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Title:

Optimal Placement and Sizing of Distributed Generators in Bechar's Electric Distribution Network

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Abstract

Optimal allocation of distributed generators (DG) in the distribution system have a significant influence on the network performance. An optimization based on DG allocation and sizing for minimizing active power loss and annual operation cost is applied to Bechar's distribution network. Meta-heuristic techniques are proposed to solve the optimization problem with the aim of improving the technical and economical benefits. The distribution system power flow is solved using the OpenDSS software, and the optimization method is created in Matlab. Grey Wolf Optimizer (GWO) shows a better and faster convergence compared to Genetic Algorithm (GA). The optimization aims to place and size distributed energy resources (DERs)(i.e., gas turbines, Photovoltaic systems) over the nine (9) electric substations of Bechar's electric network to minimize active power loss and reduce annual energy cost along with saving fuel resources. In order to investigate the impact of integrating DGs, a simulation of the optimization results is performed. Active power loss is reduced along with reducing dependency on the grid where the annual saving in fossil fuel is increased.

Acknowledgment

Praise to God, the supreme for leading us during all these years of our study path, and for giving us the courage and strength to accomplish this project successfully despite all the difficulties, Alhamdulilah.

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Dedication

I dedicate this work to the soul of my father, whom i wish he was here to see his daughter success. To my beloved mother, my sisters Ahlem, Lina, Abla, my brother Islam, and Hicham. I would not achieve this work without your sacrifices,love and support, Thank you.

To my best friend Nacira ABDOUNE, my partner Kenza, and all my friends, Taima, Amine, Abderraouf and Ryad. Thanks for being always there for me.

To all those who believed in me Thank you.

Assia Bougrid

Dedication

My dear parents, for all their sacrifices, love, tenderness, support and prayers throughout my studies,

My beloved brother and sister, Lina & Yacine,

My partner Assia, My friends, Nora, Taima, Amine, Moha, Yanis, Raouf…

who have always been there for me, and to whom I wish more success,

All the people in my life who touch my heart,

I dedicate this work to you all. May this accomplishment meet your long-held wishes and reflect your endless support.

Kenza Benslimane

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List of Abbreviations

ABC Artificial Bee Colony

ACO Ant Colony Optimization

CCGT Combined Cycle Gas Turbine

DER Distribution Energy Resources

DG Distributed Generation

DLF Distribution Load Flow

EA Evolutionary Algorithm

FPI Fixed Point Iteration

GA Genetic Algorithm

GWO Grey Wolf Optimizer

HHF High Heating Factor

HRSG Heat Recovery System Generator

HS Harmony Search

LP Linear Programming

MILP Mixed Integer Linear Programming

NLP Non Linear Programming

NSGA Non-dominated Sorting Genetic Algorithm

OPENDSS OPEN Distribution System Simulator

OPF Optimal Power Flow

PC Power Conversion

PD Power Delivery

PIAT Pôle In Salah-Adrar- Timimoune

PV Photvoltaic

RE Renewable Energy

RIN Réseau Interconnecté National

RIS Réseau Isolé Sud

SPE Société de Production de l'Eléctricité

VSI Voltage Source Inverter

General Introduction

The significant increase in load demand and limitation of conventional energy sources result in several technical and environmental problems[1]; the inability of countries to satisfy this rise, the environmental pollution and global warming effects, high power loss and poor voltage profile. One strategy for addressing the significant increase in power consumption is to advocate the widespread use of distributed generation (DG), since it is of significant interest in operating it in parallel with a utility distribution system.

DGs refer to small generation units connected to distribution system providing many positive impacts such as reduction in power losses, improving voltage profile and network reliability[2]. High penetration of distributed energy resources (DER) into a power distribution network may result in operational conflicts. As a result, DG planning is required to assure the reliable, stable, and efficient operation of a power distribution system. Many research works have been carried out in the aim of optimally size and place DGs in distribution systems for minimizing different objectives e.g. losses, cost, etc, by using various optimization techniques such as analytical methods, classical methods and meta-heuristic methods.

The objective of our project is to perform a study about the location and size of distributed generators in Bechar's distribution system that assures the optimal performance at lowest cost. Ensuring maximum electrification of Bechar city, reducing fossil fuel consumption as well as line losses raised the need for integrating photovoltaic systems into the distribution network.

The application of PV system-based DG sources depends on time of the day and season of the year, therefore, yearly data are simulated in the optimization process taking into account the developed objective functions and constraints.
The ideal generation capacity of DG units and their optimal location for the stable, reliable, and efficient functioning of a distribution system are critical issues that need to be addressed in DG planning. Due to the complexity of this sort of optimization issue, we have selected optimization methods based on meta-heuristic approaches, particularly Genetic Algorithms and Grey Wolf Optimizer. It should be noted that all simulation results are developed under the software OpenDSS and Matlab, given the richness of their libraries containing all the models necessary for the analysis of this research work.

In order to answer all the problems mentioned above, this report is composed of four chapters as follows:

The first chapter presents the Algerian network and the different types of electricity production including renewable energies and assesses the potential of solar energy and its evolution . Besides, the concept of DGs and the impact of sizing and allocation in distribution systems are discussed.

The load flow analysis in distribution system is explained in the second chapter along with the power flow solution methods . Power flow calculations in OpenDSS will be illustrated.

Chapter three cites the optimization techniques and presents the mathematical formulation of the objective functions to optimize DG allocation and sizing problem.

Finally, the distribution network of Bechar city along with simulation data are demonstrated in the last chapter. The objective functions are formulated before performing the optimization. The simulation results are commented and illustrated. Recommendation and further work are concluded eventually.

Chapter 1

Algeria’s national Electric Network

1.1 Introduction

In recent decades, electric energy is recognized as a crucial element in a country development process. This has inspired researchers to continue thinking about innovative strategies for producing high-quality power while ensuring service continuity. Electricity can be generated from renewable power plants based on non-polluting and inexhaustible renewable energy sources available in all regions of the world, and often supplemented by other conventional sources of production or storage systems to overcome interruptions caused by the intermittent nature of renewable sources.

This chapter will examine the Algerian network and the different types of electricity production, the evolution of renewable energy resources around the world and in Algeria and finally, the impact of distributed generations on the distribution network and the influence of optimization process will be discussed.

1.2 Algerian National Network

The Algerian national network is managed by the National Electricity & Gas Company (SONELGAZ) where it consists mainly of three sectors; production, transportation and distribution system that ensures electrical energy satisfaction of costumers. The national network is composed of three main networks; the interconnected national network which is named by Sonelgaz as **(RIN)**, the pole **(PIAT)** which relates Adrar, In Salah and Timimoune, and the isolated southern networks **(RIS)**. These networks rely on the production of electric energy by means of conventional power plant managed by the Electric Production Society **(SPE)**. Renewable energy stations might reinforce these networks as part of the national renewable energy strategy, which began in 2013 with the establishment of the Renewable Energy Electricity Company (SKTM)[3].

1.3 Types of Electricity Production in Algeria

Electric production in Algeria relies significantly on natural gas, with a contribution of 96% to the installed capacity of 21,400 megawatts (MW) in 2019. Oil, solar, hydro and wind technologies represent 4% of the remaining power capacity[4]. Gas turbines, steam turbines, combined cycle gas turbines power plants are the different conventional power plants that are briefly explained in the following subsection.

1.3.1 Conventional Power Plants

1.3.1.1 Gas Turbine

Gas turbine is a type of turbine that uses variety of fuels such as natural gas and fuel oil for combustion; it is formed of three basic sections mounted on the same shaft as described in [5]

[6].

- **The compressor:** where the air is drawn and compressed causing an increase in the temperature which is then fed to the combustion chamber.
- **The combustion chamber:** the fuel is injected through ring of injectors where it is mixed with the compressed air then burned at extremely high temperature and pressure. The hot air-fuel mixture enters and expands through the blades in the turbine.
- **The turbine:** the blades of turbine spin at fast speed that drives the compressor to draw more pressurized air into the combustion chamber; at the same time they rotate the generator to produce electricity.

1.3.1.2 Steam Turbine:

Steam turbine operates by heating water to extremely high temperatures until it is transformed into steam using heat sources such as gas and oil. The thermal energy contained in the pressurized steam is converted into mechanical energy by expansion through the turbine. The expansion is done as the steam passes through the revolving blades of the turbine.

Turbines are constructed in sections to control the speed, direction and pressure of the steam where the pressure drops and cools down throughout the process. The stationary nozzle and the moving blade or bucket are the two fundamental design parts of a turbine. An electrical generator is joined with the rotational motion of the blades for the generation of electricity [7]

1.3.1.3 Combined Cycle:

The capability of a combined-cycle gas turbine (CCGT) to generate up to 50 times the amount of energy from the same amount of fuel as a conventional simple-cycle plant makes it the most prevalent combined-cycle plant.

Heat recovery steam generator (HRSG), steam turbine are the primary components of gas turbine with other additional equipment, in which the HRSG recovers and converts the high temperature exhaust gas released by the gas turbine into steam, which is then directed to a steam turbine to be converted into additional electricity [6] .

1.3.2 Non-conventional Power Plants

International Energy Agency (IEA) expect a raise of 53% in global energy consumption by 2030 [8] . This causes a critical concern on the energy security as their heavy reliance on fossil fuels that are non-renewable and will diminish in the near future. Thus, many countries have expressed interest on RES to satisfy their energy requirements and reduce gas emissions. Developed countries have released new policies and RE programs as well as enormous contributions to maintain high

peneteration of RE[9].
Renewable energies are exploited in different ways around the world. The ranges of renewable resources used include biomass, hydroelectricity, geothermal energy, wind energy and solar energy. Each of these renewable technologies have their advantages and disadvantages. Hydroelectric and geothermal energies are specific to the location of their primary energy, which limits their use. The development of biomass has implications for food production, because to produce this energy with a higher yield, it is necessary to occupy fertile land and consequently, agricultural production will be reduced and lead to significant deforestation. Wind turbines require regular maintenance because of the moving parts and are not considered aesthetically appealing. Solar energy has its drawbacks as well. However, photovoltaic panels require minimal maintenance, do not generate any noise and their cost is decreasing continuously. These sources of energy can be connected either to the electrical network or to supply an isolated site.

Fig 1.1 demonstrates the global energy mix in 2019, 72.7% the total global generation is supplied by fossil fuels,15.9% by Hydro-power, that represents the biggest part of the total global RE capacity followed by 5.9 % and 2.8 % of wind and solar, respectively, while bio-power contributes with 2.2% .

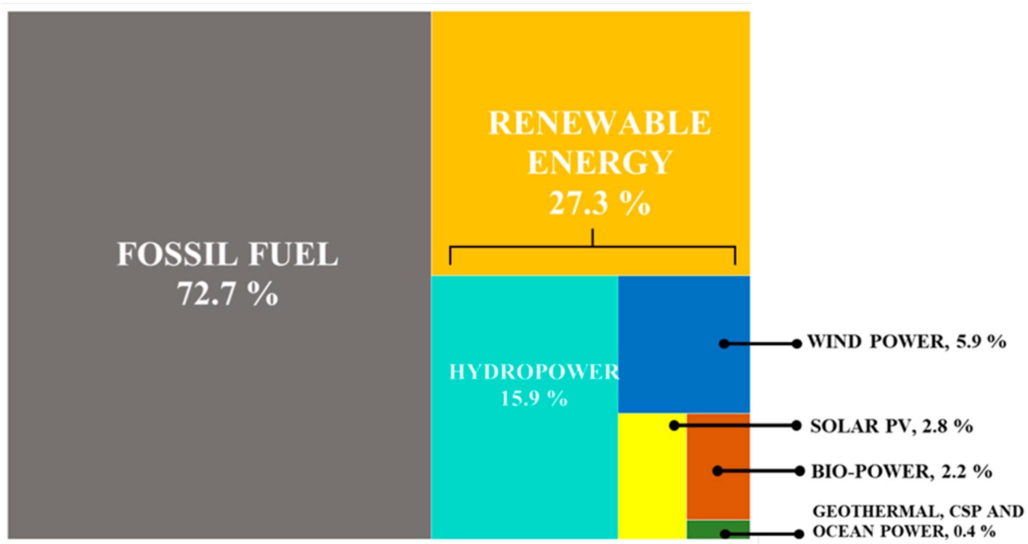


Figure 1.1: Global Energy Mix, 2019 [9]

1.3.3 Renewable Energy Options

It is a clean energy that is derived from natural resources such as solar, wind and water. The graphical location of Algeria offers several benefits for widespread usage of most promising renewable energy sources, such as hydro-power, wind, geothermal, biomass, hydroelectricity and solar energy. RE is commonly related strongly with sustainability that creates more socioeconomic stability and mitigates pollution as well as climate change compared to fossil fuels and nuclear power.

1.3.3.1 Solar Energy

Solar energy reaches the earth in various forms like heat and light. As this energy travels, majority of its portion is lost by scattering, reflection and absorption by clouds. The fact that infinite solar energy is available in nature with cost-free has led to various studies which disclosed that the total world's energy demand could be covered adequately[10].

The generation of electric power is realized by the photovoltaic generation using solar cells, which produce electricity from the absorption of the electromagnetic radiation coming from the sun without concern on the environmental impact. A tremendous radiation potential is received during the year over many countries. It has clearly been shown in Fig 1.2 the huge potential radiation that exists around the world. However, this energy is not well exploited.

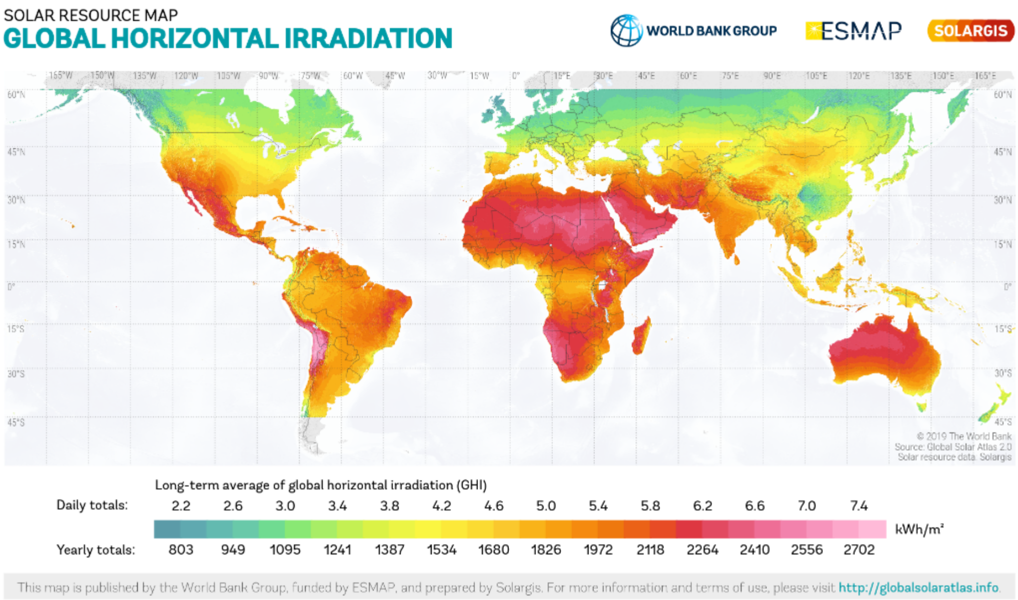


Figure 1.2: Maps of global horizontal irradiation (GHI) [11]

1.3.3.2 Wind Energy

Wind resource differs from region to another depending on the location and climate change during the four seasons of the year. In 2019, the overall world wind production reached 651 GW, that is 10.2 % increase over 2018[9]. The power generation is done by the conversion of the mechanical power coming from the wind into electricity using wind turbines. The aerodynamical construction of the wind turbine blades captures the wind energy and creates a rotational motion, which afterwards used to revolve the generator to produce electricity [12].

1.3.3.3 Hydropower

Hydroelectric power stations generate 19% of the world's electricity consumption at the present time [13] . Electricity is obtained by the conversion of the kinetic energy in the natural flow of moving water, where the elevation difference formed by a dam or diversion construction allows water to flow in on one side and out far below the other, the greater the water flow the more energy the hydropower plan can generate, mentioning that the water is only used not consumed or polluted.

1.4 Global Evolution of Solar Energy

Clean and steady energy supply is one of the crucial societal issues as a result of the fast augmentation of population. Therefore, the ideal solution for these crises is to pursue renewable energies as they are viable and environmentally safe. Among the different available renewable energies, solar energy is considered as the principle alternative resource where 1.81014 kW of solar energy is received on earth from 3.18023 kW released by the sun [10]. Fig 1.2 illustrates the raise of electricity generation from photovoltaic solar over the years, a peak generation of 678.99 GWh is reached in 2019 globally, in other words, 22% increase from 2018 to 2019 which clearly proves its prospective movement in meeting the global energy demand. China represents 32.69% of the total PV generation, followed by United States with 12%, Japan with 10% of the global PV generation[14]. Fig1.4 shows the enormous investments of 167.73 USD billion that are draped in many countries for the expansion of solar energy. An estimation is done by [15] showed that an increase of 13% by 2030 in solar PV generation which, in parallel, reduces gas emission up to three giga tonnes of CO2 per year.

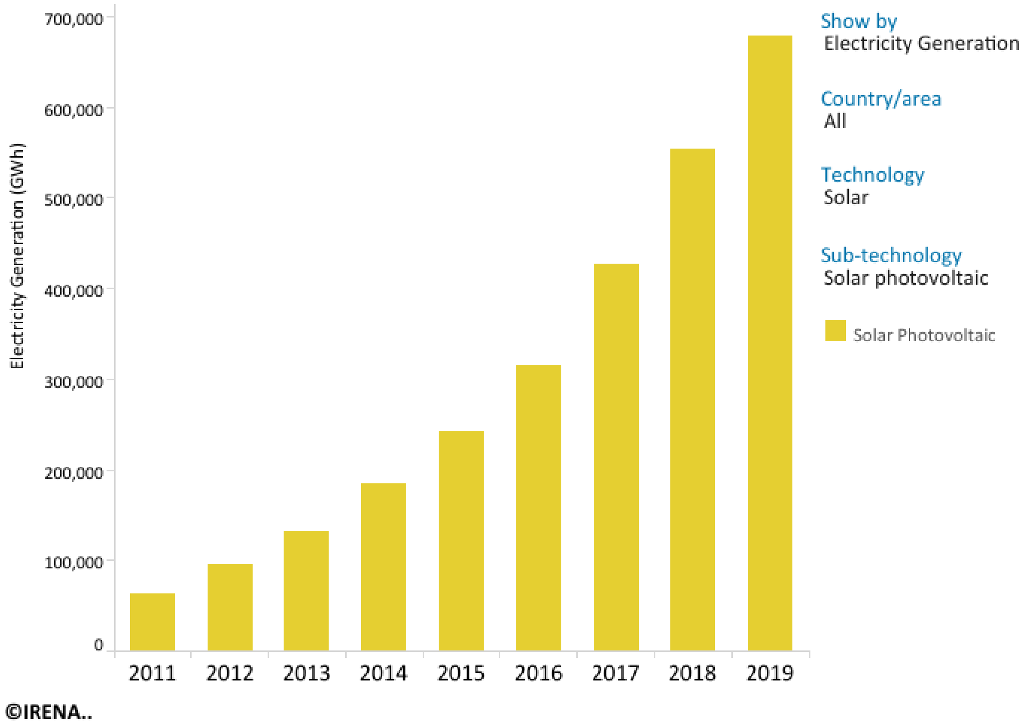


Figure 1.3: Total PV generation [16]

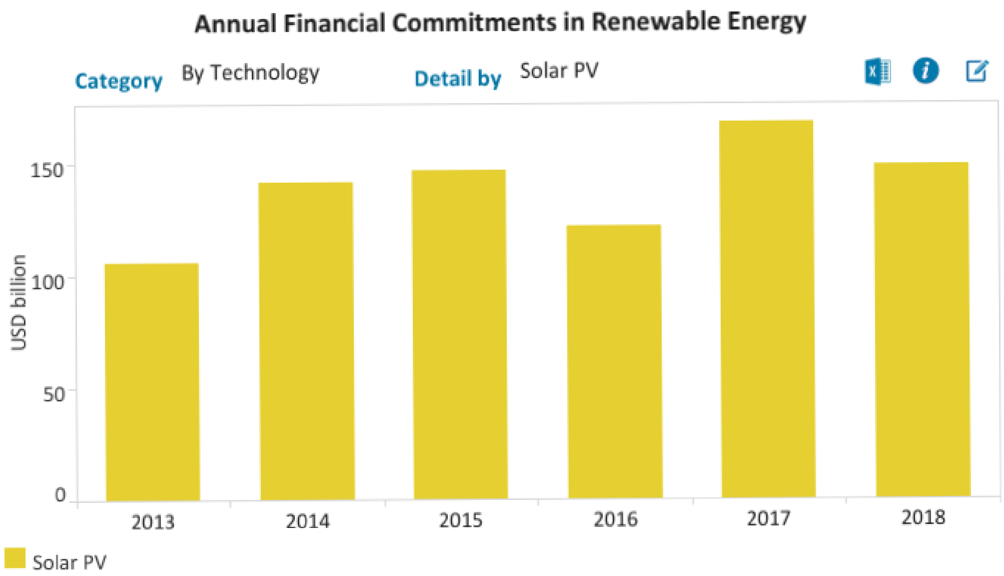


Figure 1.4: Annual Financial commitments in Solar PV [16]

1.4.1 Evolution of Solar Energy in Algeria

Algeria is among countries that fossil fuel possesses its power generation by more than 90 % of the total power. This situation has led to the extraction of large quantities of this essential source, which could be exported abroad and contribute to the enrichment of the country's financial resources. With the Russia-Ukraine crisis, Algeria might gain from the EU's energy policy change as it is the north African country biggest natural gas exporter. The Algerian government's main concern is to move out fuel dependency by relying on diversifying the economy to ensure steady and secure development.

Algeria has recently launched a renewable energy program under the flag "EnR" that aims to develop the exploitation of these renewable resources available practically throughout the country in order to increase the production capacity of electricity from various resources (wind, photovoltaic, solar thermal, biomass, and geothermal) where a target set to 22000 MW by 2030[17]. With a total solar energy potential of 169.440 $kw/m^2/year$, solar energy is a promising alternative energy source adapted by the Algerian government [9]. The installed solar capacity in Algeria is demonstrated in Fig 1.5 and has shown an increase up to 423 MW in 2021.

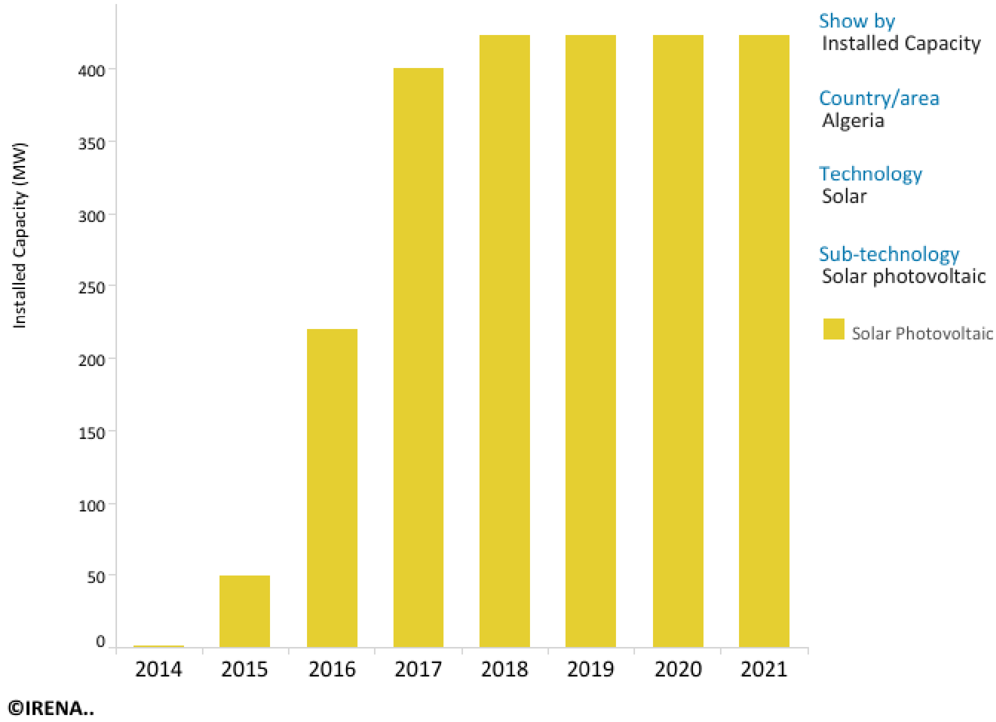


Figure 1.5: Installed Photovoltaic Capacity in Algeria [16]

1.5 Integration of Distributed Generation into the Distribution Network

Distributed generation is a new technology of supplying electricity with small capacity power generation at centralized power plants, with high efficiencies that may serve industrial sectors, military base ad hospitals during electricity outages. Also, electrifying remote areas to reduce transmission line losses and ensuring the load demand [18]. DG consists of distributed resources that generate electricity within distribution networks or at network customer sites [19] . When compared to the transmission system, the distribution system performs at low voltage and high currents, resulting in significant power loss and a poor voltage profile. Distribution losses are estimated to approximately 13% of total power generated. Introducing DGs into the distribution network is an excellent way to meet the growing energy demand by ensuring line capacity and voltage stability[20].

1.5.1 Distributed Generation Technologies

Small wind turbines and solar photovoltaic panels are among renewable DG technologies that can provide significant technical and economic benefits with power generation up to 3MW and 100MW per module, respectively. Furthermore, combined cycle gas turbine is among DG technologies with a capacity of 35MW to 400MW that are used to ensure the demand during blackouts due to their high efficiency[21].

1.5.2 Sizing and Placement Optimization of Distributed Generators

The fluctuations and unpredictability of DGs output power will affect the stability of the power system when connected to distinct locations with different capacities[22]. Hence, The optimal sizing and placement plays an important role in satisfying load demand , raising efficiencies, ensuring system's reliability and effectiveness with an optimal cost, while reducing losses. Numerous papers have been published on this project. Abu-Mouti et al [23] introduces a new optimization method that utilize an artificial bee colony (ABC) algorithm to determine the optimal DG-unit's size, power factor and location to minimize the total system real loss, where ABC algorithm demonstrated a high quality solution and convergence. A comparative study between nonlinear optimization and genetic algorithms is done in [2] for optimal placement and capacity of DGs for a minimum investment cost and losses. The authors in [24] evaluated the impact of DG installation on reliability, losses and voltage profile in distribution network. Sensitivity analysis method was proposed in [25] to select the most convenient DG allocation where results revealed the effectiveness of DGs integration in reducing power loss if proper DG planning is implemented.

1.6 Conclusion

This chapter has illustrated the Algerian network with the different types of electricity production including renewable energies. Moreover, it has discussed the concept of distributed generation and their impact on distribution system in terms of efficiencies, reliability and effectiveness of the system. Some researches on optimal size and allocation of distributed generation in the distribution network were presented. These studies have required power flow analysis of distribution systems in order to perform the optimization. Hence, a power flow analysis of distribution systems is examined in the next chapter.

Chapter 2

Load Flow Analysis in Distribution System

2.1 Introduction

Power flow (or Load flow) form a fundamental analytic tool in the field of power engineering systems for evaluating the operation and control of the power system, as well as planning future system progression. Power flow, which began with the Ward and Hale technique in 1956[26], is a set of calculations for estimating the active and reactive power flowing through the system's lines, bus voltages, generators and loads under steady state condition. System losses can be estimated eventually, which are required for operation and planning studies. Over the years, a number of numerical methods have been developed for solving the load flow problem, such as: Guass-Seidal method, Newton Raphson method and Fast Decoupled method. These classical methods can be utilized to evaluate the steady state performance of the grid at the level of the transmission network. Whereas, these approaches may become inefficient when applied to the distribution network. This chapter will present some of the well-known power flow solution techniques for radial and meshed distribution systems.

2.2 Power System Discription

The structure of the power system is based on three interconnected and synchronized levels: generation, transmission and consumption. Conventional power plants(steam or/and gas turbines) along with renewable power plants provide electric output, the three phase magnitudes and frequency have to be controlled and stabilized.

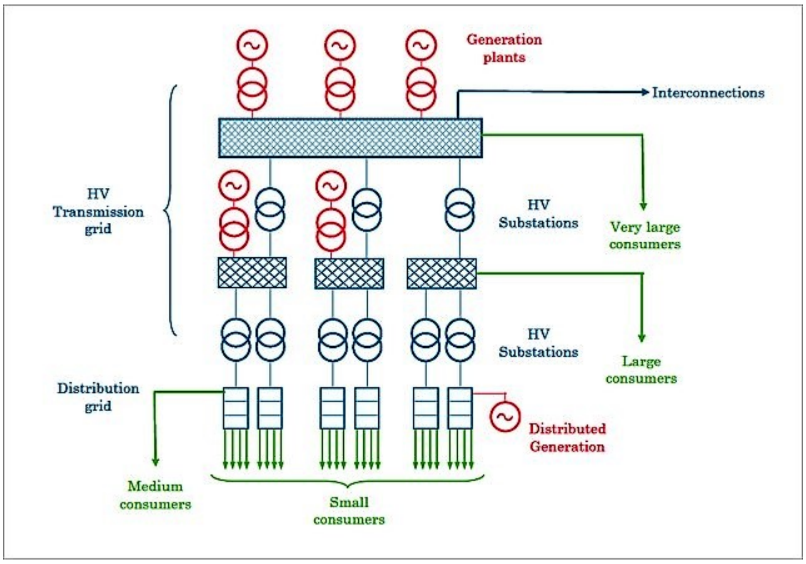


Figure 2.1: Power System Network [27]

Fig 2.1 shows a typical power system network. The output power delivered from the power plant station will be stepped up in voltage to minimize losses while transmitting power. In general, the distribution system provides a link between the substation supplied by the transmission system and both the residential and industrial customers. The distribution system operator is responsible for ensuring the security and reliability of the system.

2.3 Power Flow in Distribution System

Power system networks can be classified into well-conditioned and ill-conditioned systems. A well-conditioned system is a network with low or medium loading, in which the earlier stated methods can be applied to solve power flow problem. Unbalanced phases, radial network topology and high R/X ratio is among features that characterize the ill-conditioned network[28]. Distribution system network is considered as ill-conditioned network, where it is generally radial or weakly meshed with a high ratio of R/X lines. Besides the poor convergence of Gauss seidal method, the application of the simple Newton Raphson and Fast Decoupled power flow solutions on the distribution system may experience divergence problems or inaccurate results, which makes these solutions inefficient[29].

2.4 Power Flow Solution Methods

Generally, load flow solutions for distribution systems can be grouped into three categories: (i) backward/forward sweep methods; (ii) Newton-based methods (iii) fixed-point based methods[30]. Power flow solutions for radial distribution network might not be designed for solving the meshed networks. Thus, several methods have been developed or modified to handle meshed distribution networks.

2.4.1 Backward/Forward Sweep Method

The backward/Forward sweep method is first introduced in [29] to solve radial distribution networks with considering only PQ nodes. The method has undergone considerable modifications to expand its application; Shirmohammadi et al[31] developed a compensation method to solve weakly meshed distribution networks. It consists of breaking the interconnected points (loops) using the compensation method, enabling the meshed system structure to be transformed to a simple tree type radial system. The algorithm of the backward/forward sweep method is described in the following section.

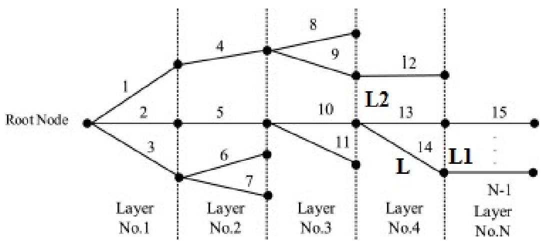


Figure 2.2: radial distribution system[32]

Step 01: The branches of the studied radial network are numbered starting from the root node as shown in Fig 2.2.

Step 02: The nodal currents are calculated at the k^{th} iteration according to the following equation:

$$I_i^k = (\frac{S_i}{V_i^{k-1}})^* - Y_i.V_i^{k-1}, \quad i = 1,2,\ldots,n \tag{2.1}$$

Where I_i^k is the nodal current injection at node i at the k^{th} iteration, S_i is the scheduled power at node i, V_i^{k-1} is the node voltage at the previous iteration, Y_i is the sum of all element's admittances.

Step 03: Backward sweep

The branch currents are computed in this step, starting from the last network branches towards the root node. J_L is the current flowing through branch L which is calculated as:

$$J_L = -I_{L2} + \sum BranchcurrentsleavingnodeL2, \quad L = 1,2,\ldots,n-1 \tag{2.2}$$

Step 04: Forward Sweep

The node voltages are updated starting from the root node towards the end nodes following equation 2.3

$$V_{L2}^k = V_{L1}^k - Z_L.J_L, \quad L = 1,2,\ldots,n-1 \tag{2.3}$$

Z_L is the series impedance of branch L.

The iterations will stop whenever the algorithm reaches the convergence criterion which is defined by the following active and reactive power formulas after updating the power injection for node i:

$$\begin{aligned} S_i^k &= V_i^k (I_i^k)^* - Y_i |V_i^k|^2 \\ \Delta P_i^k &= Re[S_i^k - Si] \qquad i = 1,2,\ldots,n \\ \Delta Q_i^k &= Im[S_i^k - Si] \end{aligned} \tag{2.4}$$

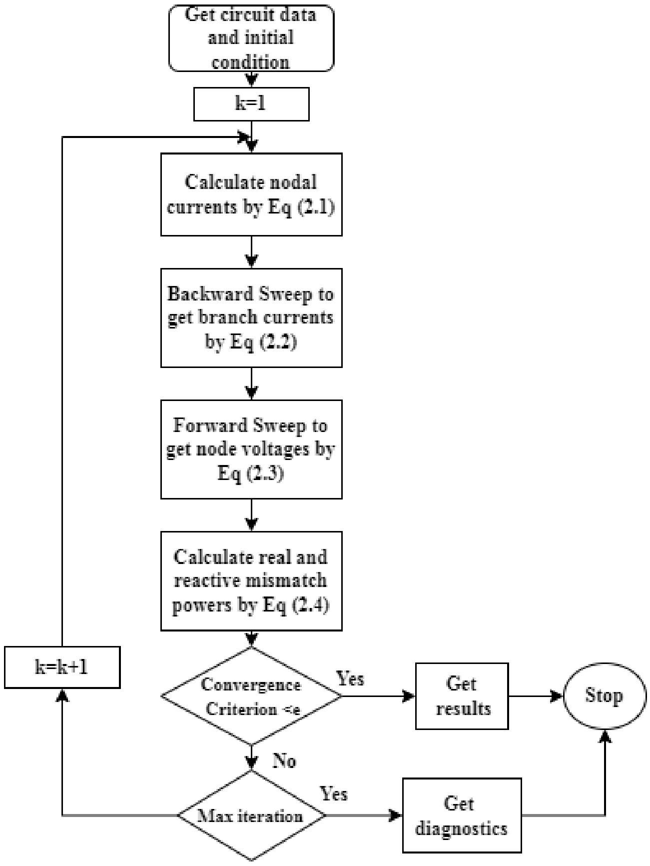


Figure 2.3: Backward/Forward Sweep algorithm for radial network

The radial power flow cannot be applied directly to weakly meshed distribution system. The interconnected points are selected and broken at a number of points called **Breakpoints** in order to convert the network to radial configuration. The branch current flowing through the branch of the broken loop will be replaced by injecting two currents, with opposite signs, to the two end nodes.

$$\begin{aligned} I_{j1}^{k} &= -J_{j}^{k} \\ I_{j2}^{k} &= J_{j}^{k} \quad , j = 1, 2, \ldots, p \end{aligned} \tag{2.5}$$

Where I_{j1}^{k} and I_{j2}^{k} are the nodal current injections at the two end nodes of the breakpoint j, J_{j}^{k} is the breakpoint current and P is the number of breakpoints.

The procedure is performed using the compensation method and a breakpoint impedance matrix[29]. These currents are calculated by the following complex linear equation at each iteration m. This set of iterations is performed outside the power flow of radial network as depicted in Fig 2.3.

$$\left[Z_B\right]\left[J\right]^{m} = \left[V\right]^{m} \tag{2.6}$$

Where $\left[V\right]$ is the vector of voltage mismatches for all breakpoints, $\left[Z_B\right]$ is the breakpoint complex impedance matrix.

For PV nodes, a correction voltage magnitude is performed right after the compensation step by determining the reactive current injections at PV nodes[31].

$$\left[Z_V\right]\left[I_q\right]^l = \left[\Delta V\right]^l \tag{2.7}$$

$\left[Z_V\right]$ is the PV node sensitivity matrix. The voltage magnitude mismatch for n PV nodes is calculated as follows:

$$\Delta V_i^l = |V_i^s| - |V_i^l| \quad , i = 1, 2, \ldots, n \tag{2.8}$$

Fig 2.3 describes the algorithm followed to perform Backward/Forward Sweep method. Fig2.4 is the modified algorithm for solving weakly meshed distribution system.

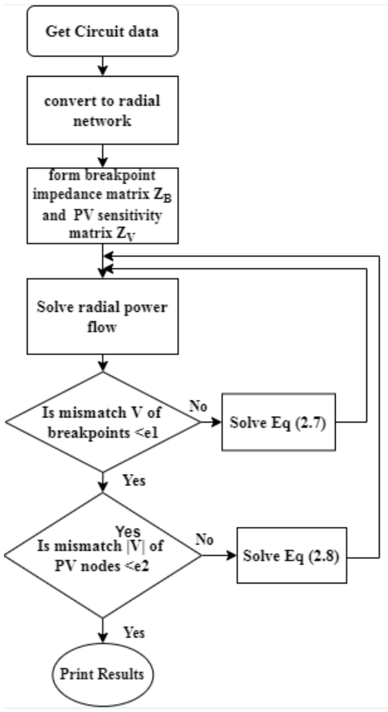


Figure 2.4: Flowchart of backward/forward sweep algorithm for weakly meshed network

2.4.2 Current Injection Method

Current injection method is a newton-based method which is based on expressing current injections in rectangular coordinates and considering the effect of voltage-dependant loads[33].

2.4.2.1 Basic Equations

For PQ bus, the current mismatch for a bus k is given by:

$$\Delta I_k = \frac{P_k^{sp} - jQ_k^{sp}}{E_k^*} - \sum_{i=1}^{n} Y_{ki}E_i \tag{2.9}$$

Where $P_k^{sp} - jQ_k^{sp}$ are the specified active and reactive power at bus$k$, E_k^* is complex conjugate of voltage phasor at bus k, Y_{ki} is the bus admittance matrix element. E_i is the voltage phasor at bus i. We consider:

$$\begin{aligned} P_k^{sp} &= P_{gk} - Plk \\ Q_k^{sp} &= Q_{gk} - Q_{lk} \end{aligned} \tag{2.10}$$

Where P_{gk}, Plk, Q_{gk} and Q_{lk} are active and reactive powers for generators and loads, respectively. Equation 2.9 can be expressed in terms of real and imaginary parts as follows:

$$\Delta I_{rk} = \frac{P_k^{sp}V_{rk} + Q_k^{sp}V_{mk}}{V_{rk}^2 + V_{mk}^2} - \sum_{i=1}^{n} G_{ki}V_{ri} - B_{ki}V_{mi} \tag{2.11}$$

$$\Delta I_{mk} = \frac{P_k^{sp}V_{mk} - Q_k^{sp}V_{rk}}{V_{rk}^2 + V_{mk}^2} - \sum_{i=1}^{n} G_{ki}V_{mi} - B_{ki}V_{ri} \tag{2.12}$$

Where, V_{rk} and V_{mk} are the complex voltage at bus k. Equations2.11 and 2.12 can be compressed to:

$$\Delta I_{rk} = I_{rk}^{sp} - I_{rk}^{calc} \tag{2.13}$$

$$\Delta I_{mk} = I_{mk}^{sp} - I_{mk}^{calc} \tag{2.14}$$

The following set of nonlinear equations are obtained by applying Newton Raphson method:

$$\begin{bmatrix} \Delta I_{m1} \\ \Delta I_{r1} \\ \Delta I_{m2} \\ \Delta I_{r2} \\ \vdots \\ \Delta I_{mn} \\ \Delta I_{rn} \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & \dots & Y_{2n} \\ \vdots & & & \\ Y_{n1} & Y_{n2} & \dots & Y_{nn} \end{bmatrix} \begin{bmatrix} \Delta V_{r1} \\ \Delta V_{m1} \\ \Delta V_{r2} \\ \Delta V_{m2} \\ \vdots \\ \Delta V_{rn} \\ \Delta V_{mn} \end{bmatrix} \tag{2.15}$$

The calculations of the Y elements are demonstrated in [34]. Equations 2.11 and 2.12 can be expressed in terms of power mismatches and voltages at a given bus k:

$$\Delta I_{rk} = \frac{V_{rk}\Delta P_k + V_{mk}\Delta Q_k}{V_{rk}^2 + V_{mk}^2} \tag{2.16}$$

$$\Delta I_{mk} = \frac{V_{mk}\Delta P_k - V_{rk}\Delta Q_k}{V_{rk}^2 + V_{mk}^2} \tag{2.17}$$

For PQ bus the real and reactive powers are known, thus, the calculations of current mismatches are direct. For PV bus, the current mismatches for bus k is expressed as follows[35]:

$$\Delta I_{rk}^* = \frac{V_{rk}\Delta P_k}{V_{rk}^2 + V_{mk}^2} \tag{2.18}$$

$$\Delta I_{mk}^* = \frac{V_{mk}\Delta P_k}{V_{rk}^2 + V_{mk}^2} \tag{2.19}$$

The convergence criteria for the correction of voltage is defined as:

$$\Delta V_k^h = V_k^{h+1} - V_k^h \tag{2.20}$$

2.4.3 Fixed Point Iteration

Considering a system with n nodes and with the application of Current Injection Method the following formulation can be obtained:

$$\bar{Y}\bar{V} = \bar{I}(\bar{V}) \tag{2.21}$$

Where $\bar{Y}$ is the admittance nxn matrix, $\bar{V}$ is the nodal voltages, $\bar{I}(\bar{V})$ is the current injections as a function of node voltages.

The algorithm for the fixed point iteration for solving load flow problem is demonstrated[36]:

1: k=0

2: **While** $E < epsilon$

3: Update current injections $\bar{I}(\bar{V_k})$

4: Calculate $\bar{I}(\bar{V_{k+1}})$

5: $E = |\bar{V_{k+1}}| - \bar{V_k}$

6: $k = k + 1$

7: **End While**

The substation voltage is taking as an initial guess, the iterations will stop whenever the convergence criteria is reached. **FPI** method has shown satisfactory results compared to the Newton method[37].

The power flow calculations for the studied distribution system is conducted on a distribution system simulator called **OPENDSS**.

2.5 Power Flow of Distribution Network in OpenDSS

According to the guide manual, OpenDSS refers to open distribution system simulator developed by EPRI (Electric Power Research Institute). OpenDSS is a powerful electrical system simulation software for electric power distribution networks. It is still under development and has been continuously introducing new technologies to address future demands relevant to the modernization of the current networks. Despite the fact that OpenDSS was designed with the intention of being used for distributed generation interconnection research, it has included new features that are suitable for harmonics analysis, energy efficiency analysis, and smart grid applications.

2.6 Power Flow Solution Algorithm

Primitive Y matrix of each network element is constructed to built the overall admittance matrix Y of the distribution system using sparse matrix solver. Fig2.5 and equation 2.22 show the development of a primitive Y matrix for a simple 2-phase coupled impedance[38].

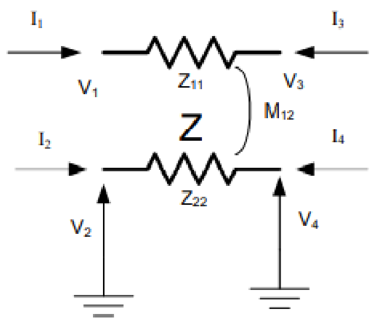


Figure 2.5: 2-phase coupled impedance

$$\mathbf{Z}= \begin{bmatrix} Z_1 1 & M_1 2 \\ M_1 2 & Z_2 2 \end{bmatrix} \tag{2.22}$$

The primitive Y matrix is the matrix that relates the voltages and currents of the circuit.

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} = \begin{bmatrix} Z^{-1} & -Z^{-1} \\ -Z^{-1} & Z^{-1} \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix} \tag{2.23}$$

The current vector along with the compensation current from power conversion elements, ie., loads, generators, transformers, etc, form an equation. The compensation current is the difference in current absorbed by the nonlinear conversion element and the linear portion of that element[38]. Fig 2.6 illustrates the process of solving power flow in OPENDSS, it is based on "Fixed Point Iteration" algorithm.
The initial voltage estimation is obtained by performing zero load flow i.e., only power delivery (PD) elements are examined. At iteration $k = 0$, the injection currents are collected from all PC elements and consistently added to the injection vector I_{inj}. The sparse set in equation 2.25, is then solved at each iteration until the convergence criteria are reached.

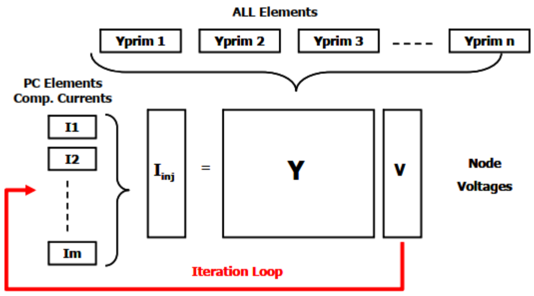


Figure 2.6: Default power flow solution[38]

$$I_{inj}(V) = YV \tag{2.24}$$

$$V_{n+1} = [Y]^{-1} I_{inj}(V_n) \tag{2.25}$$

The voltage criteria is set to 0.0001pu. The system Y matrix is not updated at each iteration. Hense, it converges rapidly.

Another solution provided in **OpenDSS** is known as "Newton" method, it couples real and imaginary parts. This method is suitable for complex circuit, however, it requires nearly twice as many arithmetic operations which can accumulate when running long time sequence simulations. The significant bulk power source eliminates the need for this method. Thus, it is rarely required when dealing with distribution systems. The default solution approach is similar to most backward-forward sweep algorithms for radial circuits in terms of convergence. For meshed networks, it is often superior to weakly meshed solvers.

OpenDSS provides several solution options for different sorts of analysis. Some of the Built-in solution modes are:

Snapshot mode Power flow is executed directly reflecting the steady state mode of the network.

Direct mode Non-iterative simulation mode

Daily mode Power flow solution is performed for 24 hours with a default of 1 hour increment. The user can adjust the increment time intentionally.

Yearly mode This mode performs simulation for 8760 hours with adjustable time duration.

Dutycycle mode Simulation within small time increment of 1 to 5 seconds.

Dynamics mode Simulation of electromechanical transients of generators. In this mode power flow is solved iteratively for each estimate at the generator voltages.

Harmonics Following the power flow solution, harmonic solution can be executed for distinct frequencies on the grounds that OPENDSS is a frequency domain system analyzer.

Fault study Power flow executed for fault analysis

2.7 Power Flow Example

We consider Fig2.7, which is a radial-based distribution network conducted to evaluate typical aspects of distribution analysis.

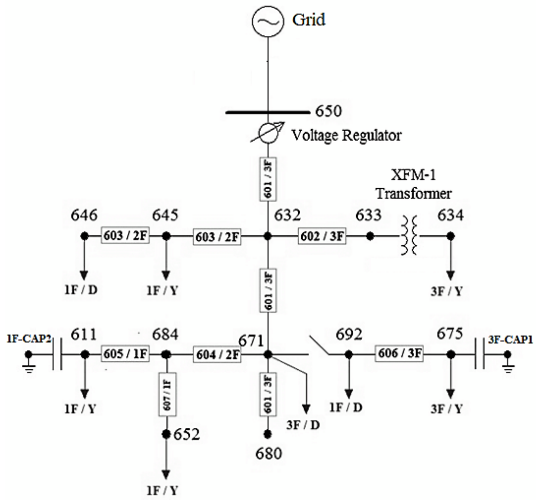


Figure 2.7: One line diagram of IEEE 13 bus test feeder.

the 13 node test feeder has the following characteristics[39]:

- 13 buses,
- 10 underground and overhead lines with different phasing,
- One substation voltage regulator composed of Y-connected three single-phase units,
- Two shunt capacitor banks,
- One inline transformer,
- Unbalanced spot and distributed loads.

The power flow was solved in **snapshot mode**, with 11 itaerations. The following tables summarize the results extracted after performing load flow solution to the IEEE13 bus feeder.
Table 2.1 compares voltage magnitudes in (p.u) at various buses obtained from OpenDSS and result published by radial distribution analysis subcommittee for 13 Node Test Feeder.

Table 2.1: Bus Voltages

Bus NO.	$V_a(OpenDSS)$	$V_a(IEEE)$	$V_b(OpenDSS)$	$V_B(IEEE)$	$V_c(OpenDSS)$	$V_c(IEEE)$
650	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
633	1.0185	1.0180	1.029	1.0401	1.0116	1.0148
634	1.0013	0.9940	1.0154	1.0218	0.9979	0.9960
671	0.9925	0.9900	1.0398	1.0529	0.9799	0.9778
645	NA	NA	1.0220	1.0329	1.0121	1.0155
646	NA	NA	1.0202	1.0311	1.0102	1.0134
692	0.9925	0.9900	1.0398	1.0529	0.9799	0.9777
675	0.9861	0.9835	1.0420	1.0553	0.9779	0.9758
611	NA	NA	NA	NA	0.9758	0.9758
652	0.9852	0.9825	NA	NA	NA	NA
632	1.0213	1.0210	1.0308	1.0420	1.0140	1.0174
680	0.9925	0.9900	1.0398	1.0529	0.9799	0.9778
684	0.9906	0.9881	NA	NA	0.9779	0.9758

Line losses as well as element losses are shown in the following table:

Table 2.2: Circuit Losses

Element	kW Losses	kVAR Losses
Transformer.REG1	0.01300	0.131723
Transformer.REG2	0.00680	0.069745
Transformer.REG3	0.01438	0.145473
Transformer.XFM1	1.96833	9.84215
Capacitor.CAP1	0.0000	-602.901
Capacitor.CAP2	0.0000	-95.368
Line.650632	59.71141	160.715
Line.632670	12.74399	33.9789
Line.670671	22.30046	59.2598
Line.671680	0.00000	-0.00353018
Line.632633	0.80395	0.859381
Line.632645	2.79312	2.01958
Line.645646	0.53906	0.357466
Line.692675	4.09133	2.06795
Line.671684	0.58487	0.395823
Line.684611	0.38210	0.32376
Line.684652	0.81435	0.197409
Line.671692	0.00001	-5.82077e-14

2.8 Modeling and Implementation of Photovoltaic Energy Source in OpenDSS

The model of PV system implemented in OpenDSS is composed of PV array connected in parallel to a DC-AC voltage source inverter (VSI). A maximum power point tracking algorithm is associated with the inverter control. Fig2.8 illustrates the element model of the PV system (**OpenDSS PV manual**) .

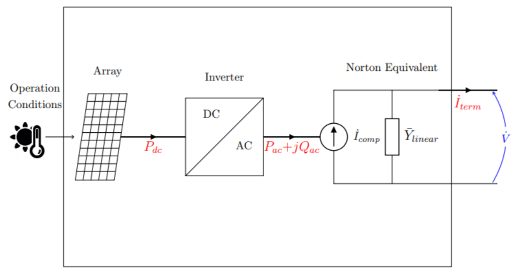


Figure 2.8: PV System Model

The properties that must be specified to define PV system are:

- Maximum power point Pmpp
- P-T Curve: PV array correction factor curve per units of Pmpp as a function of PV array temperature. The temperaure at which Pmpp is specified is 25^oC.
  When operating at 25^oC and $1kW/m^2$, the PV array produces its maximum rated power.

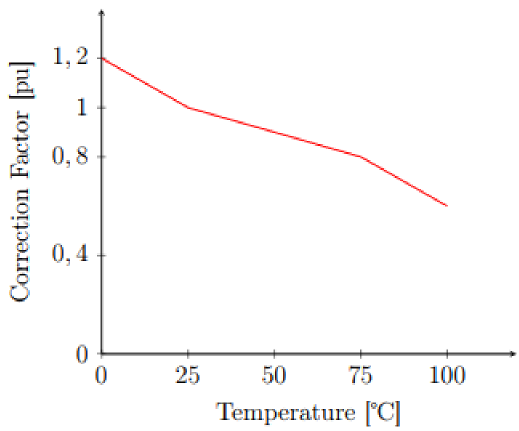


Figure 2.9: Correction factor vs Temperature

- The inverter's kVA rating and kV may be defined in the inverter model.
- Eff Curve: The inverter effeciency curve of Fig 2.10 depicts the fluctuation of inverter effeciency as a function of PV power, P_{dc}, in each unit of inverter's kVA rating.

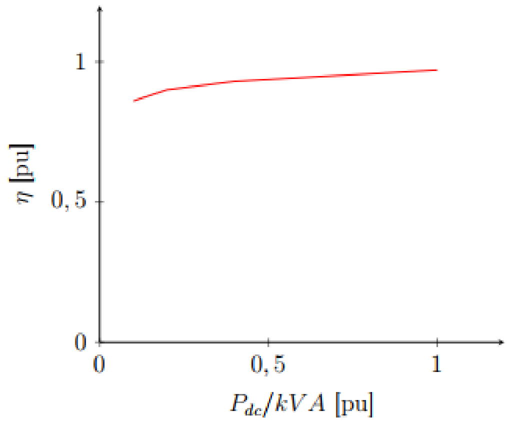


Figure 2.10: Inverter Efficiency Curve

- Irradiance and Temperature are inputs to the PV system model.

The PV system is modeled by a Nortan equivalent in which the constant linear admittance is included in $\bar{Y}$ system, while the non linear portion is represented by the compensation current.

The output power delievered to the circuit is developed in equation 2.26

$$P_{dc}[t] = Pmpp * irradiance * irradiance[t] + PTCurve(Temperature[t]) \tag{2.26}$$

2.9 Conclusion

Classical load flow solution techniques might be inefficient for solving power flow in distribution system. Therefore, different solution techniques have been developed to tackle this issue. Backward/Forward Sweep method, Current Injection Method and Fixed Point Iteration Method were discussed in this chapter.

Power flow calculations for the studied distribution network is conducted through OpenDSS which was introduced in this chapter to understand the power flow solution algorithm preformed in our network.

Chapter 3

Optimal Location and Size of Distribution Generator Units in Distribution Networks

3.1 Introduction

The appropriate allocation and sizing of DG units can solve a variety of issues in the distribution network including power loss reduction, voltage profile improvement and enhancing security, reliability and stability of the power system [40]. Therefore, the use of an optimization method to identify the best DG location and size for a distribution network to enhance the system operation characteristics is indispensable.

This chapter will introduce the optimization techniques applied so far to the problem of optimal integration of DGs, their classifications and presenting their potential and limits according to the cases studied.

3.2 Optimization Techniques

The proper design of a cost effective and reliable distributed generation units results in the increase of system performance. Several researchers have elaborated numerous techniques in the aim of optimally size and allocate DGs in distribution systems. Optimization techniques can be classified into the following categories: analytical methods, classical methods and meta-heuristic methods. The selection of the appropriate optimization techniques relies on the system configuration as well as the objective functions to be minimized or maximized.

3.2.1 Analytical Methods

Analytical methods bear upon representing the identified problem by means of computational models. The accuracy of this method necessitates extremely exact models, which are generally the results of simulations or experiments. Analytical method is simple and require less time. However, it might be ineffective for complex systems[41].

3.2.2 Classical Methods

Classical methods use differential equations to find solutions to optimization problems. This approach is not valid for objective functions that do not have a unique solution to their differential equations, or the objective function itself is not continuous. Different algorithms are used to determine the optimal location and size of renewable energy installations including:

- **Iterative technique:**
  In an iterative technique, a recursive process is performed to improve the quality of the solution and terminates when the optimal system design is achieved.

- **Linear Programming (LP) technique:**
  This technique is often utilized when the objective function is linear. **LP** can solve optimization

problems with continuous and discrete variables. Mixed integer linear programming **(MILP)** technique might be applied when the discrete variables have discrete integer values. On the other hand, non linear programming **(NLP)** technique performs the optimization of non linear objective function.

- **Other techniques:** There are other classical techniques were applied successfully by researchers, such as: optimal power flow **(OPF)**, probabilistic approaches, etc. Solutions conducted by these methods might be stuck in local optima. To tackle this issue, new optimization algorithms based on biological aspects and artificial intelligence are employed to countless optimization problems.

3.2.3 Meta-heuristic Techniques

Generally inspired by nature and species social behavior, these methods have become prevalent, especially with the increasing demand for more efficient systems with reduced costs. This has led researchers to develop and implement these methods in the field of power system. These algorithms are adapted to large scale optimization issues in order to find the optimum solution with the least amount of computing complexity. Meta-heuristic are accurate, robust, and resistant to local optima. However, they might get premature convergence[41]. Various studies have used a variety of optimization strategies, such as: Evolutionary Algorithm **(EA)**, Simulated Annealing, Differential Evolution, Particle Swarm Optimization, etc. Evolutionary Algorithm **(EA)** is a meta-heuristic approach based on populations and converges to the global optimum solution in a finite evolutionary steps, performed on a finite set of feasible solutions. Genetic Algorithm **(GA)** is a metaheuristic optimization technique that is based on natural selection.

Ant colony optimization **(ACO)**, artificial bee colony **(ABC)**, harmony search **(HS)**, grey wolf optimizer **(GWO)** are other meta-heuristic techniques that have been used in different optimization problems. In the following section, the genetic algorithm **GA** along with grey wolf optimizer **GWO** are presented.

3.2.3.1 Genetic Algorithm

Genetic algorithm (GA) was first introduced by John Holland in 1975 [42]. GA outperforms several standard search optimization techniques when it comes to the ability of solving large-scale linear and nonlinear optimization problems.

Initial set of random solutions called population is generated by taking into consideration the problem's conditions and limitations. Population is a set of genes bounded together to form chromosomes of individuals which represents the optimisation parameters. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated according to the fitness function which is the objective function desired to minimize. A new generation is created after applying different operators (recombination, mutation,...) which is subjected to a selection. [40] [43]. Details of each step in this process will be explained below:

- **Encoding:** Encoding of the potential solutions is the first and most important aspect that must be effectuated before using genetic algorithm to solve any problem. Solutions are contained in strings where their information is carried. One of these strings will represent each solution that is called chromosome. Chromosomes are structured by a string of values (genes) in binary form as can be seen in Fig 3.1. Once the final result of the problem is obtained, a conversion to the real values of each variables is needed.

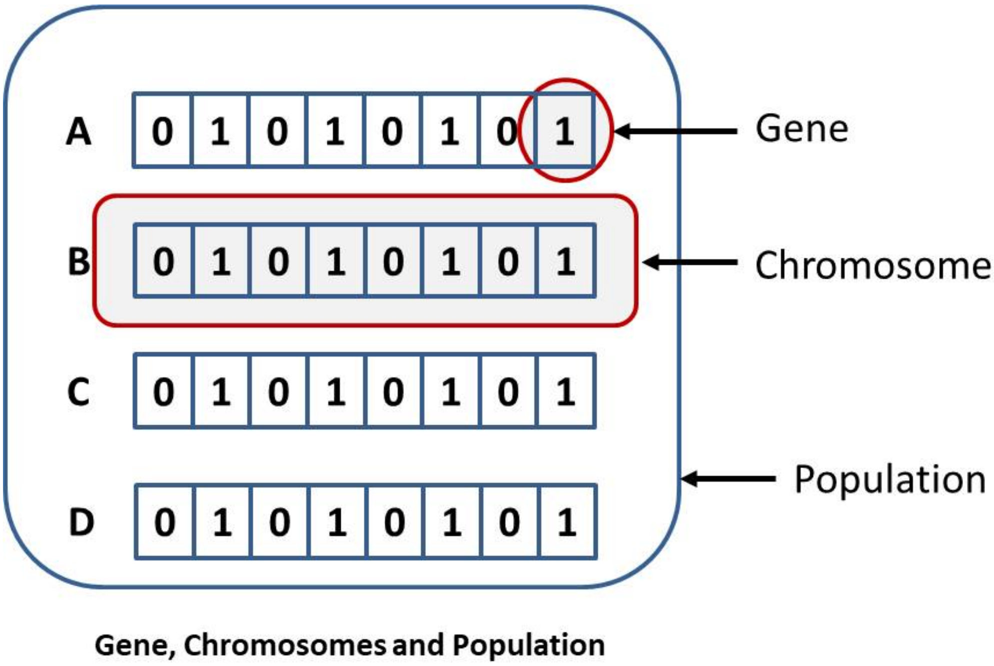


Figure 3.1: Population, Chromosomes and Genes[44]

- **Selection:** The principle of selection is to choose individuals with the highest or lowest fitness score. This process shows the proximity of an existing solution to the desired result. Higher rating indicates greater fitness, whereas lower levels indicates the opposite. The selected chromosomes are the parents of the new population and their genes will be used to construct new individuals called children for reproduction of the succeeding generation.

- **Crossover:** The surviving individuals after the selection become parents of the future populations. The crossover process is done by merging the genes of two parents of the current population up to the crossover point. The process is described in Fig 3.2

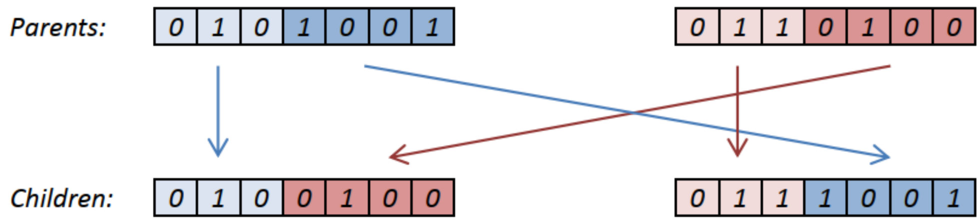


Figure 3.2: Crossover example[45]

Hence, offspring are formed and incorporated into the new population. The concept behind this point is having the possibility to produce better individuals.

- **Mutation:** This operation helps to discover new solution near to the optimal solution or move the solution away in case it is locked in a local minimum. It is done by modifying the bits of certain genes randomly aiming to retain the population diversity.

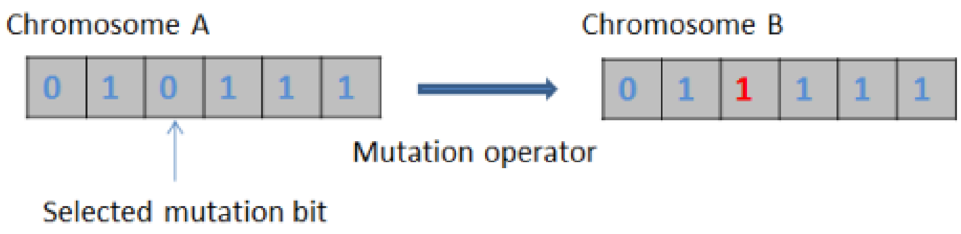


Figure 3.3: Mutation example[43]

- **Reduction:** The size of the population will be doubled throughout these procedures. Thus, a reduction is required by either eliminating the fit half of population or repeating the selection process to maintain the population size. Once the reduction is completed, evaluation of the individuals of the final population is preformed to check whether the solution is accurate enough or the iteration limit was reached [45]. Fig3.4 summarizes the process of the genetic algorithm:

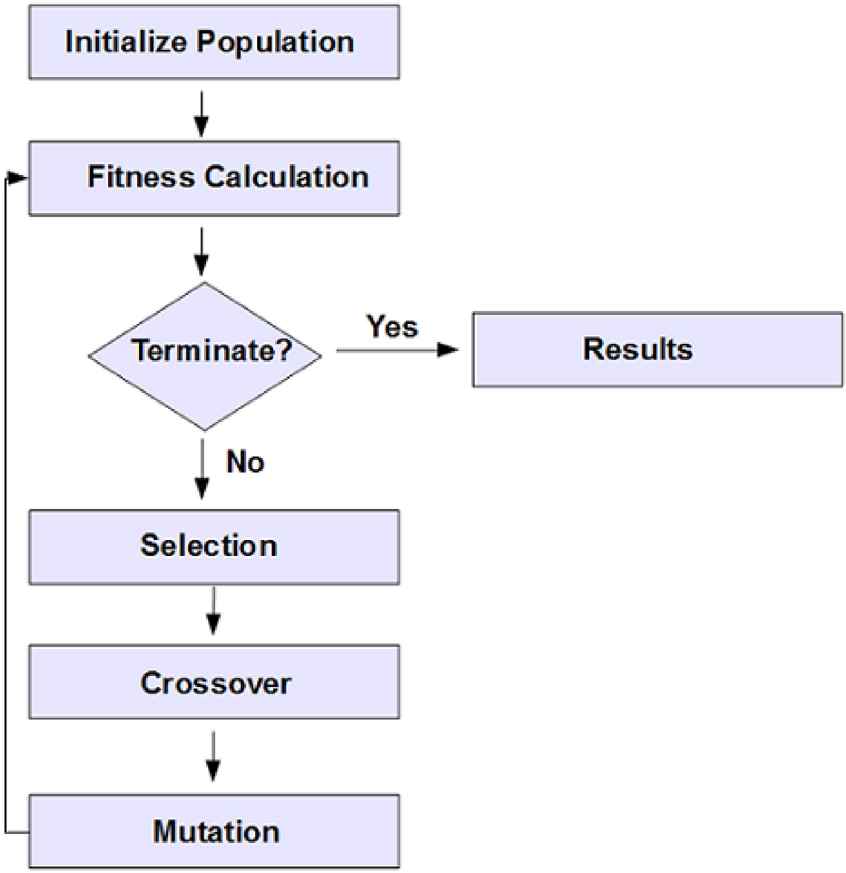


Figure 3.4: Genetic algorithm flowchart [46]

3.2.3.2 Grey Wolf Optimizer

The grey wolf optimizer (GWO) is a meta-heuristic optimization algorithm developed by Seyedali Mirjalili et al in 2014. GWO is modeled based on the internal leadership hierarchy of grey wolves, as their great ability of detecting and hunting the prey in packs and working in teams [47]. The leadership hierarchy is decomposed of four types of wolves, called serch agents: alpha(α), beta(β), delta (δ) and omega (ω) that are ranging from the most powerful wolf to the least dominant wolf, respectively. The optimization process is based on the hunting strategy of grey wolves that follows three primary steps: scouting and chasing the prey then encircling and attacking it [48].

Initially, a stochastic population of grey wolves is generated and the objective function value of each solution is calculated. The fittest solution is alpha, followed by beta and delta as the second and third best options, respectively. The remaining possible solutions are referred to as omega.
Through the hunting process, wolves encircle the prey. The distance between any wolf and the prey is determined by the following equations [47]:

$$\vec{D} = \left|\vec{C} \times \vec{X}p(t) - \vec{X}(t)\right| \tag{3.1}$$

$$\vec{X}(t+1) = \vec{X}p(t) - \vec{A} \times \vec{D} \tag{3.2}$$

Where t indicates the current iteration, $\vec{X}p$ is the prey position, $\vec{X}$ is the grey wolf position. $\vec{A}$ and $\vec{C}$ are the coefficient vectors which are calculated as follows:

$$\vec{A} = 2.\vec{a} \times \vec{r}_1 - \vec{a} \tag{3.3}$$

$$\vec{C} = 2.\vec{r}_2 \tag{3.4}$$

where $\vec{r}_1$ and $\vec{r}_2$ are irregular vectors ranging from 0 to 1, and $\vec{a}$ is linearly decreased from 2 to 0 throughout the iterations.

Alpha(α), beta(β) and delta(δ) are the best solutions which have more information about the possible position of the prey. The remaining omega (ω) wolves update their position to match the current best position as described in the following expressions:

$$\vec{D}_\alpha = \left| \vec{C}_1.\vec{X}_\alpha(t) - \vec{X}(t) \right| \tag{3.5}$$

$$\vec{D}_\beta = \left| \vec{C}_2.\vec{X}_\beta(t) - \vec{X}(t) \right| \tag{3.6}$$

$$\vec{D}_\delta = \left| \vec{C}_3.\vec{X}_\delta(t) - \vec{X}(t) \right| \tag{3.7}$$

$$\vec{X}_1 = \vec{X}_\alpha(t) - \vec{A}_1.\vec{D}_\alpha \tag{3.8}$$

$$\vec{X}_2 = \vec{X}_\beta(t) - \vec{A}_2.\vec{D}_\beta \tag{3.9}$$

$$\vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3.\vec{D}_\delta \tag{3.10}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3.11}$$

Equations (3.5-3.7) indicate the distance between ω and the three best wolves α, β and δ. Equations (3.8-3.10) are used to obtain the current positions of α, β, δ that will be used to find the new position of ω-wolf as seen in equation 3.11.

The hunting is completed once the prey stops moving; $\vec{A}$ is decreasing along with the decreasing of $\vec{a}$, where the grey wolves will attack the prey when the values of $\vec{A}$ are between -1 and 1. In order to avoid that the solutions stuck in local optima, the value of C adjusts prey weights to randomly emphasize ($C > 1$) or deemphasize ($c < 1$) the impact of prey in defining the distance [49]. Figure 3.5 presents the flowchart of GWO algorithm.

In order to enhance the GWO, a dimension learning-based hunting (DLH) search strategy is introduced in the improved version of GWO which is inspired by the individual hunting of the wolves[50]. Each wolf is informed by its neighbors that it is a potential candidate for the new position of $X_i(t)$.According to the DLH search method, each dimension of the new position of wolf $X_i(t)$ is calculated using equation 3.14, in which this individual wolf is trained by its various neighbors and a randomly chosen wolf from the population. Then, in addition to $X_{i-GWO}(t+1)$, $X_{i-DLH}(t+1)$ is another candidate

for the new position of wolf $X_i(t)$. First, a radius $R_i(t)$ is determined using the Euclidean distance between the position of X_i in its current state (t) and the potential candidate position $X_{i-GWO}(t+1)$ by equation (3.12). The neighbors of $X_i(t)$ are then created by applying equation (3.13) with regard to the radius $R_i(t)$, where Di is the Euclidean distance between $X_i(t)$ and $X_j(t)$. The d-th dimension of $X_{i-DLH,d}(t+1)$ is determined by using the d-th dimensions of a random neighbor $X_{n,d}(t)$ selected from $N_i(t)$, and a random wolf $X_{r,d}(t)$ from the population, after the neighborhood of $X_i(t)$ has been created.
The best condidate is selected by comparing the fitness value of $X_{i-GWO}(t+1)$ and $X_{i-DLH}(t+1)$ by Eq. (3.15).
If the fitness value of the selected candidate is lower than $X_i(t)$, $X_i(t)$ is then updated by the selected candidate in order to reflect the new position of $X_i(t+1)$. Otherwise, $X_i(t)$ doesn't change[50]. Figure 3.6 presents the flowchart of the improved GWO algorithm.

$$R_i(t) = \|X_i(t) - X_{i-GWO}(t+1)\| \tag{3.12}$$

$$N_i(t) = \left\{X_j(t) | D_i(X_i, X_j) \leq R_i(t)\right\} \tag{3.13}$$

$$X_{i-DLH,d}(t+1) = X_{i,d}(t) + rand \times (X_{n,d}(t) - X_{r,d}(t)) \tag{3.14}$$

$$X_i(t+1) = \begin{cases} X_{i-GWO}(t+1) & , iff(X_{i-GWO} < X_{i-DLH}) \\ X_{i-DLH}(t+1) & Otherwise \end{cases} \tag{3.15}$$

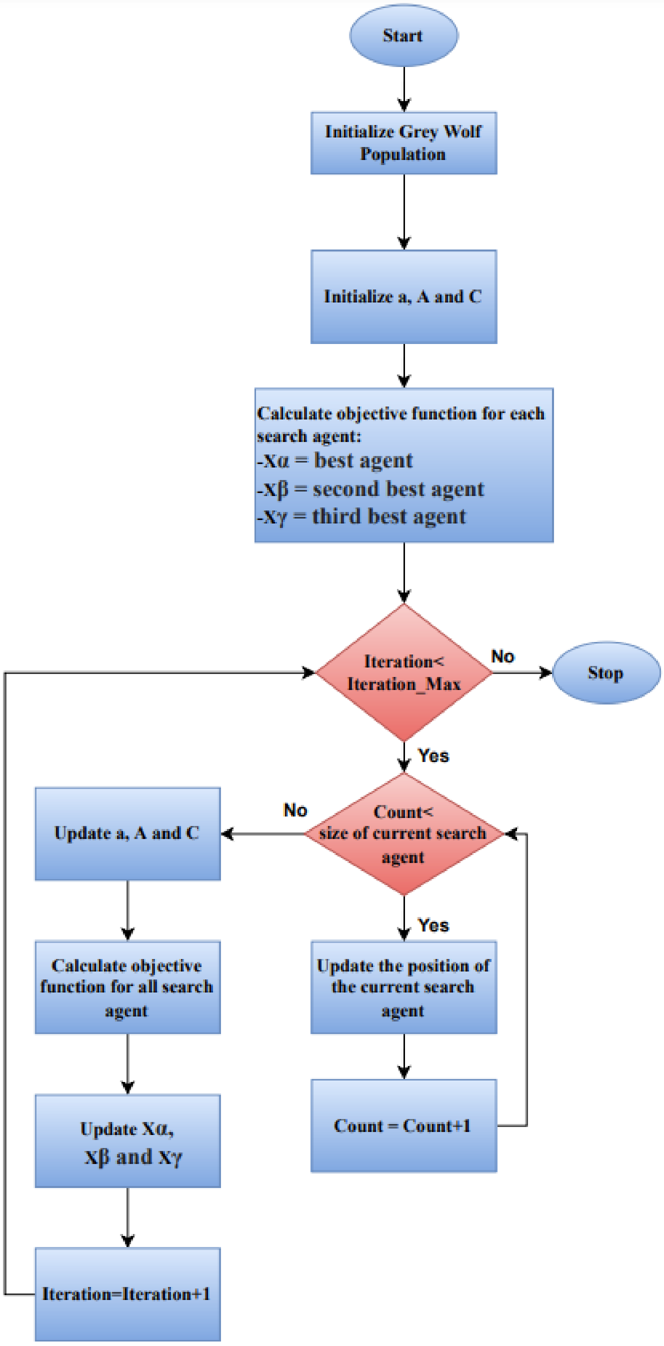


Figure 3.5: Grey Wolf Optimizer Flowchart

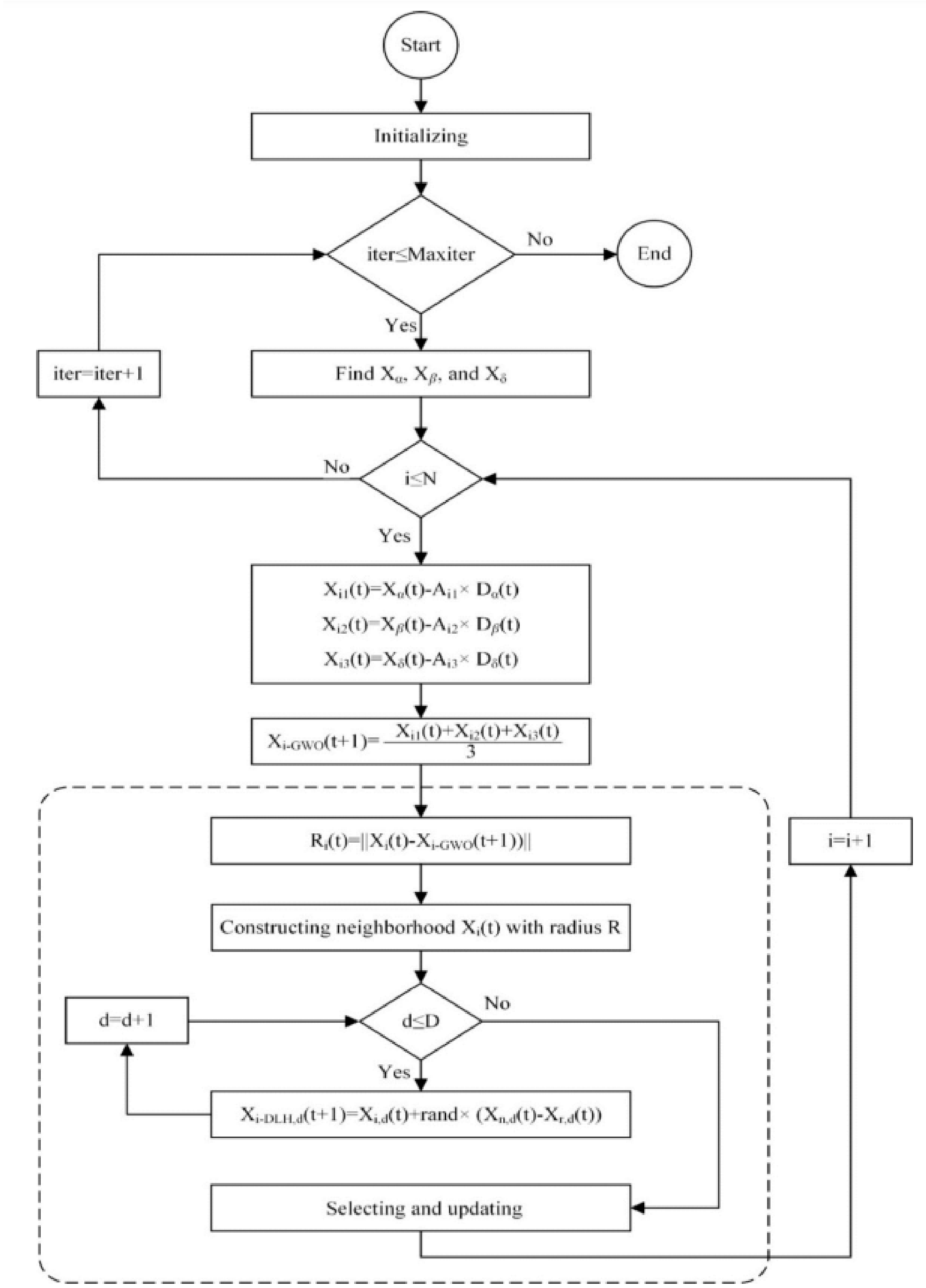


Figure 3.6: Improved Grey Wolf Optimizer Flowchart

3.3 Multi Objective Optimization

According to previous studies, multi-objective optimization is accurate and more realistic for solving complicated optimization problems since it involves optimizing multiple conflicting objective functions. Multi-objective optimization may be approached in two ways[51]. The first option is to merge the different objective functions into a single objective function by applying utility theory, weighted sum method, the ε-Constraint method, etc. The challenge is in selecting the appropriate weights or utility functions to define the decision-preferences. The second approach is to find the complete Pareto optimum solution set (or a subset). The Pareto optimum set is the set of all possible non-dominated solutions in a solution space, whereas, the Pareto front is the set of associated objective function values in objective space for a given Pareto optimal set. Moving from one pareto solution to another results in worsening one or more objective functions in order to achieve a gain in the others. In other words, the pareto front solutions are tradeoffs between different objectives. Therefore, the optimum solution can be chosen depending on the preference.

Multi-objective algorithms enable decision-makers to consider the trade-offs between distinctive properties of multiple objects and select the prior one.

3.3.1 Multi-objective Function into Single Objective Function

Weighted sum approach is used to solve multi-objective optimization. We assume that all the objective functions should be minimized by combining the n multiple objective functions into a scalar fitness function:

$$f(\bar{x}) = w_1.f_1(\bar{x}) + \dots w_i.f_i(\bar{x}) + \dots + w_n.f_n(\bar{x}) \tag{3.16}$$

Where $\bar{x}$ is the vector of the decision variables, $f_i(\bar{x})$ is the i^{th} objective function to be minimized and w_i is the associated weight.
The weights are fractional numbers[52]; $0 \leq w_i \leq 1$ and $\sum_{i=1}^{N} w_i = 1$. The weight vector controls the optimal solution where the preference of an objective function can be varied by adjusting the associated weight. The advantage of adopting this technique is that it allows controlling the importance of one objective over another, and the solution is generally a Pareto-optimal solution[52].

3.3.2 Pareto Optimal Solutions

3.3.2.1 Elitist Non-dominated Sorting GA or NSGA-II

Nondominated Sorting Genetic Algorithm **NSGA II**, developed by Deb et al[53], has become a prominent approach for tackling multi-objective optimization problems by obtaining many Pareto solutions.

It is necessary to explain the concept of non-domination as it is one of the key features that characterizes **NSGA-II**. Given two solutions, $x^{(1)}$ dominates $x^{(2)}$ or $x^{(2)}$ is dominated by $x^{(1)}$ if: In all objectives, solution $x^{(1)}$is no worse than solution $x^{(2)}$ and in at least one objective, the solution $x^{(1)}$ is strictly superior to $x^{(2)}$. A set of non-dominated solutions form a pareto solution, any solution outside the pareto front do not dominate those inside. Multi-objective genetic algorithms are based on coordinating between the objective functions where the nondomination rank and selection operator are employed to guide the population towards the Pareto optimum set. NSGA-II uses an elite-preserving technique to ensure that the previously discovered excellent solutions are preserved and it relies on a fast non-dominated sorting method. NSGA differs from GA in the way the selection operator performs. The non-dominated rank and a distance measure of the individuals in the current generation are used to generate the next population. As explained earlier, each individual receives a non-dominated rank based on their relative fitness, whereas, individuals with equal rank are sorted considering individual's distance measure that measures how far an individual is from the other individual. In other words, each individual is first compared by rank and then crowding distance[53].

The main step of NSGA-II is stated below, whereas the other operators(crossover, mutation) do not differ from the GA explained in section 3.2.3.1.
First, the N offspring $S_t$is created from the N parents Pt by using the usual operators. The two populations are then combined and subjected to non-dominated sorting (R_t with a size of 2N). Only the half of the population will be used, where the non-dominated solutions with the highest diversity(distance) are chosen for the pareto front, whereas, the others will be discarded, Fig3.7.

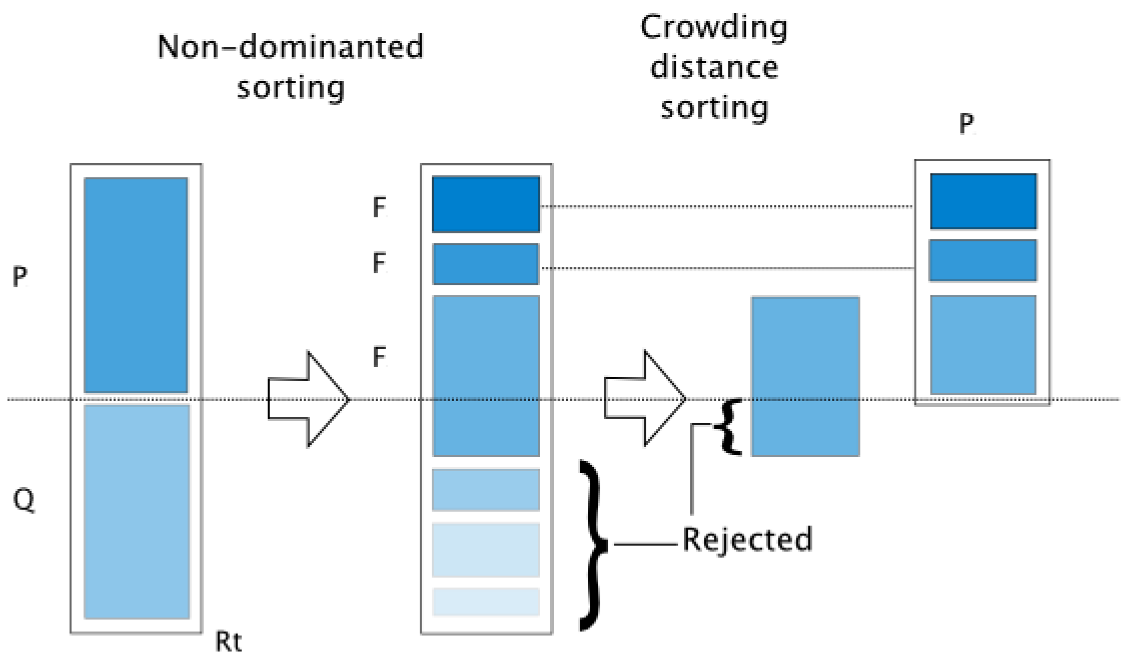


Figure 3.7: Schematic of the NSGA-II procedure[54]

3.4 Problem Formulation

The optimal integration of DGs in the distribution networks aims to find their optimal location and size in order to minimize line losses and cost of the electrical energy. This problem is mathematically formulated as follow:

$$\bar{x} = [x_1, x_2, \dots, x_n]$$
$$min(F(x))$$

Subjected to:

$$h_i(x) = 0, \quad i = 1, \dots, p$$

$$g_i(x) \leq 0, \quad i = 1, \ldots, q$$

$\bar{x}$ is the decision variables vector, $F(x)$ is the objective function to be minimized, $h_i(x)$ and $g_i(x)$ is the equality and inequality constraints, respectively.

3.5 Choice of Calculation Software

Whether it is for the coding and execution of the optimization algorithm program or for the power flow calculations concerning the networks to be optimized, we must not only choose an adequate platform but also program our script well so that not to have very long calculation times, and our choice of software is based on the following characteristics:

- Relatively fast
- Simple and well-known language
- Platform dedicated generally to the academic environment
- The availability of libraries of programs and models for many systems to reduce development time

The "Matlab" platform was chosen for this study to house the genetic algorithm's coding, while "OpenDSS" was chosen for the software that will contain our network and calculate the optimal power flow because it is simple to use and contains models of network components as well as professional calculation modules.

3.6 Conclusion

In this chapter, we have presented the different optimization techniques applied to solve distinct optimization problems. It is clear that the problem of optimizing the size and location of DERs in the distribution system with the constraints used to formulate our objective function is very complex. It is a non-linear function due to the discrete costs of PV plants, but also non-continuous. This makes the problem impossible to solve with an analytical method. Therefore, we have selected meta heuristic methods to solve our optimization problem that will be detailed in the next chapter.

Chapter 4

Simulation and Results

4.1 Introduction

The objective of this research is to find the optimal capacity and placement of DG units in terms of efficiency and stability of the distribution system. In general, choices regarding the planning process are made with the aim of reducing the operating expenses of the particular distribution region. On the other hand, since losses increase operating costs, a distributed generation allocation strategy that minimizes distribution system losses can provide important insights into how to improve the efficiency of a utility while reducing operating costs. Therefore, the objective of this research is to reduce active power losses as well as operational cost. The DG capacity allocation problem has been solved using optimization algorithms and distribution load flow method. The research was structured utilizing a co-simulation platform, with an optimization technique built in Matlab and a distribution load flow (DLF) conducted with OpenDSS.

The optimization process was carried out on the distribution network of Bechar city. Properties and system details regarding this distribution system are discussed in the upcoming section.

4.2 Distribution System Description

The case study location is the region of Bechar. It is located in the southern-west of Algeria with 31.6182492° latitude and -2.213231° longitude [55]. It is characterized by its semiarid climate, which is defined by only two seasons: a hot and dry summer and a very cold winter[56]. Bechar is a military zone and lately one of the popular touristic destinations in Algeria, where it faces an increase in electricity consumption.

The city is supplied from two lines of very high voltage of 220kV, connected to the national grid with a total length of 600 km from Naama and Mechria. However, technical failures may appear in these two lines which require maintenance that may take several hours, risking to leave the city without electricity.

In 2021, a fault occurred due to the fall of a conductor of the two transmission lines due to strong wind blowing, causing no electricity for a duration of 7 hours [57] . Moreover, the remote areas which are a challenging obstacles in constructing new long transmission lines, where high voltage lines of 60 kV are used to link Bechar to the border town of Beni-Ounif, the town of Taghit and that of Abadla over a length of 318 km [57].

Such incidents have led to a necessity of a construction of electricity production station in the city to ensure the electricity supply without any interruption. SONELGAZ proposed to transport four (04) gas turbines stations each of 20 MW. However, these gas turbines are gas consuming and unable to satisfy the load demand at its peaks. Along with the global gas crisis due to the Russia-Ukraine war, the reduction of gas consumption has become a major concern, where Algeria may take advantage from this crisis by raising its fuel resources exportation.

In the aim of reducing the cost, losses, fuel consumption and ensuring the maximum electrification of the region, we have proposed the integration of photovoltaic power systems into Bechar's distribution system, especially that the region is characterized by a high solar radiation due to its saharian climate. However, the installation of PV systems is not done randomly. Therefore, there is a need to develop optimization problem to find the optimal placement and size for these PV systems to satisfy the above mentioned objectives.

In this work, a set of data is considered for the year 2030 that are listed below:

- **Load Profile:** According to the forecast done by SONELGAZ, the load profile for the year 2030 was estimated with a maximum of 240 MW, as depicted in Fig 4.1:

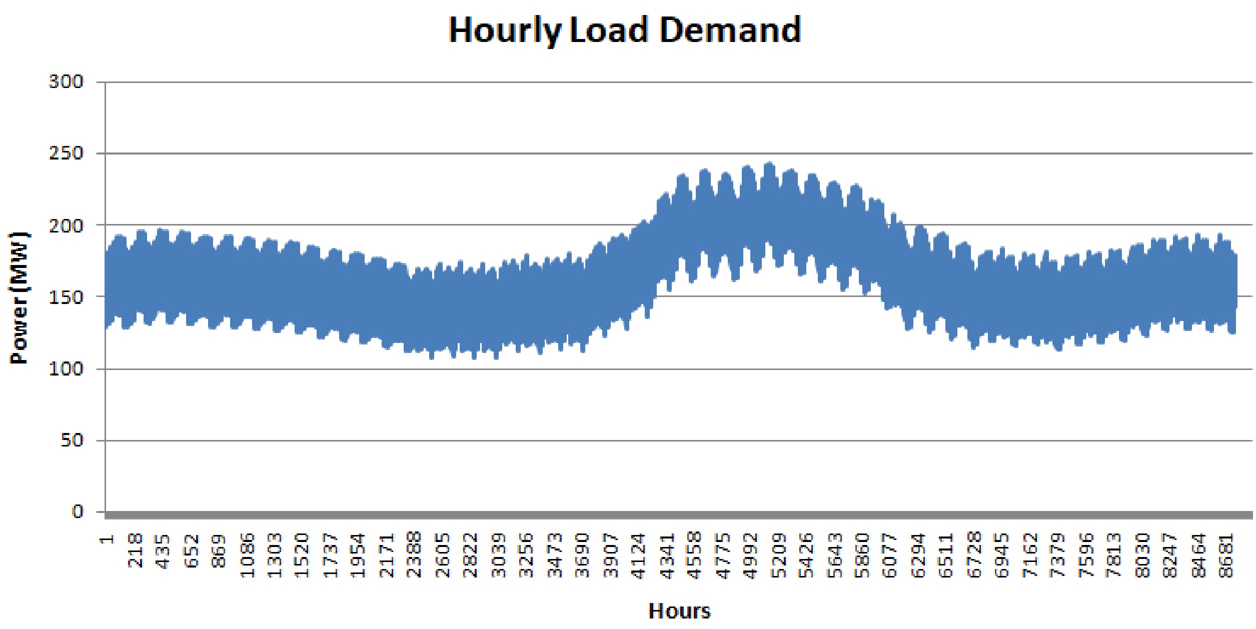


Figure 4.1: Hourly load demand

- **Irradiance and Temperature:** The data of irradiance and temperature of the city were extracted from [58].

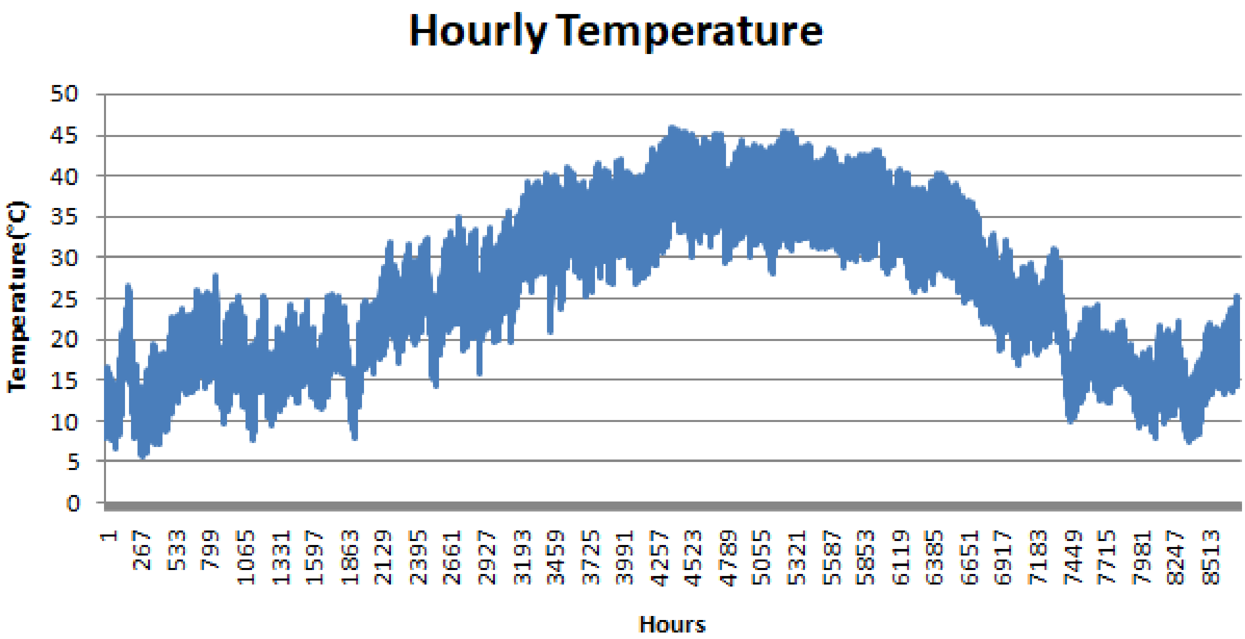


Figure 4.2: Hourly temperature

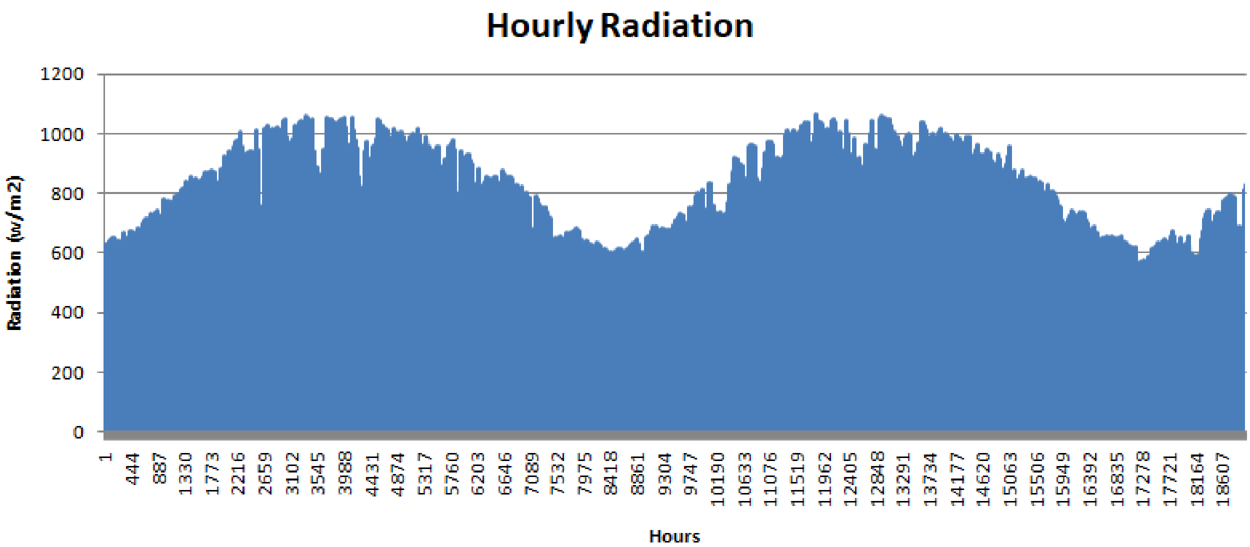


Figure 4.3: Hourly Radiation

During the simulation process, two distribution network configurations were considered.

The first configuration is the estimated network realized by SONELGAZ which is made up of 400kV/220kV substation with two 220kV/60kV substations, supplying nine regions named: Bechar, Abadla, HSO, PVN, PSD, Taghit, Beniounif, Bergua and Lahmer. The network is supplied from Naama and Mechria by two transmission lines of a very high voltage of 400kV and 220kV. The scheme in Fig 4.4 gives an overview on the estimated distribution system by the year 2030.

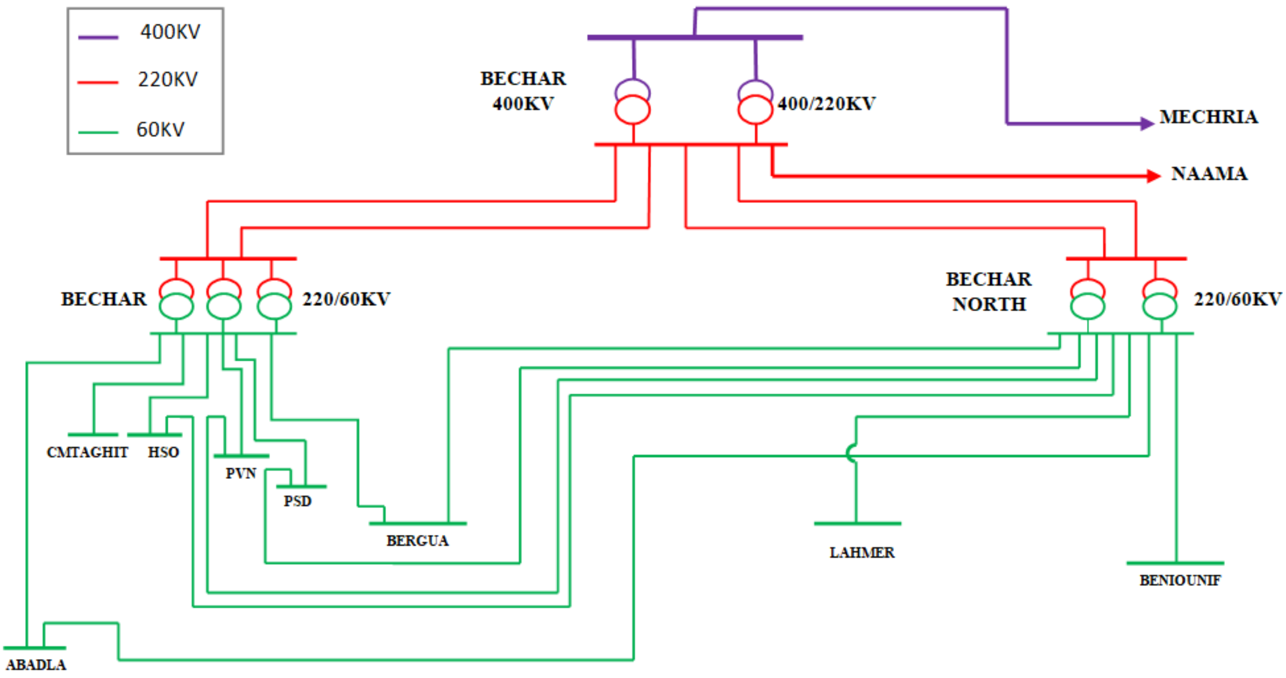


Figure 4.4: Distribution network configuration I

However the second distribution system configuration comppposed only of one 220kV/60kV substation supplying the same regions mentioned earlier. The distribution network is clearly demonstrated in Fig 4.5

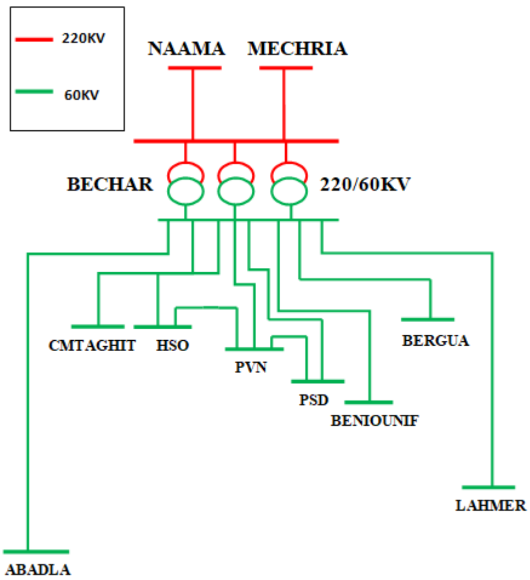


Figure 4.5: Distribution network configuration II

Transmission lines data and transformers characteristics were provided by SONELGAZ

4.3 Analysis Structure

A co-simulation framework is developed to tackle the optimal DG capacity allocation problem, as shown in Fig4.6.

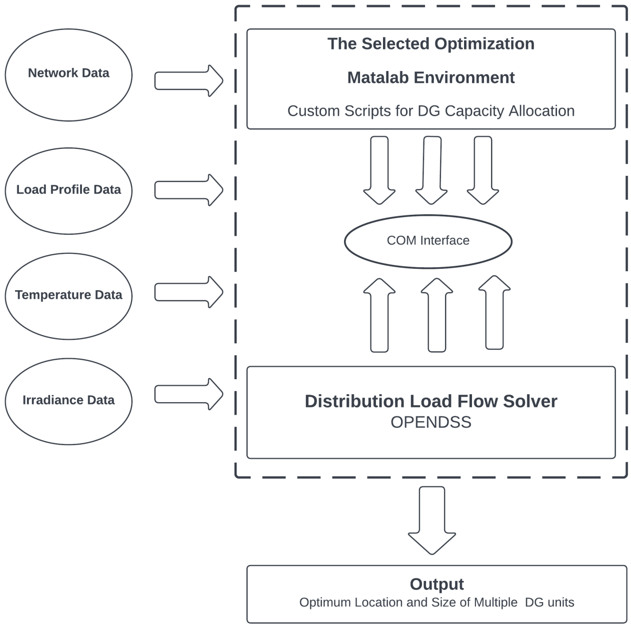


Figure 4.6: Matlab and OpenDSS co-simulation

4.4 Problem Formulation

The first step in the optimization process is to formulate the optimization problem according to the predefined objectives.

4.4.1 Decision Variables

The variables to be estimated as an output of the optimization are the placement of six(6) PV distributed generators with their corresponding capacity. Due to the unpredictable behaviour of the PV systems, we should consider the operating and spining reserve from conventional power plants. Therefore, the four (04) gas turbines will work at 50% of their nominal power and their placement in the network will be optimized. Finally, the decision variables vector is an array of 14 variables:

$$\bar{X} = [X_{PV1cap}, X_{PV2cap}, \ldots, X_{PV6cap}, X_{PV1loc}, \ldots, X_{PV6loc}, X_{GT1-2loc}, X_{GT3-4loc}]$$

where $X_{PV1cap} \ldots X_{PV6cap}$ are PV capacities, $X_{PV1loc} \ldots X_{PV6loc}$ are PV locations and $X_{GT1-2loc}, X_{GT3-4loc}$ are GT locations

4.4.2 Active Power Loss Function

As stated earlier, reducing system losses is one major issue that should be taken into account while optimizing DGs in the distribution network.

The objective function of active power losses is defined as follows:

$$F_{Loss} = \sum_{i=1}^{N} P_{Li} \tag{4.1}$$

Where P_{Li} is the active power losses in the i^{th} line and N is the total number of lines.

4.4.3 Cost Function

Another objective of this study is to reduce the annual cost of the conventional and the renewable power plants. It includes the installation cost of the new PV DG units, operation and maintenance cost.
The total cost of the PV DG units comprised of fixed and variable costs[59].

$$F_{pv} = IC + C_{O\&M} \tag{4.2}$$

$$FixedCost = IC = Capitalcost \times P_{PVDGi} \times CRF$$

$$VariableCost = C_{O\&M} = Operation\&MaintenaceCost \times P_{PVDGi}$$

IC is the installation cost €/kW, $C_{O\&M}$ is the operation and maintenace cost €/kW/year and CRF is the cost recovery factor defined by:

$$CRF(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1}$$

Where i is the interest rate and N is the lifetime cycle of the DG in years.
Equation 4.2 minimizes the annualized cost of operational and capital expenses.
The annuity rate is used in the objective function because in our study, only one year data is simulated, therefore, it is necessary to assume that the capital expenditures invested in DG are uniformly dispersed throughout the lifetime cycle of operation.
Sonelgaz is aiming to reduce fossil fuel dependency in electricity production and since this is not a private project we have considered the cost of the supplied energy depends on the gas consumption by developing a cost function from the High Heating Factor **(HHF)** provided by Sonelgaz. The cost of the conventional energy follows equation4.3 :

$$F(P) = \sum_{t=1}^{8760} (aP^2(t) + bP(t) + c) \tag{4.3}$$

a, b, c represent the cost coefficients.

Finally, the cost function is defined in equation 4.4

$$F_{cost} = [F(P) + F_{pv}] \tag{4.4}$$

4.4.4 Constraints

The optimal allocation and sizing of DGs in the distribution network must respect certain system security constraints. Equality and inequality constraints are defined as follows:

1. **Active power limits of DG units**
   The lower and upper bounds of DG capacity should be specified.

   $$P_{PVDGi}^{min} \leq P_{PVDGi} \leq P_{PVDGi}^{max}$$

2. **Bus Voltage limits**
   The voltage at each bus must be kept within the limits.

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

3. **Power balance**
   Injecting higher power from DGs may increase losses in the system, Therefore, a power balance should be verified.

   $$P_{sub} + \sum_{j=1}^{N_{DG}} P_{DG_j} - \sum_{i=1}^{N_{Load}} P_{Load_i} - P_L = 0$$

Where P_{sub} is the distribution substation power, P_{DG_i} is power delivered by DGs, P_{Load_i} is the load demand and $P_L$are losses.

Finally, our multi-objective function can be written as:

$$\begin{cases} Min \quad [F_{cost} = [F(P) + F_{pv}] \\ Min \quad [F_{Loss} = \sum_{i=1}^{N} P_{Li}] \\ \qquad\qquad P_{PVDGi}^{min} \leq P_{PVDGi} \leq P_{PVDGi}^{max} \\ \qquad\qquad V_i^{min} \leq V_i \leq V_i^{max} \\ \qquad\qquad P_{sub} + \sum_{j=1}^{N_{DG}} P_{DG_i} - \sum_{i=1}^{N_{Load}} P_{Load_i} - P_L = 0 \end{cases} \tag{4.5}$$

We opted for two optimization techniques; Genetic Algorithm and Grey Wolf Optimizer.
The GA stopping criteria are:

- maximum generations "MaxGenerations", or
- running for a definite time in seconds "MaxTime", or
- the value of the fitness function for the best point in the current population is less than or equal to a given fitness limit "FitnessLimit",
- etc.

The input to the genetic algorithm code are listed in table4.1

Table 4.1: Genetic Algorithm Inputs

Genetic Algorithm Inputs	
Objective function	$w_1.F_{cost} + w_2.F_{Loss}$
Number of variables	14
Lower bounds and upper bounds	5MW and 25MW, respectively
Nonlinear constraint	Power Balance
Integer constraint	the solution is integer numbers
Population size	100
Generations	80

The stopping criteria for our optimization code was reaching maximum generations. For the GWO, the only stopping criteria is reaching the maximum number of iterations which is set to 80 iterations.The population size is set to 50, the upper and lower bounds are the same as for the GA .

We have a multi-objective optimization problem, and as discussed in section 3.3.1 it can be considered as single objective function, by applying weighted sum method, or multi-objective function that provide the pareto set of solutions. In the next section, the different results of the optimization techniques will be presented and discussed.

4.5 Optimization Results

4.5.1 Single Objective Function

Considering the weighted sum method, the results of optimization are the buses where the PV systems will be installed and their associated capacities. Only the placement of the gas turbines are desired to optimize. Table4.2 and table4.3 presents the results of optimization with GA and GWO, respectively.

Table 4.2: Optimization Results for GA

Genetic Algorithm		
Substation	**PV Capacity**	**Installed GT**
Abadla	**9MW**	**/**
CMTaghit	**24MW**	**/**
Beniounif	**23MW**	**/**
PVN	**13MW**	**20MW(50%)**
Lahmer	**21MW**	**/**
Bechar	**10MW**	**/**
Bergua	**/**	**20MW(50%)**
Total	**100MW**	**40MW**

Table 4.3: Optimization Results for GWO

GWO		
Substation	**PV Capacity**	**Installed GT**
Abadla	**11MW**	**/**
CMTaghit	**25MW**	**/**
Beniounif	**23MW**	**/**
PVN	**7MW**	**20MW(50%)**
Lahmer	**21MW**	**20MW(50%)**
Bergua	**12MW**	**/**
Total	**99MW**	**40MW**

It is important to display the convergence curve to demonstrate the process of optimization as depicted in Fig4.7 and Fig4.8.

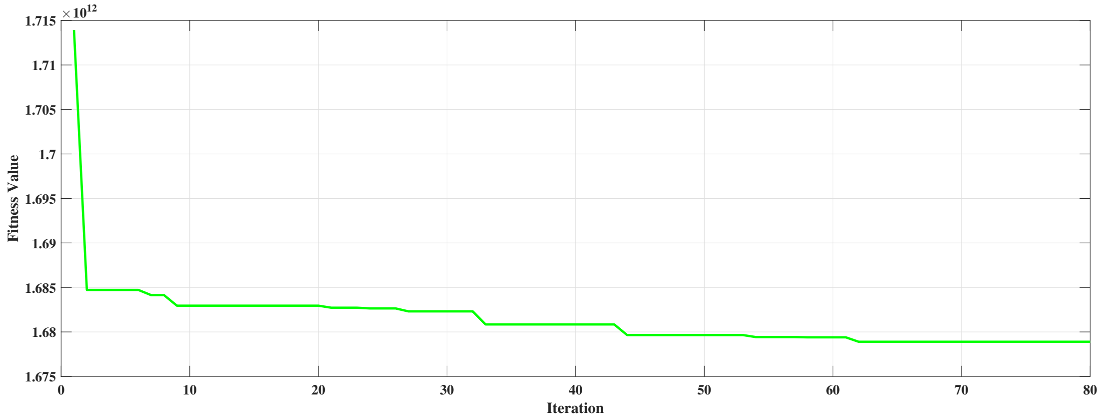


Figure 4.7: Convergence Curve of GWO

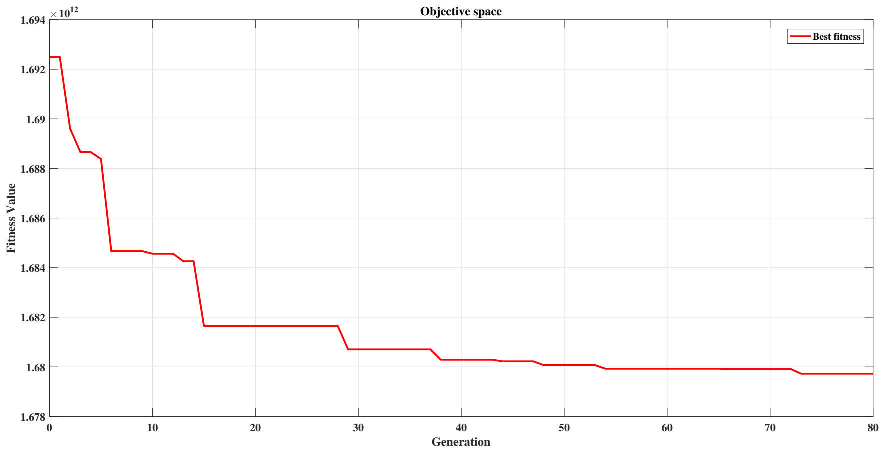


Figure 4.8: Convergence Curve of GA

The weighted sum method depends highly on the weights associated with each objective function. The fitness function of the two optimization algorithms can be compared in Table4.4 and Fig 4.9

Table 4.4: Fitness function value for network I

	GA	GWO
Fitness Function	1.679725833703299e+12	1.678896823569621e+12

The grey wolf optimizer has the lowest fitness function compared to genetic algorithm. Therefore, and for the rest of this chapter, the solution obtained from GWO will be utilized.

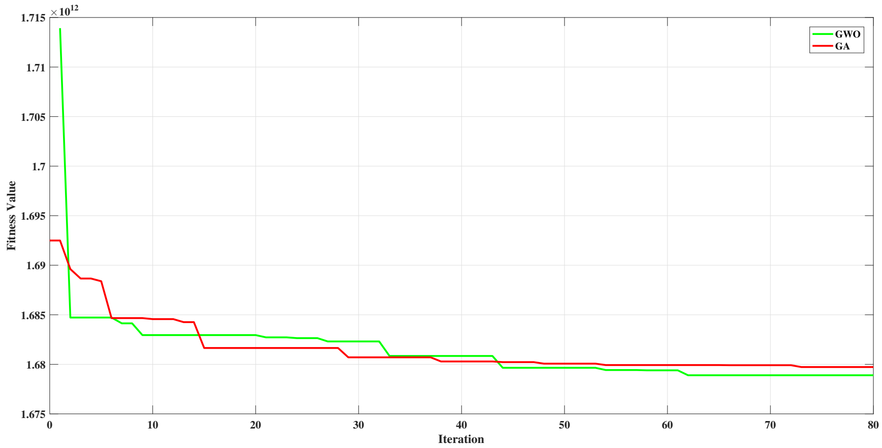


Figure 4.9: Convergence Curves of GA and GWO

The same process was conducted on the Network presented in Fig 4.5. The following tables summarize the result of optimization performed for network II

Table 4.5: Optimization Results for Network II (GA)

Genetic Algorithm		
Substation	**PV Capacity**	**Installed GT**
Abadla	**10MW**	**/**
CMTaghit	**25MW**	**/**
Beniounif	**21MW**	**/**
PVN	**11MW**	**/**
PSD	**21MW**	**20MW(50%)**
Bechar	**11MW**	**/**
Lahmer	**/**	**20MW(50%)**
Total	**99MW**	**40MW**

Table 4.6: Optimization Results for Network II (GWO)

GWO		
Substation	**PV Capacity**	**Installed GT**
Abadla	**6MW**	**/**
CMTaghit	**24MW**	**/**
Beniounif	**22MW**	**/**
PVN	**12MW**	**20MW(50%)**
PSD	**22MW**	**/**
Bergua	**13MW**	**/**
Lahmer	**/**	**20MW(50%)**
Total	**99MW**	**40MW**

The convergence curves for GA and GWO are shown in Fig 4.10 and Fig 4.11, respectively.

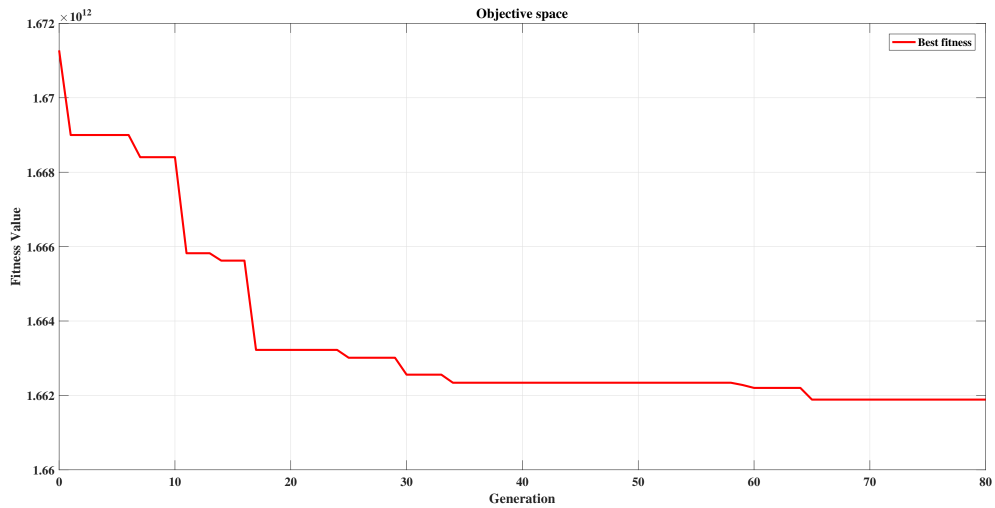


Figure 4.10: Convergence Curve of GA

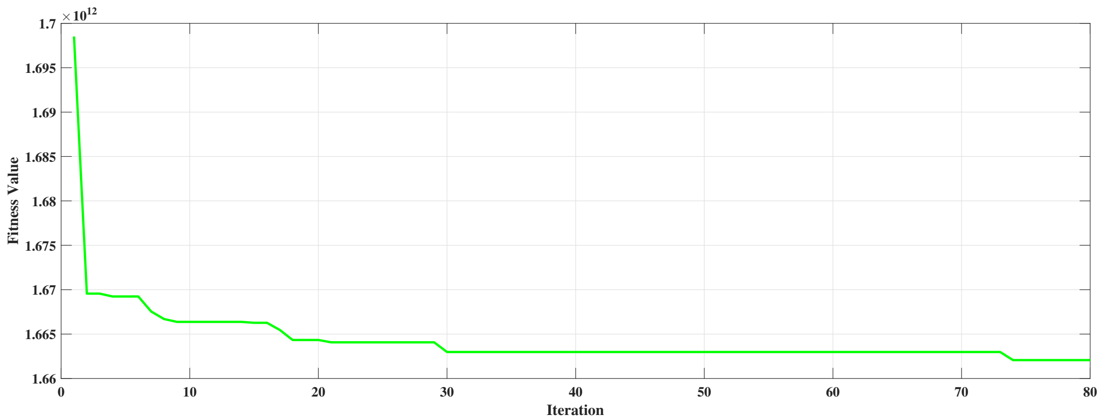


Figure 4.11: Convergence Curve of GWO

Table 4.7: Fitness function value for Network II

	GA	GWO
Fitness Function	1.66234e+12	1.66206895241764e+12

We can notice that the fitness function is much lower than the fitness function of network1. In addition, the total PV power to be injected to the networks are equal. Therefore, we can conclude that adding power transformation substations(220/60kV & 400/220kV) can be avoided, especially that this kind of investment is very costly.

4.5.2 Multi-objective Optimization

Matlab solves the multi-objective optimization based on NSGA-II explained in section 3.3.2.1. The simulation results in pareto front that represents the conflict between the two objective functions. The optimal solution is chosen depending on the preference, the pareto front is presented in Fig4.12

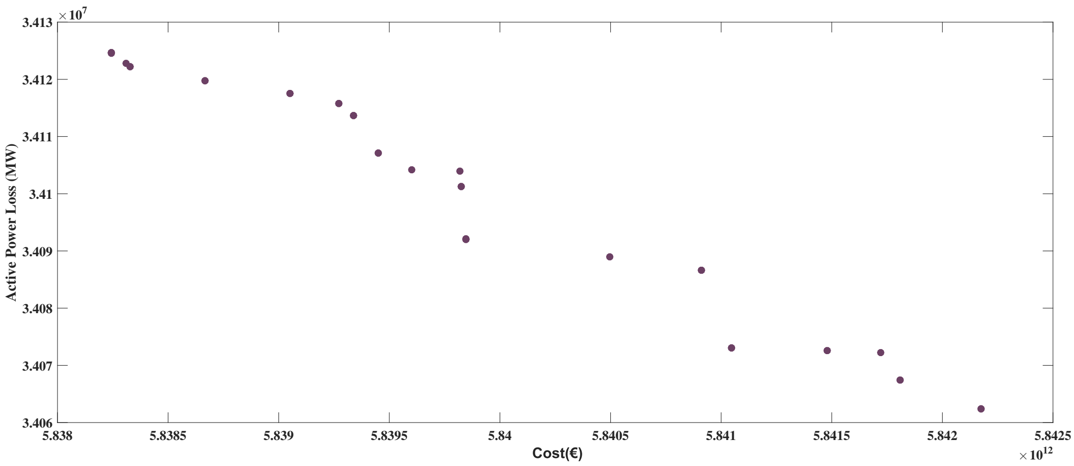


Figure 4.12: Pareto front solution set

As can be seen, prioritizing one function over another has the unintended consequence of degrading the other.

Since multi-objective optimization relies on the user's preferences and highly depends on the knowledge of the network, it is preferable to select the single objective optimization method in this case. Thus, the single objective optimization results are utilized. In the coming section, we will discuss the performance of Bechar's network after the integration of DGs for both network configurations.

4.6 Simulation Results and System Performance Analysis

In this section, the results of optimization are applied to the network to analyze the performance of the system and demonstrate the benefits derived from the integration of DGs.

4.6.1 Graphical Comparisons

4.6.1.1 Voltage Profile

Analysis of voltage profile of the distribution system was preformed to evaluate the variation of the voltage with DGs integration.

Fig 4.13 shows voltage comparison before and after DGs integration, where an improvement of 12 % was reached. This clearly demonstrates one of the important advantages of DGs integration into the distribution network.

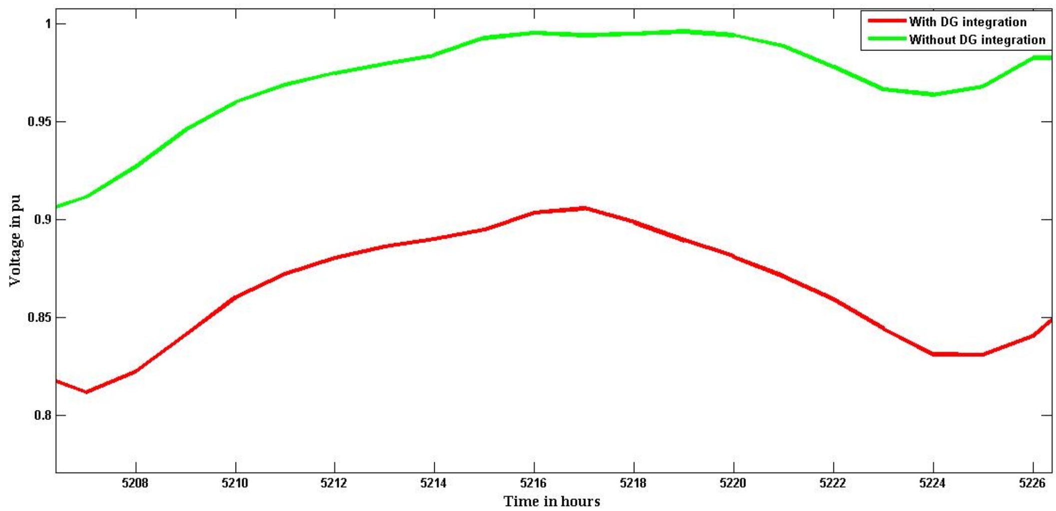


Figure 4.13: Voltage Profile

4.6.1.2 Distribution Substation Total Energy

The total energy of the distribution substation was reduced up to 35% after DGs penetration as seen in Fig4.14. The effect of this reduction can be observed in system losses and gas consumption subsequently.

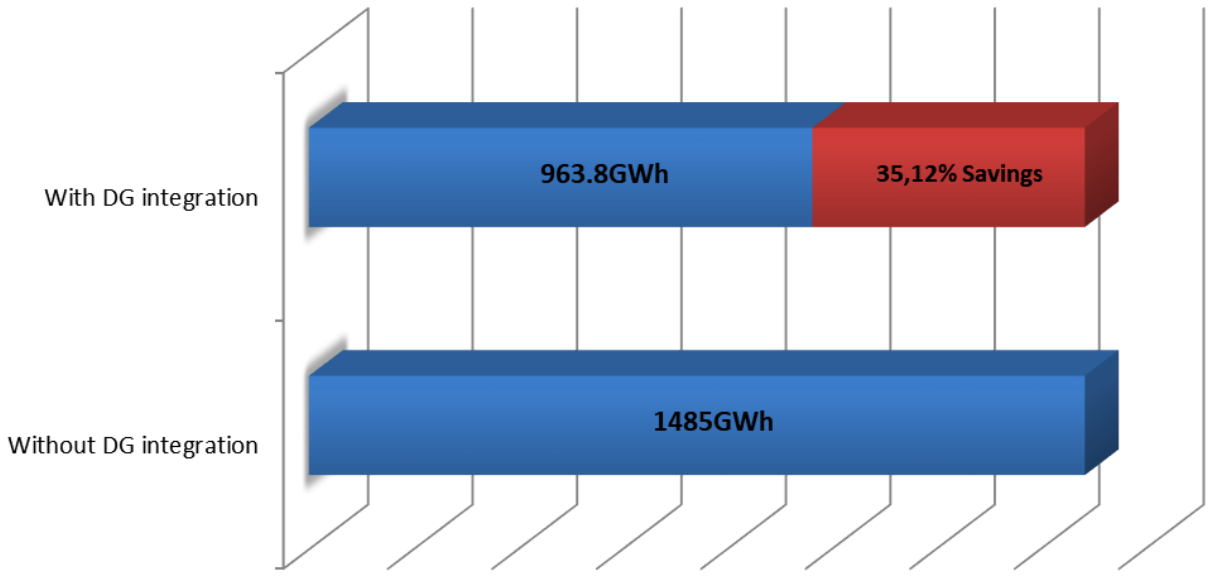


Figure 4.14: Distribution Substation Total Energy

4.6.1.3 System Losses

Reducing system losses is one major objective of the optimization. A drop of 47.7% is noted after the DGs penetration.

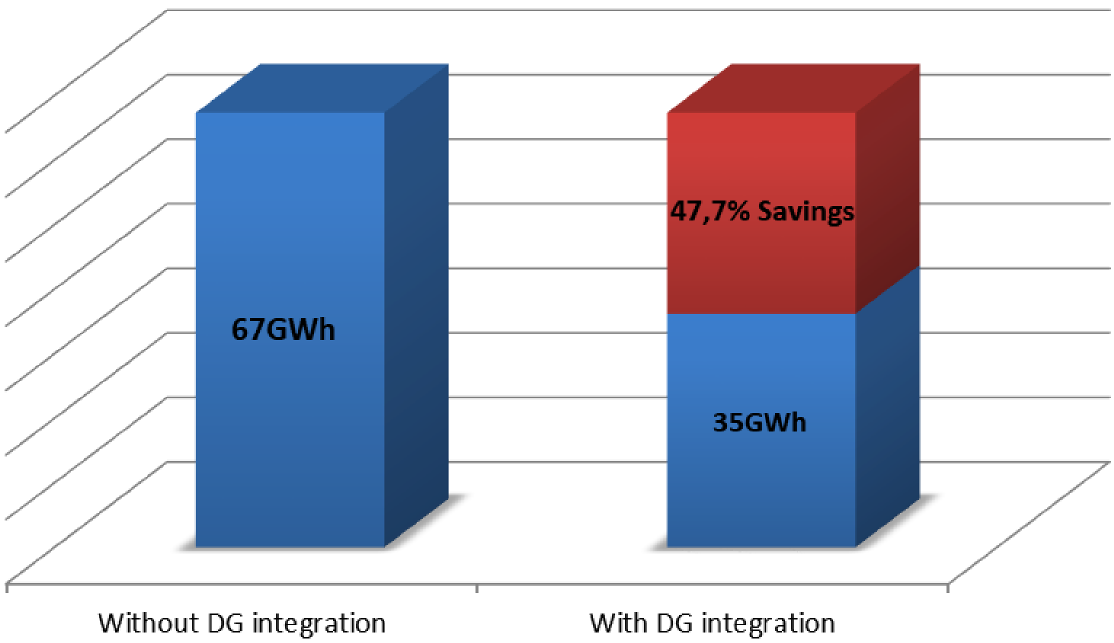


Figure 4.15: Total Losses

4.6.1.4 Gas Consumption

Fig 4.16 illustrates the 12% of gas savings. In other words, 60338 m^3 of gas will be conserved.

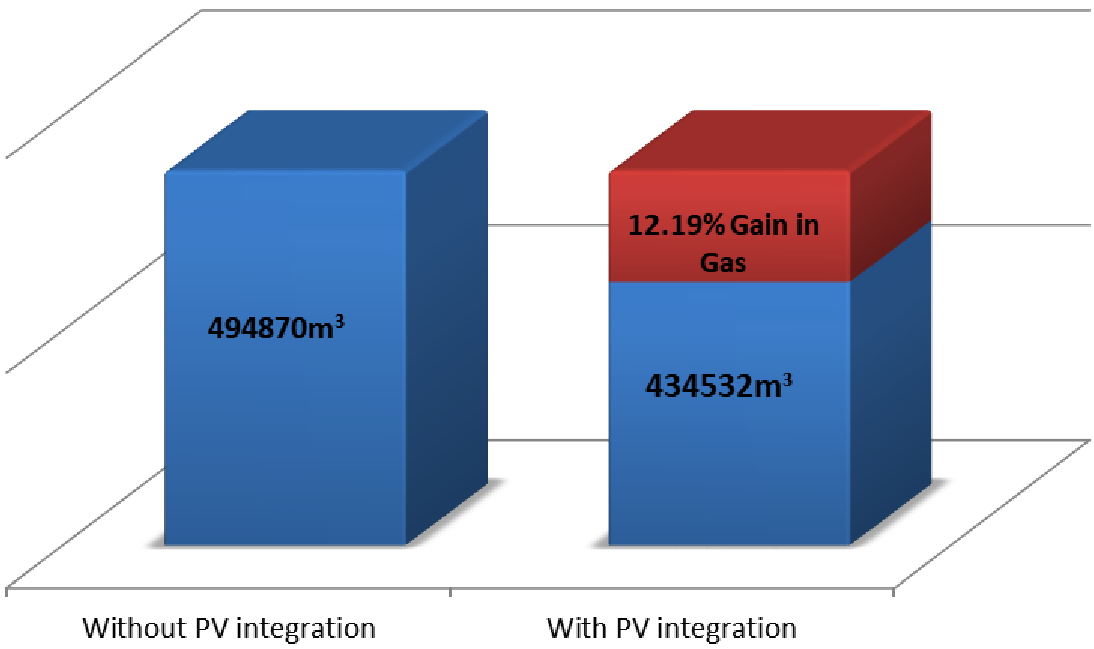


Figure 4.16: Gas Consumption

4.6.1.5 PV Power Output vs Load Demand

- **Maximum PV Power Output** Total maximum power generated from the PV systems reached 94.57MW on May. The daily output power is presented in Fig 4.17

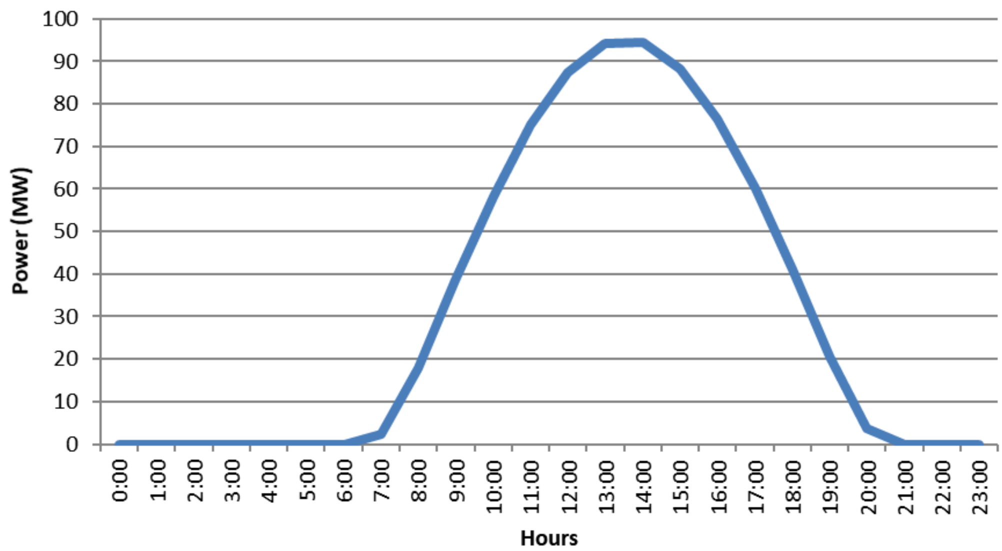


Figure 4.17: Max PV power output

- **Maximum PV power output and load demand**

  The graph below demonstrates the penetration rate of PV at its peak achieved on May 7th, where 68% of the load demand could be covered by PV power output.

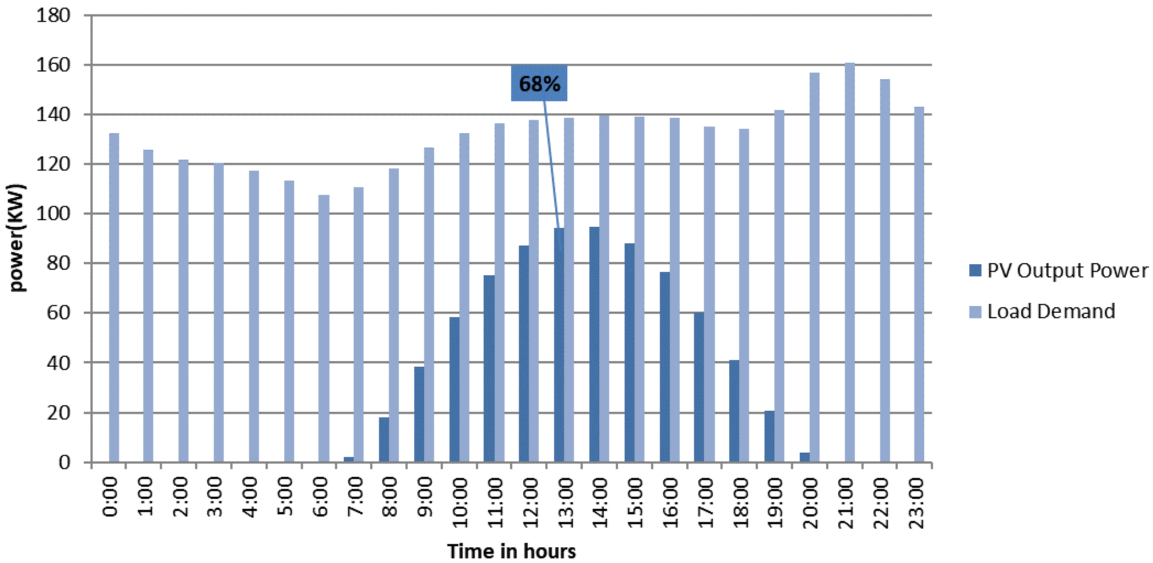


Figure 4.18: Maximum PV Power and Load Demand

- **Penetration ratio:**

1. **For Average PV Power and Load Demand:**

   The penetration ratio is computed according to the monthly average PV power and load demand along with a detailed data in Table 4.8

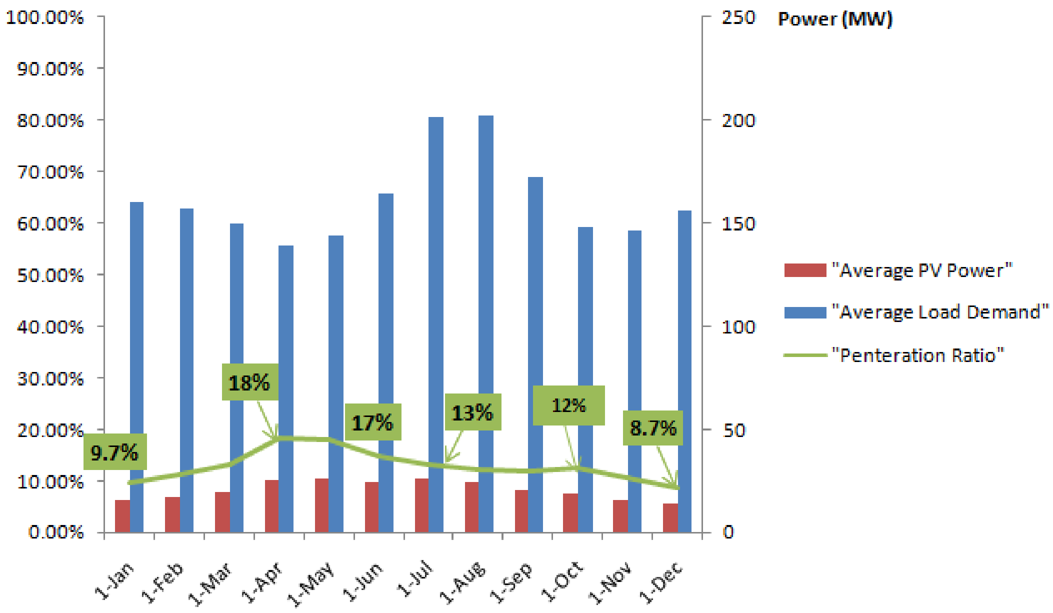


Figure 4.19: Average PV Power and Load Demand

Table 4.8: Average load demand & PV power

Months	Ploadavg(MW)	Ppvavg(MW)	Penetration ratio(%)
January	160.23	15.59	9.72
February	157.31	17.45	11.09
March	149.61	19.89	13.29
April	139.4	25.55	18.32
Mai	143.83	25.77	17.91
June	164.25	24.27	14.77
July	201.21	26.24	13.07
August	202.28	24.69	12.21
September	172.66	20.66	11.97
October	148.07	18.61	12.57
November	146.64	15.55	10.6
December	156.25	13.62	8.71
Annual	160.23	15.59	9.73

2. **For Maximum PV Power and Load Demand:**

   A better way to evaluate the performance of the DG integration is presented in Fig 4.20 where monthly penetration ratios are presented, relating the monthly maximum PV power output with the load demand at that maximum. Higher ratios were attained during the whole year ranging between 36% to 68%.

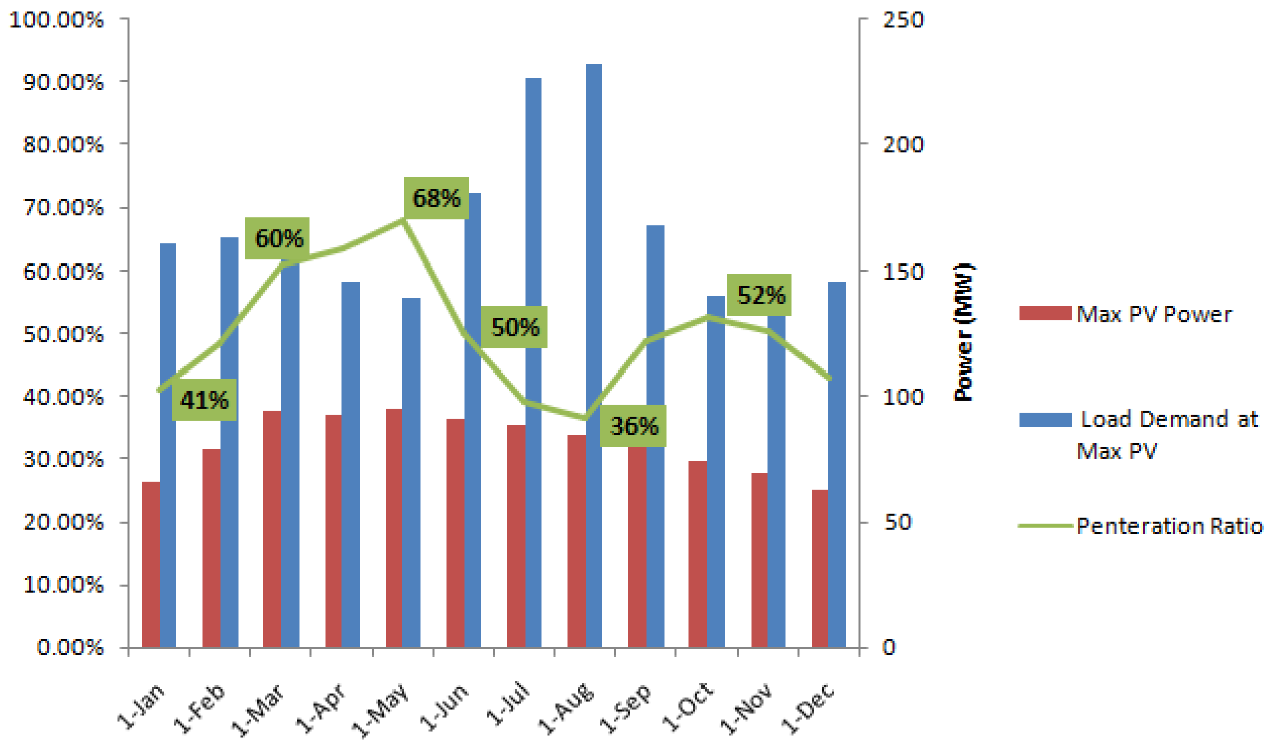


Figure 4.20: Penetration Ratios of Max PV Power and Load Demand

As mentioned earlier, we have considered two different distribution system configurations during the optimization process, where close results were obtained and summarized in the table below:

Table 4.9: Comparaison between network I and network II

	Network I	Network II
Energy Saving	35.12%	34.90%
Gain in Gas	12.19%	12.22%
Losses Reduction	47.70%	48.60%
Cost Reduction	48.8%	48.41%

As one can notice, the distribution network configuration did not affect the simulation results which reveals the unnecessary extension of the network.

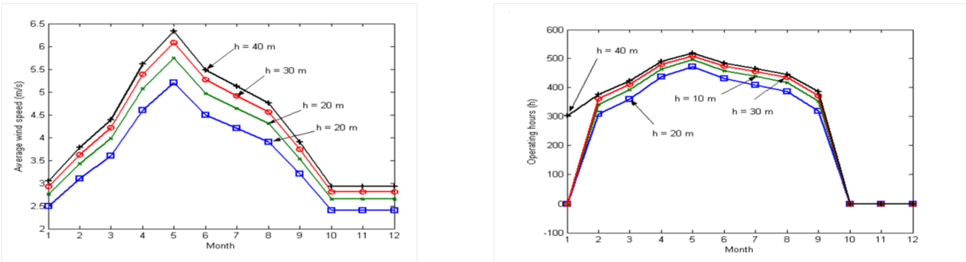
4.6.2 Autonomous Network

To ensure the security and maximum electrification of Bechar city in case of transmission lines breakdown, we propose:

- Reinforce the transmission network by adding new connections with the neighbouring cities, in order to have more than one backup in case of transmission line maintenance or breakdown.

- The total PV power ouput along with the four (4) gas turbines could cover up to 62% of the total load demand. Hence, in case of an autonomous network that the probability of its occurrence is less than 3% , these distributed generators can ensure the load demand of important consumers such as hospitals and military zones, in the time that the transmission lines will be recovered.

- The integration of wind turbines in the network, especially that PV systems are available only in the day. A paper was presented by Dahbi et al [60] entitled "Investigation on Wind Power Generation for Different Heights on Bechar, South West of Algeria" Where the potential of the region was evaluated and many graphs were presented as the monthly wind speed variation and operating hours of wind with respect to different heights as depicted in Fig 4.21a and Fig 4.21b, respectively.



a) wind speed variation

b) Operating hours

One can notice that windy seasons occur at high temperature seasons, where the demand reaches its peaks. Therefore, load demand could be covered by the integration of wind energy.

4.7 Conclusion

The results obtained from the optimization of Bechar's distribution network for configuration "I" gave 6 PV plants in total; 11MW installed in Abadla, 25MW installed in CMTaghit, 23MW installed in Beniounif, 7MW at PVN, 21MW installed in Lahmer and 12MW in Bergua (see Table 4.3). 2 gas turbine installed in PVN and 2 others in Lahmer to insure the operating and spining reserve due to PV power intermittency.

General Conclusion

Optimal DG planning strategies and solutions are key features for an efficient, reliable and stable operation of a distribution system. In this report, two meta-heuristic techniques for DG integration into Bechar's distribution system are presented. Genetic Algorithm and Grey Wolf Optimizer has been proposed to solve the capacity allocation problem. The optimization is based on a co-simulation platform where the detailed distribution system is modeled in OpenDSS and the optimization algorithm has been developed in Matlab. The simulation results are encouraging and show the effectiveness of the meta-heuristic techniques.
The efficiency enhancement of the distribution network is the major objective of this study, where the optimization is based on energy loss minimization and cost reduction. The results obtained from the application on Bechar's distribution network proved that the optimal integration of renewable energies allows to gain in fossil fuel resources consumption and reduces the dependency on the main grid.
The connection of these plants at the indicated locations with the proper capacity leads to a reduction in total energy loss of 47.7%. The annual transited energy is estimated to have a reduction of 35%. The PV power output can express the annual gain in gas who is estimated to be 12%.

Regarding the second application on the modified network, the solution of the problem of optimizing both the cost and losses gave a total PV power of 99MW (See Table 4.6). The connection of these power plants at the indicated locations leads approximately to the same gain as the first configuration. It can be deduced that no need for new transformer substations and the old network configuration can be kept and integrate DGs to enhance its performance, especially that these kind of investments are valuable.

Electricity production in Bechar city have to ensure maximum electrification since it suffers from continuous interruptions. Therefore, the total PV power output along with the gas turbines could cover up to 62% of load demand. However, maximum electrification can be achieved by introducing other renewable energy sources such as wind energy.
It is feasible to envision a continuation of this work, which includes conducting an analysis of optimal integration of wind turbines in Bechar's distribution system, and to propose solutions which are carried out in the projects of the years to come.

The combined effects of multiple DG units can change the short-circuit levels to the point where protective devices start to fail. As a result, we require fault analysis techniques that can calculate the DGs' contribution to fault currents.

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Appendix

A.1. IEEE13 Bus Line Characteristics

Table A.1: IEEE13 bus line characteristics

<table>
<tr><th>Lines</th><th>r_matrix(ohm/Km)</th><th>x_matrix(ohm/Km)</th><th>c_matrix(nF)</th></tr>
<tr><td>Line650632</td><td>[0.7526 | 0.1580 0.7375 | 0.1560 0.1535 0.3414]</td><td>[1.1814 | 0.4236 1.1983 | 0.5017 0.3849 1.2112]</td><td>/</td></tr>
<tr><td>Line632670</td><td>[0.7526 | 0.1580 0.7375 | 0.1560 0.1535 0.3414]</td><td>[1.1814 | 0.4236 1.1983 | 0.5017 0.3849 1.2112]</td><td>/</td></tr>
<tr><td>Line670671</td><td>[0.7526 | 0.1580 0.7375 | 0.1560 0.1535 0.3414]</td><td>[1.1814 | 0.4236 1.1983 | 0.5017 0.3849 1.2112]</td><td>/</td></tr>
<tr><td>Line671680</td><td>[0.7526 | 0.1580 0.7375 | 0.1560 0.1535 0.3414]</td><td>[1.1814 | 0.4236 1.1983 | 0.5017 0.3849 1.2112]</td><td>/</td></tr>
<tr><td>Line632633</td><td>[0.7526 | 0.1580 0.7475 | 0.1560 0.1535 0..7436]</td><td>[1.1814 | 0.4236 1.1983 | 0.5017 0.3849 1.112]</td><td>/</td></tr>
<tr><td>Line632645</td><td>[1.3238 | 0.2066 1.3294]</td><td>[1.3569 | 0.4591 1.3471]</td><td>/</td></tr>
<tr><td>Line645646</td><td>[1.3238 | 0.2066 1.3294]</td><td>[1.3569 | 0.4591 1.3471]</td><td>/</td></tr>
<tr><td>Line692675</td><td>[0.7982 | 0.3192 0.7891 | 0.2849 0.3192 0.7982]</td><td>[0.4463 | 0.0328 0.404 | -0.0143 0.0328 0.7982]</td><td>[257 | 0 257 | 0 0 257]</td></tr>
<tr><td>Line671684</td><td>[1.3238 | 0.2066 1.3294]</td><td>[1.3569 | 0.4591 1.3471]</td><td>/</td></tr>
<tr><td>Line684611</td><td>[1.3292]</td><td>[1.3475]</td><td>/</td></tr>
<tr><td>Line684652</td><td>[1.3425]</td><td>[0.5124]</td><td>[236]</td></tr>
</table>