dc output, inverter is required for interfacing to ac power system. Its operation is very quiet, and has virtually no harmful emissions. The major limitation of this technology is higher cost. Fuel cell technologies are much more expensive than reciprocating engines.

- ***Wind turbine*****:** A wind energy system consists of a wind turbine and a generator. Two types of generator technologies are popularly used for wind turbine, namely squirrel-cage induction generator and doubly fed induction generator. Large wind farms are interconnected to the transmission system, whereas smaller farms of few MW capacities are generally connected to distribution feeders through the power electronics interface. The major limitation of wind DG unit is the stochastic nature of wind speed.

- ***Solar Photovoltaic system*****:** The basic unit of solar photovoltaic system is PV cell. These cells are connected in series and parallel to form PV modules. These modules are connected to form an array to generate the required power. Solar photovoltaic system generates dc power and it is interfaced to the utility system through power electronics interface. Despite of the high cost, PV technology is favored from an environmental perspective. As a result, installed capacity is expected to grow at a very fast rate. The major limitations of solar PV system are intermittent nature during the cloudy season and no power during nighttime.

1.3 Types of Generators

The following types of DGs are commonly used.

- ***Synchronous Generator*****:** Synchronous generator is preferred when the capacity exceeds few MW. It is a constant speed machine and has variable power factor characteristics. With proper field and governor control, the machine can follow any load pattern within its design capability. Small machines interconnected with distribution system are generally operated with a constant power factor or constant var (exciter) control. Synchronous generators are usually used with biomass, geothermal, diesel/gas engine, solar-thermal, micro-turbine systems.

- ***Asynchronous Generator*****:** Asynchronous generator with and without converter is very common in wind energy conversion system. The main issue is that a simple induction generator requires reactive power (vars) to excite the machine from the power system to which it is connected. This is an advantage when the DG results in overvoltage, but there can also be low-voltage problems in induction generator applications. The usual fix is to add power-factor correction capacitors to supply the reactive power locally.

1.4 Power Electronic Converter

Some types of DGs produce dc or ac output (of different frequency than system frequency). Power electronic interface is required to provide the desired power output (standard voltage and frequency). However, these inverters produce harmonic currents in the system. To obtain better control and to avoid harmonics problems, pulse-width modulation with harmonic cancellation can be used. Various technologies used for distributed generation are listed in Table 1.1.

1.5 Benefits and Shortcomings of DG Integration

The benefits of integrating DGs into power systems can be classified as operational and economic benefits [5]. The major operational/technical benefits accrued are,

- Reduced line losses,
- Improved voltage profile,
- Increased overall energy efficiency,
- Enhanced system reliability and security,
- Reduced T&D congestion,

Table 1.1 Technologies for distributed generation [3]

Sr. No.	Type of distributed generator	Technology	Approx. Size per module
1.	Combined cycle gas turbine	Synchronous Generator	35MW-400MW
2.	Internal Combustion Engine	Synchronous Generator	5kW-10MW
3.	Combustion Turbine	Synchronous Generator	1MW-250MW
4.	Micro Turbine	Synchronous Generator	35kW-1MW
5.	Small Hydro	Synchronous Generator	1MW-100MW
6.	Geothermal	Synchronous Generator	5MW-100MW
7.	Solar Thermal Central Receiver	Synchronous Generator	1MW-10MW
8.	Biomass Gasification	Synchronous Generator	100kW-20MW
9.	Wind Generator	Asyn. Generator with Power Electronic converter	200Watt-3MW
10.	Photovoltaic Array	Power Electronic converter	20 Watt-100kW
11.	Fuel cells, solid oxide	Power Electronic converter	250kW-5MW
12.	Sterling Engine	Power Electronic converter	2kW-10kW
13.	Battery storage	Power Electronic converter	500kW-5MW

The major economic and environmental benefits are;

- Reduced harmful emissions and greenhouse gas (GHG), thereby earning carbon credits,
- Cost saving due to reduction in distribution system loss,
- Deferred investments for up-gradation of facilities,
- Reduced operational costs of some DG technologies, e.g. solar and wind,
- Reduced reserve requirements,
- Lower operating costs due to peak shaving,
- Increased security for critical loads,

In spite of several significant advantages, the inclusion of DGs may have negative impacts on the system [6, 7]. Demerits of DG integration are as follows:

- Integration of DG may disturb the co-ordinations of existing protective devices,
- For interconnection, use of inverters may inject harmonics into the system,
- DGs may adversely affect the system stability,
- DG units may increase the fault current levels of the system depending on their locations.

1.6 DG Integration Scenario in India

India is one of the fastest growing economics in the world. The availability of sufficient and best quality supply of electricity is very crucial for the sustainable development. Electricity demand in

India has been increasing rapidly, and generating capacity has grown manifold, from 1,712 MW in 1950 to more than 272,687.17 MW as on 30.04.2015 [8, 9]. Still, it represents only 860.72 kWh per capita per year. This per capita figure is expected to almost triple by 2020 with 6.3% annual growth.

Presently, the country is in a power deficient state. The average power deficiency is nearly 12.2% of peak demand. The power deficient situation of the country results in load shedding. This makes the distributed generation from renewable sources mandatory for the continuous growth of the country. On the other hand, India is blessed with abundant solar power potential of 748.98 GW [9]. Besides, there is the abundant availability of other forms of energy sources such as hydropower, wind, biomass, etc. Table 1.2 gives renewable energy potential in India and actual progress achieved up to 30.04.2015.

Although, the figures seem impressive, the contribution of DG technologies, especially renewable resources has not been significant. Renewable energy programs are specially designed to meet the growing energy needs in rural areas for promoting decentralized development and to stem the growing migration of rural population to urban areas. Renewable sources contribute to about 5% of the total power generating capacity in the country. Prospects for renewable are steadily increasing in India. The percentage of total installed capacity is expected to be 10% by 2020.

1.7 Challenges in DG Planning

In the last few years, the penetration of DG is rapidly increasing in many parts of the world **[**3-5**]**.

Table 1.2 Renewable energy potential in India [9]

Energy source	Estimated Potential (MW)	Cumulative Installed capacity (MW)
Wind power	100,000	23,444.00
Small Hydro (up to 25 MW)	20.000	4055.36
Biomass Power	17,000	4533.63
Bagasse Cogeneration	5,000	4418.55
Waste to energy	3,880	115.08
Solar Power (SPV)	100,000	3743.97

With high level DG penetration, distribution network is no more passive in nature. Therefore, it is in the best interest of all the stakeholders to allocate them in an optimal way. The proper allocation of DG in distribution system plays an important role in achieving economical, technical, and qualitative benefits [6]. Improper allocation may worsen the system performance [7-9]. As reported in the literature, the primary objectives of DG planning are reduction of system power or energy loss, improvement in voltage profile, enhancement in reliability, minimizing overall cost, deferral of network upgrade, etc.

In the literature, several tools and techniques have been developed to identify optimal size and location of DG in the distribution system. These techniques include analytical methods [10-20], classical optimization methods [21, 22], and heuristic search based techniques [23-32]. The following sections discuss the challenges in effective DG planning.

1. Analytical methods are popular because they give simple expressions to calculate the size and location of DG. In [15, 16], analytical expressions are derived to calculate the optimum size of the single DG unit with unity power factor. Hung [17] proposed another analytical expression for optimal sizing and power factor for four types of DG units. The placement of multiple DG units is addressed in [18]. However, since these methods consider the sequential placement of multiple DG units, sometimes they might lead to sub-optimal solution.

2. To allocate the distributed generation optimally, many classical optimization techniques have also been employed [21, 22]. These classical methods have a strong theoretical background and they are applied to solve many real life problems. However, due to the inherent nonlinearity and exhaustive search-space of the considered problem, these formulations become computationally extensive and sometimes fail to converge to the optimal solution.

3. The optimization problem of DG placements is also addressed using many heuristic techniques such as genetic algorithm (GA) [23-25], Particle Swarm Optimization (PSO) [26-31], Artificial Bee Colony (ABC) [32], etc. Although, the heuristic algorithms are derivative free and simple to implement, they need several iterations to ensure converged solution. Thus, they become computationally intensive. In addition, search based methods to some extent depend on tuning parameters. If tuning parameters are not carefully chosen, these algorithms may lead to a sub-optimal solution.

4. Many researchers have modeled DG as real power sources [17, 24,25]. Few researchers have modeled DG as real as well as a reactive power source, but with constant power factor. Moreover, simultaneous placement of DG and capacitor combination is not fully explored in the literature.

5. Researchers have investigated DG planning problem from the cost perspective. For sustainable development, DG planning with incentive for clean energy and penalty for greenhouse gas (GHG) emissions need to be explored. However, if per unit cost of energy generated is considered, then renewable DGs cannot compete with the conventional generation in its present form.

6. For planning with dispatchable DGs, most of the research is focused on peak load, which may lead to over estimation of DG sizes [6, 7]. Besides, long term DG planning with multiple load levels may affect the optimal DG size, location, and time of adding new DG units at potential locations.

1.8 Objectives of the Research

This research aims at developing novel frameworks for DG planning that assures optimal placement of multiple DG units using hybrid optimization approaches. With motivation to tackle above challenges, this research intends to target the following objectives.

1. To develop efficient hybrid optimization algorithms by integrating analytical and classical methods for simultaneous placement of multiple DG units,

2. To consider DG units capable of delivering real as well as reactive power with flexible power factor for loss minimization and voltage profile improvement,

3. To develop novel hybrid optimization techniques based on integration of heuristic methods (with few controlling parameters) and/or classical methods for improved performance,

4. To develop DG planning framework with incentive for clean energy and penalty for greenhouse gas (GHG) emissions for sustainable development.

5. To develop a long term DG planning mechanism to identify the optimum location, number of units, time of investment, the generation pattern for different load levels to minimize the DG investment, operational, grid and energy loss cost.

1.9 Organization of the Thesis

The present thesis has been organized into eight chapters and the work included in each chapter has been presented in the following sequence.

- The Chapter-1 gives an overview of DG technologies and challenges of DG planning along with the research objectives. Finally, the organization of the thesis is presented.
- The Chapter-2 presents a brief literature review on the techniques and issues related to the DG planning.
- The Chapter-3 presents mathematical modeling of the distribution system and theoretical background of various optimization techniques used in the proposed formulations.
- The Chapter-4 presents a novel Mixed Integer Nonlinear Programming (MINLP) based optimization algorithm for planning of multiple DG units with real and reactive power capabilities. To reduce search space and computational burden, the algorithm is divided in two parts namely Siting Planning Models (SPM) and Capacity Planning Model (CPM).
- The Chapter-5 presents a hybrid optimization technique based on integration of Improved Harmony Search (IHS) and Optimal Power Flow (OPF). The proposed formulation shows strong convergence property and improved results due to few controlling parameters, and embedded OPF formulation.
- The Chapter-6 presents a mathematical formulation for low carbon DG planning to minimize the annualized cost considering incentive for clean energy and penalty for greenhouse gas (GHG) emissions. The chapter explores various incentive schemes for cost intensive renewable DGs. This chapter also presents a hybrid optimization technique based on integration of IHS and TLBO.
- The Chapter-7 describes an MINLP based formulation for long term DG planning. The proposed methodology provides the optimal DG and capacitor allocation in terms of number of units, time of investment, optimal locations, and generation for each load level, and planning year.
- The Chapter-8 concludes the research work highlighting the contributions and providing the directions for the future research.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The area of DG planning is quite vast, and consequently the literature in this area is extensive. Various techniques for optimal placement of DG units are reviewed in [6, 7]. This chapter presents the overview of techniques and issues related to DG planning. A comprehensive study is conducted on techniques, objectives and problems related to DG planning such as power loss, energy loss, voltage profile, power system economics, greenhouse gas emissions etc. Finally, major limitations and gaps drawn from the study are highlighted.

The typical Optimal DG Planning (ODGP) problem is the determination of the optimum locations and sizes of DG units to be installed into existing distribution networks. It is achieving certain objectives subjected to network and DG constraints. In the literature, many objectives are considered such as minimization of the power loss [10-32] and energy losses [33-38], reliability improvement [39-41], voltage deviations and stability improvement [42-45], reactive power optimization [46-48], etc. From economic prospective, researchers have taken the objectives such as minimization of overall cost [49-55], maximization of DG profit [56-59], market based approach [60-62], maximization of techno-economic benefits [63-78], etc. Multi-objective formulations are discussed in[54, 65-71, 74, 76-77, 79-80].

2.2 Optimization Approaches for DG Planning

As discussed in the last chapter, the optimization algorithms for optimal placement of DG can be broadly classified in three categories: analytical methods [10-20], classical optimization methods [21, 22, 35-37, 63-64], and heuristic search based techniques [23-32].

2.2.1 Analytical methods

In [81], '2/3 rule' (widely used for capacitor placement) is used for DG placement to minimize the line losses. However, this method is based on the assumption of uniform line loading, and cannot be used for non-uniform loading and meshed systems. Wang and Nehrir [10] derived analytical expressions to determine the optimal location of DG in the radial as well as meshed systems. However, the authors did not consider DG size as a variable. In [11] [15], analytical expressions are derived to calculate the optimum size of the single DG with unity power factor. Hung et al. [17] proposed another analytical expression for optimal sizing and power factor for four types of DG units. However, these formulations are limited to placement of single DG with both real and reactive power capability. Abu-Mouti et al. [82] proposed best location by offsetting each load. The placement of Multiple DG units is addressed in [18-20, 33, 34, 83]. Since analytical method considers the sequential placement of multiple DG units, sometimes it might lead to sub-optimal solution. Moreover, results of analytical techniques are only indicative [6].

2.2.2 Classical or numerical optimization methods

To allocate the distributed generation optimally, many numerical techniques have also been employed. The linear programming (LP) based technique is applied in [84-86]. The LP approach has better convergence property and it can accommodate large variety of power system operating constraints. However, the LP method can handle only linear constraints and objective. Despite of number of advantages, its range of application in OPF formulation is restricted because of the inaccurate evaluation of system losses and inadequate capability to find the exact solution [87]. In [63], Medina et al. formulated optimal sizing and siting problem as Mixed Integer Linear Programming (MILP) problem. However, optimal allocation of DG is non-convex Mixed Integer Non-Linear problem (MINLP).

2.2.3 Evolutionary and heuristic search based techniques

The optimization problem of DG placements is also addressed using many evolutionary techniques [6-7]. Sundhararajanet. al [88] proposed GA based optimal capacitor placement model for radial distribution system. Genetic Algorithm (GA) is applied to solve an ODGP problem with distributed loads [23], constant power concentrated loads [24], and variable power concentrated load models [89]. PSO is applied by many researchers to solve an ODGP model in [26-31, 90-91]. Moreover, recently developed optimization techniques, namely Backtracking Search Optimization (BSOA) and Bacteria Foraging Optimization (BFOA) algorithm, are discussed in [92] and [93],respectively. An Artificial Bee Colony (ABC) with two controlling parameters is presented in

[32]. Optimal location is computed by bus sensitivity and size is determined by differential evolution (DE) algorithm [38] and harmony search (HS) algorithm [94-95]. The advantage of using BSOA is a single control parameter that is independent of the initial value.

2.2.4 Hybrid optimization techniques

To rejoice the benefit of two or more optimization techniques many researchers have solved ODGP problem using hybrid formulations [29, 45, 72, 90, 96-101]. Hybrid formulation integrating GA and PSO is suggested in [45]. In [72], benefit of evolutionary and numerical method is achieved using hybrid approach. Discrete PSO computes the optimal DG location and OPF calculates the optimal DG size [72]. Viability analysis for DG resources using probabilistic load flow and PSO is conducted in [29]. Thus, there is still lot of scope available to develop hybrid techniques to solve the problem of DG planning by integrating two or more optimization methods.

2.3 Energy Loss Minimization

Energy loss minimization is also one of the important objectives considered by researchers. Energy loss cost minimization with dispachable DGs is discussed in [100]. In [71], dispachable as well as renewable DGs are considered, but uncertainty of wind and photovoltaic DG is not taken into account. Energy loss minimization with stochastic renewable generation is obtained using analytical [33-34], classical [35-37], and heuristic [38, 100] methods. In [36], a probabilistic planning technique is proposed for determining the optimal fuel mix of different types of renewable (wind, solar, and biomass) DG units to minimize the annual energy losses without violating the system constraints. The problem is formulated as MINLP, which takes into account the uncertainty associated with the renewable DG sources as well as the hourly variations in the load profile. Minimization of energy loss cost and reliability improvement in an unbalanced network is proposed in [77]. It is observed that the power and energy losses alone may not optimize the DG benefits to the society. Techno-economic analysis is more beneficial for energy planners.

2.4 Techno-Economic Multi-Objective DG Planning

Distributed generation has given a paradigm shift to the traditional planning of the distribution system. Researchers have considered the DG planning with various objectives such as profit maximization, DG injection maximization, cost minimization, etc.

In [29], a comprehensive DG planning model is proposed for minimization of cost. The formulations for cost minimization in deregulated market scenario are proposed in [51-52, 60-61].However, these models are single objective. In [66, 79], multi-objective models, in deregulated market, are proposed, which includes uncertainty and reliability factors. Techno-economic multi-objective formulation is proposed in [65]. It includes stability and voltage deviation as part of objective function. In traditional market scenario, techno-economic models for profit maximization are discussed in [64,72, 78].

Cost benefit analyses with dispachable DGs are proposed in [50, 54]. It is further extended as multi-objective with dispachable and renewable DGs in [55]. In the literature, most of the formulations have considered only the dispachable DGs due to two reasons: 1) investment cost is more for renewable DGs, 2) intermittency makes the model more complex. Environment aspects are not addressed in most of the planning models. Multi-objective formulations from cost and environment prospective are presented in [67-70]. A two stage algorithm for cost minimization and benefit maximization is proposed in [69]. Soroudi et al. [69, 74] developed a techno-economic DG planning model with network expansion. A multi-objective model to minimize technical, economic and environmental risk in presented in [70]. The network constraints are handled by fuzzy sets in [69, 70]. Uncertainty in demand and generation price is considered in [70] using fuzzy logic.

2.5 Distribution System Expansion Planning with DG

Researchers have also considered optimal DG allocation during long term planning. In [77], a five year DG planning model is presented for minimization of energy loss cost and reliability improvement. Gonen et al. [102] proposed substation up-gradation and feeder expansion planning using mixed integer linear programming. It is further refined by modeling loss equation as quadratic MIP in [103]. A heuristic technique for feeder reconfiguration is proposed in [104]. Novel planning model with peak load, using MIP and MINLP formulation, is presented in [105].

Multi-objective DG placement with network reconfiguration is proposed in [106]. Multi-objective long term DG planning with network reconfiguration for minimization of cost and GHG emissions is proposed in [76].

The summary of optimization techniques and DG modeling, the summary of objectives, and the comparison of method for techno-economic analyses are presented in Table 2.1, Table 2.2 and Table 2.3, respectively.

2.6 Summary

In this chapter, literature review of various techniques and issues related to optimal DG planning are presented. In the first section, various performance parameters such as minimization of the power loss, energy loss, reliability improvement, voltage deviations and stability improvement are discussed. Moreover, other objectives based on techno-economic, eco-environmental and system expansions are discussed. Comparative summaries of techniques, objectives and problems related to DG planning are also presented at the end of the chapter.

Table 2.1 Summary of techniques for power loss minimization

Objective	DG locations	DG modeling	Techniques	Remarks
Minimization of losses	[10] Single optimal location, [11] Single DG with uniform, central and increasing load, [12] Only optimal locations, [13,14,15,17,83] Single DG placement, [16] Exhaustive search for each DG, [18-32] Multiple DG units, [28] Type I, II, or III DG at single optimal location,	[10,11,13-15,23-27] Real power, [17-22, 28-29,95] Real and reactive power, [30] Type I as real power and type II as a reactive power source [32,83] Real and reactive with constant power factor [93] DG as real power and capacitor for reactive power	**Analytical** [10-20] Analytical, [11] Analytical with different load models, [12,13] Iterative technique with constant current and constant impedance load models, **Classical** [21] FSQP, [22] hybrid SQP& BAB, **Heuristic** [23-25,64,65,86] GA, [26-28, 29, 30] PSO, [92 Bacteria forging (BFOA), [32] Artificial Bee Colony algorithm, [95] Improved Harmony Search (IHS),	1) It is observed that most of the researchers have used either analytical an evolutionary method. Optimal siting and sizing problem by classical method is not fully explored. 2) DG is modeled as a real power source by most of the researches. To exploit its full potential DG should be modeled as both real and reactive source. 3) DGs are modeled as either with unity power factor or constant power factor. Therefore, DG modeling should include optimizing DG power factor.

Table 2.2 Summary of various objectives

Objective Function	Techniques used
Minimization of Energy loss	[33,34] Analytical, [35] Classical using AIMMS, [36,37] Classical using GAMS, [38] Differential Evolution, [100] GA,
Minimization of power loss and voltage profile improvement,	[80] IMOHS Multi-objective harmony search, [92] Bacteria forging (BFOA), [94] Harmony search (HS),
Minimization of power loss, voltage profile improvement and voltage stability improvement	[43] Quasi oppositional Teaching-learning, [45] GA and PSO,
Minimization of power loss, voltage profile improvement, DG capacity maximization,	[90] Hybrid PSO with gravitational search, [85] Integrated GA with linear programming, [89] GA,
Multi-objective with weighted average for voltage profile improvement, line-loss reduction, line loading and short circuit,	[96] GA and fuzzy set theory, [91] PSO with different load models,
Reliability improvement in terms of expected energy outage cost (ECOST),	[39-41] Analytical method for benefit maximization and reliability improvement using GA,
Multi-objective for maximization of DG owner profit and minimization of DISCO cost,	[41,50] GA, [54] MOPSO, [55] Immune GA,

Table 2.3 Comparison of different techniques considered for Techno-economic criterion

Objective	Objectives considered	Technique implemented	Remarks
Minimization of cost	[51, 64, 65] Minimization of cost with discrete size of DG, [63] Minimization of investment and operational cost, [66] Minimization of cost with economic and technical aspect, [67] Minimization of cost with grant function for pollution free generation, [68, 69] Planning with renewable resources for emission reduction along with cost minimization, [70] Minimization of cost with technical and environment criterion, [71] Minimization of energy and loss cost along with emission reduction. [72] Minimization of generation cost and line loss cost, [73] Minimization of investment deferral cost, [74] Minimization of generation, operational and network re-enforcement cost, [75] Probabilistic approach for cost and emission reduction, [76] Minimization of cost and emission, [77] Minimization of cost with unbalanced load, [78] Minimization of economic, emission and reliability cost with load and generation uncertainty,	[51] Classical with GAMS and MATLAB, [63] MILP approach, [64] MINLP approach, [64, 67, 69, 74, 76, 77] Multi-objective with GA and NSGA, [66, 70] Multi-objective using NSGA and fuzzy set to handle uncertainty, [72, 78] PSO, [68] Multi-objective with modified honey bee mating optimization, [71] Multi-objective using Shuffled Frog Leap Algorithm, [98] Classical with HOMER software, [73] Successive elimination method, [74] ε-constraint method,	1) DG modeling without reactive power capability may lead to sub-optimal location, thereby under-utilization of DG power. 2) DG planning at peak load may lead to overestimation of DG size. Therefore, DG planning at discrete load levels gives more realistic DG location, size and time of installing a new unit. 3) The Eco-environment criterion should be considered for sustainable development. 4) Some RES cannot compete with conventional sources in its present form. Incentive schemes offered may form part of the DG planning problem.

CHAPTER 3

PROBLEM FORMULATIONS AND OPTIMIZATION TECHNIQUES

3.1 Introduction

An accurate modeling of DG and distribution system can help in computing the optimal penetration of DG in terms of location and size [2-3]. Studies have indicated that the proper allocation of DG units in distribution system plays a crucial role in achieving technical as well as economic benefits [6-7]. This chapter provides an overview of the mathematical modeling of the distribution system for power loss calculation and sensitivity analysis for optimal location of DG units. The objective functions and constraints of Optimal Power Flow Formulation for loss reductions are presented. To solve the ODGP problem, basic approaches required for the proposed integrated and hybrid algorithms are discussed.

3.2 Mathematical Modeling

3.2.1 Power loss calculation

Consider the *N* bus distribution system as shown in Figure 3.1. It shows the single-line diagram of radial distribution feeder. Bus no. 0 is the root bus and all other buses are load buses with constant power load. The power flow through the i^{th} branch is given as,

$$P_{j+1} = P_j - P_{L(j+1)} - R_{j,j+1}\frac{(P_j^2 + Q_j^2)}{\left|V_j\right|^2} \tag{3.1}$$

$$Q_{j+1} = Q_j - Q_{L(j+1)} - X_{j,j+1}\frac{(P_j^2 + Q_j^2)}{\left|V_j\right|^2} \tag{3.2}$$

where,

P_j *and* Q_j	=	Real and reactive power leaving bus *j*,
$P_{L(j)}$ and $Q_{L(j)}$	=	Real and reactive power load at bus *j*,
$R_{j,j+1}$ and $X_{j,j+1}$	=	Resistance and reactance of the line section between bus *j* and *j+1*,

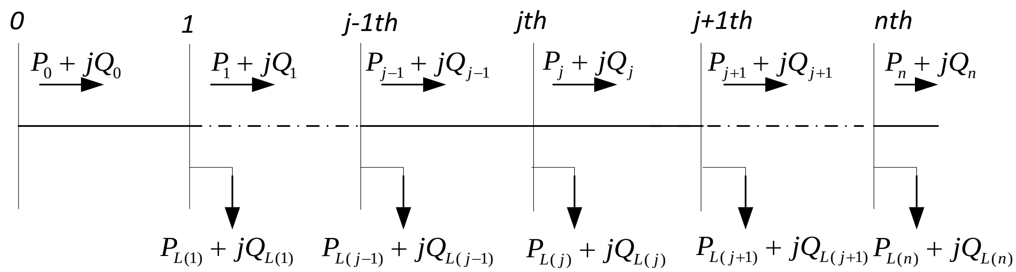

Figure 3.1 Single-line diagram of radial distribution feeder

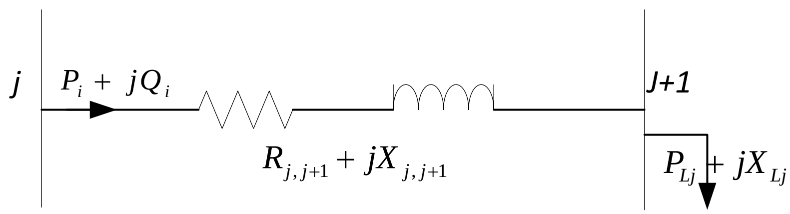

Figure 3.2 Branch model

$|V_j|$ = Voltage magnitude of bus *j*,

The power loss in the branch connected between bus *j* and *j*+1is given as,

$$P_{loss(j,j+1)} = R_{j,j+1} \frac{(P_j^2 + Q_j^2)}{|V_j|^2} \tag{3.3}$$

Figure 3.2 shows a line segment of distribution system having an impedance of $R_{j,j+1}+jX_{j,j+1}$ connected between bus *j* and *j*+1. The real and reactive power loss for k^{th} branch connected between bus *j* and *j*+1 can be represented as,

$$P_{loss(k)} = \frac{P_j^2 + Q_j^2}{V_j^2} R_{j,j+1} \tag{3.4}$$

$$Q_{loss(k)} = \frac{P_j^2 + Q_j^2}{V_j^2} X_{j,j+1} \tag{3.5}$$

where,

V_j = Voltage magnitude of bus *j*,

$P_{loss(k)}$ and $Q_{loss(k)}$ = Real and reactive power loss in k^{th} branch,

P_j *and* Q_j = Active and reactive power flows through k^{th} branch,

$R_{j,j+1}$ and $X_{j,j+1}$ = Resistance and reactance of k^{th} branch,

The total real and reactive power loss can be calculated as,

$$P_{loss} = \sum_{k=1}^{NBr} P_{loss(k)} \tag{3.6}$$

$$Q_{loss} = \sum_{k=1}^{NBr} Q_{loss(k)} \tag{3.7}$$

where,

P_{loss} and Q_{loss} = Total real and reactive power loss,

NBr = Number of branches in the distribution system,

3.2.2 Sensitivity analysis

Sensitivity analysis is used to find the potential candidate buses for optimal DG locations. It helps in reducing the search space and hence expedites the optimization process. The loss sensitivities of each bus with respect to real and reactive power injections are given by,

$$\frac{\delta P_{loss}}{\delta P_i} = \frac{2P_i}{V_i^2} R_{ij} \tag{3.8}$$

$$\frac{\delta P_{loss}}{\delta Q_i} = \frac{2Q_i}{V_i^2} R_{ij} \tag{3.9}$$

$$\frac{\delta Q_{loss}}{\delta P_i} = \frac{2P_i}{V_i^2} X_{ij} \tag{3.10}$$

$$\frac{\delta Q_{loss}}{\delta Q_i} = \frac{2Q_i}{V_i^2} X_{ij} \tag{3.11}$$

where,

$\frac{\delta P_{loss}}{\delta P_i}$ = Sensitivity of active power losses with respect to active injection,

$\frac{\delta P_{loss}}{\delta Q_i}$ = Sensitivity of active power losses with respect to reactive injection,

$\frac{\delta Q_{loss}}{\delta P_i}$ = Sensitivity of reactive power losses with respect to active injection,

$\frac{\delta Q_{loss}}{\delta Q_i}$ = Sensitivity of reactive power losses with respect to reactive injection.

The combined loss sensitivity of each bus with respect to real, reactive and apparent power injection can be given as

$$\frac{\partial S_{loss}}{\partial P_i} = \frac{\partial P_{loss}}{\partial P_i} + j\frac{\partial Q_{loss}}{\partial P_i} \tag{3.12}$$

$$\frac{\partial S_{loss}}{\partial Q_i} = \frac{\partial P_{loss}}{\partial Q_i} + j\frac{\partial Q_{loss}}{\partial Q_i} \tag{3.13}$$

where,

$\frac{\delta S_{loss}}{\delta P_i}$ = Sensitivity of apparent power losses with respect to active injection,

$\frac{\delta S_{loss}}{\delta Q_i}$ = Sensitivity of apparent power losses with respect to reactive injection,

3.3 Optimal Power Flow (OPF) Formulation

The optimal power flow (OPF) problem is very useful tool to optimize various power system objectives [107-109]. Optimal penetration of distributed generation can be obtained by solving OPF of distribution network. The OPF problem in the presence of distributed generation is non-convex, non-linear mixed integer problem due to the non-linear power flow constraints and discrete optimal locations of DG units.

OPF achieves power flow solution while minimizing or maximizing the objective function subjected to various constraints such as power balance, voltage limit, thermal limit, active and reactive power limit, substation power limit, etc. The objective function for power loss minimization is,

$$F = \min \sum_{ij=1}^{Nbr} P_{loss}^{ij} = P_i(V,\delta) \tag{3.14}$$

Following are the constraints of the optimization problem.

I. Active and reactive power balance: real and reactive power balance for each PQ bus is given as,

$$P_i(V,\delta) - P_{Gi} + P_{Di} = 0 \ \forall i \in \{1,2,3...NB\} \tag{3.15}$$

$$Q_i(V,\delta) - Q_{Gi} + Q_{Di} = 0 \forall i \in \{1,2,3...NB\} \tag{3.16}$$

where,

$$P_i(V,\delta) = \sum_{j=1}^{NB} |V_i||V_j|\left(G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right) \text{ where } j \in \{1,2....NB\} \text{and } ij \in \{1,2....NBr\} \tag{3.17}$$

$$Q_i(V,\delta) = \sum_{j=1}^{NB} |V_i||V_j|\left(G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right) \tag{3.18}$$

where,

P_i and Q_i = Real and reactive power injected at bus *i*,

P_{Gi} and Q_{Gi} = Real and reactive power generation at bus *i*,

P_{Di} and Q_{Di} = Real and reactive power demand at bus *i*,

NB = Number of buses,

G_{ij} and B_{ij} = Conductance and susceptance of branch connecting bus *i* to bus *j*,

δ_i and δ_j = Voltage angle at i^{th} and j^{th} bus.

II. ***Active and reactive power generation limits:*** the generated real and reactive power of generator units must lie within minimum and maximum pre-specified capacity given as,

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad \forall\, i \in NG \tag{3.19}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad \forall\, i \in NG \tag{3.20}$$

where,

$P_{Gi}^{\min}, P_{Gi}^{\max}$ = Minimum and maximum real power limit of i^{th} generator,

$Q_{Gi}^{\min}, Q_{Gi}^{\max}$ = Minimum and maximum reactive power limit of i^{th} generator,

NG = Number of generators,

III. ***System voltage limits:*** voltage magnitude of all the buses must be within the allowed upper and lower limits given by,

$$|V_i|_{\min} \le |V_i| \le |V_i|_{\max} \qquad \forall\ i \in NB \tag{3.21}$$

where ,

$|V_i|_{\min}$ = Lower bound on the voltage magnitude of system buses,

$|V_i|_{\max}$ = Upper bound on the voltage magnitude of system buses,

IV. ***Line power flow limit:*** maximum power flow in a feeder section should not exceed the thermal limit of the feeder section. The line flow limits can be expressed as,

$$0 \le S_{ij} \le S_{ij(\max)} \qquad \forall ij \in NBr \tag{3.22}$$

where,

$S_{ij(\max)}, S_{ij}$ = Thermal limit and power flow through the branch between i^{th} and j^{th} bus.

3.4 Classical Methods of Optimization

3.4.1 Sequential Quadratic Programming (SQP)

This algorithm is used for nonlinear constrained optimization problems [21, 22, 110]. The technique is implemented for minimization of a nonlinear objective function of say n variables subjected to equality and/or inequality constraints. The basic statement of the problem is given as,

$$\left.\begin{array}{l} Minimize\ f(x) \\ s.t\ g(x) \le 0 \\ s.t\ h(x) = 0 \\ x \in \{x_1, x_2 \ldots x_{N-1}, x_N\} \quad \text{where } N \text{ is number of decision variables} \end{array}\right\} \qquad (3.23)$$

The Lagrangian function of resulting NLP problem is given as,

$$L(x,\lambda,\sigma) = f(x) + \lambda^T g(x) + \sigma^T h(x) \qquad \text{Where } \lambda \text{ and } \sigma \text{ are lagrangian multipliers.} \qquad (3.24)$$

The SQP algorithm replaces the objective function with quadratic approximation and constraint functions with linear approximations. SQP is an iterative method that models the NLP problem as quadratic programming sub-problem for say k^{th} iteration and then uses the solution to construct the $(k+1)^{th}$ iteration. The Lagrangian function of resulting NLP problem is[21, 22],

$$\begin{array}{l} f^{(k)} + \nabla f^{(k)^T} d^k + \frac{1}{2} d^{k^T} \nabla^2 f^{(k)} L(f^{(k)}, \lambda^k, \sigma^k) d^{\ k} \\ s.t \quad \mathrm{g}^k + \nabla g^{k^T} d^k \le 0 \\ \qquad h^k + \nabla h^{k^T} d^k = 0 \\ x^{k+1} = x^k + \alpha^k d^k \quad \text{where } d^k,\ \alpha^k \text{ step size and direction vector.} \end{array} \qquad (3.25)$$

Then the NLP problem is solved by a sequence of quadratic programming approximations obtained by replacing the nonlinear constraints by a linear Taylor series approximation. Methods like line-search and trust-region are used to compute the step size.

3.4.2 Branch and Bound (BAB) method

In this method, all integer variables are relaxed and resulting NLP problem is solved. If all the integer variables converge to integer solution, then feasible solution for MINLP problem is obtained. Usually, some integer variables converge to non-integer values. The algorithm proceeds by selecting one of those integer variables (say y_i) which take non-integer values and branch on it. This branching yields two new NLP problems by adding upper and lower bounds given as,

$$y_i \le [\hat{y}_i] \; and \; y_i \ge [\hat{y}_i]+1 \qquad \text{where } [\hat{y}_i] \text{ is integer value} \tag{3.26}$$

Then, one of the NLP problems is selected and solved. If the integer variable again takes a non-integer value, then process is repeated. It generates a tree whose nodes correspond to NLP problem. If one of the following fathoming rules is satisfied, then no branching is required. The corresponding node is fully explored and can be abandoned. The fathoming rules are,

1) *An infeasible node is detected*: In this case, whole sub-tree starting at this node is infeasible and the node should be fathomed.
2) *An integer feasible node is detected*: Upper bound on optimal solution is achieved. Therefore, no branching is possible and node should be fathomed.
3) *Lower bound on the NLP solution at that node is greater than the calculated upper bound*: A node is fathomed.

Once a node is fathomed, another node is explored until all the nodes are examined. Thus, in branch and bound (BAB) method, when integer variables take non-integer values, large numbers of NLP problems are solved iteratively without much physical significance.

3.5 Evolutionary Techniques of Optimization

3.5.1 Harmony Search (HS)

Harmony search (HS) is recently developed meta-heuristic optimization algorithm by Zong Wee Geem [111]. It mimics the improvisation process of music players, where they adjust the pitch of their instruments to improve the harmony. Musical performances seek a best harmony determined by aesthetic estimation in the same manner as the optimization algorithms seek a best solution by the objective function evaluation. This technique is applied to a wide variety of optimization problems [112]. HS algorithm possesses following merits in comparison to traditional evolutionary optimization techniques.

- It does not require initial settings of decision variables.
- HS technique is simple to implement and computationally efficient.
- Due to the random search, HS algorithm is derivative free.
- In genetic algorithm, only two parent vectors are considered for generating the new vector. However, in HS, new vector is generated by considering all the vectors. This feature increases the probability of exploring the better solutions.

The steps in harmony search algorithm are as follows:

I. ***Initialization parameters:*** The optimization problem can be modeled as,

$$\left.\begin{array}{lll} Min. & f(x) & \\ s.t. & h_p(x)=0 & p\in\{1,2,3...p\} \\ s.t. & g_{\min}\le g_q(x)\le g_{\max} & q\in\{1,2,3...q\} \\ s.t. & x_i\in[x_i^{Lower},x_i^{Upper}] & \\ x\in\{x_1,x_2...x_{N-1},x_N\} & & \end{array}\right\} \tag{3.27}$$

where,

$f(x)$	=	Objection function to be minimized,
x	=	Set of decision variables,
N	=	Number of decision variables,
x_i^{Lower}, x_i^{Upper}	=	Lower and upper limit of i^{th} decision variable,
p, q	=	Number of equalities and inequality constraints,

The HS parameters (Harmony Memory Size (*HMS*), Harmony Memory Consideration Rate (*HMCR*), Pitch Adjustment Rate (*PAR*), bandwidth (*bw*) and number of improvisations (NI_{max})) are initialized. HMS harmony vectors for continuous and discrete variables are generated randomly as,

$$x_i^j=x_i^{lower}+rand()(x_i^{upper}-x_i^{lower}) \quad \text{where } i=1...N,\ j=1...HMS \tag{3.28}$$

$$x_i^j=Round(x_i^{lower}+rand()(x_i^{upper}-x_i^{lower})) \quad \text{where } i=1,2,...N \quad j=1,2,...HMS \tag{3.29}$$

where,

x_i^j	=	i^{th} decision variable of j^{th} vector,
$rand()$	=	Function to generate random number between 0 and 1.

The harmony vectors in the *HM* database are given as,

$$HM=\begin{pmatrix} x_1^1 & x_2^1 & \dots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \dots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & & x_{N-1}^{HMS} & x_N^{HMS} \end{pmatrix} \tag{3.30}$$

Each *HM* is evaluated for its objective function value.

II. Improvisation of harmony vector

The new harmony vector is selected randomly from the HM database as,

$$x^{new} = x^{j} \quad where\ j \in \{1, 2, 3 \ldots HMS\} \tag{3.31}$$

The selected harmony vector is then improvised with the harmony memory consideration rate (*HMCR*), parity adjustment rate (*PAR*) or random selection. In memory consideration, the i^{th} design variable for the selected new vector is swapped with the variable from *HM* database as given below with probability of *HMCR*.

$$x_i^{new} = x_i^{j}, \quad \text{where } j \in \{1, 2, 3, \ldots HMS\} \text{ and } i = \{1, 2, \ldots N\} \text{ with probility } HMCR \tag{3.32}$$

$$x_i^{new} = x_i^{lower} + rand()(x_i^{upper} - x_i^{lower}) \ \text{ where } i = 1 \ldots N \text{ with probability} (1 - HMCR) \tag{3.33}$$

Every variable obtained from the memory consideration is pitch adjusted with following probability.

$$\text{Pitch adjustment decision for } x_i^{new} \leftarrow \begin{cases} \text{Yes} & \text{with probability } PAR, \\ \text{No} & \text{with probability } (1 - PAR). \end{cases} \tag{3.34}$$

If the pitch adjustment decision is yes, then the selected variable is improved as given below

$$\left. \begin{aligned} x_i^{new} &= x_i^{new} \pm rand() * bw(i) \\ x_i^{new} &= \min(\max(x_i^{new}, x_i^{lower}), x_i^{upper}) \end{aligned} \right\} \tag{3.35}$$

III. Updating the harmony vector

When all the design variables of target vector have undergone the improvisation process, fitness function of the new improved vector is evaluated. If the solution of the new vector is better than the worst harmony vector in HM, then worst harmony vector is replaced with the improved harmony vector, else improved vector is rejected.

IV. Stopping criterion

If the stopping criterion or number of improvisation is satisfied, then select the best solution vector, otherwise go to step ***II***.

3.5.2 Improved Harmony Search (IHS)

In the original HS algorithm, *PAR* and *bw* are very important parameters which decides the rate of convergence to the optimal solution. The traditional HS algorithm uses fixed values for *PAR* and *bw* throughout the solution. Due to the static tuning parameters, classical algorithm sometimes suffers from premature convergence or it may take too many iterations to arrive at optimal solution. To improve the performance of the HS method, IHS algorithm uses variables *PAR* and *bw* during the improvisation process. It improves the algorithm performance in terms of exploration and exploitation [113]. The steps of this algorithm are similar to original HM method. The flow chart of the algorithm is shown in Figure 3.3. Improved Harmony Search, *PAR* and bandwidth (*bw*) are tuned dynamically and is given as,

$$PAR = PAR_{\min} + \left[(PAR_{\max} - PAR_{\min}) \left(\frac{NI}{NI_{\max}} \right) \right] \tag{3.36}$$

$$bw(i) = bw_{\max} * \exp\left[\ln\left(\frac{bw_{\min}}{bw_{\max}} \right) \frac{NI}{NI_{\max}} \right] \tag{3.37}$$

where,

$PAR_{\max}, PAR_{\min}$	=	Maximum and minimum values of *PAR* selected initially,
NI	=	Current improvisation,
$NI_{\max}$	=	Maximum number of improvisations,
$bw_{\max}, bw_{\min}$	=	Maximum and minimum values of *bw* selected initially,
$bw(i)$	=	Bandwidth calculated for i^{th} iteration,

3.5.3 Teaching-Learning Based Optimization(TLBO)

TLBO is another optimization algorithm inspired by nature in which solution vector is improved through the teaching and learner phase [114-115]. The Algorithm tries to improve the solution by two modes of operation. Consider two different teachers, T1 and T2, teach a subject with the same content to the same merit level students in two different classes. If the mean or average of the class taught by teacher T2 is better than T1, then it can be concluded that teacher T2 is better than T1. It is also considered that the learners also learn from interaction between themselves to raise their level of knowledge.

Based on the above process, a mathematical model for Teaching–Learning-Based Optimization (TLBO) is developed. TLBO is also a population based method. In TLBO, the population is considered as a group of learners or a class of learners. Here, different design variables are analogous to different subjects offered to the learners and their result is analogous to the ‘fitness’.

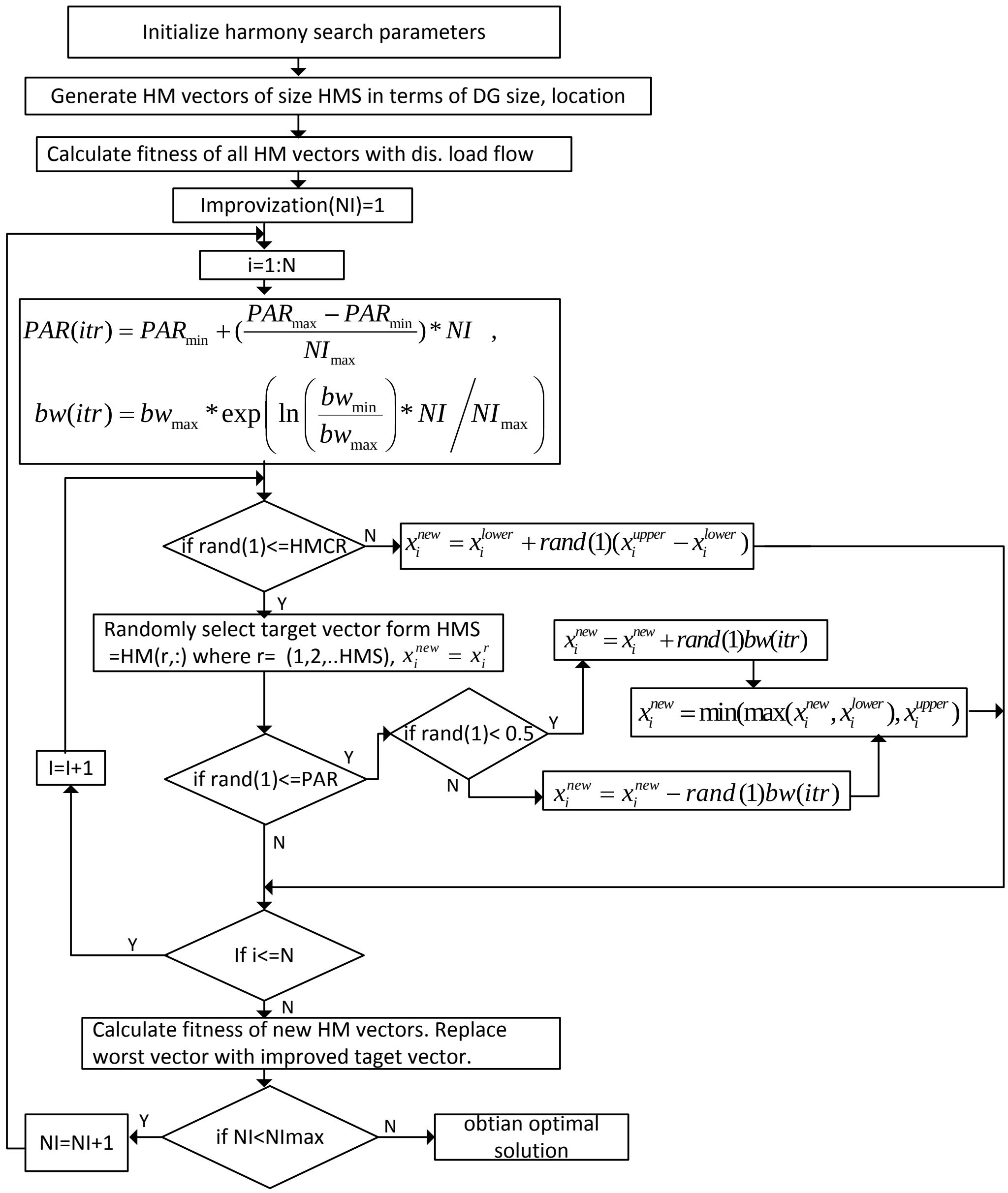

Figure 3.3 Flow chart for IHS based optimization algorithm

The process of TLBO is divided into two parts. The first part consists of the 'Teacher Phase' and the second part consists of the 'Learner Phase'. The 'Teacher Phase' means learning from the teacher and the 'Learner Phase' means learning through the interaction between learners. Flow chart for TBLO technique is shown in Figure 3.4.

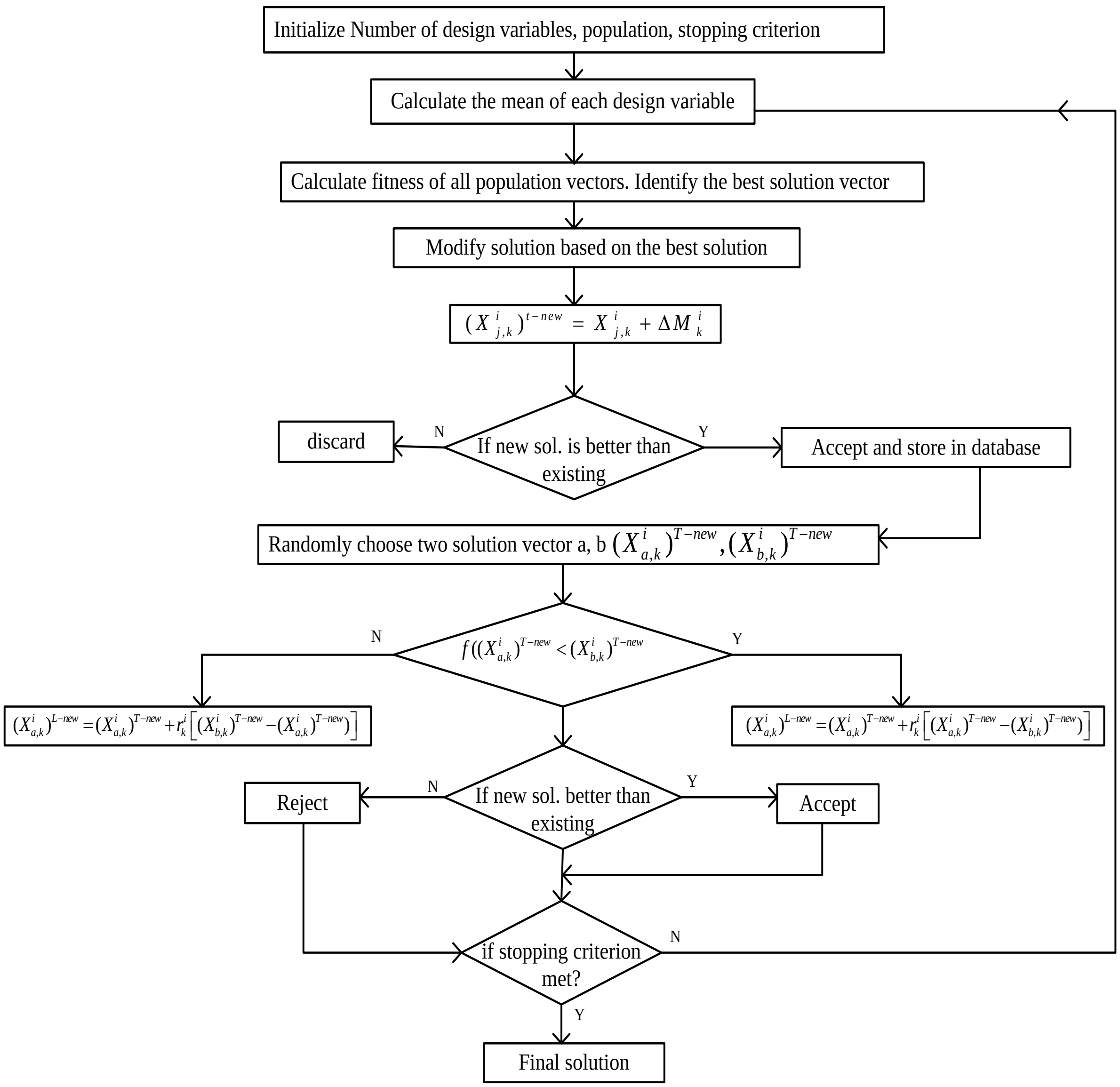

Figure 3.4 Flow chart for Teaching-Learning Based Optimization (TBLO) technique

I. ***Teaching phase***: Let $X^{i}_{j,k}$ represent any population vector, where *j* represents the population count, *k* represents subject count taken as design variables, and *i* represents the iteration count. Steps in teaching phase are as follows.

- Obtain the objective function value and select the teacher with the best solution. A good teacher raises the mean of the class.

- Let X_{jbest}^{i} be the best solution of k^{th} subject, M_k^i is the mean of k^{th} subject and T_i be the teacher in the i^{th} iteration. T_i will try to improve current mean M_k^i towards its own level, so now the new mean is designated as M_{new}. The solution is updated according to the difference between the current and the new mean and is given by,

$$\Delta M_k^i = r_k^i (X_{k,jbest}^i - TF * M_k^i) \tag{3.38}$$

where r_k^i is random number for k^{th} subject and i^{th} iteration. TF is a teaching factor (either 1 or 2) selected randomly as given in (3.39) that decides the value of mean to be changed.

$$TF = round\,(1 + rand\,(0,1)[2-1]) \tag{3.39}$$

- Current population vector is updated and given as,

$$(X_{j,k}^i)^{T-new} = X_{j,k}^i + \Delta M_k^i \tag{3.40}$$

where $(X_{j,k}^i)^{T-new}$ is a new vector generated during teaching phase.

- Obtain the objective function value with the new vector. Retain the new vector if the value obtained in superior otherwise discard it. All the updated population vectors become input for the II^{nd} stage i.e. learning phase.

II. ***Learning phase***: Each learner interacts with other learners to upgrade their knowledge i.e. objective function value. Steps of the algorithm for learning phase are given below.

- Randomly choose two dis-similar learners *a*, *b*. Update the learner *a* as,

$$\begin{aligned}
(X_{a,k}^i)^{L-new} &= (X_{a,k}^i)^{T-new} + r_k^i \left[(X_{a,k}^i)^{T-new} - (X_{b,k}^i)^{T-new} \right] \quad if\ f((X_{a,k}^i)^{T-new} < (X_{b,k}^i)^{T-new} \\
(X_{a,k}^i)^{L-new} &= (X_{a,k}^i)^{T-new} + r_k^i \left[(X_{b,k}^i)^{T-new} - (X_{a,k}^i)^{T-new} \right] \quad if\ f((X_{b,k}^i)^{T-new} < (X_{a,k}^i)^{T-new}
\end{aligned} \tag{3.41}$$

where, $(X_{a,k}^i)^{L-new}$ is a new vector generated during learning phase.

- If the solution is improved, accept the updated learner vector else discard it.
- All the updated learner vectors become input for the teaching phase for the next iteration.
- Check for the stopping criteria or maximum number of iterations.
- If stopping criterion is satisfied, then stop and get the final solution, else repeat the Teaching-Learning phase till the termination condition is met.

3.6 Summary

This chapter gives the overview of the methodology used for loss calculation and sensitivity analysis. It presents the objective function and constraints used during OPF formulation. It also discusses the classical and heuristic optimization techniques, which are further used in this research work. Integrated and hybrid approaches using these algorithms along with their problem formulations are discussed in the subsequent chapters.

CHAPTER 4

INTEGRATED MINLP FORMULATION FOR LOSS MINIMIZATION

4.1 Introduction

Power loss reduction is one of the important criteria of DG planning. The factors, which must be taken into consideration while planning of DG for power loss reduction, are capacity, location, and type of DG. Due to the inherent nonlinearity and exhaustive search space, DG planning for loss reduction is a complex MINLP model with excessive computational burden. Conventional numerical methods with a poor initial start may obtain the sub optimal solution. As a result, proposed MINLP based formulation is solved in two stages with a novel hybrid approach to accrue the benefit of reduced search space, computation burden and consistent optimal or nearly optimal solution. The two stages are Siting Planning Model (SPM) and Capacity Planning Model (CPM). Firstly, SPM identifies the potential candidate buses through sensitivity analysis and rank these buses as per the sensitivity ranking. A list of top ranked potential buses with higher sensitivity, out of all the buses is passed to CPM. It reduces the search space to a large extent. In CPM, MINLP based formulation is solved using a hybrid approach. An integrated algorithm with Sequential Quadratic Programming (SQP) and Branch and Bound (BAB) method is adopted to select optimal solution.

In SQP, only continuous variables are handled. Every NLP problem is solved through quadratic programming to optimality. Under certain conditions, SQP converges quadratically near the optimal solution. The major drawback of this method is that it fails to converge with poor initial start. In BAB method, both continuous variables (NLP part) and integer variables are handled, but solved as a separate entity, wherein the NLP part is searched at each node of the tree. BAB method is not efficient practically as one NLP problem per node need to be solved by quadratic programming. Computation burden in terms of time and memory is increased in BAB, as it is useless to solve NLP problem at that node where integer variables take non-integer values. Therefore, if SQP or BAB is considered independently, it leads to enormous computational time as a large number of NLP problems are to be solved at each node. Therefore, a hybrid approach integrating SQP and BAB is adopted. In this approach, continuous variables are solved simultaneously along with the tree search. Early branching is adopted after a single iteration of SQP. Therefore, the NLP problem needs not to be solved to optimality before branching. This integrated approach combines the benefit of both the techniques by judiciously searching the search space and reducing the computation burden. The developed model is applied to 33-bus distribution system and 69-bus distribution system. The performance of the proposed formulation is compared with the results of the recently published work [18], [29].

4.2 Problem Formulation

Optimal allocation of DG is non-convex mixed integer nonlinear problem. Due to the inherent nonlinearity and exhaustive search space, these formulations become computationally extensive and sometimes fail to converge to the optimal solution. To reduce this computational burden, this optimization problem is solved as two-tier model, namely Siting Planning Model (SPM) and Capacity Planning Model (CPM).

4.2.1 DG and load modeling

DG units can be modeled as PV bus or PQ bus depending on connection and operating mode. DGs are either converter based or machine based. Converter control methodology determines the modeling type of inverter based DG units. Machine based DG units are modeled as PQ or PV bus. A DG unit with constant P and Q generation is modeled as negative PQ load. A DG unit with specified P and power factor is modeled as constant power factor PQ generator. In the presented formulation, DGs are modeled as a negative PQ load.

For the load modeling, three types of loads i.e. constant power, constant impedance, and constant current are usually considered. In this chapter, loads are modeled as constant power load.

4.2.2 Siting Planning Model (SPM)

The objective of SPM is to determine the list of prospective best locations for DG units. To obtain the potential locations, sensitivity analysis is explained in the section 3.2.2. The loss sensitivity of each bus with respect to real, reactive and apparent power injection is given as,

$$\left.\begin{aligned}\frac{\partial S_{loss}}{\partial P_i} &= \frac{\partial P_{loss}}{\partial P_i} + j\frac{\partial Q_{loss}}{\partial P_i}\\ \frac{\partial S_{loss}}{\partial Q_i} &= \frac{\partial P_{loss}}{\partial Q_i} + j\frac{\partial Q_{loss}}{\partial Q_i}\end{aligned}\right\} \tag{4.1}$$

The Combined Loss Sensitivity (CLS) at each bus is calculated as [116]

$$CLS = \begin{vmatrix} \dfrac{\partial P_{loss}}{\partial P_i} & \dfrac{\partial Q_{loss}}{\partial P_i} \\ \dfrac{\partial P_{loss}}{\partial Q_i} & \dfrac{\partial Q_{loss}}{\partial Q_i} \end{vmatrix} \tag{4.2}$$

The buses are then arranged in descending order of their Combined Loss Sensitivity values. To ensure the optimal solution, a list of the top 30 % buses is prepared as potential candidates for CPM. Search space is also reduced significantly, since a small percentage of total number of buses is passed as potential candidates to the CPM model.

4.2.3 Capacity Planning Model (CPM)

In CPM, MINLP based formulation for optimal locations (out of the potential candidate buses from SPM) and size is defined by the following objective function and constraints. Objective function to minimize the real power losses in the distribution system is given as,

$$F = 0.5 * \sum_{i=1}^{NB}\sum_{j=1}^{NB} G_{ij}[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad where\ i, j \in \{1, 2....NB\} \tag{4.3}$$

Following are the constraints of this optimization problem.

- ***Power balance:*** The power flow in terms of active and reactive power should be balanced at each bus. It can be represented as (4.4) and (4.5).

$$P_G^i - P_D^i - \sum_{j=1}^{NB}|V_i||V_j|\left(G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right) = 0 \text{ where } j \in \{1, 2....NB\} \text{and } ij \in \{1, 2....NBr\} \tag{4.4}$$

$$Q_G^i - Q_D^i - \sum_{j=1}^{NB}|V_i||V_j|\left(G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right) = 0 \text{ where } j \in \{1, 2....NB\} \text{and } ij \in \{1, 2....NBr\} \tag{4.5}$$

where,

P_G^i *and* Q_G^i = Real and reactive power generation at i^{th} bus,

P_D^i *and* Q_D^i = Real and reactive power demand at i^{th} bus,

G_{ij} *and* B_{ij} = Conductance and susceptance of branch connecting i^{th} bus to j^{th} bus,

δ_i *and* δ_j = Voltage angle at i^{th} and j^{th} bus.

- ***System voltage limits:*** The voltage magnitudes of all the buses in the system must be within the allowed upper and lower limits. These constraints can be mathematically given as,

$$|V_i|_{\min} \leq |V_i| \leq |V_i|_{\max} \qquad \forall\ i \in NB \tag{4.6}$$

where,

$|V_i|$ = Voltage magnitude at i^{th} bus,

NB = Number of buses in the system

$|V_i|_{\min}$ = Lower bound on the voltage magnitude at i^{th} bus,

$|V_i|_{\max}$ = Upper bound on the voltage magnitude at i^{th} bus.

- ***Distribution substation capacity:*** The slack bus power must be within permissible limit of substation capacity. It can be represented as,

$$0 \leq P_G^i \leq P_{G(\max)} \qquad i \in \{\text{Slack bus}\} \tag{4.7}$$

$$Q_{G(\min)} \leq Q_G^i \leq Q_{G(\max)} \qquad i \in \{\text{Slack bus}\} \tag{4.8}$$

where,

P_G^i = Real power generation at i^{th} bus,

Q_G^i = Reactive power generation at i^{th} bus,

$P_{G(\max)}$ = Maximum real power generation at slack bus,

$Q_{G(\min)}$ and $Q_{G(\max)}$ = Minimum and maximum reactive power generation at slack bus.

- ***DG capacity limit:*** The generated power of DG units must lie within the minimum and maximum pre-specified DG capacity.

$$(P_{DG})_{\min}\sigma_{DG}^k \leq P_{DG}^k \leq (P_{DG})_{\max}\sigma_{DG}^k \qquad k \in \{\text{Set of candidate DG buses}\} \tag{4.9}$$

$$(Q_{DG})_{\min}\sigma_{DG}^k \leq Q_{DG}^k \leq (Q_{DG})_{\max}\sigma_{DG}^k \qquad k \in \{\text{Set of candidate DG buses}\} \tag{4.10}$$

where,

$(P_{DG})_{\min}$ *and* $(P_{DG})_{\max}$ = Minimum and maximum real power injection by DG unit,

$(Q_{DG})_{\min}$ *and* $(Q_{DG})_{\max}$ = Minimum and maximum reactive power injection by DG unit,

P_{DG}^{k} *and* Q_{DG}^{k} = Real and reactive power injected by DG unit at k^{th} bus,

σ_{DG}^{k} = Binary variable for location of DG unit at k^{th} bus.

- ***Number of DG units:*** Total number of DG units installed on candidate buses should not exceed the maximum permissible DG units to be installed.

$$0 \le NDG \le N_{DG}^{\max} \qquad NDG \in \{\text{No. of DG units placed on candidate buses}\} \tag{4.11}$$

where,

$N_{DG}^{\max}$ = Maximum number of DG units.

- ***Power factor of DG units:*** Power factor of DG should adhere to the upper and lower DG power factor limits.

$$pf_{DG_{lower}} < \frac{P_{DG}^{i}}{\sqrt{(P_{DG}^{i})^2 + (Q_{DG}^{i})^2}} < pf_{DG_{upper}} \tag{4.12}$$

where,

P_{DG}^{i} *and* Q_{DG}^{i} = Real and reactive power injection by DG unit at i^{th} bus,

$pf_{DG_{lower}}$ *and* $pf_{DG_{upper}}$ = Lower and upper limit of DG power factor,

- ***Line flow limit:*** Maximum power flow in a feeder section should not exceed the thermal limit of the feeder section. The line flow limit can be expressed as,

$$0 \le S_{ij} \le S_{ij(\max)} \qquad where \;\; ij \in \{1, 2, ...NBr\} \tag{4.13}$$

where,

$S_{ij(\max)}, S_{ij}$ = Thermal limit and power flow through branch between i^{th} and j^{th} bus.

Proposed formulation eq.(4.3-4.13) is solved using integrated SQP and BAB technique. The algorithm is explained in the subsequent section.

4.3 Integrated SQP and BAB Algorithm

Mixed Integer Non-linear Programming (MINLP) optimization problem can be modeled as follows.

$$\left.\begin{array}{l} Min.\, f\left(x,y\right) \\ s.t\;\; g\left(x,y\right)\le 0 \\ s.t\, h\left(x,y\right)=0 \\ x\in \mathrm{X},\;\; \mathrm{y}\in\{0,1\} \end{array}\right\} \tag{4.14}$$

where, *x* is set of continuous variables and *y* is the set of binary decision variables such as the number of devices, locations of DG units, size of DG units, etc. Classical methods such as Decomposition, Branch and Cut, and Branch and Bound solve the MINLP problem by separating the non-linear part from the integer part. The major demerit of the conventional approaches is that solving an NLP problem at each node of the tree to optimality increases the computational burden. In contrast to the conventional methods, presented MINLP formulation is solved using an integrated approach of Sequential Quadratic Programming (SQP) and Branch and Bound approach. In this formulation, early branching on integer variables gives a faster convergence and better computational performance [117]. The steps of the algorithm are as follows and the flow chart is shown in Figure 4.1.

I. In this step, bus and branch data of the considered distribution system is read. List of potential candidate buses for DG placement is also read. Set upper bound $U = \infty$. All binary variables y_i are relaxed and resulting NLP problem is solved [117] using SQP algorithm with following formulation.

$$\left.\begin{array}{l} \min\;\; f^{(k)}+\nabla f^{(k)^T} d^k+\frac{1}{2} d^{k^T} w^{(k)} d^k \text{ where } w^{(k)} \text{ is hessian of Langrangian function given as} \\ L(X,Y)= f(X,Y)+\sum \lambda_i g(X,Y)+\mu_i h(X,Y) \\ s.t\quad \mathrm{g}^k+\nabla g^{k^T} d^k \le 0 \\ h^k+\nabla h^{k^T} d^k =0 \\ x^k+d_x^k \in X, y^k+d_y^k\;\; \in Y \end{array}\right\} \tag{4.15}$$

II. If variables *y* are 0 or 1, the solution is obtained. Otherwise, go to the next step.

III. Select the variable y_i, which does not have value 0 or 1. Generate a binary tree with edges from root node as 0 and 1 indicating the values of the selected variable to the NLP relaxation. Select one of the two relaxed NLP problems and solve (4.15). If the problem is infeasible, then fathom the node and go to other unexplored node, otherwise proceed to the next step.

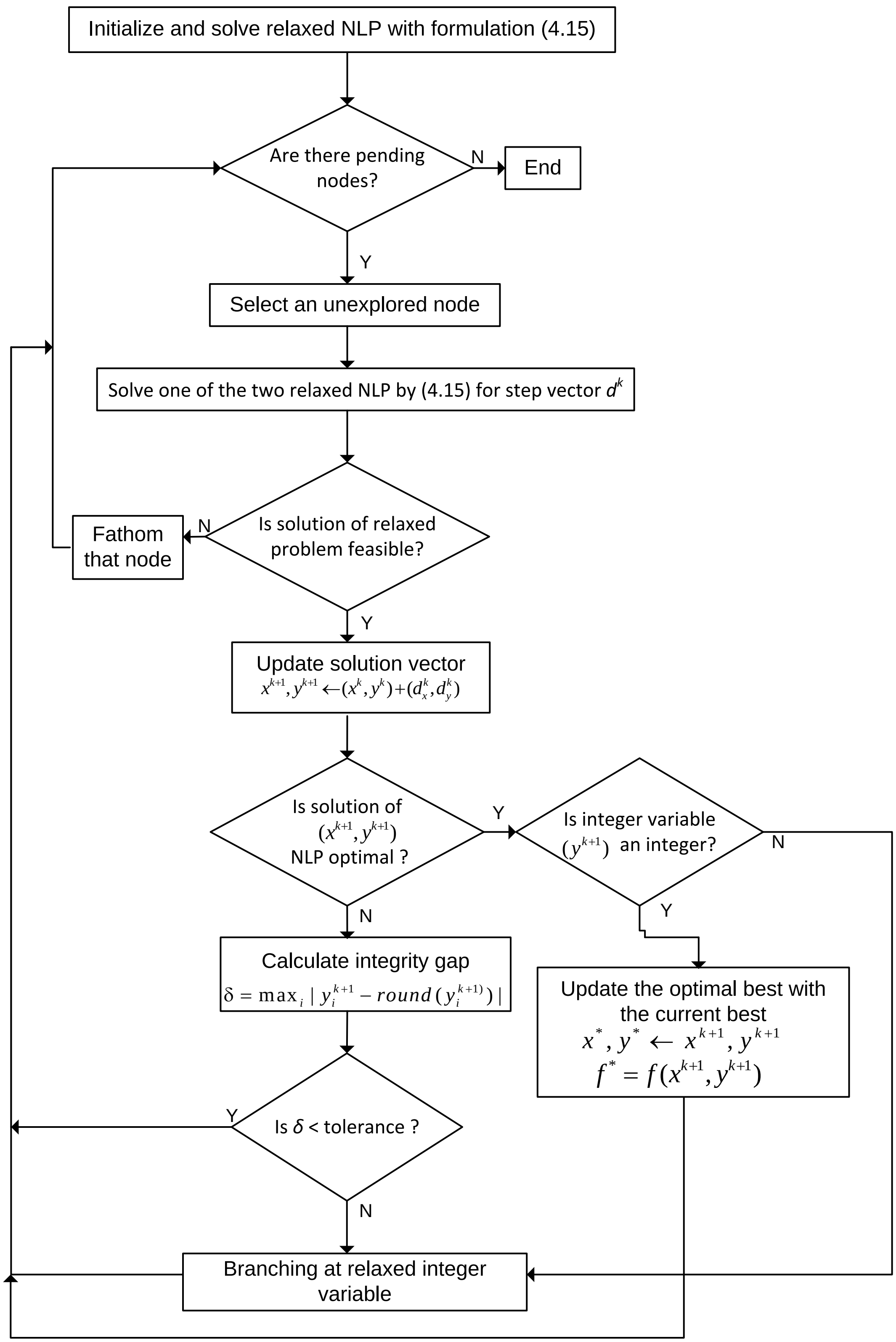

Figure 4.1 Flow chart for integrated SQP and BAB based MINLP algorithm

IV. Update the solution vector as given in (4.16)

$$(x^{k+1}, y^{k+1}) \leftarrow (x^k, y^k) + (d_x^k, d_y^k) \tag{4.16}$$

V. If the solution is optimal and y^{k+1} is 0 or 1, then update current best as (4.17-4.18). Go to next unexplored node and solve using (4.15).

$$(x^*, y^*) \leftarrow (x^{k+1}, \mathrm{y}^{k+1}) \tag{4.17}$$

$$f^* \leftarrow f(x^{k+1}, y^{k+1})\, and\, U \leftarrow f^* \tag{4.18}$$

VI. If a solution is not optimal then calculate integrity gap (δ) as (4.19)

$$\delta \leftarrow \max \left| \mathrm{y}_i^{k+1} - round(y_i^{k+1}) \right| \tag{4.19}$$

VII. If (δ < τ) then examine other unexplored node.

VIII. If (δ > τ) and binary variable appear to converge to integer value, go to step ***III***.

IX. If all the nodes are examined end the program, else go to other unexplored node.

4.4 Results and Discussion

In this section, two case studies are presented to show the effectiveness of the proposed MINLP Algorithm. The SPM and CPM models are implemented in MATLAB and AMPL (Algebraic Mathematical Programming Language), respectively. Knitro solver [118] was used to solve the proposed MINLP formulation on personal computer with 2.93 GHz, Intel core™ 2 duo CPU with 4 GB RAM using windows XP. The formulation is tested on the IEEE 33 bus and 69 bus distribution systems. The results are then compared with the Exhaustive Load Flow (ELF), Improved Analytical (IA) [17], [18] and Particle Swarm Optimization (PSO) [29], which are the promising methods for multiple DG placements.

All the simulations are carried out considering the system peak load. The lower and upper limits of bus voltages used in the simulations are 0.90 pu and 1.05 pu respectively [18]. In addition, the maximum DG power is constrained such that it should not exceed the total load and losses. The results are obtained with DG units of Type-1 (capable of delivering real power) and Type-3 (capable of delivering real and reactive power). However, proposed formulation is generalized and can be implemented for any type of DGs. The power factor of DG unit, capable of providing real and reactive power, is constrained between 0.8 and 1.0.

Table 4.1 Placement of DG units with real power capability

No. of DGs	Method	Bus No.	DG power (MW)	Losses (kW)	Loss Reduction (%)	Time (s)
1 DG	**ELF**	6	2.60	111.10	47.39	1.06
	IA	6	2.60	111.10	47.39	0.16
	MINLP	**6**	**2.59**	**111.01**	**47.39**	**0.09**
	PSO	6	2.59	111.10	47.39	-
2 DG	**ELF**	12	1.02	87.63	58.51	2.03
		30	1.02			
	IA	6	1.80	91.63	56.61	0.27
		14	0.72			
	MINLP	**13**	**0.85**	**87.16**	**58.69**	**0.80**
		30	**1.15**			
	PSO	12	1.00	87.50	58.52	-
		30	1.02			
3 DG	**ELF**	13	0.90	74.27	64.83	3.06
		24	0.90			
		30	0.90			
	IA	6	0.90	81.05	61.62	0.40
		12	0.90			
		31	0.72			
	MINLP	**13**	**0.80**	**72.79**	**65.50**	**1.20**
		24	**1.09**			
		30	**1.05**			
	PSO	13	0.88	73.20	65.34	-
		24	1.09			
		30	1.01			

4.4.1 IEEE 33-bus System

The total real and reactive power demands in IEEE 33-bus system are 3.7 MW and 2.3 MVAr respectively (Appendix A). System line loss without DG is 211 kW. The list of potential buses for IEEE 33-bus system provided by SPM model is {5, 6, 8, 9, 10, 13, 24, 28, 29, 30}. The proposed MINLP based CPM model is solved with reduced search space to obtain optimal DG locations and sizes.

The simulation results of placement of single and multiple DG units with real power are presented in Table 4.1 All the methods converge to the same solution for single DG placement. However, MINLP based proposed formulation takes least time to converge. The major advantage of the proposed formulation is evident from placement of multiple DG units. In the case of 2 DG

Table 4.2 Placement of single DG unit with real and reactive power capability

Method	Bus no.	DG power			Optimal p.f.	Losses (kW)	Loss Reduction (%)
		MW	MVAR	MVA			
IA	6	2.637	1.634	3.102	0.850	68.157	67.69
MINLP	**6**	**2.558**	**1.761**	**3.105**	**0.823**	**67.854**	**67.84**
PSO	6	2.557	1.746	3.096	0.826	67.857	67.84

Table 4.3 Placement of two DG units with real and reactive power capability

Method	Bus no.	DG power			Optimal p.f.	Losses (kW)	Loss Reduction (%)
		MW	MVAR	MVA			
IA	6	1.800	1.115	3.177	0.850	44.84	78.77
	30	0.900	0.557				
MINLP	**13**	**0.819**	**0.434**	**2.477**	**0.883**	**29.31**	**86.10**
	30	**1.550**	**1.240**		**0.800**		
PSO	12	0.818	0.566	3.774	0.822	39.10	81.49
	29	1.699	1.191		0.819		

Table 4.4 Placement of three DG units with real and reactive power capability

Method	Bus no.	DG power			Optimal p.f.	Losses (kW)	Loss Reduction (%)
		MW	MVAR	MVA			
IA	06	0.900	0.557	2.859	0.85	23.05	89.09
	14	0.630	0.390				
	30	0.900	0.557				
MINLP	**13**	**0.766**	**0.411**	**3.481**	**0.87**	**12.74**	**93.96**
	24	**1.044**	**0.552**		**0.88**		
	30	**1.146**	**0.859**		**0.80**		
PSO	13	0.764	0.535	3.395	0.82	15.0	92.89
	24	1.068	0.613		0.87		
	30	1.016	0.691		0.83		

units, minimum losses with lowest DG size is obtained with the proposed method in comparison to the other methods. The proposed locations are found to be optimal as verified by exhaustive search for 2 and 3 DG scheme. Moreover, in the case of 3 DG units, proposed method gives minimum losses with slightly higher DG size than IA method.

Table 4.2-4.4 presents the simulation results of placement of single and multiple DG units with real and reactive power capability. In Table 4.2, MINLP based proposed formulation shows its improved performance in reaching most optimum solution. In the case of 2 DG units (Table 4.3), it can be observed that the proposed method reaches to the optimal locations and sizes, thereby giving maximum loss reduction with least total DG power. In the case of 3 DG units

(Table 4.4), optimal locations are identical for MINLP and PSO. However, proposed method gives maximum loss reduction with DG size slightly higher than PSO.

Since Exhaustive Load Flow (ELF) explores entire search space, it gives more accurate results. Although, ELF is straightforward and simple, it is very time consuming. In IA method, multiple DG units are placed sequentially, i.e. next optimal location is obtained in the presence of previously placed DG units. Even though, IA method is quite fast, the separate evaluation of multiple DG units may lead to sub-optimal locations [6]. As observed in Table 4.3 and Table 4.4, IA method leads to sub-optimal locations for multiple DG units. For example, to place 2 and 3 DG units, optimal locations given by IA method are bus numbers {6, 30} and {6, 14, 30}, respectively. However, the actual optimal locations, to place 2 and 3 DG units, are bus numbers {13, 30} and {13, 24, 30}, respectively. Similar trends are observed in the results given in Table 4.1for multiple DG units with real power capabilities.

It is evident from the results that the MINLP based proposed algorithm shows better performance as compared to other methods. The superior performance of the MINLP formulation is attributed to the simultaneous placement of multiple DG units. In addition, selective list of candidate buses by SPM model decrease the computational time and improves the search ability while maintaining the balance between explorative and exploitative search. This is the reason that DG locations obtained by proposed method are identical to ELF.

In IA method, power factor is fixed based on load profile. Whereas, in proposed formulation, optimal power factor for each DG is obtained by optimizing real and reactive power simultaneously. DG real and reactive powers are considered as two design variables and updated iteratively by calculating the step vector d^k. As shown in Figure 4.2 and 4.3, optimal reactive power generation by each DG at optimal location results in the improved voltage profile. In 33-bus system, bus number 31 requires maximum reactive power. The proposed formulation met this demand optimally by placing DG of higher size with optimal power factor. As a result, the proposed formulation achieves minimum losses with improved voltage profile. It can be observed that the proposed method gives most flat voltage profiles. The effect of DG units on the voltage profile for all the methods with unity as well as non-unity power factor is shown in Table 4.5.

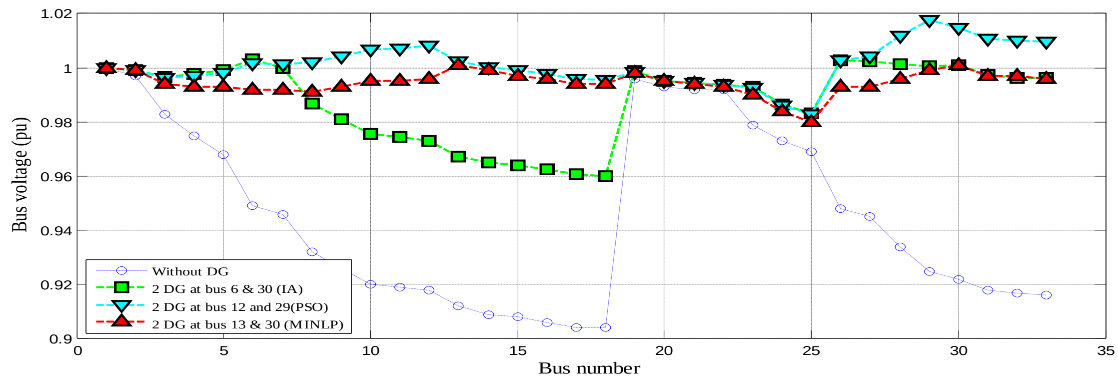

Figure 4.2 Voltage profile of IEEE 33-bus system with 2 DG units

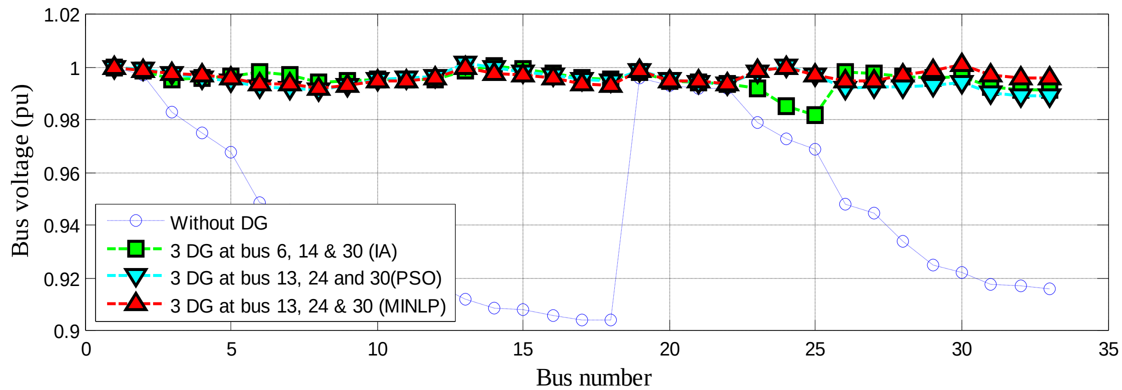

Figure 4.3 Voltage profile of IEEE 33-bus system with 3 DG units

Table 4.5 Critical voltages on 33 bus system with DG

Case	Method	Minimum Voltage pu (Bus no)		Maximum voltage pu (Bus no)	
		UPF	NUPF	UPF	NUPF
Without DG		0.904(18)		1.0(1)	
1 DG	IA	0.9425(18)	0.9575(18)	1.0000(1)	1.0007(6)
	MINLP	**0.9424(18)**	**0.9584(18)**	**1.0000(1)**	**1.0010(6)**
	PSO	0.9424(18)	0.9598(18)	1.0000(1)	1.0029(6)
2 DG	IA	0.9539(33)	0.9600(18)	1.0000(1)	1.0031(6)
	MINLP	**0.9685(33)**	**0.9804(25)**	**1.0000(1)**	**1.0010(13,30)**
	PSO	0.9650(18)	0.9828(25)	1.0000(1)	1.0178(29)
3 DG	IA	0.9690(18)	0.9821(25)	1.0000(1)	1.0006(14)
	MINLP	**0.9687(18,33)**	**0.9924(8)**	**1.0000(1)**	**1.0010(30)**
	PSO	0.9684(33)	0.9892(33)	1.0000(1)	1.0020(13)

Table 4.6 Placement of DG units with real power capability

No. of DGs	Method	Bus no.	DG power (MW)	Loss Reduction (%)
1 DG	**IA**	61	1.90	62.91
	MINLP	**61**	**1.87**	**62.94**
	PSO	61	1.81	64.09
2 DG	**IA**	61	1.70	67.94
		17	0.51	
	MINLP	**61**	**1.78**	**68.07**
		17	**0.53**	
	PSO	61	1.81	69.39
		17	0.51	
3 DG	**IA**	61	1.70	68.82
		17	0.51	
		11	0.34	
	MINLP	**61**	**1.72**	**69.07**
		17	**0.38**	
		11	**0.53**	
	PSO	61	1.81	70.08
		17	0.51	
		50	0.72	

4.4.2 IEEE 69-bus System

The total real and reactive power demands in IEEE 69-bus system are 3.8 MW and 2.69 MVAr respectively (Appendix A). System line loss without DG is 225.27 kW. The simulation results of placement of single and multiple DG units with real power are presented in Table 4.6. The proposed technique gives improved performance than IA method. However, loss reduction is maximum with PSO technique.

Table 4.7-4.9 presents the simulation results for placement of single and multiple DG units with real and reactive power capability for IEEE 69-bus system. To place a single DG unit, all the methods lead to the location (see Table 4.7). The proposed model gives a maximum loss reduction for placement of two and three DG units (see Table 4.8 and 4.9). In the IEEE 69-bus system, load demands at bus number 11 and 61 are high. In the case of 3 DG units (Table 4.9), the proposed method, due to its capability of variable power factors, provides adequate real and reactive at those buses. The optimum power factor at the buses 11 and 61 are 0.813 and 0.814 respectively.

Table 4.7 Placement of single DG unit with real and reactive power capability

No of DGs	Method	Bus no.	DG power		Total DG Power	Optimal power factor	Loss reduction (%)
			MW	MVAr	MVA		
1 DG	IA	61	1.839	1.284	2.243	0.82	89.68
	MINLP	**61**	**1.828**	**1.300**	**2.244**	**0.815**	**89.65**
	PSO	61	1.818	1.250	2.207	0.824	89.68

Table 4.8 Placement of two DG units with real and reactive power capability

No of DGs	Method	Bus no.	DG power		Total DG Power	Optimal power factor	Loss reduction (%)
			MW	MVAr	MVA		
2 DG	IA	17	0.540	0.377	2.854	0.82	96.69
		61	1.799	1.2563			
	MINLP	**17**	**0.522**	**0.359**	**2.765**	**0.824**	**96.80**
		61	**1.735**	**1.238**		**0.814**	
	PSO	17	0.524	0.371	2.749	0.816	96.69
		61	1.743	1.184		0.827	

Table 4.9 Placement of three DG units with real and reactive power capability

No of DGs	Method	Bus no.	DG power		Total DG Power	Optimal power factor	Loss Reduction (%)
			MW	MVAr	MVA		
3 DG	IA	61	0.900	0.557	3.524	0.82	97.74
		17	0.630	0.390			
		50	0.900	0.557			
	MINLP	**11**	**0.494**	**0.354**	**3.123**	**0.813**	**98.10**
		17	**0.379**	**0.257**		**0.828**	
		61	**1.674**	**1.195**		**0.814**	
	PSO	18	0.5078	0.344	3.545	0.828	97.74
		50	0.6996	0.474		0.828	
		61	1.7351	1.158		0.832	

From Table 4.8 and 4.9, it can be noted that the proposed MINLP based method gives superior performance for placement of multiple DG with real and reactive power capability as compared to the other two methods. The maximum and minimum voltages for different methods are shown in Table 4.10. It is observed that the system voltage improves in addition to loss reduction. The voltage profile is more flat with PSO and proposed method as observed from Table 4.10.

Table 4.10 Critical voltages on 69-bus system with DG

Case	Method	Minimum Voltage pu (Bus no)		Maximum voltage pu (Bus no)	
		UPF	NUPF	UPF	NUPF
Without DG Unit		0.9092(65)		1.0(1)	
1 DG	IA	0.9692(27)	0.9732(27)	1.0000(1)	1.0000(1)
	MINLP	**0.9682(27)**	**0.9724(27)**	**1.0000(1)**	**1.0000(1)**
	PSO	0.9681(27)	0.9724(27)	1.0000(1)	1.0000(1)
2 DG	IA	0.9765(65)	0.9944(50)	1.0000(1)	1.0024(61)
	MINLP	**0.9789(65)**	**0.9943(69)**	**1.0000(1)**	**1.0000(1)**
	PSO	0.9806(65)	0.9943(50)	1.0000(1)	1.0020(61)
3 DG	IA	0.9785(65)	0.9939(69)	1.0000(1)	1.0000(1)
	MINLP	**0.9790(65)**	**0.9943(50)**	**1.0000(1)**	**1.0000(1)**
	PSO	0.9806(65)	0.9940(69)	1.0000(1)	1.0000(1)

4.5 Summary

In this chapter, a MINLP based approach for optimal placement of single and multiple DG units to minimize the losses in the distribution networks are presented. To reduce the search space and computational time, two-step scheme is proposed. Firstly, in Siting Planning Models (SPM), prospective candidate buses are shortlisted based on Combined Loss Sensitivity (CLS). This short list is then passed to Capacity Planning Model (CPM). In CPM, the optimal locations and DG sizes are computed using MINLP based formulation. In this formulation, Sequential Quadratic Programming (SQP) and Branch and Bound (BAB) algorithms are integrated to handle discrete and continuous variables for solving the proposed formulation. This approach gives improved computational performance and strong convergence property. Due to reduced search space, by means of SPM model, solution converges in very less time. The proposed methodology is implemented on IEEE 33-bus and IEEE 69-bus test systems. A comparative analysis is done among the three popular classes of optimization methods for DG placement. Comparative study in terms of DG size, distribution loss, and computational efforts is carried out with ELF, IA, and PSO techniques. It is observed that the proposed algorithm based on MINLP gives improved performance due to its property of simultaneous placement of multiple DG units. In addition, due to flexibility in power factor, the algorithm gives further improved results in the case of DG units capable of delivering real and reactive power. Proposed formulation is generalized and can be implemented for any type and any number of DG unit.

CHAPTER 5

HYBRID APPROACH BASED ON IHS AND OPF FOR LOSS MINIMIZATION

5.1 Introduction

In the previous chapter, MINLP based formulation is proposed and solved in two stages, viz., Sitting Planning Model (SPM) and Capacity Planning Model (CPM). In this chapter, a hybrid optimization algorithm based on Improved Harmony Search (IHS) and Optimal Power Flow is developed for loss reduction in DG planning.

Harmony search (HS) is recently developed meta-heuristic optimization algorithm by Zong Wee Geem [111]. It has been applied to a wide variety of optimization problems[112] due to its few controlling parameters [119]. It is derivative free random search optimization technique, which does not require the initial setting of decision variables [6, 7, 111]. The classical HS algorithm may get trapped in local minima, may converge prematurely or may take a large number of iterations due to the static tuning parameters. To improve the performance of the HS algorithm, tuning parameters are made dynamic and are implemented in Improved Harmony Search (IHS). It is observed that IHS improves the algorithm performance in terms of exploration and exploitation. Further improvement in the solution algorithm can be achieved by exploiting the merits of both heuristic and classical techniques explained in previous chapters. As a result, a hybrid algorithm integrating IHS and classical method is developed and implemented on standard test system. Hybrid approach exhibits the improved performance in terms of number of iterations and optimal solution, over the HS and IHS algorithms.

5.2 Hybrid Approach with IHS and OPF

The desired objective function to be minimized is as given in (5.1) while meeting the constraints referred in the Chapter 4 (4.3-4.13).

$$F = 0.5 * \sum_{i=1}^{NB}\sum_{j=1}^{NB} G_{ij}[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad where\ i, j \in \{1, 2....NB\} \tag{5.1}$$

DG location vectors are generated in HM database. An OPF is performed on each selected vector. Therefore, IHS generates the locations and optimal capacity is obtained by OPF. Steps of the proposed algorithm are as follows:

I. All harmony search parameters e.g. harmony vector (*HM*), number of solution vectors (*HMS*), number of design variables (*N*), harmony memory consideration rate (*HMCR*), maximum number of improvisations (NI_{max}), *PAR* and *bw* are defined. Minimum and maximum values for *PAR* are taken as 0.4 and 0.9 respectively. In addition, the minimum and maximum values for *bw* are 0.001 and 1 respectively. The harmony vectors in HM is given as,

$$HM = \begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & {}^{2}_{N-1} & x_N^2 \\ \vdots & \vdots & \vdots & & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & & x_{N-1}^{HMS} & x_N^{HMS} \end{pmatrix} \tag{5.2}$$

II. HMS harmony vectors for discrete variables are generated randomly as,

$$x_i^j = round(x_i^{lower} + rand()(x_i^{upper} - x_i^{lower})) \text{ where } i = 1...N, \;\; j = 1...HMS \tag{5.3}$$

where *N* is the number of design variables.

III. Calculate the fitness function of the each *HM* as explained in the Section 3.5.

IV. Generate new improved vector by *HMCR*, *PAR* and *bw* as given in the Figure 5.1. Calculate the fitness function of the new improved vector using OPF formulation explained in the Section 4.2 and 4.3.

V. If the solution is better than the worst harmony vector in *HMS*, replace the worst harmony vector in HM with the improved one.

VI. If the stopping criterion is satisfied, then select the best solution vector. Otherwise, go to Step IV.

The flow chart of the proposed hybrid algorithm is shown in Figure 5.1.

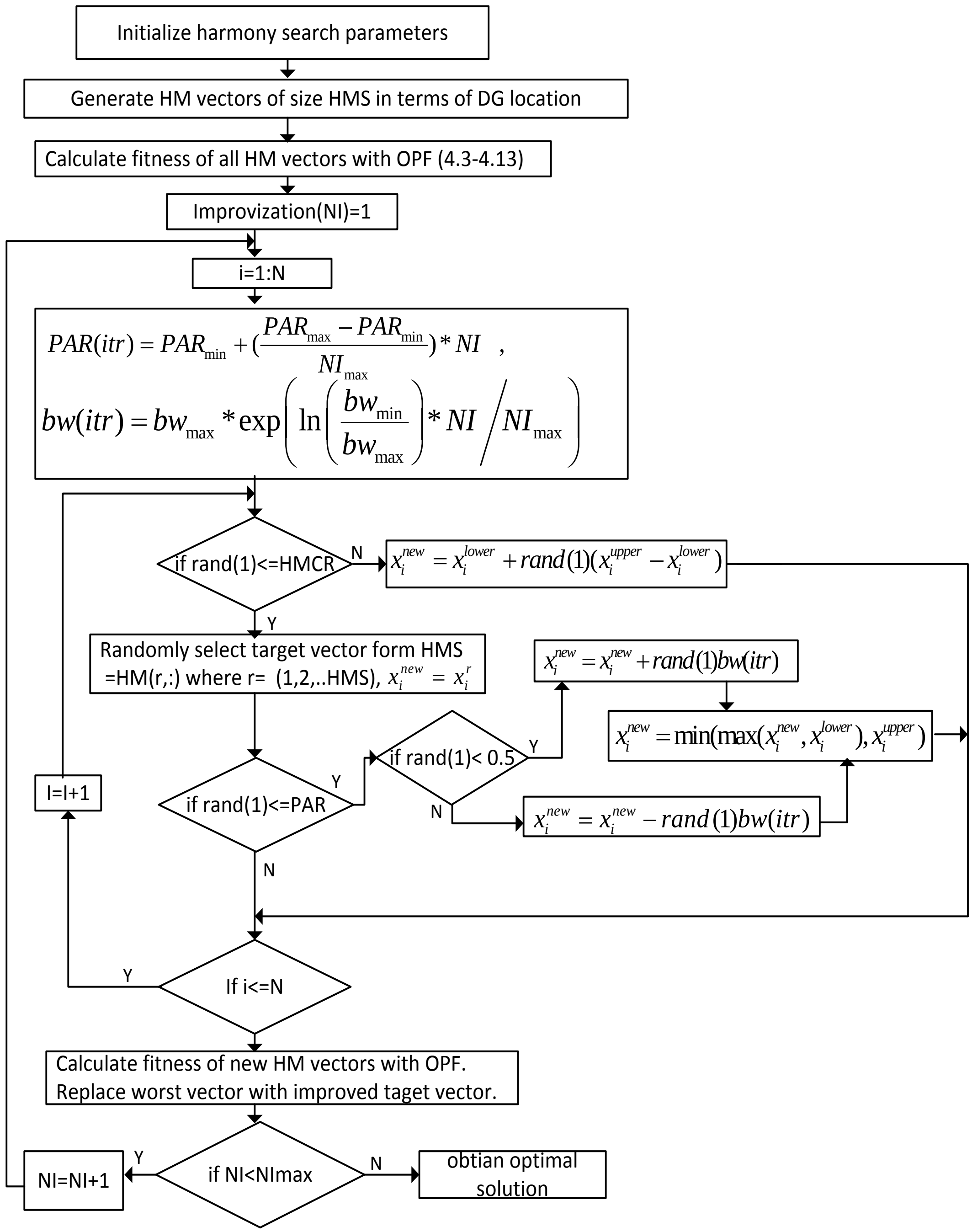

Figure 5.1 Flow chart for IHS and OPF based optimization algorithm

5.3 Results and Discussion

The proposed formulation is tested on the IEEE 33-Bus system with total load of 3.7 MW and 2.3 MVAr. Real power loss without DG injection is 211 kW. It is assumed that the maximum DG capacity could be equal to the total peak load demand [18]. The lower and upper limits of bus voltages used in the simulations are 0.90 pu and 1.05 pu respectively.

The power factor of the DG unit is constrained to vary between 0.8 and 1.0. The proposed hybrid algorithm is coded in AMPL (A Mathematical Programming Language) environment on a personal computer with 2.93 GHz, Intel core™ 2 duo CPU with 4 GB RAM. The simulated results are compared with IA [18], PSO [29] and IHS method. The proposed hybrid approach can be used for placement of any number of DG units. However, in this study, It is used for placement of maximum three DG units. The discrete variables for locations are considered. DG location vectors are generated in HM database. An OPF is performed on each selected vector. Therefore, IHS generates the locations and optimal capacity is obtained by OPF.

5.3.1 Comparison of convergence rate

To show the effectiveness, the convergence rate of proposed algorithm is compared with simple IHS technique. As evident from Figure 5.2 and Figure 5.3 that proposed method gives improved performance. For 2 DG placement, IHS technique converges in 330 iterations, whereas hybrid method converges in 25 iterations with better optimal solution. For 3 DG placement, IHS technique converges in 460 iterations, whereas hybrid method converges in 70 iterations.

5.3.2 Comparison of loss reduction and DG sizes

a) ***Placement of DG units with real power*:** The results of optimal placement of 1, 2 and 3 DG units with unity power factor are presented in Table 5.1. All the techniques converge to the same optimal solution for 1 DG placement. A major benefit in terms of optimal solutions and computational time is accrued with multiple DGs capable of real and both real and reactive power injection.

For placement of 2 and 3 DG units, minimum losses are obtained with the proposed method followed by IA and PSO technique. The simultaneous placement of DG units by the proposed hybrid method leads to the improved solution with lower losses and smaller size of DG units. However, in the case of 3 DG placement, DG size obtained by the proposed formulation is slightly higher than the PSO technique.

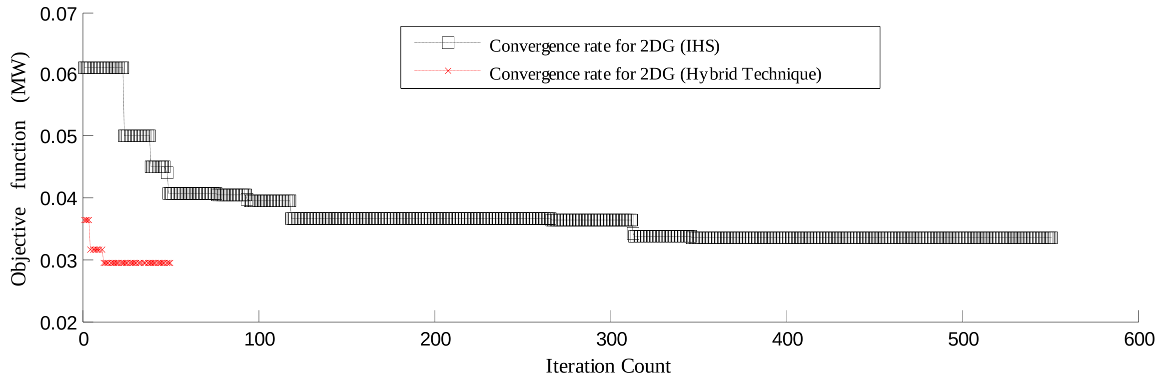

Figure 5.2 Convergence rate of 2 DG placement by hybrid and IHS method

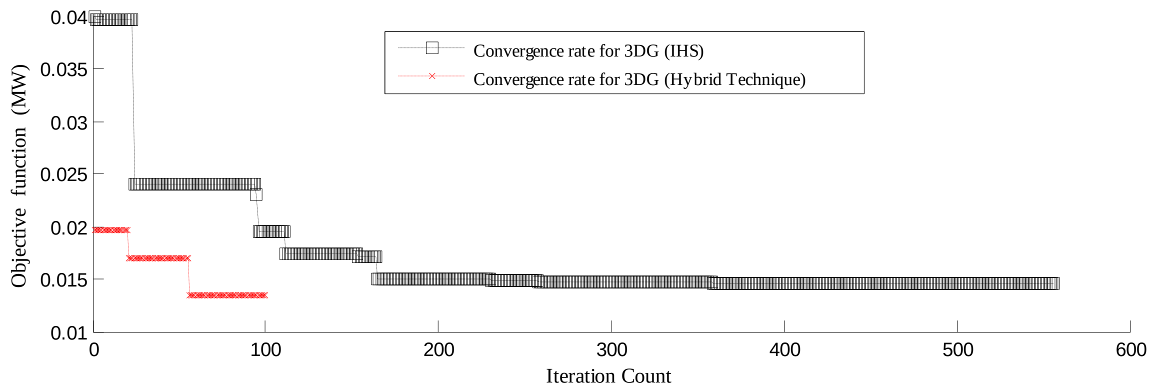

Figure 5.3 Convergence rate of 3 DG placement by hybrid and IHS method

b) ***Placement of DG units with both real and reactive power*:** Hybrid technique optimizes real and reactive generation separately, thereby obtaining the optimal power factor apart from location and size. Results of optimal placement of 1, 2 and 3 DG units for real and reactive injection are presented in Table 5.2, 5.3 and 5.4 respectively. Optimal location for one DG placement is same for all the techniques.

In the case of 2 DG units, the proposed method gives a significant reduction in losses with smallest DG capacity (see the Table 5.3). In the case of a placement of 3 DG units, hybrid technique gives minimum losses (see the Table 5.4).

Table 5.1 Placement of DG units with real power capability

No. of DGs	Method	Bus no.	DG Power (MW)	Losses (kW)	(%) Loss reduction
1 DG	IA	6	2.60	111.10	47.39
	PSO	6	2.59	111.10	47.39
	IHS	6	2.59	111.0	47.39
	HYBRID	**6**	**2.59**	**111.10**	**47.39**
2 DG	IA	6	1.80	91.63	56.61
		14	0.72		
	PSO	12	1.00	87.50	58.52
		30	1.02		
	IHS	13	0.85	87.16	58.69
		30	1.15		
	HYBRID	**13**	**0.85**	**87.16**	**58.69**
		30	**1.15**		
3 DG	IA	6	0.90	81.05	61.62
		12	0.90		
		31	0.72		
	PSO	13	0.88	73.20	65.34
		24	1.09		
		30	1.01		
	IHS	13	0.804	72.80	65.50
		24	1.108		
		30	1.058		
	HYBRID	**13**	**0.80**	**72.79**	**65.50**
		24	**1.09**		
		30	**1.05**		

5.3.3 Comparison of bus voltage profiles

Comparisons of the voltage profiles of various methods, with 2 and 3 DG units are shown in Figure 5.4 and 5.5 respectively. Without DG, the lowest voltage recorded is 0.904 pu at bus number 18.

In the case of 2 DG units, the proposed method gives improved voltage profile as compared to the IA and PSO techniques (see the Figure 5.4). The voltage at bus number 18 is raised to 0.988 pu. Bus voltages are further improved with three DGs (see the Figure5.5). The proposed method gives a flat voltage profile as compared to IA and PSO techniques.

Table 5.2 Placement of single DG unit with real and reactive power injection

Method	Bus No.	DG power		PLoss (kW)	PLoss red (%)
		MW	MVAR		
IA	6	2.637	1.634	68.2	67.67
PSO	6	2.557	1.746	67.857	67.84
IHS	6	2.60	1.612	68.18	67.68
HYBRID	**6**	**2.554**	**1.761**	**67.854**	**67.84**

Table 5.3 Placement of 2 DG units with real and reactive power injection

Method	Bus No.	DG Size		PLoss (kW)	PLoss red (%)
		MW	MVAR		
IA	6	1.800	1.115	44.84	78.77
	30	0.900	0.557		
PSO	12	0.818	0.5665	39.10	81.49
	29	1.699	1.1909		
IHS	11	0.946	0.586	31.50	85.07
	30	1.228	0.761		
Hybrid	**12**	**0.91**	**0.490**	**29.48**	**86.04**
	30	**1.20**	**0.90**		

Table 5.4 Placement of 3 DG units with real and reactive power injection

Method	Bus no.	DG Size		PLoss (kW)	PLoss red (%)
		MW	MVAR		
IA	06	0.900	0.557	23.05	89.09
	14	0.629	0.390		
	30	0.900	0.557		
PSO	13	0.764	0.535	15.0	92.9
	24	1.068	0.613		
	30	1.016	0.691		
IHS	13	0.787	0.425	14.60	91.4
	24	0.954	0.715		
	30	1.229	0.595		
Hybrid	**13**	**0.78**	**0.42**	**13.47**	**93.62**
	25	**0.83**	**0.43**		
	30	**1.150**	**0.86**		

5.4 Summary

In this chapter, IHS and OPF based hybrid optimization techniques is presented for optimal placement of DG units to minimize the losses. The proposed formulation gives improved computational performance and strong convergence property. The proposed algorithm can be

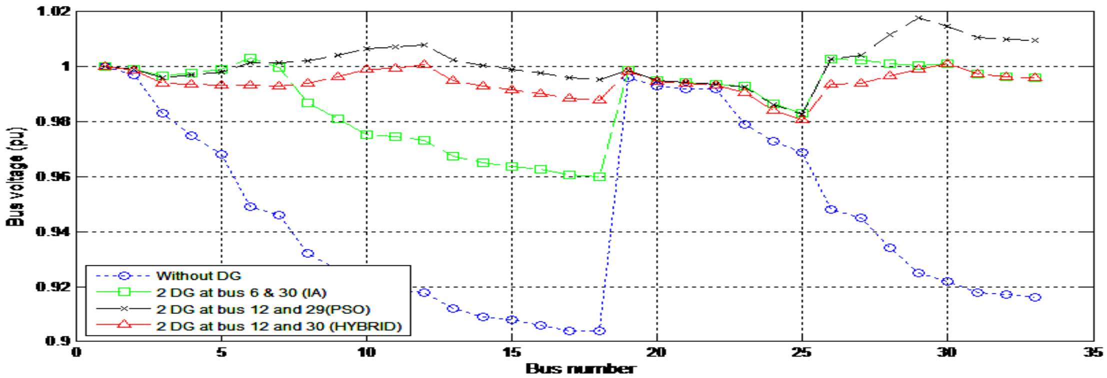

Figure 5.4 Comparison of the voltage profiles for placement of 2 DG units

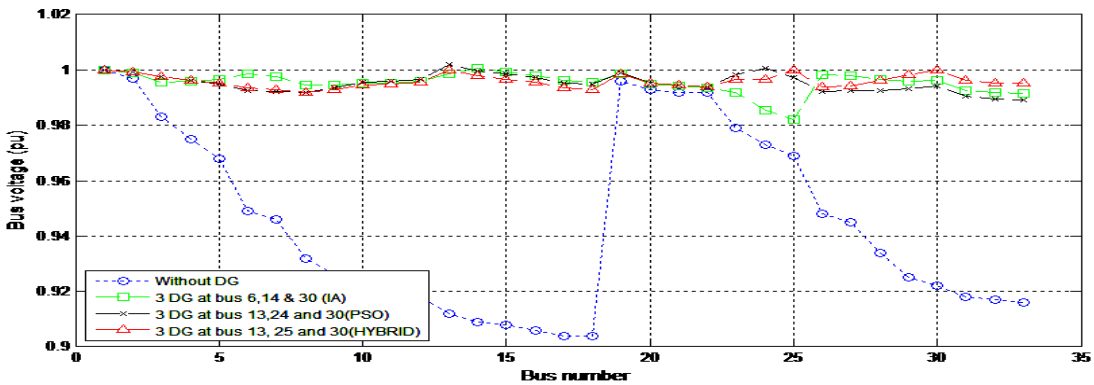

Figure 5.5 Comparison of the voltage profiles for placement of 3 DG units

implemented for small, medium, and large-scale problems. Proposed formulation with few controlling parameters and embedded OPF leads to faster convergence and improved solution in comparison to conventional heuristic techniques.

Comparative analysis of the proposed hybrid method with IA and other popular heuristic technique is carried out in terms of loss reduction, DG size, and voltage profile improvement. The proposed method gives improved performance in terms of lower losses with smaller DG sizes and better voltage profile.

CHAPTER 6

INTEGRATED IHS AND TLBO FORMULATION FOR ANNUAL COST MINIMIZATION

6.1 Introduction

Traditional distribution system planning is aimed at the least cost scenario for fulfilling the load demand. However, environmental factors and regulatory considerations have gained equal importance against stakeholder's interest. In recent years, exponential load growth, sustainable development, power system deregulation, and environmental concern have paved ways for the renewable generations. Therefore, DG planning, with incentive for clean energy and penalty for greenhouse gas (GHG) emissions, needs to be explored for sustainable development. In this regard, National Action Plan on Climatic Change in India has set an ambitious Renewable Purchase Obligation (RPO) target of 15% by 2020 [8-9]. Since renewable DGs in their present form, cannot compete with the conventional generators, most of the states have reduced their RPO targets.

The present work is motivated towards the planning of renewable DG units. The proposed model, with Emission Offset Incentive (EOI) and Generation Based Incentive (GBI) along with penalty for high carbon energy, is an effort to encourage the power operators for renewable power generation to meet RPO targets. To solve the proposed formulation, a hybrid approach implementing Improved Harmony Search (IHS) algorithm interlaced with the Teaching-Learning based Optimization (TLBO) is presented. The algorithm is implemented to achieve optimal size, type, and location of DG units for minimizing the annualized cost comprising grid energy, DG injection, incentive, and penalty cost.

6.2 Problem Formulation

The basic aim of the proposed optimization problem is sustainable economic planning with renewable DGs to minimize the annualized cost. DG technology, location and size are taken as decision variables. The objective is formulated as minimization of the annualized cost comprised of DG's capital, operation, maintenance, grid energy, loss, emission, incentive, and penalty cost is expressed as,

$$Min\, C_{tc} = C_{cpt}^{DG} + C_{op}^{DG} + C_{o\&m}^{DG} + C_{en}^{SS} + C_{Loss} + C_{emi} - C_{inc\_emi}^{DG} + C_{pen} \tag{6.1}$$

where,

$C_{cpt}^{DG}, C_{op}^{DG}, C_{o\&m}^{DG}, C_{inc\_emi}^{DG}$ = Annual capital, operational, maintenance and emission-offset incentive costs of DG,

$C_{tc}, C_{en}^{SS}, C_{Loss}, C_{emi}$, C_{pen} = Total, substation energy, loss, emission and penalty costs,

- ***Annual capital cost*****:** The annualized capital cost of selected DGs is evaluated in terms of its net present value and is represented as,

$$C_{cpt}^{DG} = PWF \sum_{n=1}^{NB} (c_{cpt}^{bmg} S_n^{bmg} + c_{cpt}^{wg} S_n^{wg} + c_{cpt}^{spv} S_n^{spv}) \tag{6.2}$$

where,

$$PWF = 1 / \left[\frac{(1+r)^t - 1}{r(1+r)^t} \right] \text{ is the Present Worth Factor} \tag{6.3}$$

where,

$c_{cpt}^{bmg}, c_{cpt}^{wg}, c_{cpt}^{spv}$ = Capital cost factor($/MVA) for biomass, wind and SPV DG,

$S_n^{bmg}, S_n^{wg}, S_n^{spv}$ = Installed capacity of biomass, wind, and SPV DG at n^{th} DG bus,

r, t = Rate of interest, lifetime of considered DG,

- ***Operational cost*****:** The operating cost of DG is calculated by considering fuel cost factor. The operational (fuel) costs of wind and solar PV DG units are considered as zero. Thus, the operating cost of biomass generator is expressed as,

$$C_{op}^{DG} = \sum_{n=1}^{NB} c_{fl}^{bmg} E_n^{bmg} \tag{6.4}$$

where

c_{fl}^{bmg} = Fuel cost factor($/MWh) of biomass DG,

E_n^{bmg} = Annual energy produced by biomass DG,

- ***Annual maintenance cost*:** It is calculated based on energy generated and associated cost factors. The annual maintenance cost is given as,

$$C_{o\&m}^{DG} = \sum_{n=1}^{NB} (c_{o\&m}^{bmg} E_n^{bmg} + c_{o\&m}^{wg} E_n^{wg} + c_{o\&m}^{spv} E_n^{spv}) \tag{6.5}$$

where,

$c_{o\&m}^{bmg}, c_{o\&m}^{wg}, c_{o\&m}^{spv}$ = Maintenance cost factor (\$/MWh) for biomass, wind and SPV DG

$E_n^{bmg}, E_n^{wg}, E_n^{spv}$ = Annual energy produced by biomass, wind, and SPV DG

- ***Grid energy and loss cost***: The cost of energy supplied by grid is calculated depending on total power demand and DG power. The total cost of grid energy, including energy losses is given as,

$$C_{en}^{SS} + C_{Loss} = c_{en}^{ss} H \left(\sum_{n=1}^{NB} (P_{LD} LF - (P_n^{bmg} Cf^{\,bmg} + P_n^{wg} Cf^{\,wg} + P_n^{spv} Cf^{\,spv})) + \sum_{l \in NBr} I_l^2 R_l LLF \right) \tag{6.6}$$

where,

LF, LLF, P_{LD}, H = load factor, loss load factor, peak load, annual time of operation in hours,

I_l, R_l = peak line current and line resistance of feeder section l,

$P_n^{bmg}, P_n^{wg}, P_n^{spv}$ = power out of biomass, wind, and SPV DG,

$Cf^{\,bmg}, Cf^{\,wg}, Cf^{\,spv}$ = Capacity factor of biomass, wind and SPV DG

- ***GHG emissions penalty***: The penalty for GHG emissions is imposed on part of grid energy generated from fossil fuels and biomass DG. The emission cost is represented as,

$$C_{emi} = c_{co2}^{emi} \left(\sum_{n=1}^{NB} c_{ef}^{bmg} E_n^{bmg} + \beta c_{ef}^{ss} E_{ss} \right) \tag{6.7}$$

where,

c_{co2}^{emi} = Cost factor (\$/ton) for carbon emission,

$c_{ef}^{ss}, c_{ef}^{bmg}$ = Emission factor (ton/MWh) for grid and biomass energy,

E_{ss} = Grid energy,

β = fraction of grid energy responsible for GHG emissions,

- ***GHG emission offset incentive***: The DG incentive for equivalent emission offset for major pollutant is described as,

$$C_{inc\_emi}^{DG} = \sum_{n=1}^{NB}\sum_{i=1}^{p} c_i^{em} e_i (E_n^{Bmg} + E_n^{wg} + E_n^{spv}) \quad i \in \{CO_2, SO_x, NO_x \text{ pollutant}\} \tag{6.8}$$

where

c_i^{emi} = Cost factor ($/ton) for offsetting i^{th} emission pollutant,

e_i = Emission factor of i^{th} pollutant,

- ***Penalty for constraint violations***: A penalty is imposed for violating voltage and thermal limits. The penalty cost for violations of constraints of the network is,

$$C_{pen} = CV_{pen} + CS_{pen} \tag{6.9}$$

$$CV_{pen} = \sum_{i=1}^{NB} VP_i$$

$$CS_{pen} = \sum_{ij=1}^{NBr} SP_{ij}$$

where CV_{pen}, CS_{pen} is penalty cost for voltage and thermal limits violation. VP_i is the penalty for voltage violation at i^{th} bus and SP_{ij} is the penalty for violating of thermal limit of ij^{th} line feeder. VP_i and SP_{ij} are represented as,

$$VP_i = \begin{cases} cv_{pen}(V_{\max} - V_i)^2 & if\ V_i > V_{\max} \\ cv_{pen}(V_i - V_{\min})^2 & if\ V_i < V_{\min} \\ 0 & otherwise \end{cases} \tag{6.10}$$

$$SP_{ij} = \begin{cases} cs_{pen}(S_{ij(\max)} - S_{ij})^2 & if\ S_{ij} > S_{ij(\max)} \\ 0 & otherwise \end{cases} \tag{6.11}$$

Where, cv_{pen} and cs_{pen} are voltage penalty factor (in $/volt) and line loading penalty factor (in $/MVA), respectively.

- ***Other network constraints:***

I. *Power balance*: The real and reactive power balance must be maintained at each bus.

$$\left.\begin{aligned}
&P_G^i - P_D^i - \sum_{j=1}^{NB}(V_iV_j(G_{ij}\cos(\delta_i-\delta_j)+B_{ij}\sin(\delta_i-\delta_j)) = 0\\
&Q_G^i - Q_D^i - \sum_{j=1}^{N}(V_iV_j(G_{ij}\sin(\delta_i-\delta_j)-B_{ij}\cos(\delta_i-\delta_j)) = 0\\
&\text{where } i, j \in \{1,2...NB\} \text{ and } ij \in \{1,2...NBr\}
\end{aligned}\right\} \tag{6.12}$$

II. *Penetration limit for DG units*: The injected power of DG units must be less than the maximum defined penetration limit.

$$\sum_{n=1}^{NB}(S_n^{bmg}+S_n^{wg}+S_n^{spv}) \le \chi S_{LD} \qquad \text{where } \chi \text{ is ratio of DG penetration and peak load } S_{LD} \tag{6.13}$$

III. *Maximum number of DG units*: The total number of DG units should not exceed the maximum permissible number of DG units to be installed.

$$0 \le NDG \le N_{DG}^{\max} \qquad NDG \in \{\text{No. of DG units placed on candidate buses}\} \tag{6.14}$$

6.3 Hybrid Approach Integrating IHS and TLBO

Improved Harmony Search (IHS) and Teaching Learning Based Optimization (TLBO) methods are already discussed in the Chapter 3. In this chapter, IHS is improvised by integrating with TLBO. This hybrid method exhibits a strong search mechanism by improving exploration and exploitation [120]. This Improved Harmony Search with Teaching-Learning (HSTL) algorithm is used for solving above formulation. The optimization problem is modeled as,

$$\left.\begin{aligned}
&Min.\ \ f(x)\\
&s.t.\quad h_p(x)=0 \qquad\qquad p\in\{1,2,3...p\}\\
&s.t.\quad g_{\min}\le g_q(x)\le g_{\max} \quad q\in\{1,2,3...q\}\\
&s.t.\quad x_i \in [x_i^{Lower}, x_i^{Upper}]\\
&x\in\{x_1,x_2...x_{N-1},x_N\}
\end{aligned}\right\} \tag{6.15}$$

where, $f(x)$ is the objective function to be minimized. x is the set of decision variables. N is the number of decision variables. x_i^{Lower}, x_i^{Upper} are the lower and the upper limit of i^{th} decision variable. g_q and h_p are the equality and the inequality constraints. The steps for executing HSTL algorithm are as follows.

I. ***Initialization of parameters and generation of Harmony Memory***: The harmony memory size (HMS) vectors of continuous and discrete variables are generated randomly from a uniform distribution in the search space as,

$$x_i^j = x_i^{lower} + rand()(x_i^{upper} - x_i^{lower}) \quad i = 1, 2, \ldots N \quad j = 1, 2, \ldots HMS \tag{6.16}$$

$$x_i^j = Round(x_i^{lower} + rand()(x_i^{upper} - x_i^{lower})) \quad i = 1, 2, \ldots N \quad j = 1, 2, \ldots HMS \tag{6.17}$$

Where *rand*() is a function to generate random number between 0 and 1. The harmony vectors in the HM database are,

$$HM = \begin{pmatrix} x_1^1 & x_2^1 & \ldots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \ldots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & & \vdots & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & & x_{N-1}^{HMS} & x_N^{HMS} \end{pmatrix} \tag{6.18}$$

II. ***Improvisation of harmony vector***: The new harmony vector to be improved is selected randomly from the HM database as shown.

$$x^{new} = x^j, where\ j \in \{1, 2, 3 \ldots HMS\} \tag{6.19}$$

The selected harmony vector is improvised with the harmony memory consideration rate (*HMCR*), teaching-learning probability (*TLP*), parity adjustment rate (*PAR*) or mutation option [120].

- *Improvisation with HMCR*: *HMCR* is dynamically updated between upper and lower limits as,

$$HMCR = HMCR_{\min} + (HMCR_{\max} - HMCR_{\min})\left(\frac{NI}{NI_{\max}}\right)^2 \tag{6.20}$$

where NI and NI_{max} represent the current and maximum number of iterations respectively.

The i^{th} design variable of the selected target vector is swapped with the variable from HM database with probability of *HMCR* as,

$$x_i^{new} = x_i^j, \quad \text{where } j \in \{1, 2, 3, \ldots HMS\} \text{ and } i = \{1, 2, \ldots N\} \tag{6.21}$$

- *Teaching-Learning based improvisation*: If the i^{th} design variable is not improved by *HMCR*, then it is improved either by teaching or by learning with equal probability of *TLP*. It is given as,

$$TLP = TLP_{\min} + (TLP_{\max} - TLP_{\min})\left(\frac{NI}{NI_{\max}}\right)^{k} \qquad \text{where } k \in \{5\} \tag{6.22}$$

The i^{th} design variable of target vector is improvised by the best HM (teacher) given as,

$$\left.\begin{aligned} x_i^{new} &= x_i^{new} + rand()\left(x_i^{best} - 0.5TF(x_i^{worst} + x_i^{new})\right) \\ TF &= round(1 + rand()) \end{aligned}\right] \tag{6.23}$$

where, TF, x_i^{best} and x_i^{worst} are teaching factor, best and worst harmony in HM.

Similarly, the target vector is improved by comparison with other two learners r_1, r_2 randomly selected from the HM database as,

$$x_i^{new} = x_i^{new} + rand()(x_i^{r1} - x_i^{r2}) \qquad \text{if } f(x^{r1}) \text{ better than } f(x^{r2}) \tag{6.24}$$

$$x_i^{new} = x_i^{new} + rand()(x_i^{r2} - x_i^{r1}) \qquad \text{if } f(x^{r2}) \text{ better than } f(x^{r1}) \tag{6.25}$$

- *Improvement by pitch adjustment*: If the selected design variable is not improved by either *HMCR* or *TLP*, then it can be improved with the probability of *PAR*. To improve the performance of HS algorithm, *PAR* and bandwidth (*bw*) are changed as

$$PAR = PAR_{\max} - \left[(PAR_{\max} - PAR_{\min})\left(\frac{NI}{NI_{\max}}\right)\right] \tag{6.26}$$

$$bw(i) = bw_{\max} + \exp\left[\ln\left(\frac{bw_{\min}}{bw_{\max}}\sqrt{\frac{NI}{NI_{\max}}}\right)\right] \tag{6.27}$$

The selected variable is improved as,

$$\left.\begin{aligned} x_i^{new} &= x_i^{new} \pm rand() * bw(i) \\ x_i^{new} &= \min(\max(x_i^{new}, x_i^{lower}), x_i^{upper}) \end{aligned}\right\} \tag{6.28}$$

- *Mutation operation*: If a design variable has not undergone any of the previous improvements, then it is improved by mutation with the probability p_m as,

$$x_i^{new} = x_i^{lower} + rand()(x_i^{upper} - x_i^{lower}) \tag{6.29}$$

Table 6.1 Parameter selection for HSTL algorithm [120]

Technique	Tuning parameters					
	HMS	***HMCR***	***PAR***	***bw***	***Mutation***	***TL***
HSTL	10	$HMCR_{max}$=0.9 $HMCR_{min}$=0.7	PAR_{max}=0.8 PAR_{min}=0.2	$bw_{max}=\frac{UB\text{-}LB}{30}$ $bw_{min}=\frac{UB\text{-}LB}{10{,}000}$	0.15	TLP_{max}=0.5 TLP_{min}=0.15 k=5

III. ***Updating the harmony vector***: Once, all the design variables of target vectors undergo the improvisation process, fitness function of the new improved vector is calculated. If the solution of the new vector is better than the worst harmony vector in HM, then worst HM is replaced with the improved harmony vector, else improved vector is neglected.

IV. ***Stopping criterion***: If the number of improvisations is reached or improvement in the objective function is less than 1e-5 in 100 consecutive iterations, then the best solution vector is selected. Otherwise, improvisation procedure is repeated. Flow chart and various tuning parameters of the proposed HSTL algorithm are given in Figure 6.1 and Table 6.1 [120], respectively.

6.4 Results and Discussion

The proposed formulation is studied on IEEE 33-bus distribution system. Load factor (*LF*) and Loss Load Factor (*LLF*) for the considered load profile are 0.78 and 0.66 respectively [29, 121]. Three types of DGs, namely biomass, wind and Solar Photo-Voltaic (SPV), are considered for planning. The parameters used in the study are presented in Table 6.2. The lifetime and interest rate of all the DGs are considered as 25 years and 10%, respectively. Since SPV DG unit has low capacity factor and high capital cost in comparison to biomass and wind, 20% subsidy is considered on the capital cost of SPV.

Distribution utilities in India are bound to meet its Renewable Purchase Obligation (RPO) target by means of its own generation or power procurement from eligible renewable energy developers [9]. National policy in 12th five-year plan has targeted for 15% energy from the renewable sources by 2020. Generation Based Incentives (GBI) is offered on certain minimum

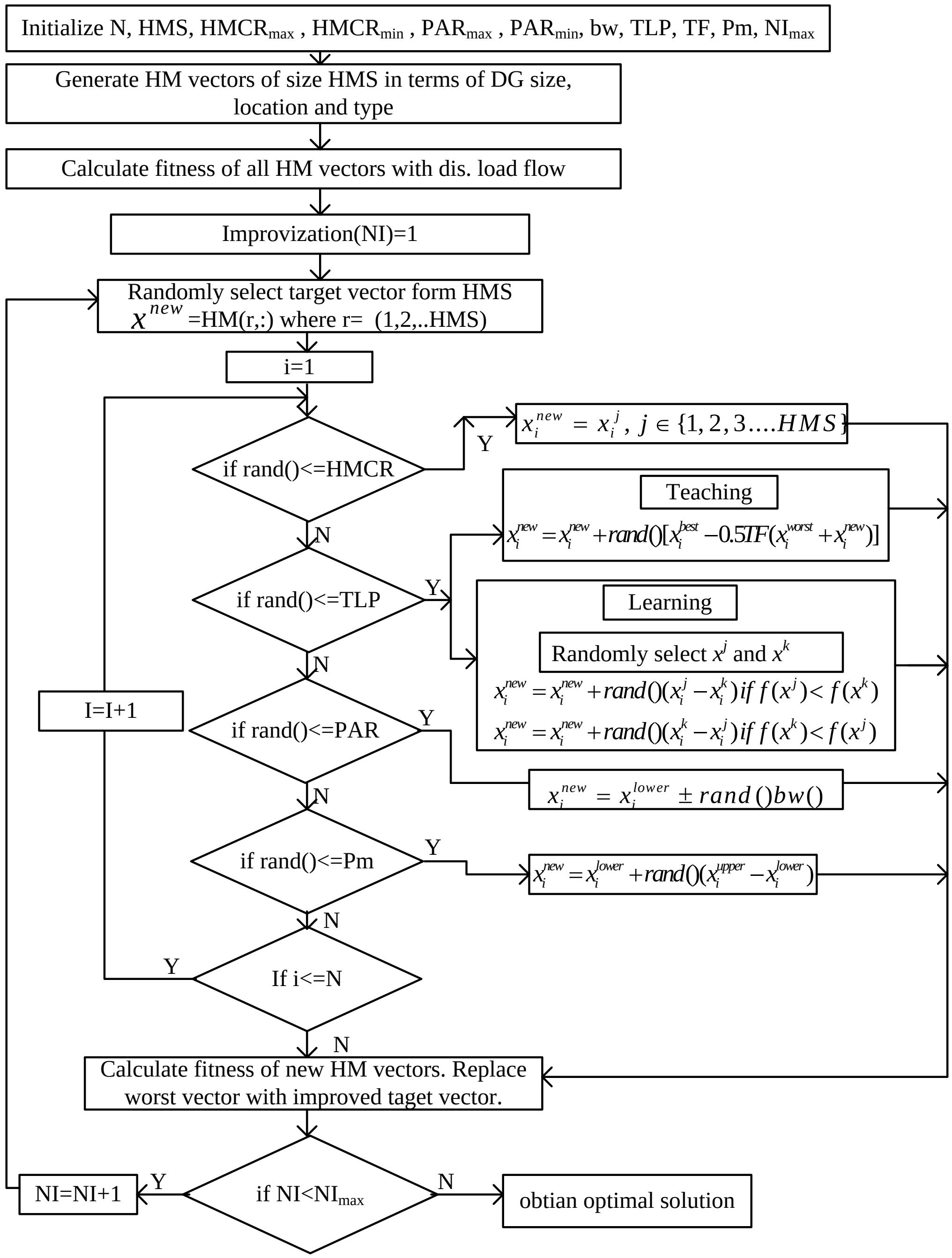

Figure 6.1 Flow chart of proposed HSTL algorithm

solar or wind injection. Emission Offset Incentive (EOI) can be offered for all pollutants, i.e. carbon, nitrogen, and sulfur.

In the present study, EOI is offered only on carbon pollutant. Further, part of energy responsible for harmful emissions from grid and DG is penalized for carbon emissions. Optimal planning schemes with an obligation on distribution network operators (DNO) for wind or solar or

Table 6.2 Parameters used in the proposed formulation [29, 78, 122-123]

Cost parameter	Value
Capital cost for biomass DG unit with stoker boiler	$2296/kVA
Capital cost for wind DG unit	$1882/kVA
Capital cost of SPV DG unit	$4004/kVA
O & M cost for biomass DG unit	$0.012/kWh
O & M cost for wind and SPV DG unit	$0.01/kWh
Fuel cost of biomass DG	$0.04/kWh
Emission rate of biomass DG unit	0.003kg/kWh
Power factor of biomass, wind and SPV DG unit	0.88,0.8,1.0
Capacity factor of biomass, wind and SPV DG unit	0.85, 0.3,0.25
Feeder emission factor	0.9kg/kWh
Generation based incentive for the wind injection	$8.33/MWh (Rs. 0.50/kWh)
Generation based incentive for the solar injection	$200/MWh (Rs. 12.41/kWh)
Grid energy cost	$60/kWh
Carbon emission price	$20/ton

both injections are discussed in the following sections. Following scenarios are considered in renewable DG planning.

- Scenario 1:Base case without DG
- Scenario 2: Mandatory wind or solar or both injections (5% each) with EOI
- Scenario 3: Mandatory wind or solar or both injections (5% each) with GBI
- Scenario 4: Mandatory wind injection (5%) with EOI and solar injection (5%) with GBI

6.4.1 Scenario1: Base case without DG

In this scenario, load flow solution is obtained without any DG injection. At peak load, real and reactive power losses are 211 kW and 143 kVAr respectively. Real and reactive power drawn from the grid is 3.92 MW and 2.44 MVAr respectively. The total annualized cost of 1.91M$ is incurred. Minimum voltage of 0.90 pu is found at bus 18.

6.4.2 Scenario 2: Mandatory wind or solar or both injections (5% each) with EOI

The results for mandatory wind, solar or both injections (5% each) with EOI are presented in Table 6.3. It is concluded that the high cost is incurred with wind and SPV DG. With this DG combination, the annual cost is even more than the without DG scenario. DNO has to bear the additional burden of 0.02M$ annually in comparison to the base case.

Figure 6.2 shows the cost components associated with different optimal allocation schemes. When only wind DG is considered, 0.5 MVA wind injection is optimal thereby saving 6% grid energy cost and 0.44% annual cost as compared to base case investment. The minimum annualized cost is associated with biomass and wind DG combination. High capital cost and lower capacity factor of SPV lead to higher cost of biomass and SPV DG. When all the three technologies are considered simultaneously, highest capital cost results in higher annual cost in-spite of the lowest

Table 6.3 Optimal locations and sizes of DGs for Scenario 2

DG type	Biomass and wind DG	Wind DG	SPV and wind DG	Biomass and SPV DG	Biomass, wind and SPV DG
DG size (MVA)	1.5, 0.3	0.5	0.5, 0.2	1.6, 0.2	1.5, 0.3, 0.2
Bus no	30, 17	15	32, 17	30, 17	30, 14, 17
Annual cost (M$)	1.86	1.899	1.92	1.8917	1.8949

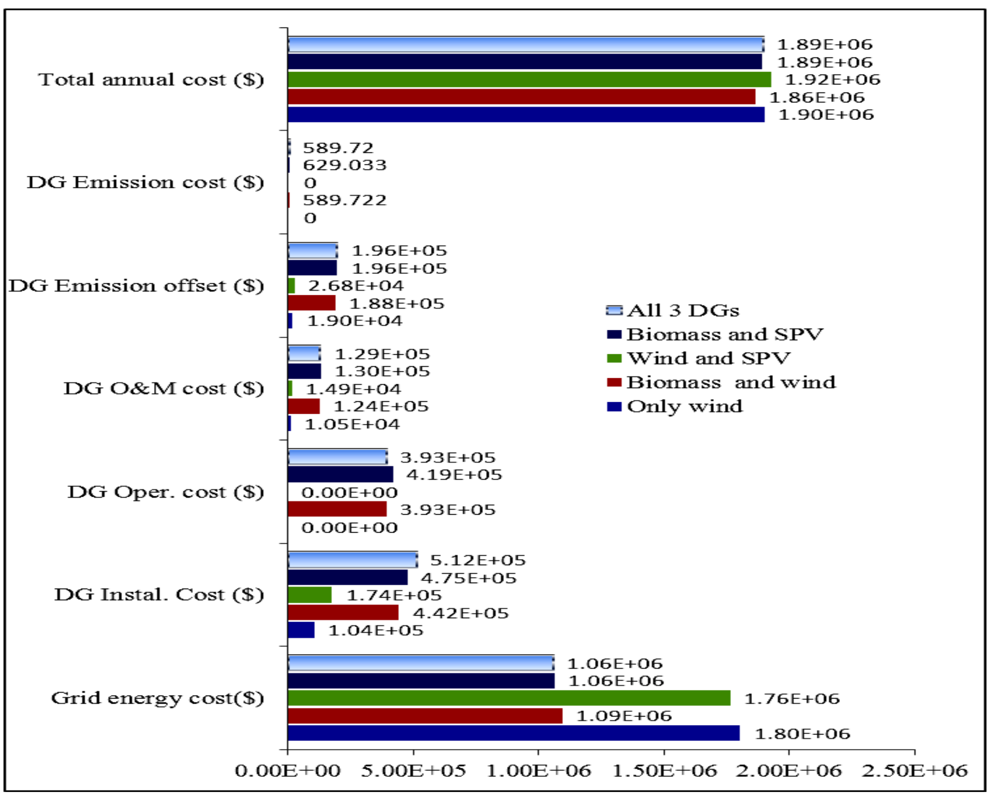

Figure 6.2 Comparison of costs associated with the optimal allocation of DGs for Scenario 2.

grid energy requirement. EOI earned for 3 DG and 2 DG (biomass and SPV DG) combination is same, as the annual energy contribution for both cases are nearly same. In this scenario, Biomass and wind DG is the most promising option.

Line power flow and voltage profile at each bus is shown in Figure 6.3 and 6.4 respectively. The maximum line flow reduction is obtained with 3DG combination. Voltage profile of biomass and wind DG is close to 3 DG combination. Although the size of DG for biomass and wind DG combination is same as biomass and SPV DG combination, former combination has a better voltage profile as compared to the later due to the reactive power support at bus 17.

6.4.3 Scenario 3: Mandatory wind or solar or both injections (5% each) with GBI

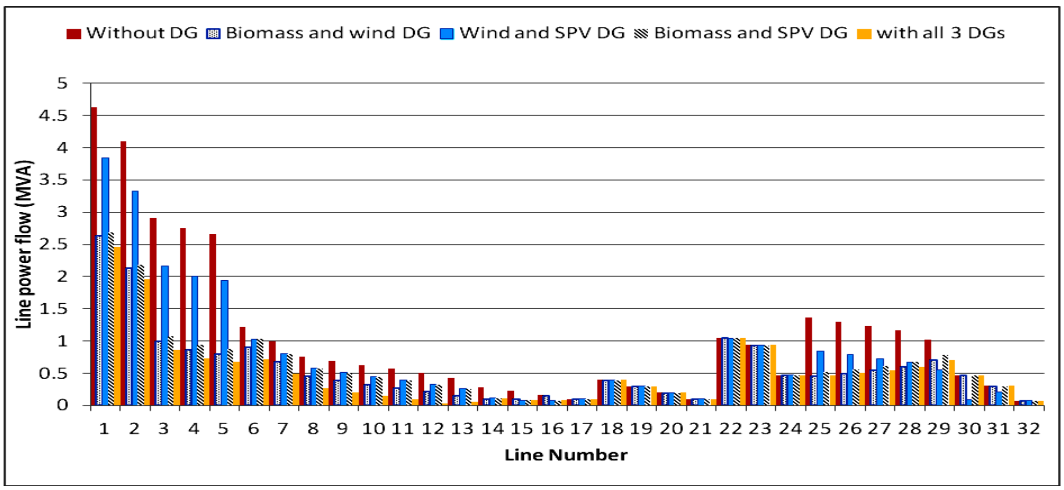

Figure 6.3 Line power flows without and with different combinations of DGs for Scenario 2

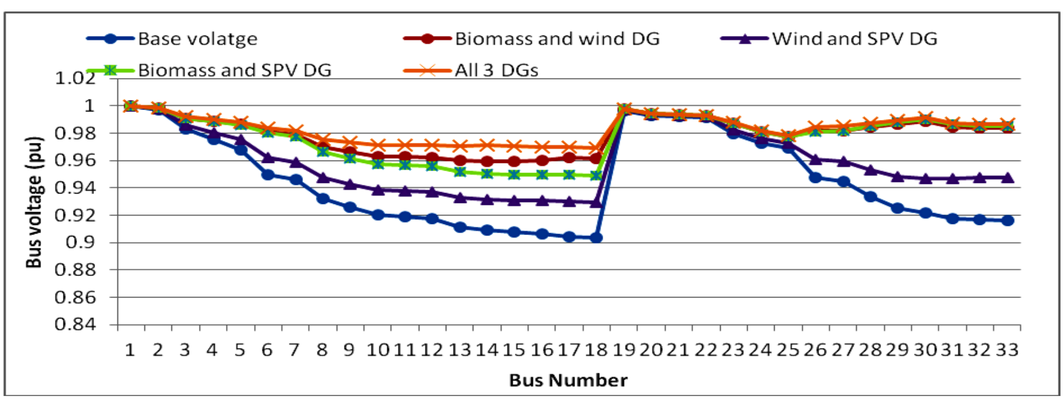

Figure 6.4 Voltage profile for all DG combinations for Scenario 2

In this scenario, a) Distribution Network Operator (DNO) is required to meet the RPO target of 5% minimum wind or solar generation, (b) GBI is offered for minimum wind and solar energy injection, and c) Remaining generation is given EOI. Comparative analysis in terms of optimal location, size, and annual cost for all cases are given in Table 6.4.The associated cost components are shown in Figure 6.5. The annual cost is less than the base case in all the combinations.

GBI for wind DG is financially less attractive than the EOI. The minimum annualized cost is obtained with biomass and SPV DG combination due to the high capacity factor of biomass DG, highest emission offset, and GBI for SPV DG. With this combination, annually, 5% cost reduction is obtained as compared to the base case. With the incentive policy proposed in this scenario,

Table 6.4 Optimal locations and sizes of DGs for Scenario 3

DG type	Biomass & wind DG	Biomass and SPV DG	Wind and SPV DG	Biomass, wind and SPV DG
DG size (MVA)	1.4, 0.3	1.7, 0.2	0.5,0.2	1.1, 0.3, 0.2
Bus no	30,17	30,17	32,17	30,14,17
Total cost (M$)	1.8701	1.8121	1.8513	1.8232

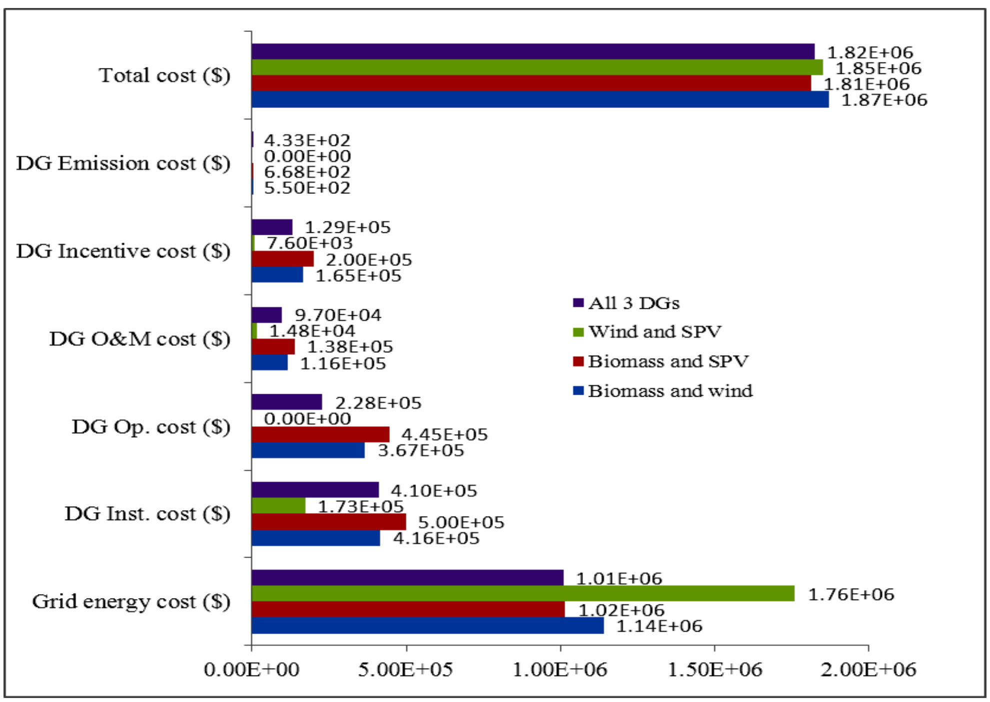

Figure 6.5 Comparison of cost associated with the optimal allocation of DG for Scenario 3.

Biomass and SPV DG combination is economically most viable.

Power flow in the line feeders is shown in Figure 6.6. Line loading is relieved maximum with biomass and wind DG, and 3 DG combination. Voltage profile improvement with each DG combinations is shown in Figure 6.7. As the optimal size of SPV and the wind DG combination is smaller due to the economic criterion, the voltage profile improvement is least. The Voltage profile for the other combinations is almost close to each other.

6.4.4 Scenario 4: Mandatory wind injection (5%) with EOI and solar injection (5%) with GBI

In this scenario, a) DNO is required to meet the RPO target of minimum 5% wind or 5% solar

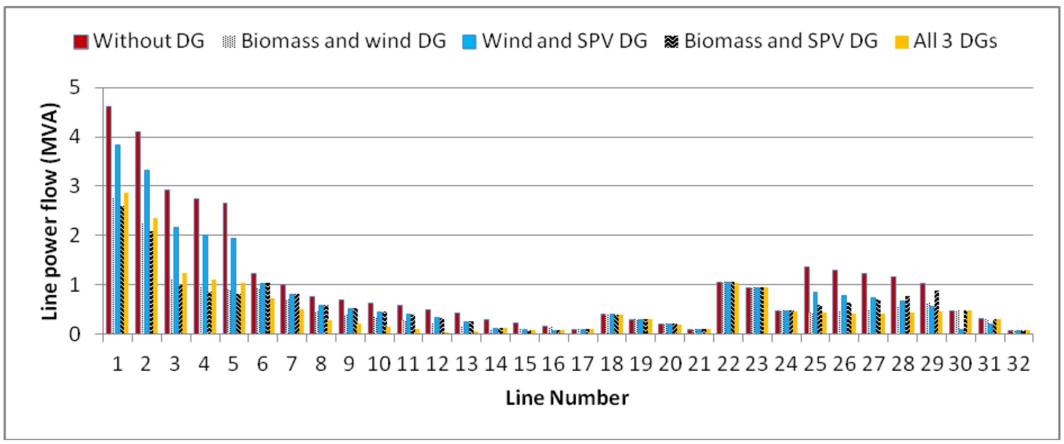

Figure 6.6 Line power flows without and with different combinations of DGs for Scenario 3

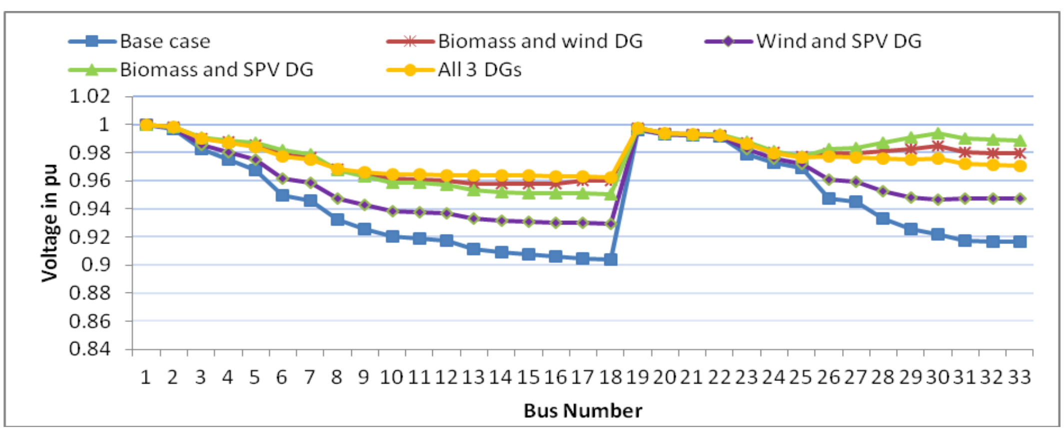

Figure 6.7 Voltage profile with all DG combinations for Scenario 3

generation, b) GBI is offered for mandatory solar injection, and c) Remaining solar generation and entire wind generation is offered EOI. A comparative analysis of all possible combinations is drawn in Table 6.5 and Figure 6.8.It is observed that Biomass and solar DG combination results in least annual cost due to the two reasons. One, lowest grid energy requirement reduced penalty costs for GHG emissions. Secondly, GBI earned by the SPV DG compensated its high capital cost. The annual cost with 3 DG combination becomes comparable to biomass and SPV DG. However, minimum loss is given by 3 DG combination. This incentive scheme is more beneficial than the Scenario 3 from DNO's prospective.

Table 6.5 Optimal locations and sizes of DGs for Scenario 4

DG type	Biomass and wind DG	Biomass and SPV DG	Wind and SPV DG	Biomass, wind and SPV DG
DG size (MVA)	1.5, 0.3	1.7, 0.2	0.5, 0.2	1.3, 0.3, 0.2
Bus no	30,17	30,17	32,17	30,14,17
Total cost (M$)	1.8637	1.8121	1.8452	1.8156

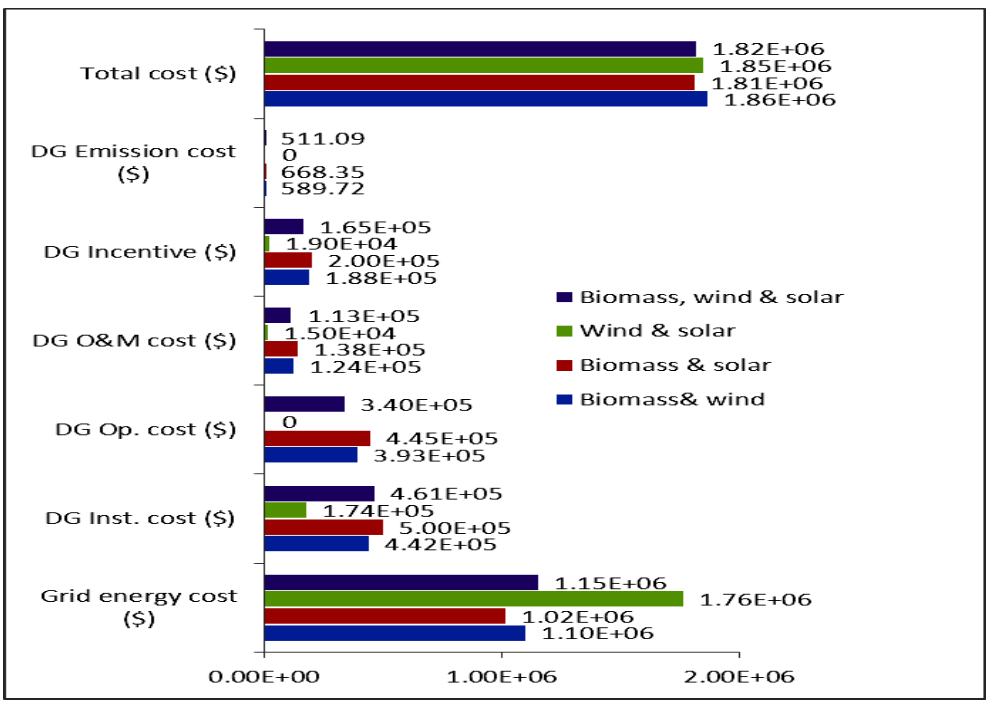

Figure 6.8 Comparison of cost associated with the optimal allocation of DG for Scenario 4.

Comparison of line flows and voltage profile are shown in Figure 6.9 and 6.10 respectively. Line power flows and voltage profile follows the same trend as in scenario 3. However, voltage profile improvement and line flow reduction is more in the Scenario 4.

6.5 Summary

This chapter presents various mechanisms for planning of renewable DG. The proposed model has minimized the annual cost while awarding incentive as EOI and/or GBI and penalizing GHG emissions. The annualized cost comprises DG capital, operation, maintenance, energy loss, grid energy and emission cost. The optimal solution is obtained in terms of optimal size, location, and DG types for different incentive schemes. It is concluded that the appropriate incentive scheme can

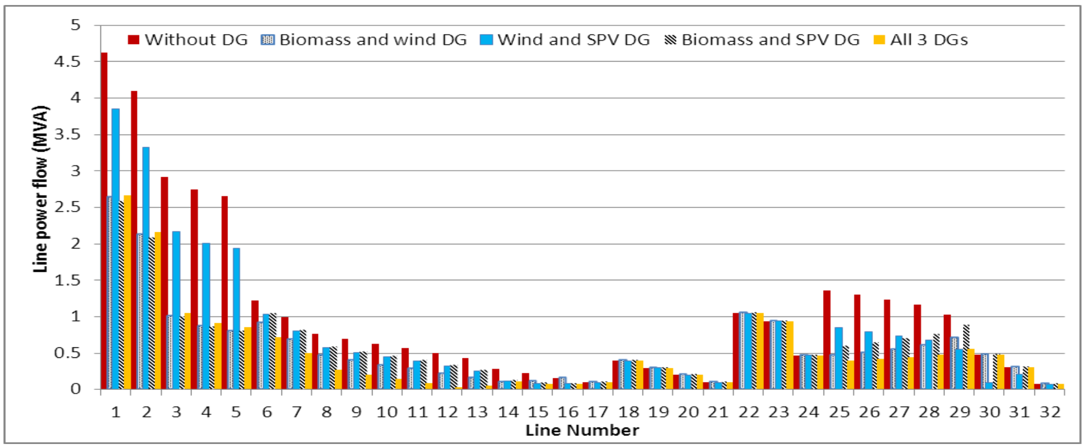

Figure 6.9 Line power flows without and with different combinations of DGs for Scenario 4

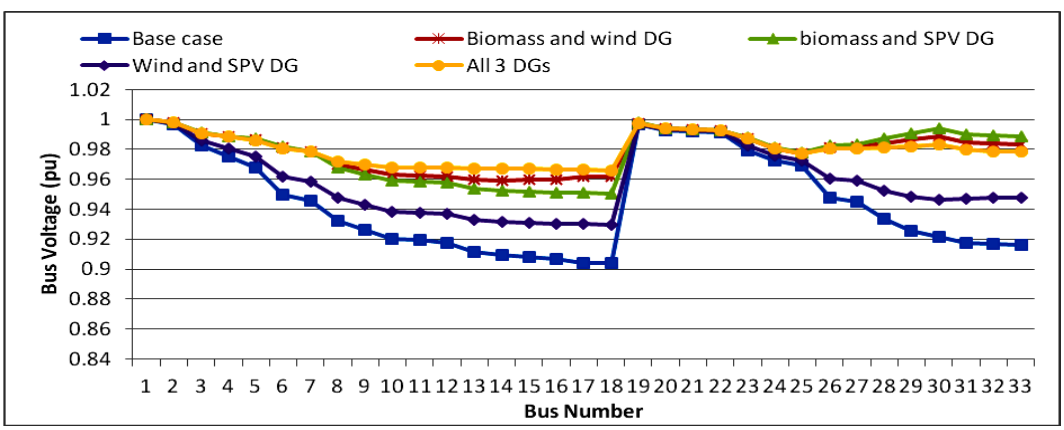

Figure 6.10 Voltage profile with all DG combinations for Scenario 4

make cost intensive DGs such as SPV and wind economically viable. To solve this optimization problem, a hybrid optimization approach integrating IHS and TLBO is proposed. The proposed formulation is useful for energy planners to devise a proper incentive mechanism to promote renewable DG technology.

CHAPTER 7

INTEGRATED MINLP FORMULATION FOR LONG TERM DG PLANNING

7.1 Introduction

Distributed generation planning is generally a long term in nature. Economic criterion is equally important along with technical parameters. Optimal expansion planning is achieved in terms of type and number of DG units on each optimal location, time of installation, and optimal size. Long term DG planning with multiple load levels may affect the optimal DG size, location, and time of adding new DG units. Planning with peak load may lead to overestimation of DG size. Therefore, multiple load levels are considered in the proposed formulation. Simultaneous placement of DG and capacitor combination is not yet fully explored. Therefore, optimal DG and capacitor placement on candidate buses is also considered.

7.2 Problem Formulation

7.2.1 Sensitivity analysis

In distribution systems, voltage is sensitive to power injection. Therefore, the voltage sensitivity is used in the optimization algorithm. The change in bus voltage magnitude and angle is related to change in injected power (ΔP , ΔQ) as given below,

$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = \begin{bmatrix} J^{-1} \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \text{Where } V,\ \theta \text{ are bus voltage and angle vector} \tag{7.1}$$

where,

$$J = \begin{pmatrix} \dfrac{\partial P}{\partial \theta} & \dfrac{\partial P}{\partial V} \\ \dfrac{\partial Q}{\partial \theta} & \dfrac{\partial Q}{\partial V} \end{pmatrix} \tag{7.2}$$

The sensitivities given in Jacobean matrix are used to find the list of candidate buses.

7.2.2 Load Modelling

The load are modeled as d demand levels with D durations. Load demand at each bus in year t is represented as

$$P_{i,d,t}^{D} = P_{i,d,t-1}^{D}(1+\alpha) \tag{7.3}$$

$$Q_{i,d,t}^{D} = Q_{i,d,t-1}^{D}(1+\alpha) \tag{7.4}$$

where

$P_{i,d,t}^{D}, P_{i,d,t-1}^{D}$	=	Real power demand at i^{th} bus in load level d, in year t and t-1,
$Q_{i,d,t}^{D}, Q_{i,d,t-1}^{D}$	=	Reactive power demand at i^{th} bus in load level d, in year t and t-1,
α	=	Percentage load growth.

7.2.3 Objective function

The objective function (7.5) is to be minimized is,

$$Min\ f(x) = f(x1) + f(x2) + f(x3) + f(x4) \tag{7.5}$$

where, $f(x1)$, $f(x2)$, $f(x3)$ and $f(x4)$ are installation, grid energy, energy loss, and DG operational cost during the planning period respectively. Various costs can be calculated as given in the following sections.

I. ***Installation cost***: The installation cost consists of cost of generators and capacitor. The $f(x1)$ is given as,

$$\left.\begin{aligned} & f(x1) = \sum_{j=1}^{CDGB} S_j^{DG} NDG_j C_{DG}^{ins} + \sum_{k=1}^{CAPB} Q_k^{cap} C_{cap}^{ins} \\ & j \in \{\text{Candidate DG buses}\}, k \in \{Candidate\ capacitor\ buses\} \end{aligned}\right\} \tag{7.6}$$

where,

S_j^{DG}	=	Rated capacity of each unit of DG at candidate bus j
$C_{DG}^{inst}, C_{cap}^{inst}$	=	Installation cost factor of each DG unit (\$/MVA) and capacitor (\$/MVAr)
Q_k^{cap}	=	Rated capacity of capacitor at candidate bus k
CDGB, CAPB	=	List of DG and capacitor buses
NDG_j	=	Number of DG units installed at candidate bus j

II. ***Grid energy cost***: The grid energy cost ($f(x2)$) is calculated as,

$$f(x2)=\sum_{t=1}^{T}\sum_{d=1}^{LL}\left(\frac{1}{1+r}\right)^{t}P_{d,t}^{SS}H_{d,t}C_{en}^{ss} \qquad \forall d\in\{\text{load level } LL\},T\in\{\textit{planning period}\} \tag{7.7}$$

where,

T = Planning period,

LL = Number of load levels,

r = Discount rate,

$P_{d,t}^{SS}$ = Grid power drawn (MW) in load level *d* and year *t*,

$H_{d,t}$ = Duration of load level *d* in year *t*,

C_{en}^{ss} = Cost of grid energy ($/MWh),

III. ***Cost of energy loss***: The cost of energy loss ($f(x3)$) is calculated as,

$$f(x3)=\sum_{t=1}^{T}\sum_{d=1}^{LL}\left(\frac{1}{1+r}\right)^{t}P_{d,t}^{loss}H_{d,t}C^{loss} \tag{7.8}$$

where,

$P_{d,t}^{loss}$ = Power loss in load level *d* and year *t*,

C^{loss} = Cost of energy loss ($/MWh),

Power loss in load level *d* and year *t* ($P_{d,t}^{loss}$) is given as,

$$P_{d,t}^{loss}=0.5*\sum_{i=1}^{NB}\sum_{j=1}^{NB}G_{ij}[V_{i,d,t}^{2}+V_{j,d,t}^{2}-2V_{i,d,t}V_{j,d,t}\cos(\delta_{i,d,t}-\delta_{j,d,t}) \tag{7.9}$$

where,

$V_{i,d,t},V_{j,d,t}$ = Voltage at bus *i* and *j*, respectively, in load level *d*, in year *t*,

$\delta_{i,d,t},\delta_{j,d,t}$ = Voltage angle at bus *i* and *j*, respectively, in load level *d*, in year *t*,

NB = Number of buses,

IV. ***DG operational cost*****:** The operational cost ($f(x4)$) of DG is calculated as,

$$f(x4)=\sum_{t=1}^{T}\sum_{j=1}^{CDGB}\sum_{d=1}^{LL}\left(\frac{1}{1+r}\right)^{t}P_{j,d,t}^{DG}H_{d,t}C_{op}^{DG} \tag{7.10}$$

where,

$P_{j,d,t}^{DG}$ = Real power injected by DG unit at j^{th} bus in load level *d*, in time *t*,

C_{op}^{DG} = Operational cost of DG ($/MWh),

7.2.4 Constraints

The constraints of this optimization problem are as follows.

I. ***Power balance constraint:*** All incoming and outgoing real and reactive power at each bus must be balanced. The corresponding constraints are,

$$\left.\begin{aligned} P_{i,d,t}^{G} - P_{i,d,t}^{D} - \left|V_{i,d,t}\right| \sum_{j=1}^{NB} \left|V_{j,d,t}\right| (G_{ij}\cos(\delta_{i,d,t} - \delta_{j,d,t}) + B_{ij}\sin(\delta_{i,d,t} - \delta_{j,d,t})) = 0 \\ Q_{i,d,t}^{G} - Q_{i,d,t}^{D} - \left|V_{i,d,t}\right| \sum_{j=1}^{NB} \left|V_{j,d,t}\right| (G_{ij}\sin(\delta_{i,d,t} - \delta_{j,d,t}) - B_{ij}\cos(\delta_{i,d,t} - \delta_{j,d,t})) = 0 \end{aligned}\right\} \forall i, j \in NB \qquad (7.11)$$

where, $P_{i,d,t}^{G}, Q_{i,d,t}^{G}$ are real and reactive power generations, and $P_{i,d,t}^{D}, Q_{i,d,t}^{D}$ are real and reactive power demands, respectively, at i^{th} bus in load level *d* and year *t*.

II. ***Substation/ Grid capacity limit:*** The power drawn from grid cannot exceed the agreed power transfer limits.

$$0 \le S_{i,d,t}^{SS} \le S_{rated}^{SS} \qquad i \in \{\text{Slack bus}\} \qquad (7.12)$$

where,

$S_{i,d,t}^{SS}$ = Power drawn (MVA) from the substation at i^{th} bus in load level *d*, in time *t*,

S_{rated}^{SS} = Rated power (MVA) of substation,

III. ***System voltage limit:*** Voltage magnitude of all the buses must be within the allowed upper and lower limits.

$$|V_{\min}| \le |V_{i,d,t}| \le |V_{\max}| \qquad (7.13)$$

where,

$|V_{\min}|$, $|V_{\max}|$ = Minimum and maximum permissible voltage limits,

$|V_{i,d,t}|$ = Voltage at i^{th} bus in load level *d*, at time *t*,

IV. ***Installed DG capacity limit at each bus:*** As per technical and geographical considerations, sometimes, maximum generation limit at each bus is specified. The DG capacity allocated must be less than maximum permissible capacity.

$$P_{i,d,t}^{DG} \leq S_i^{DG} NDG_{i,d,t} \tag{7.14}$$

where, $NDG_{i,d,t}$ is number of DG units at i^{th} bus in load level d, in time t.

V. ***Reactive power capability limit***: The reactive power output limit of synchronous generator is given as,

$$Q_{i,d,t}^{DG} \leq S_i^{DG} NDG_{i,d,t} \tag{7.15}$$

VI. ***DG power limit:*** Sum of active and reactive power injected by DG at any bus should not exceed a DG power rating, and is expressed as,

$$\sqrt{(P_{i,d,t}^{DG})^2 + (Q_{i,d,t}^{DG})^2} \leq S_i^{DG} NDG_{i,d,t} \tag{7.16}$$

VII. ***Capacitive Power limit:*** Capacitive generation should not exceed the maximum capacitive injection limit at the candidate bus.

$$0 \leq Q_{i,d,t}^{cap} \leq Q_i^{\max} \tag{7.17}$$

where,

$Q_{i,d,t}^{cap}$ = Reactive generation (\$/MVAr) at i^{th} capacitor candidate bus, load level d, time t,

$Q_i^{\max}$ = Maximum reactive power specified at i^{th} candidate bus,

VIII. ***Line flow limits:*** Feeder power flow should not exceed its thermal limit. The line flow limit can be written as,

$$0 \leq S_{ij,d,t} \leq S_{ij(\max)} \tag{7.18}$$

where,

$S_{ij,d,t}$ = Power flow (MVA) in feeder section between bus i and j, in load level d and year t,

$S_{ij(\max)}$ = Maximum power flow (MVA) limit of feeder section between bus i and j,

7.3 Solution Algorithm

The MINLP formulation of the proposed problem is given as,

$$\left.\begin{array}{l} Min.\ f(x,y) \\ s.t\ \ g(x,y) \le 0 \\ x \in \mathrm{X},\ \ \mathrm{y} \in Y \text{ integer} \end{array}\right\} \forall y \in \{0,1,2,\ldots,NDG\} \text{ for no. of DGs} \tag{7.19}$$

where, x and y are sets of continuous and discrete variables, respectively. An NLP based interior point method integrated with branch and bound algorithm is used. The algorithm involves a tree search in the space of the discrete variables using linear approximations to bound the original problem. A branch and bound search is used to obtain the lower bound by solving NLP problem until a feasible integer solution is found. NLP sub-problems are solved at nodes with integer solutions for the integer variables. The key feature in the algorithm is the dynamic generation of the linear approximations, which are derived at integer solutions in the tree. This dynamic generation avoids the sequential solution of NLP to reduce the number of nodes to be examined. Here, nonlinear part is searched simultaneously while searching the tree. The detailed algorithm and the flow chart are described in Chapter 4.

7.4 Results and Discussion

To study the proposed planning model, IEEE 33-bus radial distribution system is considered. Technical data for the same is given in Appendix A. It consists of the substation at bus number 1 with 5MVA rating to serve peak demand of 3.72 MW and 2.37 MVAR in the base year. The planning model considers three load levels of 0.5, 0.8 and 1.0 p.u. load of durations 2000, 6000 and 760 hours, respectively. Annual load growth is considered as 3.5 percent. The installation and operational costs of DGs are 0.65 M$/MVA and 50 $/MWh respectively [57]. The installation cost of transformer and capacitor are 15000 $/MVA [53] and 15000 $/MVar respectively [124]. Grid energy cost of 70 $/Mwh is considered [53] in the simulated case study. Planning is carried out for the period of 10 years. The proposed model is simulated in AMPL environment using MINLP solver BONMIN [118, 125]. Following are some assumptions during the formulation.

1. Bus-1 is considered as a substation with 5 MVA transformer.
2. Maximum DG penetration is 40% of the load demand at that year.
3. The maximum thermal limit of the lines is 1.5 times the line flows at base-year.

To evaluate the economic feasibility of DG planning over the substation up-gradation planning, following scenarios are considered.

Scenario 1: Substation expansion planning without DG

Scenario 2: Planning with real power DGs

Scenario 3: Planning with real power DGs and capacitors

Scenario 4: Planning with real and reactive power DGs

7.4.1 Comparison of total planning cost

Table 7.1 shows the comparison of cost associated with various planning scenarios.

- ***Scenario-1 Substation expansion planning without DG***: In this scenario, an additional transformer of 2 MVA capacity is required to be installed during the 5th year of the planning period. By the end of planning years, utilization of this additional transformer is about 93%. Maximum power loss occurs at load level-3. However, maximum energy loss cost is incurred with load level-2 due to the longer duration. As per Table 7.1, substation expansion planning

Table 7.1 Comparison of various costs for different Scenarios

<table>
<tr><th></th><th colspan="2">Planning without DG (Scenario–1)</th><th colspan="2">DG with upf (Scenario–2)</th><th colspan="2">DG with upf and capacitor (Scenario–3)</th><th colspan="2">DG with P and Q injection (Scenario–4)</th></tr>
<tr><td>Substation expansion cost ($)</td><td colspan="2">0.50e5</td><td colspan="2">–</td><td colspan="2">–</td><td colspan="2">–</td></tr>
<tr><td>Potential DG buses</td><td colspan="2">–</td><td colspan="2">6, 10, 13, 24, 28, 30</td><td colspan="2">10, 13, 28, 30</td><td colspan="2">6, 10, 13, 24, 28, 30</td></tr>
<tr><td rowspan="2">DG capacity (MW) and optimal locations</td><td colspan="2" rowspan="2">–</td><td>Bus</td><td>Size MW, No.</td><td>Bus</td><td>Size MW, No.</td><td>Bus</td><td>Size MVA, No.</td></tr>
<tr><td>10
13
28
30</td><td>0.1*3
0.1*5
0.1*3
0.1*5</td><td>10
13
28
30</td><td>0.1*3
0.1*5
0.1*1
0.1*5</td><td>10
13
24
28
30</td><td>0.1*3
0.1*5
0.1*1
0.1*5
0.1*5</td></tr>
<tr><td>Capacitor Location and capacity (MVAR)</td><td>18
30</td><td>–</td><td colspan="2">–</td><td>24</td><td>1.0</td><td colspan="2">–</td></tr>
<tr><td>DG capital cost ($)</td><td colspan="2">–</td><td colspan="2">0.10e7</td><td colspan="2">0.09e7</td><td colspan="2">0.12e07</td></tr>
<tr><td>Capacitor cost</td><td colspan="2">1.50e04</td><td colspan="2">–</td><td colspan="2">1.50e04</td><td colspan="2">–</td></tr>
<tr><td>DG fuel cost ($)</td><td colspan="2">–</td><td colspan="2">1.01e07</td><td colspan="2">0.89e07</td><td colspan="2">1.02e07</td></tr>
<tr><td>Grid energy cost ($)</td><td colspan="2">3.75e07</td><td colspan="2">2.27e07</td><td colspan="2">2.44e07</td><td colspan="2">2.21e07</td></tr>
<tr><td>Energy loss (Mwh)</td><td colspan="2">11043.88</td><td colspan="2">6720.27</td><td colspan="2">6394.4</td><td colspan="2">2945.69</td></tr>
<tr><td>Energy loss cost ($)</td><td colspan="2">14.4e05</td><td colspan="2">8.73e05</td><td colspan="2">8.30e05</td><td colspan="2">3.93e05</td></tr>
<tr><td>Total planning cost($)</td><td colspan="2">3.90e07</td><td colspan="2">3.47e7</td><td colspan="2">3.50e7</td><td colspan="2">3.39e07</td></tr>
</table>

(without DG) seems to be the most expensive option due to maximum grid energy cost and energy loss cost.

- ***Scenario-2 DG with unity power factor*:** Based on sensitivity analysis, a list of six candidate buses is considered for DG placement. Finally, four optimal locations are selected. Additional investment required for DG investment and operational cost is 11.18 M$. However, it leads to 10.8% savings of DISCO's cost in comparison to substation expansion planning. Optimal siting and sizing of DG units lead to 54.79% reduction in energy losses (see Table 7.1). DG planning schedule of this case is shown in Table 7.2.

- ***Scenario-3 DG with upf and capacitor units*:** In this case, simultaneous placement of DG with upf and capacitor is considered. Four buses are considered as potential candidates for DG placement. Planning schedule for this case at all the load levels is shown in Table 7.3. It

Table 7.2 Planning schedule of DG units with unity power factor (Scenario-2).

Optimal bus no.	Planning year	Load-level 1		Load-level 2		Load-level 3	
		Bus	No. of units	Bus	No. of units	Bus	No. of units
10, 13, 28, 30	1st year	10 13 28 30	2 3 1 4	10 13 28 30	3 4 2 5	10 13 28 30	3 5 3 5
	2nd year	10 13 28 30	3 4 2 4	10 13 28 30	3 4 3 5	Same as 1st year	
	4th year	10 13 28 30	3 4 3 4	10 13 28 30	3 4 3 5	Same as 1st year	
	5th to 7th year	10 13 28 30	3 4 3 5	10 13 28 30	3 4 3 5	Same as 1st year	
	8th to 10th year	10 13 28 30	3 4 3 5	10 13 28 30	3 5 3 5	Same as 1st year	

Table 7.3 Planning schedule of placement of DG with upf and capacitor (Scenario-3)

Optimal bus no.	Planning year	Load-level 1		Load-level 2		Load-level 3	
		Bus	**No. of units**	**Bus**	**No. of units**	**Bus**	**No. of units**
10, 13, 28, 30	1st year	10 13 28 30	2 3 1 4	10 13 28 30	2 4 1 5	10 13 28 30	3 5 1 5
	2nd year	10 13 28 30	2 4 1 4	10 13 28 30	2 5 1 5	Same as 1st year	
	7th year	10 13 28 30	Same as 2nd year	10 13 28 30	3 5 1 5	Same as 1st year	
	8th year	10 13 28 30	2 4 1 5	Same as previous year		Same as 1st year	
	10th year	10 13 28 30	3 4 1 5	Same as previous year		Same as 1st year	

is assumed that injected power from the DG (real power) and capacitor (reactive power) should not exceed 40% limit. It is observed that cost of planning of the Scenario 3 is relatively higher than the DG planning with real injection. Savings of about 10.25% is achieved in the present scenario in comparison to the substation expansion planning.

- ***Scenario-4 DG with both real and reactive power*****:** In this case, six buses are chosen as potential candidate buses for DG placement. Finally, five optimal locations are selected. Planning schedule for all the load levels is tabulated in Table 7.4. In this option, additional investment of 11.4 M$ is required for DG investment and operational cost. However, it leads to 13% savings to DISCO’s cost in comparison to substation expansion planning. DG planning offsets 33.6% of grid energy. It also leads to 80% reduction in energy losses. It is observed that DG planning with both real and reactive power injection leads to minimum energy losses as well as least cost out of all the considered scenarios (see the Table 7.1).

Table 7.4 Planning schedule of DG with real and reactive power (Scenario-4)

Optimal bus no.	Planning year	Load-level 1		Load-level 2		Load-level 3	
		Bus	No. of units	Bus	No. of units	Bus	No. of units
10, 13, 24, 28, 30	1st year	10 13 24 28 30	3 3 1 2 5	10 13 24 28 30	3 5 1 5 5	Same as load level-2	
	2nd year	10 13 24 28 30	3 3 1 3 5	10 13 24 28 30	3 5 1 5 5	Same as load level-2	
	3rd to 10th year	10 13 24 28 30	3 4 1 5 5	10 13 24 28 30	3 5 1 5 5	Same as load level-2	

7.4.2 Comparison of line flows and voltage profiles

The comparison of line flows for various planning scenarios are shown in the Figure 7.1. In all the Scenarios, it is observed that power flows are less than 1.5 times the base case power flows. Therefore, network up-gradation is not required. In the Scenario-1, the power-drawn from the grid increases from 4.62 to 6.46 MVA. With DG planning, line power flows are almost comparable with the base case power flows (see Figure 7.1). In addition, future load requirement is met with the existing transformer.

The comparison of voltage profiles for various planning scenarios is shown in the Figure 7.2. In the case of substation expansion planning, as the load increases, voltages at some buses fall below the permissible limits. The voltages at Bus no. 9 to 18 and 29 to 33 fall below 0.90 p.u. Minimum voltage of 0.86 p.u. is experienced at bus no. 18. Therefore, two capacitors of 0.5 MVAR each are considered at bus no. 18 and 30 respectively. Reactive power compensation boosts the voltage to 0.90 p.u. With DG planning, voltage profiles are better as compared to Scenario-1 (see Figure 7.2). Voltage profiles are almost comparable in Scenario-2 and 3. However, voltage profile is most improved with DG planning having real and reactive power injection.

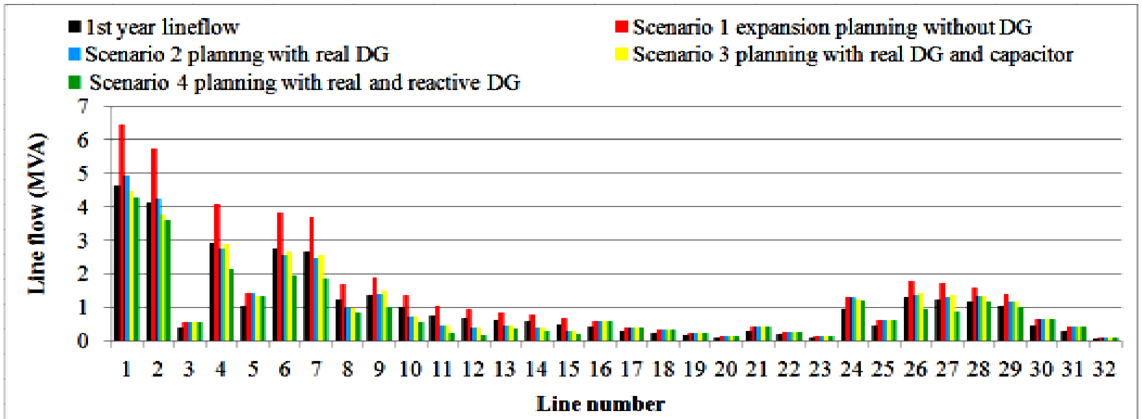

Figure 7.1 Comparison of base case line power flow with DG planning

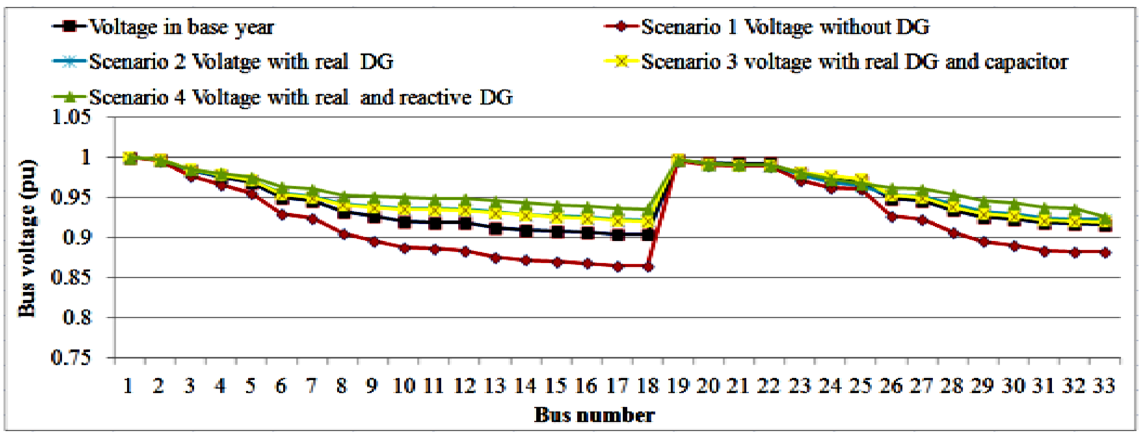

Figure 7.2 Comparison of voltage profile with and without DG planning

7.5 Summary

This chapter introduces a novel approach to obtain long term DG planning in terms of optimal number of DG units, time of investment, locations, and size. The proposed model minimizes the DG investment, operational, grid energy, and energy-loss cost. Three different Scenarios of DG planning are discussed. It is concluded that DG units are under-utilized when planned with only real power injection and leads to higher investment. In addition, optimal locations are different in three cases although the list of potential candidate buses is same. DG planning with its real and reactive power capability exploits full potential. DG planning in this scheme yields a maximum loss reduction and minimum planning cost.

Simulated results show that apart from the financial benefit, improvement in network voltage profile, energy loss, and relieved line feeders due to reduction in grid power import is additional benefits earned by DISCO. DG planning utilizes the existing network without the need of substation up-gradation.

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

8.1 Introduction

The proper allocation of DG units in distribution system plays a decisive role in achieving economical, technical, and qualitative benefits. Therefore, the aim of this dissertation is to study various issues related to DG planning and develop the framework for optimal planning for objectives such as loss minimization, cost minimization and maximization of renewable generation. The developed methodologies will be useful for integrating the distributed generation into the distribution systems.

It was observed that many researchers modeled DG with unity power factor or pre-specified power factor. Most of the researchers have used either analytical or evolutionary methods for optimal DG placement. Optimal siting and sizing problem by classical method is not fully explored. In addition, traditional DG planning was focused on peak demand leading to inflated investment and sub-optimal planning. Lastly, eco-environment criterion and incentive policy for cost intensive DGs need to be fully addressed for sustainable and viable DG planning. In this chapter, the important findings of the research work are highlighted and the suggestions for future work are presented.

8.2 Summary of Major Findings

The important findings of the presented work in the area of optimal placement and planning of distributed generation can be summarized as follows.

In the Chapter 1, brief overview of DG system and the research objectives are given. The literature review of optimal DG placement is presented in the Chapter 2. It contains a comprehensive study on techniques, objectives, and problems related to DG planning, such as power loss, energy loss, economics, etc. Modeling of distribution system, generalized OPF formulation, and basic optimization techniques used to formulate the integrated algorithms are presented in the Chapter 3.

In the Chapter 4, a MINLP based integrated approach, for optimal placement of single and multiple DG units to minimize the losses, is presented. To reduce the search space and computational time, two-step scheme is proposed. Firstly, in Siting Planning Models (SPM), potential candidate buses are shortlisted based on Combined Loss Sensitivity (CLS). These short listed buses are then passed to Capacity Planning Model (CPM). In CPM, the optimal locations and DG sizes are computed using MINLP based formulation. In this formulation, Sequential Quadratic Programming (SQP) and Branch and Bound (BAB) algorithms are integrated to handle discrete and continuous variables. Due to reduced search space, by means of SPM model, solution converges in very less time. The proposed methodology is implemented on IEEE 33-bus and IEEE 69-bus test systems. A comparative analysis is done among the three popular classes of optimization methods for DG placement. Comparative study in terms of DG size, distribution loss, and computational efforts is carried out with Exhaustive Load Flow (ELF), Improved Analytical (IA), and Particle Swarm Optimization (PSO) techniques. It is observed that the proposed algorithm based on MINLP gives improved performance in terms of solution time, loss reduction, voltage profile improvement, etc. In addition, due to flexibility in power factor, the algorithm gives further improved results in the case of DG units capable of delivering real and reactive power. Proposed formulation is generalized and can be implemented for any type and any number of DG units.

In the Chapter 5, a new hybrid approach integrating Improved Harmony Search (IHS) and OPF is developed for optimal placement of DG units to minimize the losses. Meta-heuristic IHS is integrated due to the inherent nature of the optimal DG placement problem. Proposed formulation with few controlling parameters and embedded OPF leads to faster convergence and improved solution in comparison to conventional heuristic techniques. However, it may trap in local minima in some cases. It is concluded that MINLP based hybrid method gives better results in comparison to the hybrid approach.

In the Chapter 6, an incentive based renewable DG planning is presented. The proposed model minimizes the annual cost with emission offset or generation based incentive, and greenhouse gas (GHG) emissions penalty. The annualized cost comprises DG capital, operation, maintenance, energy loss, grid energy and emission cost. The optimal solutions for different incentive and DG schemes are obtained. It is concluded that the appropriate incentive scheme can make cost intensive DGs such as SPV and wind, viable for planning. A hybrid optimization approach, integrating IHS and Teaching-Learning Based Optimization TLBO is implemented to solve the proposed formulation. The effectiveness of the integrated algorithm is shown in the optimum results.

In the Chapter 7, a novel approach for long-term distribution system planning with DG is presented. The proposed model minimizes the DG investment, operational, grid energy, and energy loss cost. The model not only provides the optimal DG installed capacity, but also computes the optimal size for each load levels and planning year. The results show that apart from the financial profit, additional benefits such as, improvement in network voltage profile, energy loss reduction, relieved line feeders, and reduction in grid power import, can be earned by DISCO.

8.3 Important Contributions

The important contributions of this work in the field of Distributed Generation Planning are summarized as follows.

Chapter 4: A MINLP based novel optimization technique for planning of multiple DG units with real and reactive power capabilities is presented. This algorithm computes optimal DG location, size, and power factor. Due to reduced search space and less computational burden, the algorithm converges to optimal solution in less time with a consistent solution in every run. Without loss of generality, the proposed model can be extended to different type of DGs.

Chapter 5: Optimal DG placement problem is a combinatorial optimization problem with non-monotonic search space. Therefore, a novel hybrid approach with Improved Harmony Search (IHS) and OPF formulation is developed. The proposed formulation shows strong convergence property, improved results due to few controlling parameters, and embedded OPF formulation.

Chapter 6: To encourage cost intensive renewable DGs, a framework for low carbon DG planning is presented. The chapter explores various incentive schemes such as Emission Offset Incentive (EOI) and Generation Based Incentive (GBI) for renewable DG planning. The chapter also presents a hybrid optimization technique based on integration of IHS and TLBO.

Chapter 7: In this chapter, a MINLP based formulation for long term DG planning is presented. A comprehensive multi-period, multi-year formulation for cost benefit analysis is presented. Generation planning with both DG and capacitor is also explored. The proposed methodology provides the optimal DG in terms of number of units, optimal locations, and size for each load level and planning year.

8.4 Future Research Work

Research and development is an ongoing process. Each end of the research work opens many more avenues for future research. As a result, followings are the research ideas that may be explored further as the future scope of the presented work.

1. Optimal DG placement problem broadly considers constant power load, in radial distribution system. This problem can be extended further to incorporate voltage dependent loads and weakly meshed distribution systems. Simultaneous placement of multiple DGs with voltage stability index for adequate DG penetration can be explored.
2. A comprehensive distributed generation planning model with network reconfiguration, renewable DGs, capacitors, battery energy storage (BES), and plug in electric vehicle (PEV) can be considered for more realistic planning schemes. Optimal DG placement in coordination with FACT devices and switched capacitor can also be explored.
3. A formulation for Optimal DG planning with reliability and congestion management can be explored to rejoice accurate DG benefits. Optimal DG planning in smart grid with techno-economic and environmental criterion may be explored.

All the issues addressed in the presented work are relevant to the modern power system. They will continue to attract the researchers to explore them further.

LIST OF PUBLICATIONS

Based on the research work carried out, following papers have been accepted/ publised/ communicated in journals/ conferences.

1. Sandeep Kaur, Ganesh Balu Kumbhar, and J. D. Sharma, “A MINLP technique for optimal placement of multiple DG units in distribution system”, *Int. J. Electrical Power and Energy Systems,*vol. 63, pp. 609-617, Dec. 2014.

2. Sandeep Kaur and Ganesh Balu Kumbhar, “Incentive driven distributed generation planning with renewable energy resources,” *Int. J. Advances in Electrical and Computer Engineering*, vol.14, pp. 21-28,2014.

3. Sandeep Kaur, G. B. Kumbhar, and J. D. Sharma, “Performance of Mixed integer Non-linear programming and Improved Harmony Search for optimal placement of DG units,” *In Proc. IEEE PES General Meeting*, 2014, Washington D. C, July 2014.

4. Sandeep Kaur, G. B. Kumbhar and J. D. Sharma, “Harmony Search and OPF Based hybrid approach for optimal placement of multiple DG units,” *In Proc. National Power System Conference*, NPSC-2014, IIT Guwahati, Dec. 2014.

5. Sandeep Kaur, Ganesh Balu Kumbhar, and J D Sharma, “A MINLP Technique for long term DG planning in distribution network,”*Int. J. Electrical Power and Energy Systems*, (under preparation)

6. Pawar Bandopant Bhimrao, Sandeep Kaur, and Ganesh Balu Kumbhar, “Dynamic DG planning with network reconfiguration and capacitor placement,” *Int. J. Electrical Power and Energy Systems*, (under preparation)

BIBLIOGRAPHY

[1] G. Rackliffe, "Guidelines for planning distributed generation systems," in Power Engineering Society Summer Meeting, 2000, vol. 3, pp. 1666-1667, 2000.

[2] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: a definition," *Electric Power Systems Research*, vol. 57, pp. 195-204, 2001.

[3] T. Ackermann and V. Knyazkin, "Interaction between distributed generation and the distribution network: operation aspects," in *Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES,* 2002, vol. 2, pp. 1357-1362, 2002.

[4] G. Pepermans, J. Driesen, D. Haeseldonckx, R. Belmans, and W. D'haeseleer, "Distributed generation: definition, benefits and issues," *Energy Policy,* vol. 33, issue 6, pp. 787-798, 2005.

[5] W. El-Khattam and M. M. A. Salama, "Distribution system planning using distributed generation," in *Electrical and Computer Engineering, IEEE CCECE 2003*, vol. 1, pp. 579-582, 2003.

[6] A. Keane, L. F. Ochoa, C. L. T. Borges, G. W. Ault, A. D. Alarcon-Rodriguez, R. Currie, F. Pilo, C. Dent, and G. P. Harrison, "State-of-the-Arttechniques and challenges ahead for distributed generation planning and optimization," *Power Systems, IEEE Transactions on,* vol. 28, no. 2, pp. 1493-1502, 2013.

[7] P. S. Georgilakis and N. D. Hatziargyriou, "Optimal distributed generation placement in power distribution networks: models, methods, and future research," *Power Systems, IEEE Transactions on,* vol. 28, no. 3, pp. 3420-3428, 2013.

[8] Ministry of Non conventional Energy Sources, April 2015. [online] Available: http://www.mnre.gov.in/.

[9] Ministry of Power, Government of India, July 2015. [online] Available from: http://www.powermin.nic.in/.

[10] W. Caisheng and M. H. Nehrir, "Analytical approaches for optimal placement of distributed generation sources in power systems," *Power Systems, IEEE Transactions on,* vol. 19, no. 4, pp. 2068-2076, 2004.

[11] T. Gozel, M. H. Hocaoglu, U. Eminoglu, and A. Balikci, "Optimal placement and sizing of distributed generation on radial feeder with different static load models," in *Future Power Systems, 2005 International Conference on*, pp. 2-6, 2005.

[12] H. Hedayati, S. A. Nabaviniaki, and A. Akbarimajd, "A method for placement of DG units in distribution networks," *Power Delivery, IEEE Transactions on,* vol. 23, no. 3, pp. 1620-1628, 2008.

[13] M. A. Kashem, A. D. T. Le, M. Negnevitsky, and G. Ledwich, "Distributed generation for minimization of power losses in distribution systems," in *Power Engineering Society General Meeting*, pp. 8, 2006.

[14] S. Ghosh, S. P. Ghoshal, and S. Ghosh, "Optimal sizing and placement of distributed generation in a network system," *International Journal of Electrical Power & Energy Systems,* vol. 32, pp. 849-856, 2010.

[15] N. Acharya, P. Mahat, and N. Mithulananthan, "An analytical approach for DG allocation in primary distribution network," *International Journal of Electrical Power & Energy Systems,* vol. 28, pp. 669-678, 2006.

[16] A. Kazemi and M. Sadeghi, "Sitting and sizing of distributed generation for loss reduction," in *Power and Energy Engineering Conference. APPEEC*, pp. 1-4, 2009.

[17] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, "Analytical expressions for DG allocation in primary distribution networks," *Energy Conversion, IEEE Transactions on,* vol. 25, no. 3, pp. 814-820, 2010.

[18] D. Q. Hung and N. Mithulananthan, "Multiple distributed generator placement in primary distribution networks for loss reduction," *Industrial Electronics, IEEE Transactions on,* vol. 60, no. 4, pp. 1700-1708, 2013.

[19] S. Elsaiah, M. Benidris, and J. Mitra, "Analytical approach for placement and sizing of distributed generation on distribution systems," *Generation, Transmission & Distribution, IET,* vol. 8, no. 6, pp. 1039-1049, 2014.

[20] R. Viral and D. K. Khatod, "An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization," *International Journal of Electrical Power & Energy Systems,* vol. 67, pp. 191-201, 2015.

[21] M. F. AlHajri, M. R. AlRashidi, and M. E. El-Hawary, "Improved sequential quadratic programming approach for optimal distribution generation deployments via stability and sensitivity analyses," *Electric Power Components and Systems,* vol. 38, pp. 1595-1614, 2010.

[22] S. Kaur, G. Kumbhar, and J. Sharma, "A MINLP technique for optimal placement of multiple DG units in distribution systems," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 609-617, 2014.

[23] R. K. Singh and S. K. Goswami, "Optimum siting and sizing of distributed generations in radial and networked systems," *Electric Power Components and Systems,* vol. 37, pp. 127-145, 2009.

[24] T. N. Shukla, S. P. Singh, V. Srinivasarao, and K. B. Naik, "Optimal sizing of distributed generation placed on radial distribution systems," *Electric Power Components and Systems,* vol. 38, pp. 260-274, 2010.

[25] T. N. Shukla, S. P. Singh and K. B. Naik,"Allocation of optimal distributed generation using GA for minimum system losses in radial distribution networks", *Int. J. of Engineering, Science and Technology*, vol. 2, No. 3, pp. 94-106, 2010.

[26] K. D. Mistry and R. Roy, "Enhancement of loading capacity of distribution system through distributed generator placement considering techno-economic benefits with load growth," *International Journal of Electrical Power & Energy Systems,* vol. 54, pp. 505-515, 2014.

[27] M. R. AlRashidi and M. F. AlHajri, "Optimal planning of multiple distributed generation sources in distribution networks: A new approach," *Energy Conversion and Management,* vol. 52, pp. 3301-3308, 2011.

[28] N. Jain, S. N. Singh, and S. C. Srivastava, “Meta-heuristic approach for distributed generation planning in electricity market paradigm,” *IEEE Power and Energy Society General Meeting,* 2012.

[29] N. Jain, S. N. Singh, and S. C. Srivastava, "A generalized approach for DG planning and viability analysis under market scenario," *Industrial Electronics, IEEE Transactions on,* vol. 60, no. 11, pp. 5075-5085, 2013.

[30] S. Kansal, V. Kumar, and B. Tyagi, "Optimal placement of different type of DG sources in distribution networks," *International Journal of Electrical Power & Energy Systems,* vol. 53, pp. 752-760, 2013.

[31] N. Jain, S. N. Singh, and S. C. Srivastava, "Particle swarm optimization based method for optimal siting and sizing of multiple distributed generators," in *16th National Power System Conference, Univ. College of Engg. Osmania University, Hyderabad*, 15-17 December, 2010.

[32] F. S. Abu-Mouti and M. E. El-Hawary, "Optimal distributed generation allocation and sizing in distribution systems via Artificial Bee Colony algorithm," *Power Delivery, IEEE Transactions on,* vol. 26, no. 4, pp. 2090-2101, 2011.

[33] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, "Analytical strategies for renewable distributed generation integration considering energy loss minimization," *Applied Energy,* vol. 105, pp. 75-85, 2013.

[34] D. Q. Hung, N. Mithulananthan, and K. Y. Lee, "Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 179-186, 2014.

[35] L. F. Ochoa and G. P. Harrison, "Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation," *Power Systems, IEEE Transactions on,* vol. 26, no. 1, pp. 198-205, 2011.

[36] Y. M. Atwa, E. F. El-Saadany, M. Salama, and R. Seethapathy, "Distribution system loss minimization using optimal DG mix," in *Power & Energy Society General Meeting*, pp. 1-6, 2009.

[37] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, "Optimal renewable resources mix for distribution system energy loss minimization," *Power Systems, IEEE Transactions on,* vol. 25, no. 1, pp. 360-370, 2010.

[38] D. K. Khatod, V. Pant, and J. Sharma, "Evolutionary programming based optimal placement of renewable distributed generators," *Power Systems, IEEE Transactions on,* vol. 28, no.2, pp. 683-695, 2013.

[39] R. E. Brown and L. A. A. Freeman, "Analyzing the reliability impact of distributed generation," in *Power Engineering Society Summer Meeting, 2001,* vol.2, pp. 1013-1018, 2001.

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

[41] C. L. T. Borges and D. M. Falcão, "Optimal distributed generation allocation for reliability, losses, and voltage improvement," *International Journal of Electrical Power & Energy Systems,* vol. 28, pp. 413-420, 2006.

[42] R. S. Al Abri, E. F. El-Saadany, and Y. M. Atwa, "Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation," *Power Systems, IEEE Transactions on,* vol. 28, no.1, pp. 326-334, 2013.

[43] S. Sultana and P. K. Roy, "Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 534-545, 2014.

[44] R. Ishak, A. Mohamed, A. N. Abdalla, and M. Z. Che Wanik, "Optimal placement and sizing of distributed generators based on a novel MPSI index," *International Journal of Electrical Power & Energy Systems,* vol. 60, pp. 389-398, 2014.

[45] M. H. Moradi and M. Abedini, "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,* vol. 34, pp. 66-74, 2012.

[46] M. Z. C. Wanik, I. Erlich, and A. Mohamed, “Intelligent management of distributed generators reactive power for loss minimization and voltage control,” in *15th IEEE Mediterranean Electrotechnical Conference, (MELECON-2010)*, Valletta, pp. 685-690, April 2010.

[47] H. V. Pham, J. L. Rueda, and I. Erlich, "Online optimal control of reactive sources in wind power plants," *IEEE Transactions on Sustainable Energy*, vol. 5, issue 2, pp. 608-616, 2014.

[48] H. V. Pham, J. L. Rueda, and I. Erlich, "Probabilistic evaluation of voltage and reactive power control methods of wind generation in distrinution networks," *Renewable Power generation, IET,* vol. 9, issue 3, pp. 195-206, 2014.

[49] P. Agalgaonkar, S. V. Kulkarni, and S. A. Khaparde, “Evaluation of configuration plans for DGs in developing countries using interval based and DEA Based MADM techniques,” *IEEE Trans on Power Systems*, vol. 1, no.2, pp. 973-981, May 2006.

[50] J. M. López-Lezama, J. Contreras, and A. Padilha-Feltrin, "Location and contract pricing of distributed generation using a genetic algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 36, pp. 117-126, 2012.

[51] S. Porkar, P. Poure, A. Abbaspour-Tehrani-fard, and S. Saadate, "A novel optimal distribution system planning framework implementing distributed generation in a deregulated electricity market," *Electric Power Systems Research*, vol. 80, issue 7, pp. 828-837, 2010.

[52] W. El-khattam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, "Optimal investment planning for distributed generation in a competitive electricity market," *Power Systems, IEEE Transactions on*, vol. 19, no. 3, pp. 1674-1684, 2004.

[53] W. El-khattam, Y. G. Hegazy, and M. M. A. Salama, "An integrated distributed generation optimization model for distribution system planning," *Power Systems, IEEE Transactions on*, vol. 20, no. 2, pp. 1158-1165, 2005.

[54] A. Ameli, S. Bahrami, F. Khazaeli, and M. R. Haghifam, "A multiobjective Particle Swarm Optimization for sizing and placement of DGs from DG owner's and distribution company's viewpoints," *Power Delivery, IEEE Transactions on*, vol. 29, no. 4, pp. 1831-1840, 2014.

[55] A. Soroudi, M. Ehsan, R. Caire, and N. Hadjsaid, "Hybrid immune-genetic algorithm method for benefit maximisation of distribution network operators and distributed generation owners in a deregulated environment," *Generation, Transmission & Distribution, IET*, vol. 5, no. 9, pp. 961-972, 2011.

[56] R. K. Singh and S. K. Goswami, "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*, vol. 32, pp. 637-644, 2010.

[57] R. Ebrahimi, M. Ehsan, and H. Nouri, "A profit-centric strategy for distributed generation planning considering time varying voltage dependent load demand," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 168-178, 2013.

[58] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, "DG allocation for benefit maximization in distribution networks," *Power Systems, IEEE Transactions on*, vol. 28, no. 2, pp. 639-649, 2013.

[59] M. D. Hopkins, A. Pahwa, and T. Easton, "Intelligent dispatch for distributed renewable resources," *Smart Grid, IEEE Transactions on*, vol. 3, no. 2, pp. 1047-1054, June 2012.

[60] A. Kumar and W. Gao, "Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets," *Generation, Transmission & Distribution, IET,* vol. 4, pp. 281-298, 2010.

[61] A. Kumar and W. Gao, “New price area zonal based approach for optimal location of distributed generation in hybrid electricity markets,” *Electric Power Components and Systems*, vol. 37, no. 6, pp. 672-692, 2009.

[62] D. Gautam and N. Mithulananthan, "Locating Distributed Generator in the LMP-based Electricity Market for Social Welfare Maximization," *Electric Power Components and Systems*, vol. 35, pp. 489-503, 2007.

[63] A. C. Rueda-Medina, J. F. Franco, M. J. Rider, A. Padilha-Feltrin, and R. Romero, "A mixed-integer linear programming approach for optimal type, size and allocation of distributed generation in radial distribution systems," *Electric Power Systems Research,* vol. 97, pp. 133-143, 2013.

[64] M. Jalali, K. Zare, and M. T. Hagh, "A multi-stage MINLP-based model for sub-transmission system expansion planning considering the placement of DG units," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 8-16, 2014.

[65] L. Ke-yan, S. Wanxing, and L. Yuan, "Optimal allocation of distributed generation in distribution system considering time sequence data and low-carbon economy," in *PES General Meeting Conference & Exposition, 2014* , pp. 1-5, 2014.

[66] M. Haghifam, H. Falaghi, and O. P. Malik, "Risk-based distributed generation placement," *Generation, Transmission & Distribution, IET,* vol. 2, pp. 252-260, 2008.

[67] A. Zangeneh, S. Jadid, and A. Rahimi-Kian, "Promotion strategy of clean technologies in distributed generation expansion planning," *Renewable Energy,* vol. 34, issue 12, pp. 2765-2773, 2009.

[68] T. Niknam, S. I. Taheri, J. Aghaei, S. Tabatabaei, and M. Nayeripour, "A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources," *Applied Energy,* vol. 88, pp. 4817-4830, 2011.

[69] A. Soroudi, M. Ehsan, and H. Zareipour, "A practical eco-environmental distribution network planning model including fuel cells and non-renewable distributed energy resources," *Renewable Energy,* vol. 36, pp. 179-188, 2011.

[70] A. Zangeneh, S. Jadid, and A. Rahimi-Kian, "A fuzzy environmental-technical-economic model for distributed generation planning," *Energy,* vol. 36, pp. 3437-3445, 2011.

[71] H. Doagou-Mojarrad, G. B. Gharehpetian, H. Rastegar, and J. Olamaei, "Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm," *Energy,* vol. 54, pp. 129-138, 2013.

[72] M. Gomez-Gonzalez, A. López, and F. Jurado, "Optimization of distributed generation systems using a new discrete PSO and OPF," *Electric Power Systems Research,* vol. 84, pp. 174-180, 2012.

[73] D. T. C. Wang, L. F. Ochoa, and G. P. Harrison, "DG Impact on Investment Deferral: Network Planning and Security of Supply," *Power Systems, IEEE Transactions on,* vol. 25, pp. 1134-1141, 2010.

[74] A. Soroudi and M. Ehsan, "A distribution network expansion planning model considering distributed generation options and techo-economical issues," *Energy,* vol. 35, pp. 3364-3374, 2010.

[75] V. Vahidinasab, "Optimal distributed energy resources planning in a competitive electricity market: Multiobjective optimization and probabilistic design," *Renewable Energy,* vol. 66, pp. 354-363, 2014.

[76] A. Zidan, M. F. Shaaban, and E. F. El-Saadany, "Long-term multi-objective distribution network planning by DG allocation and feeders' reconfiguration," *Electric Power Systems Research,* vol. 105, pp. 95-104, 2013.

[77] J. E. Mendoza, M. E. López, S. C. Fingerhuth, H. E. Peña, and C. A. Salinas, "Low voltage distribution planning considering micro distributed generation," *Electric Power Systems Research,* vol. 103, pp. 233-240, 2013.

[78] Z. Kai, A.P.Agalgaonkar,K.M. Muttaqi, and S.Perera, " Distribution system planning with incorporating DG reactive capability and system uncertainties,"*IEEE Transactions on Sustainable Energy*, vol. 3, no. 1, pp. 112-23, 2012.

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

[80] K. Nekooei, M. M. Farsangi, H. Nezamabadi-pour, and K. Y. Lee, "An improved multi-objective Harmony Search for optimal placement of DGs in distribution systems," *Smart Grid, IEEE Transactions on*, vol. 4, no. 1, pp. 557-567, 2013.

[81] H. L. Willis, "Analytical methods and rules of thumb for modeling DG-distribution interaction," in *Power Engineering Society Summer Meeting, IEEE*, vol. 3, pp. 1643-1644, 2000.

[82] F. S. Abu-Mouti and M. E. El-hawary, "Heuristic curve-fitted technique for distributed generation optimisation in radial distribution feeder systems," *Generation, Transmission & Distribution, IET*, vol. 5, no.2, pp. 172-180, 2011.

[83] K. M. Muttaqi, A. D. T. Le, M. Negnevitsky, and G. Ledwich, "An algebraic approach for determination of DG parameters to support voltage profiles in radial distribution networks," *Smart Grid, IEEE Transactions on*, vol. 5, no.3, pp. 1351-1360, 2014.

[84] A. Keane and M. O'Malley, "Optimal allocation of embedded generation on distribution networks," *Power Systems, IEEE Transactions on*, vol. 20, no.3, pp. 1640-1646, 2005.

[85] A. A. Abou El-Ela, S. M. Allam, and M. M. Shatla, "Maximal optimal benefits of distributed generation using genetic algorithms," *Electric Power Systems Research*, vol. 80, pp. 869-877, 2010.

[86] A. Keane and M. O'Malley, "Optimal utilization of distribution networks for energy harvesting," *Power Systems, IEEE Transactions on*, vol. 22, no. 1, pp. 467-475, 2007.

[87] Z. Wenjuan, L. Fangxing, and L. M. Tolbert, "Review of reactive power planning: objectives, constraints, and algorithms," *Power Systems, IEEE Transactions on*, vol. 22, no. 4, pp. 2177-2186, 2007.

[88] S. Sundhararajan, A. Pahwa, "Optimal selection of capacitors for radial distribution systems using a genetic algorithm," *Power Systems, IEEE Transactions on*, vol. 9, no. 3, pp. 1499-1507, Aug 1994.

[89] D. Singh and K. S. Verma, "Multiobjective optimization for DG planning with load models, "*Power Systems, IEEE Transactions on*, vol. 24, no. 1, pp. 427-436, 2009.

[90] T. Wen Shan, M. Y. Hassan, H. A. Rahman, M. P. Abdullah, and F. Hussin, "Multi-distributed generation planning using hybrid particle swarm optimisation- gravitational search algorithm including voltage rise issue," *Generation, Transmission & Distribution, IET*, vol. 7, no. 9, pp. 929-942, 2013.

[91] A. M. El-Zonkoly, "Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation," *Generation, Transmission & Distribution, IET*, vol. 5, no. 7, pp. 760-771, 2011.

[92] A. El-Fergany, "Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 1197-1205, 2015.

[93] A. M. Imran and M. Kowsalya, "Optimal distributed generation and capacitor placement in power distribution networks for power loss minimization," in *Advances in Electrical Engineering (ICAEE)*, pp. 1-6, 2014.

[94] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation," *Power Systems, IEEE Transactions on*, vol. 28, no. 1, pp. 317-325, 2013.

[95] S. Kaur, G. B. Kumbhar, and J. Sharma, "Performance of Mixed Integer Non-linear Programming and Improved Harmony Search for optimal placement of DG units," in *IEEEPES General Meeting*, Washington D.C., 2014.

[96] K. Vinothkumar and M. P. Selvan, "Distributed generation planning: A new approach based on goal programming," *Electric Power Components and Systems*, vol. 40, pp. 497-512, 2012.

[97] G. P. Harrison, A. Piccolo, P. Siano, and A. R. Wallace, "Hybrid GA and OPF evaluation of network capacity for distributed generation connections," *Electric Power Systems Research*, vol. 78, pp. 392-398, 2008.

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

[99] M. H. Moradi and M. Abedini, "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*, vol. 34, pp. 66-74, 2012.

[100] K. Kyu-Ho, L. Yu-Jeong, R. Sang-Bong, L. Sang-Kuen, and Y. Seok-Ku, "Dispersed generator placement using fuzzy-GA in distribution systems," in *Power Engineering Society Summer Meeting,* vol. 3, pp. 1148-1153, 2002.

[101] K. Vinothkumar and M. P. Selvan, "Fuzzy embedded genetic algorithm method for distributed generation planning," *Electric Power Components and Systems,* vol. 39, pp. 346-366, 2011.

[102] T. Gonen and B. L. Foote, "Distribution-system planning using mixed-integer programming," *Generation, Transmission and Distribution, IEE Proceedings C,* vol. 128, no. 2, pp. 70-79, 1981.

[103] N. Ponnavaikko, K. S. P. Rao, and S. S. Venkata, "Distribution system planning through a Quadratic Mixed Integer Programming approach," *Power Delivery, IEEE Transactions on,* vol. 2, no. 4, pp. 1157-1163, 1987.

[104] S. P. Singh, G. S. Raju, G. K. Rao, and M. Afsari, "A heuristic method for feeder reconfiguration and service restoration and distribution network, *Int. Journal of Electrical power and Energy System* vol. 31, no. 9, pp. 309-314, 2009.

[105] J. D. Foster, A. M. Berry, N. Boland, and H. Waterer, "Comparison of Mixed-Integer Programming and genetic algorithm methods for distributed generation planning," *Power Systems, IEEE Transactions on*, vol. 29, no. 2, pp. 833-843, 2014.

[106] A. R. Malekpour, T. Niknam, A. Pahwa, and A. K. Fard, "Multi-objective stochastic distribution feeder reconfiguration in systems with wind power generators and fuel cells using the point estimate method," *Power Systems, IEEE Transactions on* , vol. 28, no. 2, pp.1483-1492, May 2013.

[107] M. Varadarajan, K. S. Swarup, "Solving multi-objective optimal power flow using differential evolution," *Generation, Transmission & Distribution, IET* , vol. 2, no. 5, pp.720-730, 2008.

[108] M. P. Selvan, K. S. Swarup, "Development of power flow software using design patterns," *Power Systems, IEEE Transactions on*, vol. 21, no. 2, pp. 611-618, 2006.

[109] R. Abhyankar, S. A. Soman, and S. A. Khaparde, “Optimization approach to real power tracing: an application to transmission fixed cost allocation,” Power Systems, IEEE Transaction, vol. 21, no. 3, pp.1350-1361, 2006.

[110] S. Sivasubramani, K. S. Swarup, "Sequential quadratic programming based differential evolution algorithm for optimal power flow problem," *Generation, Transmission & Distribution, IET* , vol. 5, no. 11, pp. 1149-1154, Nov. 2011.

[111] K. S. Lee, and Z. W. Geem, "A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice,"*Computer Methods in Applied Mechanics and Engineering*, vol. 194, pp. 3902-3933, 2005

[112] D. Manjarres, I. Landa-Torres, S. Gil-Lopez, J. Del Ser, M. N. Bilbao, S. Salcedo-Sanz, and Z. W. Geem., "A survey on applications of the harmony search algorithm, "*Engineering Applications of Artificial Intelligence*, vol. 26, issue 8, pp. 1818-1831.

[113] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems, "*Applied Mathematics and Computation*, vol. 188, pp. 1567-1579, 2007.

[114] R. V. Rao,V. J. Savsani, D. P. Vakharia, "Teaching–Learning-Based Optimization: An optimization method for continuous non-linear large scale problems,"*Information Sciences*, vol. 183, pp.1-15, 2012.

[115] R. V. Rao, V. J. S. Savsani, and J. Balic, "Teaching–learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems, "*Engineering Optimization*, vol. 44, pp.1447-1462, 2012.

[116] V. V. S. N Murthy, and A. Kumar," Comparison of optimal DG allocation methods in radial distribution systems based on sensitivity approaches, "*Int J Electr Power Energy Syst*vol. 53, pp. 450-467, 2013.

[117] S. Leyffer, "Integrating SQP and BAB method for mixed integer programming,"*Computational Optimization and Applications*, vol. 18, no. 3, pp. 295-309, 2001.

[118] R. Fourer, D. Gay, and B. Kernighan, AMPL: A Modeling Language for Mathematical Programming," 2nd ed. Pacific Grove, CA, USA: Brooks/Cole, 2003.

[119] S. Das, A. Mukhopadhyay, A. Roy, A. Abraham, and B. K.Panigrahi, "Exploratory power of the Harmony Search algorithm: analysis and improvements for global numerical optimization. systems, " Man, and Cybernetics, Part B: IEEE Transactions on Cybernetics , vol. 41, pp. 89-106, 2011.

[120] Shouheng Tuo L. Y., and Tao Zhou., "An Improved harmony search based on teaching-learning strategy for unconstrained optimization problems, "*Hindawi* 2013;http://dx.doi.org/10.1155/2013/413565

[121] M. E. De Oliveira, A. Padilha-Feltrin, and F. J. Candian, "Investigation of the relationship between load and loss factors for a Brazilian electric utility, " In: *IEEE/PES Transmission & Distribution Conference and Exposition: Latin America*, TDC '06, 2006.

[122] Pub. L. No. 53/10/2011-WE, Sep 2013, Ministry of New and Renewable Energy,“Extension of the Scheme for continuation of Generation Based Incentive for Grid interactive Wind Power Projects for 12th Plan period,”.

[123] Biomass for power generation, International Renewable Energy Agency, IRENA, [Online]. Available: www.irena.org/.../RE_Technologies_Cost_Analysis-BIOMASS.pdf/.

[124] K. Zou, A. P. Agalgaonkar, S. Perera, and K. Muttaqi, "Optimization of distributed generation units and shunt capacitors for economic operation of distribution systems," in *Australasian Universities Power Engineering Conference*, AUPEC 2008.

[125] P. Bonami and J. Lee, *BONMIN User’s Manual*, Jul. 2011.

[126] M. E. Baran, and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing, "*IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401-1407, 1989.

APPENDIX - A

A.1 IEEE 33-Bus Distribution System

The schematic diagram of a 12.66 kV, 33-bus distribution test system is illustrated in Figure A.1. The relevant data for this test system have been acquired from [126] and is given in Table A.1.

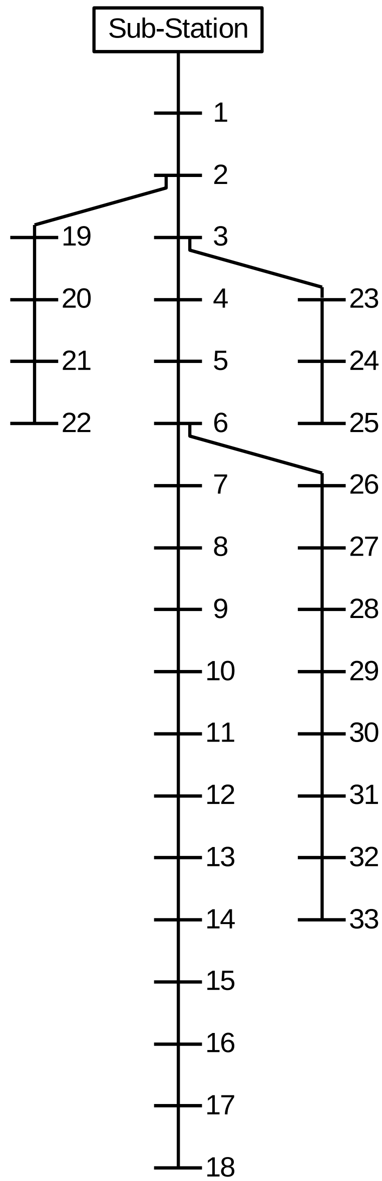

Figure A.1 Single line diagram of 12.66 kV, 33-bus distribution system

Table A.1 Branch data and bus data for 12.66 kV, 33-bus distribution system

Branch Number	Bus Number		Branch Parameters		Load at Receiving End Bus	
	Sending End	Receiving End	Resistance (ohm)	Reactance (ohm)	Real (kW)	Reactive (kVAR)
1	1	2	0.0922	0.0470	0.0	0.0
2	2	3	0.4930	0.2511	100.0	60.0
3	3	4	0.3660	0.1864	90.0	40.0
4	4	5	0.3811	0.1941	120.0	80.0
5	5	6	0.8190	0.7070	60.0	30.0
6	6	7	0.1872	0.6188	60.0	20.0
7	7	8	1.7114	0.2351	200.0	100.0
8	8	9	1.0300	0.7400	200.0	100.0
9	9	10	1.0400	0.7400	60.0	20.0
10	10	11	0.1966	0.0650	60.0	20.0
11	11	12	0.3744	0.1238	45.0	30.0
12	12	13	1.4680	1.1550	60.0	35.0
13	13	14	0.5416	0.7129	60.0	35.0
14	14	15	0.5910	0.5260	120.0	80.0
15	15	16	0.7463	0.5450	60.0	10.0
16	16	17	1.2890	1.7210	60.0	20.0
17	17	18	0.7320	0.5740	60.0	20.0
18	2	19	0.1640	0.1565	90.0	40.0
19	19	20	1.5042	1.3554	90.0	40.0
20	20	21	0.4095	0.4784	90.0	40.0
21	21	22	0.7089	0.9373	90.0	40.0
22	3	23	0.4512	0.3083	90.0	40.0
23	23	24	0.8980	0.7091	90.0	50.0
24	24	25	0.8960	0.7011	420.0	200.0
25	6	26	0.2030	0.1034	420.0	200.0
26	26	27	0.2842	0.1447	60.0	25.0
27	27	28	1.0590	0.9337	60.0	25.0
28	28	29	0.8042	0.7006	60.0	20.0
29	29	30	0.5075	0.2585	120.0	70.0
30	30	31	0.9744	0.9630	200.0	600.0
31	31	32	0.3105	0.3619	150.0	70.0
32	32	33	0.3410	0.5302	210.0	100.0

A.2 IEEE 69-Bus Distribution System

The single line diagram of a 12.66 kV, 69-bus distribution test system is shown in Figure A.2. The necessary data for 69-bus distribution test system have been obtained from [29] and is presented in Table A.2.

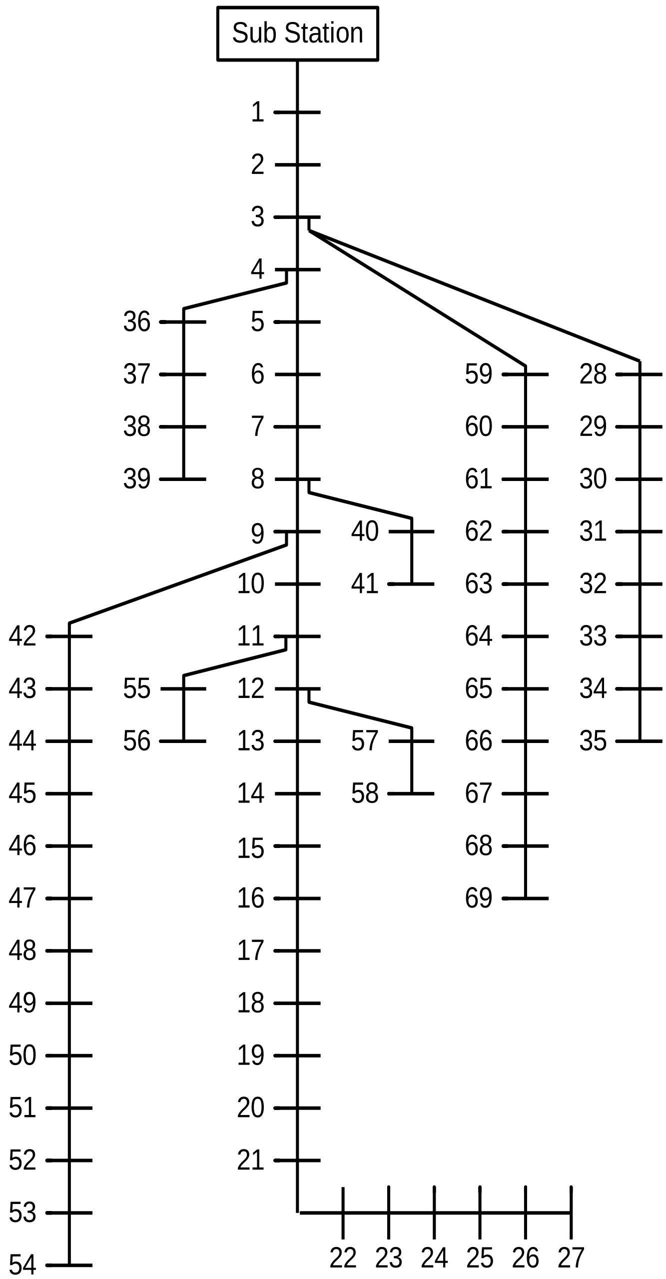

Figure A.2 Single line diagram of 12.66 kV, 69-bus distribution system

Table A.2 Branch data and bus data for 12.66 kV, 69-bus distribution system

Branch Number	Bus Number		Branch Parameters		Load at Receiving End Bus	
	Sending End	Receiving End	Resistance (ohm)	Reactance (ohm)	Real (kW)	Reactive (kVAR)
1	1	2	0.0005	0.0012	0.0000	0.0000
2	2	3	0.0005	0.0012	0.0000	0.0000
3	3	4	0.0015	0.0036	0.0000	0.0000
4	4	5	0.0251	0.0294	0.0000	0.0000
5	5	6	0.3660	0.1864	2.600	2.200
6	6	7	0.3811	0.1941	40.40	30.00
7	7	8	0.0922	0.0470	75.00	54.00
8	8	9	0.0493	0.0251	30.00	22.000
9	9	10	0.8190	0.2707	28.00	19.00
10	10	11	0.1872	0.0619	145.00	104.00
11	11	12	0.7114	0.2351	145.00	104.000
12	12	13	1.0300	0.3400	8.00	5.500
13	13	14	1.0440	0.3450	8.00	5.500
14	14	15	1.0580	0.3496	0.0000	0.0000
15	15	16	0.1966	0.0650	45.50	30.00
16	16	17	0.3744	0.1238	60.00	35.00
17	17	18	0.0047	0.0016	60.00	35.000
18	18	19	0.3276	0.1083	0.0000	0.0000
19	19	20	0.2106	0.0696	1.000	0.600
20	20	21	0.3416	0.1129	114.00	81.00
21	21	22	0.0140	0.0046	5.300	3.500
22	22	23	0.1591	0.0526	0.0000	0.0000
23	23	24	0.3463	0.1145	28.00	20.00
24	24	25	0.7488	0.2475	0.0000	0.0000
25	25	26	0.3089	0.1021	14.00	10.00
26	26	27	0.1732	0.0572	14.000	10.00
27	3	28	0.0044	0.0108	26.000	18.600
28	28	29	0.0640	0.1565	26.00	18.600
29	29	30	0.3978	0.1315	0.0000	0.0000
30	30	31	0.0702	0.0232	0.0000	0.0000
31	31	32	0.3510	0.1160	0.0000	0.0000
32	32	33	0.8390	0.2816	14.000	10.00
33	33	34	1.7080	0.5646	19.50	14.00
34	34	35	1.4740	0.4873	6.0000	4.000
35	4	36	0.0034	0.0084	0.0000	0.0000

36	36	37	0.0851	0.2083	79.00	56.40
37	37	38	0.2898	0.7091	384.70	274.50
38	38	39	0.0822	0.2011	384.70	274.50
39	8	40	0.0928	0.0473	40.50	28.30
40	40	41	0.3319	0.1114	3.600	2.700
41	9	42	0.1740	0.0886	4.35	3.500
42	42	43	0.2030	0.1034	26.40	19.00
43	43	44	0.2842	0.1447	24.00	17.20
44	44	45	0.2813	0.1433	0.0000	0.0000
45	45	46	1.5900	0.5337	0.0000	0.0000
46	46	47	0.7837	0.2630	0.0000	0.0000
47	47	48	0.3042	0.1006	100.0	72.00
48	48	49	0.3861	0.1172	0.0000	0.0000
49	49	50	0.5075	0.2585	1244.00	888.00
50	50	51	0.0974	0.0496	32.000	23.00
51	51	52	0.1450	0.0738	0.0000	0.0000
52	52	53	0.7105	0.3619	227.00	162.00
53	53	54	1.0410	0.5302	59.000	42.000
54	11	55	0.2012	0.0611	18.00	13.00
55	55	56	0.0047	0.0014	18.000	13.00
56	12	57	0.7394	0.2444	28.00	20.00
57	57	58	0.0047	0.0016	28.00	20.00
58	3	59	0.0044	0.0108	26.00	18.55
59	59	60	0.0640	0.1565	26.00	18.55
60	60	61	0.1053	0.1230	0.0000	0.0000
61	61	62	0.0304	0.0355	24.00	17.00
62	62	63	0.0018	0.0021	24.00	17.00
63	63	64	0.7283	0.8509	1.20	1.00
64	64	65	0.3100	0.3623	0.0000	0.0000
65	65	66	0.0410	0.0478	6.00	4.30
66	66	67	0.0092	0.0116	0.0000	0.0000
67	67	68	0.1089	0.1373	39.22	26.30
68	68	69	0.0009	0.0012	39.22	26.30