

Optimal Allocation of Distributed Generation and Distribution Static Compensator in the Radial Distribution System

Khalid Elhadi Mohamed Ibrahim

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Approval of the Institute of Graduate Studies and Research

Assoc. Prof. Dr. Ali Hakan Ulusoy
Acting Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science in Electrical and Electronic Engineering.

Prof. Dr. Hasan Demirel
Chair, Department of Electrical and
Electronic Engineering

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Electrical and Electronic Engineering.

Assoc. Prof. Dr. Reza Sirjani
Supervisor

Examining Committee

1. Prof. Dr. Osman Kükreler

2. Assoc. Prof. Dr. Murat Fahrioğlu

3. Assoc. Prof. Dr. Reza Sirjani

ABSTRACT

This thesis investigates the optimum allocation and capacity of the Distribution Generators (DGs) and Distribution Static Synchronous Compensator (DSTATCOM) in the radial distribution grid to attain the best reduction in the active power dissipations, voltage drop, and annual loss cost. Four various optimization algorithms are proposed in this research namely Differential Evolution (DE), Genetics Algorithms (GA), Multi-Objective Differential Evolution (MODE), and Multi-Objective Genetic Algorithm (MOGA).

First, the multi-objective function is changed into a solitary one by multiplying each objective function with a weight factor. Then, GA and DE are used to attain the optimum capacity and place of the DG and DSTATCOM in the radial distribution grid. For the case of the MOGA and MODE, the multi-objective functions are directly used without applying the weighted vector approach. After the Pareto Front are obtained, the weighted vector approach is applied to select one solution.

Finally, to check the performance of the methods, IEEE 33 bus bars radial distribution network with three different loading levels namely light (62.5%), nominal (100%), and heavy (125%) is used. Furthermore, the simulated results are contrasted with the previous research works to prove the effectiveness of the proposed methods.

Keywords: Distributed Generation, Distribution Static Compensator, Optimal placement, Optimal sizing, Optimization, Radial distribution system.

ÖZ

Bu tez, etkin güç dağılımı, gerilim düşüşü en iyi azalma elde etmek için radyal dağıtım ızgarasında dağıtılmış jeneratörler (DGs) ve dağıtılmış statik senkron dengelenir (DSTATCOM) optimum konumu ve boyutunu inceler ve yıllık kayıp maliyeti. Dört çeşitli optimizasyon algoritmaları bu araştırma olarak bilinen diferansiyel evrimi (DE), genetik algoritmalar (GA), çok objektif diferansiyel evrimi (MODE) ve çok objektif genetik algoritması (MOGA) önerilmektedir.

İlk olarak, Multi-objektif fonksiyonu bir ağırlık faktörü ile her objektif fonksiyonu çarparak bir yalnız biri olarak değiştirilir. Sonra, GA ve DE en uygun boyutu ve DG ve DSTATCOM yer radyal dağıtım ızgarasında almak için kullanılır. MOGA ve MODE için, Multi-objektif fonksiyonları doğrudan ağırlıklı vektör yaklaşımı uygulamadan kullanılır. Pareto cephesi alındıktan sonra, bir çözüm seçilmesi için ağırlıklı vektör yaklaşımı uygulanır.

Son olarak, Yukarıdaki yöntemlerin performansını onaylamak için, IEEE 33 Bus barlar radyal dağıtım ağı ile üç farklı yükleme seviyeleri olarak bilinen hafif (62,5%), normal (100%), ve ağır (125%) test edilir. Ayrıca, benzetilmiş sonuçlar, önerilen yöntemlerin etkinliğini kanıtlamak için önceki araştırma çalışmaları ile kontrastlı.

Anahtar Kelimeler: Dağıtılmış jeneratörler, Dağıtılmış statik senkron dengelenir, Radyal dağıtım ızgarasında, Optimizasyon, Optimum konumu ve boyutunu

To my beloved Family

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ALO	Ant Lion Optimization Algorithm
BA	Bat Algorithm
BCBV	Branch Current to Bus Voltage matrix
BFOA	Bacterial Foraging Optimization Algorithm
BIBC	Bus Injection to Branch Current matrix
CPDs	Custom Power Devices
DE	Differential Evolution
D-FACTS	Distributed Flexible Alternate Current Transmitting Systems
DGs	Distributed Generations
DSTATCOM	Distribution Static Synchronous Compensator
EA	Evolutionary Algorithm
GA	Genetic Algorithm
ICSO	Improved Cat Swarm Optimization
KHA	Krill Herd Algorithm
MODE	Multi-Objective Differential Evolution
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
PV	Photo-Voltaic
QOL	Quasi Opposition based Learning
SA	Simulated Annealing
THD	Total Harmonic Distortion

UPS Uninterrupted Power Supply

Chapter 1

INTRODUCTION

1.1 Background

The electrical power grid is composed of production, transmitting, and distribution system, where the distribution system is a portion of the energy transmitting substructure that takes the electrical energy from the side of high voltage transmission networks by scaling down the voltage through substations and carries it over lower voltage wires under to supply industrial, commercial, and residential consumers. The principal role of the power system is to generate the electricity and transmit it to the consumers in the trustiest way by providing the full protection along with consideration of the financial issues [1].

As of late, there are some issues related to the electrical distribution system because of an aimless increment in non-linear loads, for example, stability problems, high energy dissipations, and excessive voltage drop in buses as well as lines [2]. In this way, remembering the end goal to handle these issues and to enhance the execution of this system Distribution Generators (DGs) and Distribution Flexible Alternate Current Transmitting Systems (D-FACTS) like Distribution Static Synchronous Compensator (DSTATCOM), devices take place in the distribution network [3].

The DG is a little generating innovation found near the client. In the recent years, the integrating of this technology in the electrical distribution system has increased for

many reasons such as it is environmentally friendly, cheaper, and it can provide a solution for some problems, like power quality problems. While the DSTATCOM is power electronic based devices which uses a capacitor and an inductor to add or consume reactive power from the network by using the Thyristor technology [4].

Contrasted DSTATCOM and the conventional reactive power compensation gadgets, DSTATCOM has fundamental preferences, for example, the capability to control well, the low harmonic, small device, no noise and little power dissipation. The DSTATCOM can supply a compensation current so that, the load can fulfil the specification for a utility connection. On the other hand, it can likewise mitigate the harmonic distortion from the voltage of the utility [5].

Nowadays, with the improvement of the technology and the necessity to obtain the maximum efficiency from the electrical distribution network the planning of such devices like DG and Distributed Static Synchronous Compensator (DSTATCOM) has turned into a true challenge. So that, these devices are incorporated into the grid to enhance the quality of that network, but the improper capacity and site of these devices may lead to many problems like increasing the power losses instead of decrease it [6].

Currently, there are numerous optimization methods have been used in the electrical distribution networks to attain the best performance of the grid while satisfying the constraints of the network, DG, and DSTATCOM such as enumerative techniques, calculus-based techniques, and the heuristics techniques. Among these strategies, the powerful one is the heuristic algorithms because they are simple to implement, faster than the classical ones because they do not need too much calculation, by one run we can get a set of the solution, their accuracy is high which stick to the optimum solution

or near to the optimum point. In contrast, the classical approaches depend on the initial guess so that, they may not always lead to the global optima sometimes may stick in the local optimum solution [7].

1.2 Thesis Statements

Due to the rapid increase in the industrialization and the population growth, the electrical distribution system experiences a huge increment in the load. This increment in the load demand can cause many serious problems if it is not tackled by building new power stations or transmission line to feed the new load. Furthermore, the load increase can lead to problems such as voltage stability, harmonics, poor power factor, and large power dissipation.

Of late, the DG and DSTATCOM have considered as a great solution for these problems for the reasons of the cost and the environmental impact manner. It is necessary for the planner to make sure that these devices are addressed in the right place with the optimum capacity in order to achieve the maximum benefit. The improper location for these devices may cause an increase in the losses or network failure.

The DG and DSTATCOM portion is a complex combinatorial streamlining issue which has pulled in numerous designers and researchers. The solution methods for the optimum allocation and capacity of the DG and DSTATCOM in the distribution grid can get by applying the analytical techniques or the heuristic ones. In the recent days, the most common techniques are the heuristic ones because of their simplicity and speed. The heuristic methods incorporate different algorithms such as the Genetic

Algorithm (GA), Ant Colony Optimization (ACO), Differential Evolution (DE), Artificial Bee Colony (ABC), etc.

As a consequent, in multi-objective optimization problems, there is more than one objective functions to be optimized at the same time, instead of having only one. So, it means to use these techniques we need to convert our objective functions into a solitary one by multiplying each objective function with an importance factor. In addition to that, they can stick to the local optimal solution.

1.3 Objectives of the Thesis

The intention of this study is twofold. On the one hand, it is to propose the ideal multi-objective differential evolution optimization technique to investigate the optimum allocation and sizing of the distributed generations and the distribution static synchronous compensator to lessen the power dissipations, the voltage descent and the cost. Furthermore, the objective is to find the Pareto front and to compare the results of the ideal multi-objective optimizer with the single objective optimizer.

Chapter 2

LITERATURE REVIEW

2.1 Distribution Generators (DGs)

In recent years, a small home or industrial based distributed generation has become more popular as people install solar photovoltaic (PV) cells on their farms, companies, and the roof of their homes. Since these distribution generation facilities are connected to the grid, they affect the electrical distribution grid.

The distribution generator (DG) is a generation unit that is similar to the traditional centralized one in the working principle while one of the differences between them is that, the DG is small generation unit located closer to the customers in the distribution system. DGs can be categorized based on the unit capacity from 1 kW photovoltaic cell to 300 MW wind farms [8]:

- Micro DG unit: (1 - 5000 W).
- Small DG unit: (5 - 5000 kW).
- Medium DG unit: (5 - 50 MW).
- Large DG unit: (50 - 300 MW).

In addition to that, it can be classified based on the DG type to many topologies such as renewable, non-renewable, and batteries, but the trend of using renewable types such as solar photovoltaic (PV) cells, wind turbines, fuel cells... etc. have been increased. The main reason for that, because they have some advantages such as

inexhaustible resources and eco-friendly whereas the drawbacks of these kinds of systems are low efficiency and the high cost [9].

2.2 The Application of the DG

DG is recently being employed by a scarce of clients to provide a percentage of their power demands. There is a widespread of possible applications of DG innovations. For instance, several consumers employ DG to decrease request charges forced by their electric utility, while others use it to enhance the quality of the power or lessen natural discharges. DG can similarly be employed by electric utilities to upgrade their distribution networks. The DG can be characterized by its applications into numerous classes. The summary of DG applications is shown in Table 2.1 below

Table 2.1: DG Applications

Application	Objective
Continuous Power	Generate control nearby less expensive than utility consistently
Back up	Replace the typical source on the off chance that it comes up short.
Regulation	Balancing generating power and demand on seconds timescale
Reserves	Balancing generating power and demand on a 5-20 min timescale.
Supply Capacity	Participating in the limit advertise, intended to guarantee future asset sufficiency.
Uninterrupted Power Supply (UPS)	Replace the typical source on the off chance that it falls flat. Programmed and prompt reaction.
Combined Heat and Power	Generate power and warmth for space/water warming or steam production

2.3 Distribution Static Synchronous Compensator (DSTATCOM)

DSTATCOMs are power electronics controllers used in the distribution power grid to supply power with the best efficiency and quality for consumers and it is called custom power devices (CPDs), which are not different from FACTS devices in terms of technical base, but they have diverse goals. Distribution Static Synchronous Compensator (DSTATCOM), is a parallel CPD used in distribution networks to enhance the power excellence by injecting the electric current into the grid at the node of common connection [10]. It is a static compensator (STATCOM) formed with a coupler voltage transformer, a power stored device (battery) and an inverter as shown in Figure 2.1. One of the upsides of this gadget that, its capacity to infuse and retaining the reactive power quick [11].

The DSTATCOM is a voltage control source that operates the inverter in order convert the voltage on the capacitor to an adjustable source of the voltage. The working procedure of the DSTATCOM is as per the following: in the first place, the voltage in the DSTATCOM is contrasted and framework voltage so that, if the AC bus voltage is over that of the voltage source inverter, the grid will regard the DSTATCOM as an inductance associated with its terminals. Otherwise, if the AC bus voltage is below the voltage source inverters, the system will see the DSTATCOM as a capacitance. When the voltage magnitudes are the same there is no reactive power transfer between the bus and the DSTATCOM [12].

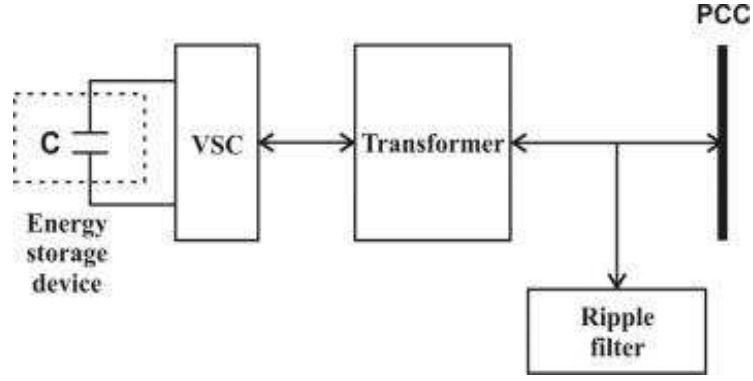


Figure 2.1: Block Diagram of DSTATCOM [13]

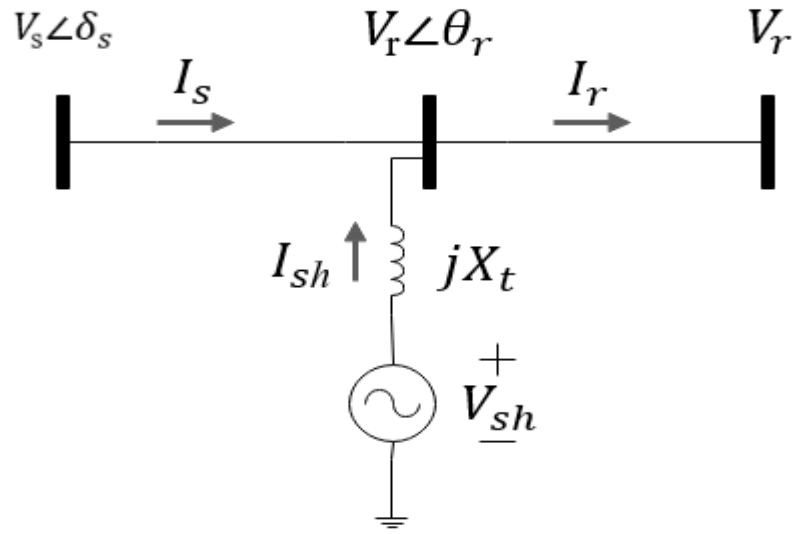


Figure 2.2: DSTATCOM Equivalent Circuit

From Figure 2.2 above by setting the voltage common point in the following equation $\vec{V}_{sh} = V_{sh} \angle \delta_{sh}$ as a reference phase and the main component of the voltage source converter is $\vec{V}_s = V_s \angle 0$. The reactive power exchanged with the grid is shown by the following equation below:

$$Q = \frac{V_s^2}{X_t} - \frac{V_s V_{sh}}{X_t} \cos \delta_{sh} \quad (2.1)$$

Where:

V_s : The voltage of the source

V_{sh} : The voltage of the common point

X_t : Shunt reactance

2.3 Electrical Distribution System Configurations

An important characteristic of the electrical distribution network is their configurations, or how the lines are connected in the grid. In general, the electrical distribution grid can be sorted according to the scheme of connection to radial and mesh system, which are shown in Figure 2.1 and Figure 2.2.

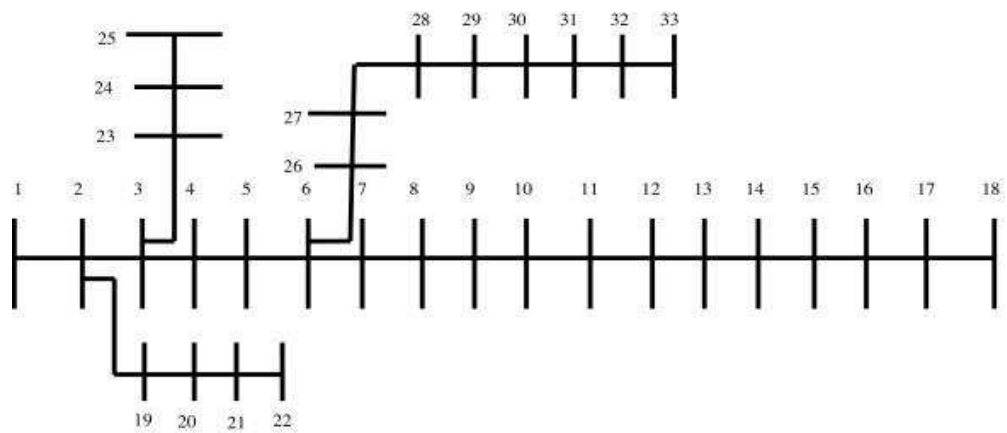


Figure 2.3: 33 Bus Radial Distribution System [13]

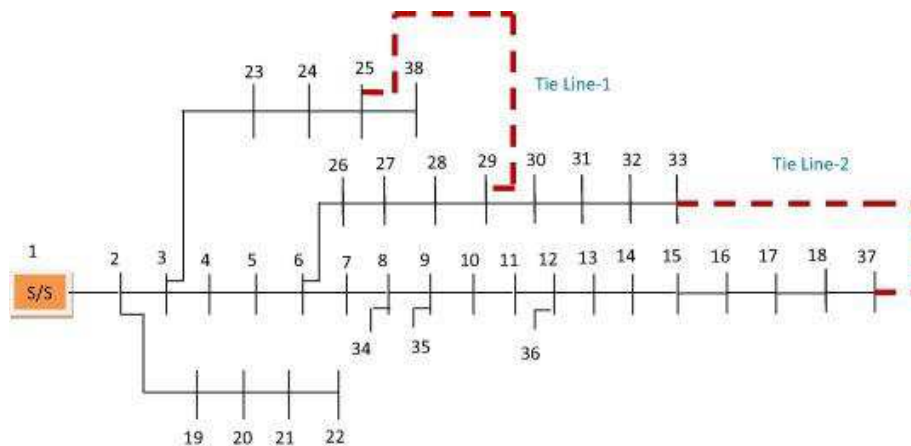


Figure 2.4: 38 Mesh distribution System [14]

2.3.1 Radial System

In this scheme, remote feeders transmit the electricity from a single substation in a way that every distribution line is supplied at one point only. Numerous distribution

framework work utilizing a radial feeder scheme on account of its straightforwardness and cheapness. Recently, many research works have been done to determine the optimum capacities as well as sites of DSTATCOM and DGs in radial distribution grids aiming to decrease the cost, power dissipation, and enhance the voltage.

In 2013, Injeti et al have determined the best site and size for inserting several DGs in the smallish, intermediate and the outsized radial distribution grids [15]. In 2014, Roy et al have proposed the combination of teaching-learning based optimization technique with quasi-opposition based learning to investigate the best placement of an only one DG to decrease the active power dissipation in the standard 33, 69, and 118 node grid[16].

Furthermore, in 2015 the same authors combined the opposition based learning algorithm with another heuristic algorithm called krill herd to get the best site of DGs while considering the deduction of the yearly cost as a target [17]. In the same year, Gupta et al have determined the optimal allocation and the size of DSTATCOM under reconfigured network to lessen the power loss [18].

Moreover, Prabha, D. R., & Jayabarathi, T. proposed invasive weed algorithm for determining the optimum allocation to insert several DGs in the distribution grids and their capacities to achieve several goals such as voltage enhancement, alleviation of the energy dissipations, and energy retrenchment [19]. In E.S. Ali, et al presented Ant Lion Optimization Algorithm to determine the optimum sites to add several renewable DGs to the network also to calculate the most suitable size for them to decrease the energy dissipation and to enhance the voltage stability [20].

2.3.2 Mesh System

Mesh system is a topology of networks which is an outcome of the combination of the symmetric and the ring networks. In 2016 Gupta et al have proposed sensitivity methods to determine the perfect place for DSTATCOM in a mesh distribution grid with a varied electrical power demand under load development to achieve some goals such as voltage stability margin improvement, energy dissipation lessening, and cost of energy saving. The suggested method was examined in the UK 38 practical mesh distribution grid [14]. The summary of topology classification is shown in Table 2.2.

Table 2.2: Classification According to Topology

Scheme of connection	Remarks	References
Radial system	<ul style="list-style-type: none"> IEEE 33, 69, and 119 nodes Single DG is used 	[16] Sultana, S., & Roy, P. K. (2014)
	<ul style="list-style-type: none"> IEEE 33 and 69 nodes Multiple DG units 	[19] Prabha, D. R., & Jayabarathi, T. (2016), [20] Ali, E. S., Elazim, S. A., & Abdelaziz, A. Y. (2017)
	<ul style="list-style-type: none"> IEEE 33, 69, and 119 nodes Multiple DGs are used 	[15] Injeti, S. K., & Kumar, N. P. (2013),
Mesh system	<ul style="list-style-type: none"> DSTATCOM is used UK 38 bus practical mesh distribution system 	[14] Gupta, A. R., & Kumar, A. (2016)

2.4 Design Objectives of the Electrical Distribution Networks

Recently, numerous researches have been done for optimizing the distribution system with different objective functions, which can be summarized as follow:

2.4.1 Loss Reduction

In recent years, many types of research have been done while applying various optimization techniques to investigate the optimum sites and the capacities of DGs and a DSTATCOM in the distribution grid to achieve some optimization aims such as energy dissipation reduction [21]. In 2015 T. Yuvaraj et al have found the optimum site and the best capacity for a DSTATCOM by combining the voltage stability index with Bat algorithm, under load variation condition [22].

While, in 2016, Senha Sultana and Provas Kumar Ray proposed a heuristic algorithm called the Krill herd to find the most appropriate site of individual DG in a radial distribution grid to decrease the energy dissipation, so to show the performance of the suggested method, it was examined in a 33, 69, and 118 bus bars radial distribution grid by utilizing three types of different loads [13].

Moreover, In 2017 Partha P.Biswas, et al determined the optimum allocation and the capacity of several DGs and capacitors in the distribution grid by applying a multi-objective approach for minimizing the power dissipation. Both DGs and capacitors are utilized to lessen the real and the reactive power dissipations. The method was evaluated with similar previous studies and notable improvement is observed [23].

In Mahesh Kumar et al determined the optimal positioning and the capacity of DGs for voltage-dependent load module in the radial distribution grid. One and several DGs are used (real, reactive, and a combination of them). Likewise, five distinct sorts of load models are utilized. In addition, the load growth for the base and next three years predicted [14].

2.4.2 Voltage Improvement

Here we give a review of the literature concerning voltage improvement as a target, which considered the optimum capacity and place of the DGs and DSTATCOM as design parameters.

In 2014, Sultana et al proposed multi-objective quasi-oppositional teaching learning-based optimization for the optimum site of the DG in the loop distribution grids to increase the voltage stability; thus, to confirm the efficiency of the suggested method is verified on 33 nodes, 69 nodes, and 118 nodes radial distribution grids [16]. Moreover, the consequences are compared with other algorithms. In 2015 Kumar et al determined the optimum allocation of DSTATCOM, while considering the voltage enhancement as the objective function under the reconfigured network. The technique is verified on IEEE 69busbars radial distribution grids [18].

2.4.3 Cost Reduction

The literature different goals for electricity production cost have been considered for DG such as building, operation, and maintenance costs [25, 26]. In 2015 Chu-Sheng Lee et al applied particle swarm optimization approaches for finding capacitor location on the distribution grids to decrease the yearly cost [27]. Moreover, in 2016 Gupta, A. R., & Kumar, A. used sensitivity methods, and determined the optimum site of DSTATCOM in mesh distribution grid with varied load models along the time under load growth, while considering the cost reduction as the objective function [14]. The summary of the review studies according to the objective function is shown in Table 2.3 below.

Table 2.3: Typical Design Objectives

Objective	No. of units	Remarks	References
Loss Lessening	Single	<ul style="list-style-type: none"> Placement of DSTATCOM for real power loss mitigation 	[28] Hussain, S. S., & Subbaramiah, M. (2013)
	Single	<ul style="list-style-type: none"> The place and the capacity of DSTATCOM for varied load 	[22] T. Yuvaraj et al. (2015)
	Multiple	<ul style="list-style-type: none"> Allocation of both DSTATCOM and DGs 	[29] Kanwar, N., et al. (2015), [30] Devabalaji, K. R., & Ravi, K. (2016),
	Single	<ul style="list-style-type: none"> Active power dissipation and energy dissipation Various types of renewable DGs 	[13] Senha Sultana and Provas Kumar Roy (2016),
	Multiple	<ul style="list-style-type: none"> Active and reactive power dissipation lessening DG and shunt capacitors 	[23] Partha P.Biswas, et al. (2017),
Voltage enhancement	Single	<ul style="list-style-type: none"> Single DG allocation 	[16] Sultana, S., & Roy, P. K. (2014),
	Single	<ul style="list-style-type: none"> Placement of DSTATCOM 	[18] Gupta, A. R., & Kumar, A. (2015)
Cost reduction	Single	<ul style="list-style-type: none"> Placement of DSTATCOM with time variant load Load growth 	[14] Gupta, A. R., & Kumar, A. (2016)

2.5 Optimization Techniques

Recently, various types of the optimization methods have been projected to get the optimum site of DGs and DSTATCOM in the distribution grids which lead to improving the characteristics of the networks. The methods used to solve this optimization problem can be categorized into different groups such as analytical and heuristic algorithms or multi-objective techniques and single ones.

Heuristic algorithms are critical thinking strategy in which the most fitting solution or partial solution is chosen utilizing relative principles. They are regularly utilized as a part of solving the optimization problem of the optimum allocation of the DG and DSTATCOM. In light of the working system of these methods, the solution acquired frequently have a tendency to be stuck at a good estimate [7].

2.5.1 Analytical Methods

These approaches involving of simple algorithms that can be projected with the need of powerful computing assets. The point of using the analytical techniques in the problem of the site assignment of DSTATCOM to attain the optimum solution without putting in mind the non-linearity and complexity of it. For decreasing the calculation process, some approximations should also be applied to these methods.

In [28], an analytical technique has been proposed for finding the best site of DSTATCOM in the distribution grids. The author has considered the voltage index and power dissipations as the goals of this optimization process. The suggested technique was verified in a 33 nodes radial distribution grid. Furthermore, the number of the nodes that have an under/over voltage problem and the emf regulation were checked. DSTATCOM cost and other related benefits were likewise considered. This technique was contrasted with the Genetic Algorithm (GA). The main weaknesses of this algorithm are its large computation time and its slow convergence, in addition, it can consider only a single objective.

2.5.2 Quasi Opposition based Learning (QOL)

Quasi-opposition based-learning (QOL) is a symbiosis organism's search algorithm. So that, the word symbiosis is a Greek word which is used to describe the relationship between any two different species. It consists of a combination of oppositional learning based technique in traditional evolutionary development algorithmic-programs to

advance the convergence and the exactness, was first presented by Mandal to figure out optimum reactive power dispatch issue of the transmitting grid. In 2014, Sultana et al have proposed multi-goals QOBL to determine optimum positioning of the singular DG to reduce the active energy dissipation of 33 nodes, 69 nodes, and 118 nodes radial distribution grid [16].

2.5.4 Krill Herd Algorithm (KHA)

Krill herd algorithm (KHA) is an organically roused algorithm in view of crowding phoneme of krill individuals. It is an original a common sense rule intended to rise the probability of obtaining the solutions of some problems by using swarm intelligence, optimization technique improved by Gandomi et al in the year 2012 [31]. The goal function for the moving of krill is calculated by the minimum distance of every krill individual from the food source and maximum density of the herd.

In the Krill Herd Algorithm, the location of krill individuals represents the various design variables while the space between krill individual and the food source, and the richness of the source represents the objective function. The time-reliant point of the separate krill in a coplanar space is influenced by 3 primary actions namely: motion introduced by other krill's separately, hunting behavior, and physical diffusion [31].

In [17] Roy et al have applied oppositional krill herd method to getting the optimum place of several DGs in the grid to optimize power dissipations. Moreover, to confirm the high quality of the projected method was collated with a principle KHA method, so from the result, the proposed algorithm is more efficient than other reported algorithm.

2.5.4 Ant Lion Optimization Algorithm (ALO)

Ant-lion optimization method (ALO) was proposed by Mirjalili in 2015. It is inspired by biological motivation as it mimics the intelligence behaviour of Ant-lions to hunt ants in nature. To simulate, such collaborations ants are compulsory to travel above the exploration blank, and Ant-Lions are allowable to fetch them and become fitter using traps [32].

The ALO can be implemented by simulating the five steps of the hunt in larvae: random walk to update the location of ants, building traps can be simulated by using a roulette wheel selection, entrapment of ants in traps or sliding ants towards ant-lions, catching victims which happens when ants get fitter or dive inside the sands then ant-lions is required to update its location, and rebuilding the pit. In [20] E.S. Ali et al have presented the Ant-Lion Optimization method to obtain the optimum positioning and capacity of the inexhaustible distributed generators to decrease the energy dissipation also to develop the voltage stability.

2.5.5 Simulated Annealing (SA)

In this algorithm, the issue of improvement is displayed as a strengthening procedure which is a thermal procedure for acquiring low energy conditions of a solid in a heat bath. So that, it contains two stages: to start, with rising up the temperature of the heat bath to a most extreme value at which the solid melts. Then, diminish the temperature of the heat bath carefully until the point that particles organize themselves in a base minimum energy state of the solid.

In this method a probability function is being used for accepting or rejecting new results or random ascent moves, to escape being stuck to the local optimum solutions. The algorithm has been projected in [33] for the first time, then its usage has increased

for some reasons such as its easiness and its reliable findings [34]. The method consist of initialization, mutation, cooling schedule, and probability processes.

The cooling and temperature initialization in this technique play the main parts in getting good outcomes [35]. In 2013 Injeti, S. K., & Kumar, N. P. have applied SA to minimalize dissipation and maintain voltage stability by optimum capacity and place of several DG units in small, medium, and large-scale radial distribution system [15]. The main defect of this algorithm is it is required initial values and cooling parameters setting.

2.5.6 Bacterial Foraging Optimization Algorithm (BFOA)

The BFOA is inspired by the chemo-taxis phenomenon of bacteria that will observe chemical gradients in the surroundings then start to move in the direction or far away from the particular signals. BFOA is an effective team brilliance based random search method invented by Passino [36]. Lately, it has been proposed to resolve abundant optimization issues in the electrical power grid.

So basically the BFOA consists of four principal mechanisms known as chemo-taxis which simulates the small movement of the bacteria by tumbling, swarming so that cells arrange themselves in a travelling ring, reproduction so that the least healthy bacteria die while the healthier bacteria divide into two bacteria cell and elimination-dispersal.

In 2016, Devabalaji et al determined the optimum capacity and site of several DSTATCOM and DG in the radial distribution grid by projecting bacterial foraging optimization technique. The proposed algorithm is verified on standard 33 nodes and

an 119 nodes loop distribution grid with varied power factors, while the outcomes were collated with other existing techniques [30].

2.5.7 Bat Algorithm (BA)

Bat technique has been suggested by Yang. It is a novel nature-inspired meta-heuristic algorithm based on the echolocation phenomenon of micro-bats. In general, Bats produce sonar signals in order to detect potential prey from the reflection of the signals. When those signals hit an item they will reflect back, and bats can get some information from the reflected signals such as the size and the distance after [37].

In BA, bats fly haphazardly (speed and position) with a fixed frequency, varying wavelength, and loudness to scan for prey. In 2015 T. Yuvaraj et al determined the optimum site and the capacity of a DSTATCOM by using voltage stability index and Bat algorithm, under load variation condition [22]. The summary of the review studies according to the optimization algorithm is shown in Table 2.4.

Table 2.4: Typical Optimization Techniques

Algorithm	References	Remarks
Analytical methods	[28] Hussain, S. S., & Subbaramiah, M. (2013)	<ul style="list-style-type: none"> • Optimal position of DSTATCOM
QOBL	[16] Sultana, S., & Roy, P. K. (2014)	<ul style="list-style-type: none"> • Optimal location of single DG • Better results than GA, PSO, GA/PSO, and LSFSA in terms of solution quality
KHA	[17] Sultana, S., & Roy, P. K (2015)	<ul style="list-style-type: none"> • Location and size of different types of renewable DGs
ALO	[20] E.S. Ali, et al (2017)	<ul style="list-style-type: none"> • Implemented with loss sensitivity factor • Location and sizing of single and multiple DGs • The superiority is confirmed via Wilcoxon test
MOEA/D	[23] Partha P.Biswas, et al. (2017)	<ul style="list-style-type: none"> • The computation complexity of it is less. • Optimal size and site of multiple DGs and shunt capacitors

Algorithm	References	Remarks
ICSO	[29] Kanwar, N, et al (2015)	<ul style="list-style-type: none"> • Placement of both DG and DSTATCOM • Three diverse loading levels (Light, nominal, and heavy)
BFOA	[30] Devabalaji, K. R., & Ravi, K (2016)	<ul style="list-style-type: none"> • Allocation of several DSTATCOMs and DGs with different power factor

2.6 Summary and Researches Gaps

Most of the papers for optimizing the distribution grids are carried out based on optimization algorithms including heuristic algorithms and classical methods. The heuristic algorithm has the ability to search for local and global optima and offers a set of optimal outcomes with the less computational interval. Therefore, the heuristic algorithm has attracted more attention in the design and optimization of the distribution system than classical methods. Nevertheless, power factor, the accuracy and the speed were not put into account by the researchers in reviewing literature. The summary of the reviewing literature is shown in Table 2.5 and Table 2.6

Table 2.5: Summary of the Reviewing Literature According to Case study, Objectives, and Design parameters

Author	CASE STUDY				Practical network	OBJECTIVES			VARIABLES			
	IEEE 33-bus	IEEE 69-bus	IEEE 119-bus	IEEE 118-bus		Power loss reduction	Voltage enhancement	Cost reduction	Placement	Capacity	DG	DSTATCOM
[15] Injeti, S. K., & Kumar, N. P. (2013)	♦	♦				♦			♦	♦	♦	
[28] Hussain, S. S., & Subbaramiah, M. (2013)						♦	♦		♦	♦		♦
[38] Devi, S., & Geethanjali, M. (2014)	♦	♦				♦			♦	♦		♦
[16] Sultana, S., & Roy, P. K. (2014)	♦	♦		♦		♦	♦		♦	♦	♦	
[17] Sultana, S., & Roy, P. K. (2015)	♦	♦		♦		♦			♦	♦	♦	
[18] Gupta, A. R., & Kumar, A. (2015)		♦				♦	♦		♦	♦		♦
[22] Yuvaraj, T. et al (2015)	♦	♦				♦			♦	♦		♦

Author	CASE STUDY				OBJECTIVES			VARIABLES				
	IEEE 33-bus	IEEE 69-bus	IEEE 119-bus	IEEE 118-bus	Practical network	Power loss reduction	Voltage enhancement	Cost reduction	Placement	Capacity	DG	DSTATCOM
[29] Kanwar, N. et al (2015)	♦	♦				♦			♦	♦		
[14] Gupta, A. R., & Kumar, A. (2016)					♦	♦	♦	♦	♦	♦		♦
[30] Devabalaji, K. R., & Ravi, K. (2016)	♦		♦			♦	♦	♦	♦	♦	♦	♦
[19] Prabha, D. R., & Jayabarathi, T. (2016)	♦	♦				♦	♦	♦	♦	♦	♦	
[39] Khairuddin, A. et al (2016)		♦				♦	♦		♦	♦	♦	
[40] Bhattacharya, A. (2016)	♦	♦				♦	♦		♦	♦	♦	
[41] Kowsalya, S. K. S. M. (2016).	♦					♦			♦		♦	
[20] Ali, E. S. et al (2017)	♦	♦				♦	♦		♦	♦	♦	
[23] Biswas, P. P. et al (2017)	♦	♦	♦			♦			♦	♦	♦	
[42] Srinivasan, G., & Visalakshi, S. (2017)	♦	♦				♦			♦	♦	♦	
[43] Luo, L. et al (2017)	♦							♦	♦	♦		♦
[24] Kumar, M. et al (2017)	♦					♦			♦	♦	♦	
[44] Sharma, A. et al (2017)	♦				♦	♦	♦		♦	♦		
[45] Ramadan, H. S. et al (2017)					♦	♦		♦	♦	♦	♦	

Table 2.6: Summary of the Reviewing Literature According to Constraints and Optimization Algorithms

Author	CONSTRAINTS						OPTIMIZATION ALGORITHM															
	Power balance	Voltage	Current	Cost	Power	Capacity	Total harmonic distortion	Krill herd algorithm	Ant Lion Optimization Algorithm	Multi-objective approach	Autonomous group particle swarm	Particle Swarm Optimization	Limaçon inspired spider monkey	Bat algorithm	Quasi oppositional swine influenza based	invasive weed optimization algorithm	Improved cat swarm optimization	Bacterial Foraging optimization Algorithm	Grey wolf optimizer	simulated annealing	intersect mutation differential evolution	Analytical method
[15] Injeti, S. K., & Kumar, N. P. (2013)	♦	♦	♦		♦	♦															♦	♦
[28] Hussain, S. S., & Subbaramiah, M. (2013)	♦																					♦
[38] Devi, S., & Geethanjali, M. (2014)		♦			♦						♦											

Author	CONSTRAINTS						OPTIMIZATION ALGORITHM																
	Power balance	Voltage	Current	Cost	Power	Capacity	Total harmonic distortion	Krill herd algorithm	Ant Lion Optimization Algorithm	Multi-objective approach	Autonomous group particle swarm	Particle Swarm Optimization	Limaçon inspired spider monkey	Bat algorithm	Quasi oppositional swine influenza based	invasive weed optimization algorithm	Improved cat swarm optimization	Bacterial Foraging optimization Algorithm	Grey wolf optimizer	simulated annealing	intersect mutation differential evolution	Analytical method	
[16] Sultana, S., & Roy, P. K. (2014)	♦	♦			♦	♦			♦		♦										♦	♦	
[17] Sultana, S., & Roy, P. K. (2015)	♦	♦			♦		♦																
[18] Gupta, A. R., & Kumar, A. (2015)																						♦	
[22] Yuvaraj, T. et al (2015)		♦		♦	♦									♦									♦
[29] Kanwar, N. et al (2015)	♦				♦						♦												
[14] Gupta, A. R., & Kumar, A. (2016)																							♦
[30] Devabalaji, K. R., & Ravi, K. (2016)	♦	♦			♦												♦						♦
[19] Prabha, D. R., & Jayabarathi, T. (2016)	♦	♦			♦	♦										♦							♦
[39] Khairuddin, A. et al (2016)		♦			♦	♦													♦				
[40] Bhattacharya, A. (2016)	♦	♦	♦		♦	♦									♦								
[41] Kowsalya, S. K. S. M. (2016).	♦	♦												♦									
[20] Ali, E. S. et al (2017)		♦			♦	♦		♦															♦
[23] Biswas, P. P. et al (2017)		♦			♦	♦			♦														♦
[42] Srinivasan, G., & Visalakshi, S. (2017)		♦			♦	♦				♦													
[43] Luo, L. et al (2017)		♦			♦																		♦
[24] Kumar, M. et al (2017)		♦			♦						♦												
[44] Sharma, A. et al (2017)													♦										
[45] Ramadan, H. S. et al (2017)	♦				♦						♦												

Chapter 3

OPTIMIZATION TECHNIQUE

3.1 Introduction

Optimization can be characterized as the issue of finding the vector of the choice factors which fulfills the constraints or the restrictions in the problem and optimize the objective function in other words optimization aims to obtain the values of the design variables which gives the minimum or the maximum values of the objective function while considering the restriction in the problem.

Recently, there are several optimization methods which can be applied to solve the optimization problem of the site and size of the DG and the DSTATCOM in the electrical distribution grid so as to ensure reduced the power dissipations, reduced costs, minimized the THD, and improved the voltage profile. Those methods can be categorized into many groups like single objective and multi-objective methods. With this in mind, there is a necessity to find the most effective optimization method to tackle this problem with the most reliable solutions are obtained.

In this study, the work of Manafi et al [46] in 2013 and Sanam et al [47] in 2017 was the key in selecting Differential Evolution (DE) algorithm with its two versions the single and the multi-objective one as one of these methods. In this work, DE is proposed as an optimization technique which is simple to formulate, and has the ability to search a vast area and obtain reliable solutions very fast. This is because DE uses

vector perturbation for updating the solution and at the end of each iteration the bad solutions are discarded.

3.2 Optimization Terminologies

As mentioned in the definition the optimization problem is referred to as the problem of seeking for the values of the decision variables which fulfils the constraints and enhance the objective function. This definition contains some terms related to optimization.

3.2.1 Decision Variables

They are called the choice factors likewise the plan parameters, are the numerical amounts for which esteems are to be picked in the optimization problems. So that, the solution of the optimization problem begins with the definition of the problem, and the first step in the definition is to identify the decision variables from the set of the parameters which has a direct impact in the objective function.

In general, the set of the decision variables represents a solution for the optimization problem, and their quantities are donated as $x_j, j = 1, 2, \dots, n$. The vector x of n plan factors can be denoted as follow.

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} \quad \text{OR} \quad x = [x_1 x_2 x_3 \cdots x_n]^T \quad (3.1)$$

For the issue of the area and size of the DG and DSTATCOM, the choice factors are the area and limit of DG and additionally DSTATCOM. Where the vector of the decision variables consist of different bit strings, so that for the location of the DG and DSTATCOM positive integer numbers are used, and for the capacity positive real numbers are used. Thus, our problem is a combination of the continuous and integer

bit strings. For the allocation of a single DG and DSTATCOM the vector of the decision variables can be defined as follow:

$$x = [DG_{Location}, DSTATCOM_{Location}, DG_{size}, DSTATCOM_{size}]^T \quad (3.2)$$

Where: $DG_{Location}$ and $DSTATCOM_{Location}$ are integer numbers between 2 and the number of the buses while, DG_{size} and $DSTATCOM_{size}$ are positive real numbers.

3.2.2 Constraints

In the most optimization problems are always boundaries forced by the specific attributes of the environment or accessible assets, for example, physical limitations, time restrictions, cost limitations, etc. While solving the optimization problem these restrictions must be satisfied in order to accept the solution. All these limitations in the optimization are called constraints, and they portray conditions among the choice factors and constants or parameters associated with the problem. These constraints are expressed in form of mathematical equality or inequality as follow.

Mathematical inequalities:

$$g_i(x) \leq 0, \quad i = 1, 2, \dots, m \quad (3.3)$$

Mathematical equalities:

$$h_j(x) = 0, \quad j = 1, 2, \dots, p \quad (3.4)$$

Where:

$p < m$, if $p \geq m$ the problem is called over constrained. So that, the degree of the freedom is $n - p$.

In the optimization problem if the solution is not satisfied the constrained is called infeasible and if it is satisfied is called feasible. The main aim for the optimization is to seek for a feasible solution. Here in the problem of the optimal capacity and place

of the DSTATCOM and DG, there are too many constraints such as current boundaries, voltage boundaries, power balance, and the limit of the appropriation lines as well as DG limit, DSTATCOM limit, and so forth.

3.2.3 Objective Function

The objective function is a mathematical description of the performance criteria. With respect to the number of the optimization goals, optimization problems can be categorized as a single objective and multi-objective optimization. So that, in multi-target optimization there at least two targets or more to be upgraded in the meantime. In general, most of the real world optimization problems are multi-objective problems and usually have several conflicting objective.

Putting in mind the final goal to tackle the multi-target optimization issues, there are two different ways one of them is to change over the multi-target issue into a solitary one by multiplying the objective by the scaling factor. So that, in this method every objective function should be given a weight which decides the importance of the objective function. Then again, the ideal multi-target optimization techniques can be utilized specifically. The difficulty of this method comes from the fact of having a conflicting function so that, it is difficult to compare between them.

The problem of finding the optimum capacity and place of the DG and DSTATCOM is a multi-objective problem which seeks to optimize several goals such as power dissipation lessening, minimization of the bus voltage differences, cost diminishment, the boost of the voltage stability, and lessening of the total harmonic distortion.

3.3 Differential Evolution (DE)

Differential Evolution (DE) is an Evolutionary Algorithm (EA) for continuous function optimization proposed by Kenneth Price and Rainer Storn in 1994 and it can be used for discrete function optimization. The Term EA refers to heuristics algorithm that uses natural selection as their search engine for solving the optimization problems. DE is likewise a populace based technique, in which each solution is called an agent, and is frequently represented as multi-dimensional real vectors. So that, the dimension of the agent vector represents the number of the decision variables, in which every design variable represent by one dimension in the decision space.

The key idea of the DE is to use vector differences (addition and subtraction of the agent vectors) for mutating the vector population, not like Genetic Algorithm which uses conventional methods for the operations of crossover and mutation of the solutions. All the more particularly, DE essential system can be portrayed as takes after:

- Initialization: in this stage, an underlying populace (set of arrangements) is produced haphazardly with a distribution uniform. This step is shown in the following equation below.

$$x_{i,j}(0) = x_j^L + \text{rand}(0, 1) \cdot (x_j^U - x_j^L) \quad (3.4)$$

Where:

$$i = 1, 2, \dots, N \quad (N: \text{Population size})$$

$$j = 1, 2, \dots, D \quad (D: \text{Length of the agent})$$

U : Upper bound

L : Lower bound

- Mutation: in this step, randomly three diverse vectors are chosen from the populace vectors. So that, we subtract two of them and the differences are multiplied by a given weight factor. Then, the result of the differences is added to the third vector. Generally, an agent x is mutated in two steps.

➤ First step: Find Mutation vector u :

Here, we select in a random way three different agents, which are mutually different from the agent x . So that, the perturbation vector is found as follow.

$$u_i = r_{3i} + F (r_{1i} + r_{2i}), \quad i = 1, 2, \dots, D \quad (3.5)$$

Where D is the length of the agents, and F is the differential weight factor ranges in $[0, 2]$. The factor F is usually chosen in $[0.4, 1]$.

➤ Second step: is to obtain the perturbed vector y through the operation of the crossover between the vectors x and u which is shown as follow

```

j = rand[1, D]; % Find and index at random
for i = 1 to D
if (rand[1, D] < CR or i == j) (CR is the crossover rate)
y_i = u_i;
else y_i = x_i;
end

```

The vector u is also known as a donor vector for the reason that it is produced only for donating some of its parts to the new agent.

- Selection: after the mutation of the agents the next step is to select the old agent or the new one with respect to its fitness. In this operation, we have the parent $y_i(t)$ and its fitness $f(y_i(t))$ besides the offspring $y_i'(t)$ and its fitness $f(y_i'(t))$. So that, our aim is to select the best vector between them as follow

```

if  $f(y_i'(t))$  is better than  $f(y_i(t))$ 
Replace parent  $x_i(t)$  with offspring  $x_i'(t)$ 
else Retain parent;
end

```

The complete Pseudo code for this algorithm is shown below:

- 1: Initialize a population and set control parameter values
- 2: While a convergence criterion is not satisfied
- 3: Select parent $x_i(t)$
- 4: Select three random vector for reproduction
- 5: Find the donor vector u_i
- 6: Produce one offspring vector $x_i'(t)$
- 7: $y_i(t)$ = generated bit-string from $x_i(t)$
- 8: $y_i'(t)$ = generated bit-string from $x_i'(t)$
- 9: if $f(y_i'(t))$ is better than $f(y_i(t))$ then
- 10: Replace parent $x_i(t)$ with offspring $x_i'(t)$
- 11: else Retain parent
- 12: end if
- 13: end while

Generally, according to the perturbation process, DE can be categorized in many schemes. So that, the general convention are used to name the DE scheme, is DE/ x/y . Here, DE remains for DE, x represents to a string giving the kind of the vector to be bothered (Whether it is arbitrarily chosen or it is the finest vector in the populace with respect to the fitness value) and y is the number of the difference vectors considered for mutation of x . Below we outline the various mutation scheme suggested by Storn and Price.

DE/rand/1	$u_i = x_{r_1} + F_1(x_{r_2} - x_{r_3})$
DE/best/1	$u_i = x_{\text{best}} + F_1(x_{r_2} - x_{r_3})$
DE/rand to best/1	$u_i = x_{r_1} + F_1(x_{r_2} - x_{r_3}) + F_2(x_{\text{best}} - x_{r_1})$
DE/current to best/1	$u_i = x_i + F_1(x_{r_2} - x_{r_3}) + F_2(x_{\text{best}} - x_i)$
DE/rand/2	$u_i = x_{r_1} + F_1(x_{r_2} - x_{r_3} + x_{r_4} - x_{r_5})$
DE/best/2	$u_i = x_{\text{best}} + F_1(x_{r_2} - x_{r_3} + x_{r_4} - x_{r_5})$

3.4 Multi-Objective Differential Evolution (MODE)

As it was said in the presentation of this part the multi-target optimization problem can be illuminated in two different methods: On the one hand, we can treat the multi-objective functions as a single one by multiply each objective function with coefficient. So that, the summation of this coefficient must equal one. After that, we can apply DE for solving the optimization problem. This procedure is called vector aggregation technique and it is shown in the flowchart in Figure 3.1.

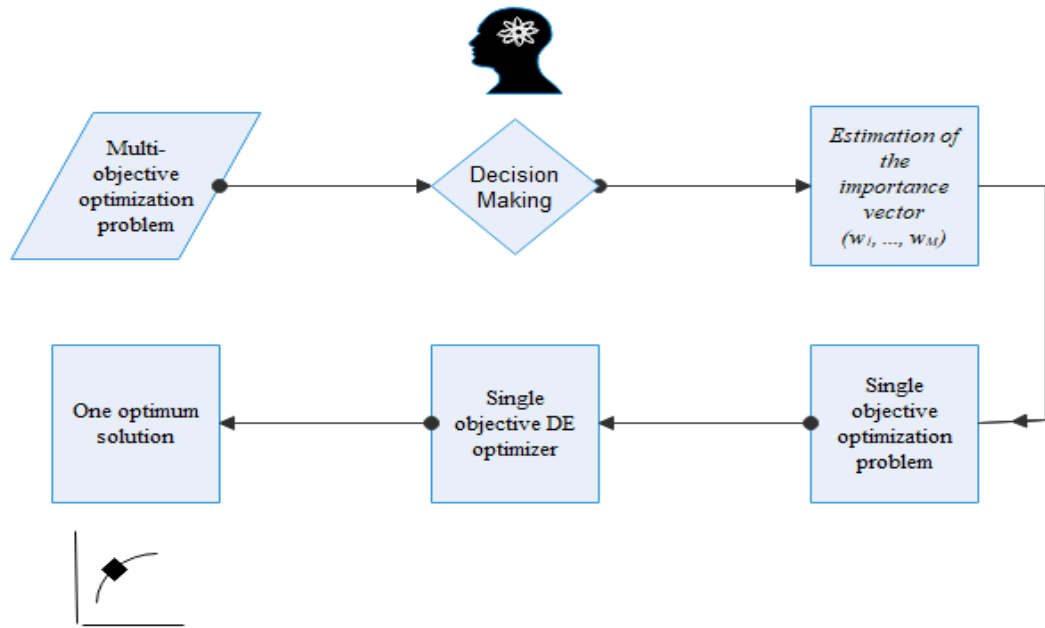


Figure 3.1: Aggregation Method

On the other hand, the ideal multi-objective DE optimizer can be used. In this method, instead of having one optimum solution at the final stage of the optimization procedure we will get the trade of optimal solutions, which is known as Pareto solutions or the non-dominated solution. Here the non-dominated term refers to the set of solution which cannot be compared. Figure 3.2 below shows the flow-process of this technique.

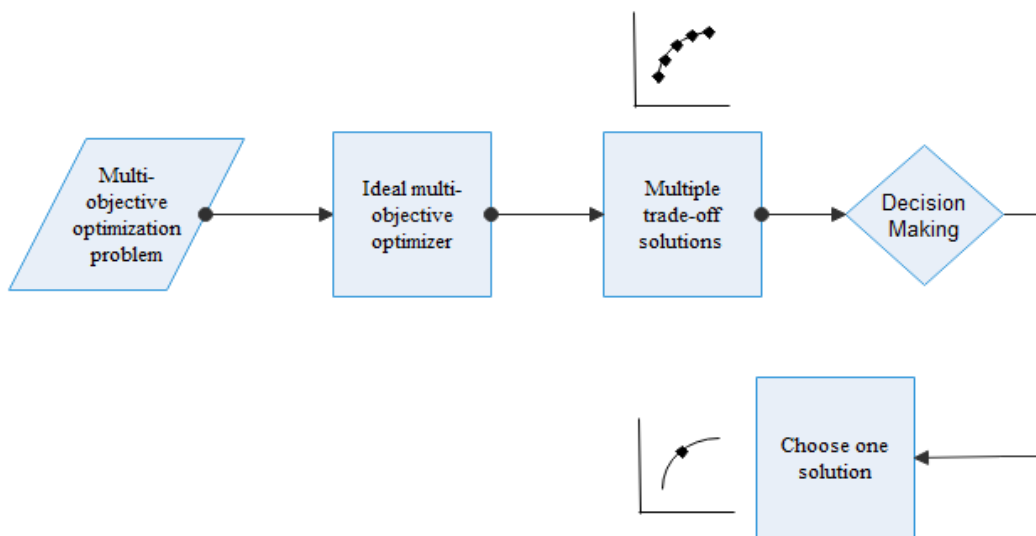


Figure 3.2: Ideal Multi-Objective Optimizer

The ideal MODE method has three main mechanisms, which are the selection, reproduction, and Pareto-based evaluation. The illustration of these mechanisms are shown below:

- **Reproduction:** in order to mimic this process in the DE approach the differential vector and the donor vector should be defined for each individual in the population. In like manner, a Pareto-based method is acquainted with actualizing the choice of the finest solution to characterize the differential vector for the proliferation task of the solution. So that, the population is sorted into different ranks according to its dominance.

So as to apply the crossover operation to a solution, p_i , we should check if the solution is dominated by the other solutions or not. On the off chance that this solution is dominated by others, a subset of the non-dominated solutions, D_i that dominates this solution can be recognized. Then the "fittest" solution, p_{best} , is selected in a random way from the D_i . If the solution is already a non-dominated one, the p_{best} will be the solution itself.

$$\hat{p}_i = \begin{cases} p_i + F \cdot \sum_{k=1}^K (p_{ia}^k - p_{ib}^k) & p_i \text{ is non - dominated} \\ \gamma \cdot p_{best} + (1 - \gamma) \cdot p_i + F \cdot \sum_{k=1}^K (p_{ia}^k - p_{ib}^k) & p_i \text{ is dominated} \end{cases} \quad (3.5)$$

- **Pareto-based assessment:** this Pareto-based rank task is utilized in an approach to allocate solutions to people in view of their Pareto predominance connection to different people in a similar populace. At in the first place, the entire populace is checked and all the solutions which are not dominated are doled out rank 1, which shows they have the most noteworthy wellness esteems among all the solutions. At the subsequent stage, the effectively named individuals are expelled and just the rest subset of the populace is taken into account again the same procedure has used and rank 2 is assigned to the next

non-dominated results in that subset, which shows they have the next highest fitness values. The same procedure has repeated until every solution is ranked according to its fitness value.

- Selection: this procedure is described in the reproduction step for the selection of the individuals. The flowchart of the MODE is shown in Figure 3.3

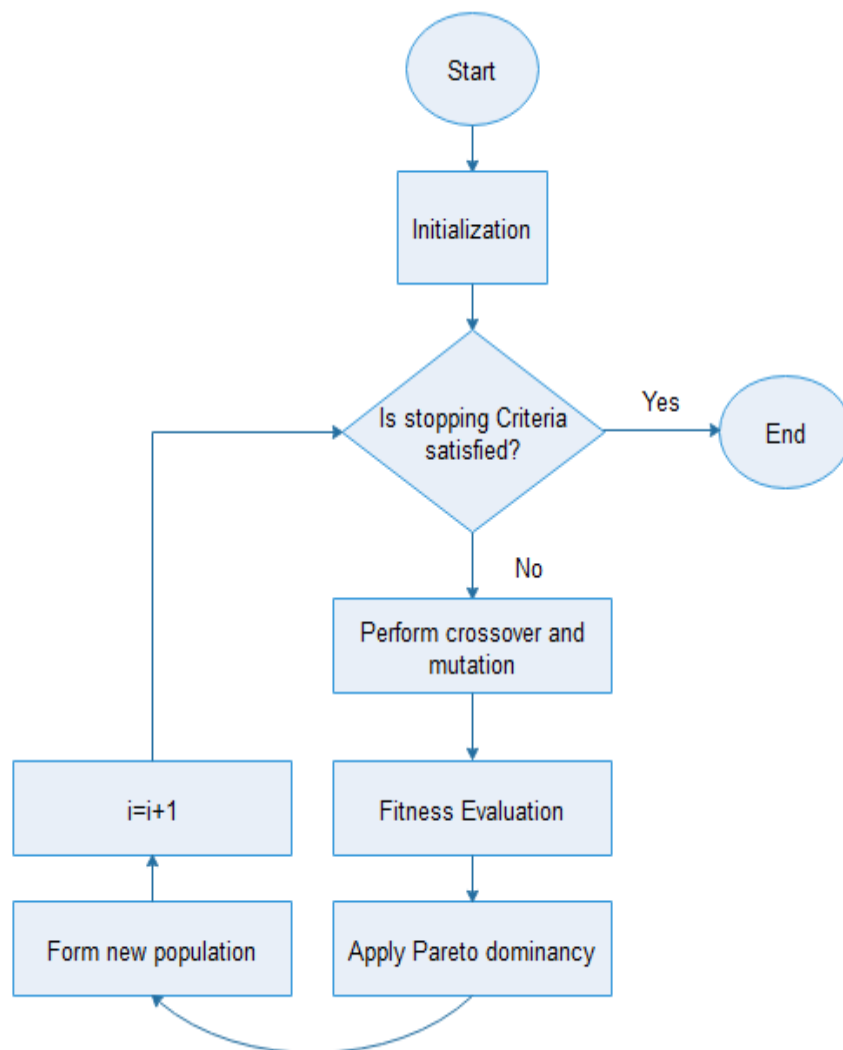


Figure 3.3: MODE Flowchart

Chapter 4

OPTIMAL PLACEMENT AND SIZING OF THE DGs AND DSTATCOMs

4.1 Problem Formulation

The problem of the optimum size and place of the DSTATCOM and DG can be expressed as a minimization problem. Thus, to formulate this problem it is crucial to state the goal as a function to be optimized, the constraint to be satisfied. Contingent on the quantity of the objectives to be met all the while, the problem can appear in a single target optimization problem or multi-target one. In this chapter, the optimization problems aim at lessening of the real power dissipation of the system, the voltage drop, and the annual energy operation cost. The design variables for this problem are the size and the place of the DSTATCOM and DG in the grid, while the constraint is the capacity of the DSTATCOM and DG.

Firstly, the problem is treated as a single objective optimization problem by giving each objective function a weight factor. So that, the summation of the weight factors should equal one. This problem aims to minimize the summation of the scaled objective functions. Secondly, for a multi-objective optimization problem, the solution aims to minimize the vector of the objective functions, which consist of the real power dissipation in the grid, the voltage deviation, and the annual energy operation cost simultaneously.

For a single objective optimization:

$$\text{minimizing } F = \sum_{i=1}^n k_i f_i \quad (4.1)$$

$$\sum_{i=1}^n k_i = 1 \quad (4.2)$$

Where: k_i is the weight that is given to the i -th objective function to decide it is of corresponding importance. k_i is decided according to priority of the operation which in our case 0.5 for the power loss, 0.4 for the voltage deviation, and 0.1 for the cost according to reference [30].

For a multi-objective optimization:

$$\text{minimizing } F = [f_1 f_2 \cdots f_n] \quad (4.3)$$

Where: n denotes the amount of goals to be optimized. In this case the objective functions will be minimized separately.

4.1.1 Objective Function

The main target of this optimization problem is to obtain the best size and the suitable place of the DSTATCOM and DG in the grid which will optimize different targets related to the performance of the radial distribution system. As mentioned earlier, three objective functions are considered to be optimized. These objectives are the reduction of the total active power dissipation, decrease of the voltage deviation, and minimization of the yearly operation cost of energy. For this minimization problem first each objective function is normalized by dividing it by its base. These functions are explained below in the following equations.

$$\text{The weighted vector objective function} = k_1 * f_1 + k_2 * f_2 + k_3 * f_3 \quad (4.4)$$

- **Active power dissipation in the system** [19]

$$f_1 = \sum_{i=1}^{nb} \left| \frac{P_{Loss_i}}{P_{Loss_{base}}} \right| \quad (4.5)$$

Where:

P_{Loss_i} : The active power dissipation in branch number i in kW.

$P_{Loss_{base}}$: The base value for the active power dissipation in kW.

nb : The number of the branches.

- **Voltage deviation** [19]

Here the deviation in the voltage at every bus from the nominal voltage is calculated.

$$f_2 = \max\left(\left|\frac{V_i - V_{rated}}{V_{rated}}\right|\right) \quad (4.6)$$

$$V_{rated} = 1 \text{ pu.}$$

Where:

N : the number of the nodes in the grid.

V_i : the voltage at bus number i in pu.

- **Annual energy operation cost** [48]

Here the annual energy operation cost is calculated, while the cost of the DG and DSTATCOM themselves are neglected.

$$\text{Cost} = 0.05 * 8760 * P_{Tloss} \text{ , in \$} \quad (4.7)$$

$$f_3 = \frac{\text{Cost}}{\text{Cost}_{base}} \quad (4.8)$$

Where:

P_{Tloss} : The total active power loss in the system in kW.

$P_{Loss_{base}}$: The base value for the active power dissipation in kW.

4.1.2 Constraints

The objective functions in the above equations are subjected to the DG capacity limit and DSTATCOM capacity limit, voltage limit, and thermal limit.

- **DG capacity limit** [19]

$$DG_{min} \leq DG_{capacity} \leq DG_{max} \quad (4.9)$$

Where: DG_{min} and DG_{max} are the minimum and the maximum capacity of the DG respectively in kW. In this study $DG_{max} \leq 2.5$ MW according to [19]

- DSTATCOM capacity limit [24]

$$DSTATCOM_{min} \leq DSTATCOM_{capacity} \leq DSTATCOM_{max} \quad (4.10)$$

Where: $DSTATCOM_{min}$ and $DSTATCOM_{max}$ are the minimum and maximum capacity of the DSTATCOM respectively in kVar.

- Voltage limit [20]

$$V_{min} \leq |V_i| \leq V_{max} \quad (4.11)$$

Where: V_{min} and V_{max} are the minimum and maximum bus voltage respectively in pu.

- Thermal limit [13]

$$I_{m,n} \leq I_{m,n}^{max} \quad (4.12)$$

Where:

$I_{m,n}^{max}$: The maximum loading of the distribution line connected between the m -th and the n -th bus in pu.

$I_{m,n}$: The current flowing through the line connected between the m -th and the n -th branch in pu.

4.2 Radial Load Flow

The load flow is done to obtain the performance of the system (voltage, current, power loss..etc) in the steady state. It is important to check if the system is stable and to find if there is a need to insert compensation devices to the system. Furthermore, it is necessary to plan in advance. Due to the low X/R ratio in the distribution system (radiality of the distribution system), the ordinary techniques such as Newton Raphson and Gauss-Seidel cannot converge to obtain the power flow from the distribution system. So as to get the power flow of this grid, the backwards-forward sweep strategy can be utilized. The backward forward sweep method is an iterative method in which,

at every iteration, two calculation stage is performed namely are the backward sweep and the forward sweep [39].

Backward sweep: In this stage, the load current of every bus of an N bus radial distribution grid is obtained as:

$$\vec{I}_L(m) = \left(\frac{P_L(m) - jQ_L(m)}{\vec{V}^*(m)} \right) \quad (4.13)$$

Where:

$$m = 1, 2, 3, \dots, N.$$

$P_L(m)$: The active power demand at bus m .

$Q_L(m)$: The reactive power demand at bus m .

$\vec{I}_L(m)$: The Load current at bus m .

$\vec{V}(m)$: The voltage at bus m .

The current in each branch of the grid is computed as follow:

$$\vec{I}(mn) = \vec{I}_L(n) + \sum_{m \in \tau} \vec{I}_L(m) \quad (4.14)$$

Where: τ is the set that consists of every bus which is located beyond bus n .

Forward sweep: this stage comes after the backward sweep to obtain the voltage at every bus of the distribution grid as follow:

$$\vec{V}(n) = \vec{V}(m) - \vec{I}(mn)Z(mn) \quad (4.15)$$

Where:

m and n : The receiving and sending end bus respectively.

$Z(mn)$: The impedance of the branch mn .

The calculation methodology used for the backwards-forward sweep load flow is based on equivalent current injection, the bus injection to branch current (BIBC), and

the branch current to bus voltage matrix (BCBV). Load flow for radial distribution grid with fixed power load model under the balanced operating condition can be under remained [39].

4.2.1 Equivalent Current Injection

The strategy depends on the bus equivalent current injection in the radial distribution system. For each bus of a radial distribution grid, the complex demand S_i is represented by:

$$\vec{S}_i = P_i + jQ_i \quad , \quad i = 1, 2, 3, \dots, N \quad (4.16)$$

Therefore, the equivalent current injection is shown as follow:

$$\vec{I}_i = \left(\frac{P_i + jQ_i}{\vec{V}_i} \right)^* \quad (4.17)$$

For the load flow calculation of the i -th bus current at iteration, k is expressed as follow:

$$\vec{I}_i^k = \left(\frac{P_i + jQ_i}{\vec{V}_i^k} \right)^* \quad (4.18)$$

3.2.2 Formation of BIBC Matrix

The active and reactive power injected at each bus can be transformed into the equivalent current injections at a bus using equation 4.15 and by using Kirchhoff's current law (KCL) at every bus and each iteration many comparisons could be composed. Then, each branch current in the grid can be calculated by expressing it as a function of the equivalent current injections. Figure 4.1 shows the branch currents $I_{B6}, I_{B5}, I_{B4}, I_{B3}, I_{B2}$, and I_{B1} and the equations are shown as follow:

$$I_{B6} = I_7 \quad (4.19)$$

$$I_{B5} = I_7 + I_6 \quad (4.20)$$

$$I_{B4} = I_7 + I_6 + I_5 \quad (4.21)$$

$$I_{B3} = I_4 \quad (4.22)$$

$$I_{B2} = I_4 + I_3 \quad (4.23)$$

$$I_{B1} = I_2 + I_3 + I_4 + I_5 + I_6 + I_7 \quad (4.24)$$

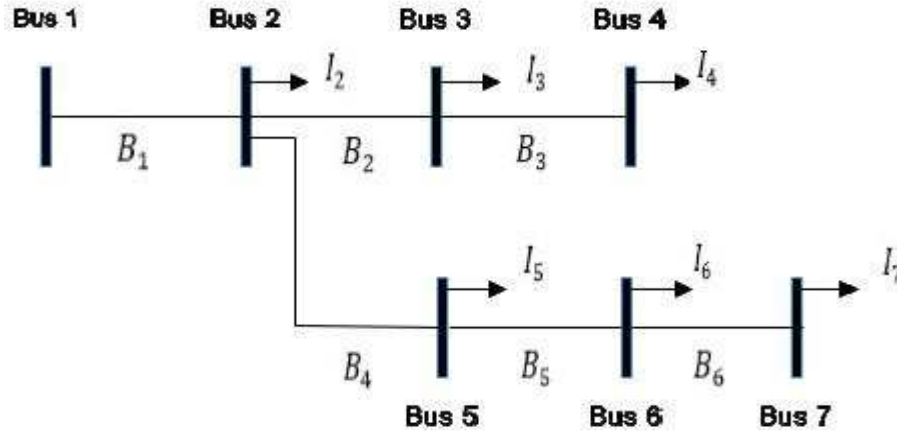


Figure 4.1: Simple Radial Distribution System

From the above equations, the BIBC matrix can be shown as follow:

$$\begin{bmatrix} I_{B1} \\ I_{B2} \\ I_{B3} \\ I_{B4} \\ I_{B5} \\ I_{B6} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \\ I_7 \end{bmatrix} \quad (4.25)$$

Equation 4.22 can be expressed in a general form as follow:

$$[I_B] = [\text{BIBC}][I] \quad (4.26)$$

The steps for building BIBC matrix for any radial distribution system:

Step 1: Make an initial BIBC matrix (zeros($m \times (n - 1)$)). Where m is the number of branches and n is the number of the buses in the radial distribution system.

Step 2: Initially, set $i = 1$ and read the I_{Bi} ($i = 1, 2, \dots, m$) branch data (sending end bus and receiving end bus). If a branch I_{Bi} is between bus ' x ' and bus ' y '. Check that the I_{Bi} line belongs to the sending end bus or not. If it belongs, then make ($y - 1, y - 1$)-th bit of BIBC matrix by '+1'. Increment ' $i = i + 1$ '.

Step 3: If the I_{Bi} line in step #2 does not belong to the sending end bus of the grid. After that repeat the column segment of the '(x - 1)-th' of BIBC matrix to the column segment of '(y - 1)-th' bus and fill (y - 1, y - 1)-th bit of the BIBC matrix by '+1'. Increment ' $i = i + 1$ '.

Step 4: Repeat step #2 and step #3 until all the lines of the grid included into the BIBC matrix.

4.2.3 Formation of BCBV Matrix

The BCBV matrix represents the relation between the branch current and bus voltage. The formation of this matrix can be found by applying Kirchhoff's Voltage Law (KVL) as shown below:

$$V_2 = V_1 - I_{B1}Z_{12} \quad (4.27)$$

$$V_3 = V_2 - I_{B2}Z_{23} \quad (4.28)$$

$$V_4 = V_3 - I_{B3}Z_{34} \quad (4.29)$$

$$V_5 = V_2 - I_{B4}Z_{25} \quad (4.30)$$

$$V_6 = V_5 - I_{B5}Z_{56} \quad (4.31)$$

$$V_7 = V_6 - I_{B6}Z_{67} \quad (4.32)$$

Substituting equations 4.24 and 4.25 into equation 4.26, the voltage of bus 4 can be expressed as:

$$V_4 = V_1 - I_{B1}Z_{12} - I_{B2}Z_{23} - I_{B3}Z_{34} \quad (4.33)$$

By using the same method the BCBV matrix can be expressed as:

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \\ V_7 \end{bmatrix} = \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 & 0 & 0 \\ Z_{12} & 0 & 0 & Z_{25} & 0 & 0 \\ Z_{12} & 0 & 0 & Z_{25} & Z_{56} & 0 \\ Z_{12} & 0 & 0 & Z_{25} & Z_{56} & Z_{67} \end{bmatrix} \begin{bmatrix} I_{B1} \\ I_{B2} \\ I_{B3} \\ I_{B4} \\ I_{B5} \\ I_{B6} \end{bmatrix} \quad (4.34)$$

The general form of BCBV matrix is shown below:

$$[\Delta V] = [\text{BCBV}][I_B] \quad (4.35)$$

In general, the BCBV matrix can be formed to any radial distribution network by using the same steps of forming the BIBC matrix. The only difference is that, If I_{Bi} belongs to the first node of the grid, then make $(y - 1, y - 1)$ -th bit of BCBV matrix by the corresponding line impedance ' Z_{xy} '. Else copy the row segment of the ' $(x - 1)$ -th' of BCBV matrix to the row segment of ' $(y - 1)$ -th' bus and fill $(y - 1, y - 1)$ -th bit of the BCBV matrix by the corresponding line impedance ' Z_{xy} '.

4.2.4 Algorithm for the Radial Distribution System Load Flow

Algorithm steps for a radial distribution system load flow calculation are shown below:

Step 1: Read the radial distribution system data (line data and bus data).

Step 2: Calculate the current injection matrix.

Step 3: Build the BIBC matrix.

Step 4: Calculate the branch currents $[I_B] = [\text{BIBC}][I]$.

Step 4: Obtain the BCBV matrix.

Step 5: Calculate the DLF matrix so that, $[\text{DLF}] = [\text{BCBV}][\text{BIBC}]$.

Also, $[\Delta V] = [\text{DLF}][I]$.

Step 6: Set iteration $k = 0$.

Step 7: Iteration $k = k + 1$.

Step 8: Update the voltage by using the following equations:

$$\vec{I}_i^k = \left(\frac{P_i + jQ_i}{\bar{V}_i^k} \right)^*$$

$$[\Delta V^{k+1}] = [\text{DLF}][I^k]. \quad (4.36)$$

$$[V^{k+1}] = [V^0] + \Delta V^{k+1}. \quad (4.37)$$

Step 9: If $\max (([V^{k+1}] - [V^k]) > \text{tolerance})$ go to step 5.

Step 10: Find branch currents and the power dissipation from the final bus voltages.

Step 11: Show the bus voltage magnitudes and, branch currents, and the dissipation.

Step 12: End.

4.2.5 Incorporation of the DG and DSTATCOM

To place the DSTATCOM and DG in the radial distribution grid the real and the reactive load power at the bus where DSTATCOM and DG are placed will change.

Assume that DG PV type is placed at the i -th bus, the real power is modified as follow:

$$P_i = P_i - P_{DGi} \quad (4.38)$$

In the case of the DSTATCOM, the reactive power is changed by:

$$Q_i = Q_i - Q_{DSTATCOMi} \quad (4.39)$$

4.3 Methodology

In this thesis, a single objective and multi-objective Evolutionary Algorithms (EA) are used. For the single objective EA, Genetic Algorithm (GA) and Differential Evolution (DE) are used. So that, the only difference between the GA and DE is that the DE uses vector differences for the mutation instead of the randomness in the GA. For the multi-objective EA, Multi-Objective Genetic Algorithm (MOGA) and Multi-Objective DE are used. The algorithm of each one of these algorithms are shown below.

Moreover, to obtain the best parameters for each algorithm the trial and error technique were used because of there is no rule by which they can be fixed. The normalized vector results of GA, DE, MOGA, and MODE at the nominal load for three runs have been tabulated in Table 4.1, Table 4.2, Table 4.3, and Table 4.4 respectively. These results were obtained by using a single DG with maximum size of 2.5 MW [12] and the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30].

4.3.1 GA

The algorithm of the GA for finding the optimum capacity and place of a one and several DGs and DSTATCOMs in the radial distribution grid shown below. Moreover, Table 4.2 displays the trial and error method results for GA parameters while the best parameters highlighted in the table.

Algorithm of GA:

Step 1: Input the data of the grid.

Step 2: Initialize GA parameters (population size, crossover and mutation percentage, and maximum iteration).

Step 3: Initialize the population.

Step 4: Run the radial load flow and calculate the objective function.

Step 5: Sort the population.

Step 6: Keep the best.

Step 7: While the stopping criteria is not satisfied.

Step 8: Select from the old population randomly.

Step 9: Apply crossover (single point and double points according to the numbers of DGs and DSTATCOMs).

Step 10: If random number less than mutation percentage apply mutation (Change the location and the size of the agent randomly).

Step 11: Run the radial load flow and calculate the objective function.

Step 12: Sort the population.

Step 13: Keep the best.

Step 14: End while.

Step 15: print the output (the best location and size).

Table 4.1: GA Paramters

Population size	Crossover percentage	Mutation percentage	Maximum iteration	The result			
				1st run normalized vector results	2nd run normalized vector results	3rd run normalized vector results	Avarage of the results
10	0.9	0.1	20	0.32136	0.30285	0.31812	0.314110
			30	0.33433	0.31563	0.30538	0.318446
			40	0.29055	0.30561	0.31687	0.304343
	0.8	0.2	20	0.32321	0.29415	0.30518	0.307513
			30	0.31448	0.30939	0.3054	0.309756
			40	0.30536	0.29105	0.32341	0.306606
30	0.9	0.1	20	0.28957	0.29344	0.29741	0.293473
			30	0.29069	0.29668	0.29078	0.292716
			40	0.29484	0.29992	0.29165	0.29547
	0.8	0.2	20	0.29943	0.28972	0.29067	0.293273
			30	0.29421	0.29032	0.29049	0.291673
			40	0.30151	0.31479	0.29411	0.303470
50	0.9	0.1	20	0.28975	0.28999	0.29222	0.290653
			30	0.29123	0.29076	0.29214	0.291376
			40	0.29149	0.29121	0.29692	0.293206
	0.8	0.2	20	0.29356	0.29059	0.29946	0.294536
			30	0.29162	0.29031	0.29427	0.292066
			40	0.29337	0.2924	0.29144	0.292403

4.3.2 DE

The algorithm of the DE for finding the optimum capacity and place of a one and several DGs and DSTATCOMs in the radial distribution system shown below. Moreover, Table 4.2 displays the trial and error method results for DE parameters while the best parameters highlighted in the table.

Algorithm of DE:

Step 1: Input the data of the grid.

Step 2: Initialize DE parameters (population size, differential weight, crossover probability, and maximum iteration).

Step 3: Initialize the population.

Step 4: Run the radial load flow and calculate the objective function.

Step 5: Sort the population.

Step 6: Keep the best.

Step 7: While the stopping criteria is not satisfied.

Step 8: For each agent x .

Step 9: Find the perturbation vector U .

Step 10: Find the perturbed vector y through the crossover of x and U .

Step 11: Run the radial load flow and calculate the objective function.

Step 12: Change x to y if y is better than x .

Step 14: End while.

Table 4.2: DE Parameters

Population size	Crossover probability	Maximum iteration	The result			
			1st run normalized vector results	2nd run normalized vector results	3rd run normalized vector results	Average of the results
10	0.1	20	0.29078	0.31731	0.33607	0.31472
		30	0.29013	0.33022	0.34801	0.32278
		40	0.33166	0.32403	0.29874	0.31814
	0.15	20	0.32299	0.31282	0.32397	0.31992
		30	0.31487	0.30484	0.31448	0.31139
		40	0.34575	0.30071	0.29712	0.31452
	0.2	20	0.33279	0.30139	0.31158	0.31525
		30	0.32525	0.30706	0.32377	0.31869
		40	0.33923	0.33287	0.33234	0.33481
30	0.1	20	0.30102	0.30332	0.30134	0.30189
		30	0.30249	0.33269	0.29146	0.30888
		40	0.2941	0.30496	0.29596	0.29834

Population size	Crossover probability	Maximum iteration	The result			
			1st run normalized vector results	2nd run normalized vector results	3rd run normalized vector results	Average of the results
	0.15	20	0.29965	0.31487	0.3238	0.31277
		30	0.30555	0.29118	0.29052	0.29575
		40	0.29218	0.31437	0.30753	0.30469
	0.2	20	0.31614	0.29803	0.32104	0.31173
		30	0.30772	0.29196	0.29803	0.29923
		40	0.30695	0.34716	0.29693	0.31701
50	0.1	20	0.3149	0.29493	0.30154	0.30379
		30	0.29348	0.29107	0.29304	0.29253
		40	0.29124	0.31906	0.29018	0.30016
	0.15	20	0.29615	0.30444	0.29049	0.29702
		30	0.29701	0.29702	0.29478	0.29627
		40	0.29743	0.29467	0.30684	0.29964
	0.2	20	0.29884	0.29322	0.31276	0.30160
		30	0.29302	0.29049	0.30096	0.29482
		40	0.31953	0.29303	0.29473	0.30243

4.3.3 MOGA

The algorithm of the MOGA for finding the optimum capacity and place of a one and several DGs and DSTATCOMs in the radial distribution system shown below. Moreover, Table 4.4 shows the parameters of the MOGA, so that, the best parameters highlighted in the table.

Algorithm of MOGA:

Step 1: Initialize population P and P^{iv} .

Step 2: Run the radial power flow and Evaluate the objective functions of P .

Step 3: Assign rank based on Pareto dominance.

Step 4: While not terminal condition.

Step 5: Select individuals from $P \rightarrow P^i$.

Step 6: Apply crossover and mutation $P^i \rightarrow P^{ii}$.

Step 7: Run the radial power flow and Evaluate the objective functions of P^{ii} .

Step 8: Rank (P^i union P^{ii}) $\rightarrow P^{iii}$ based on Pareto dominance.

Step 9: Reduce $P^{iii} \rightarrow P$.

Step 10: Copy $P^{iii} \rightarrow P^{iv}$ based on Pareto dominance.

Step 11: End while.

Step 12: Display the results.

Step 13: Plot the Pareto front.

Table 4.3: MOGA Parameters

Population size	Crossover percentage	Mutation percentage	Maximum iteration	The result			
				1st run normalized vector results	2nd run normalized vector results	3rd run normalized vector results	Average of the results
10	0.9	0.1	20	0.2915	0.29071	0.29221	0.29147
			30	0.30126	0.30981	0.29136	0.30081
			40	0.30071	0.29702	0.30409	0.30060
	0.8	0.2	20	0.29946	0.29564	0.30079	0.29863
			30	0.2962	0.30026	0.29613	0.29753
			40	0.28977	0.30616	0.29096	0.29563
30	0.9	0.1	20	0.29477	0.30165	0.29664	0.29768
			30	0.29163	0.3068	0.29262	0.29701
			40	0.29082	0.29000	0.29065	0.29049
	0.8	0.2	20	0.29179	0.29028	0.28971	0.29059
			30	0.29423	0.28957	0.29157	0.29179
			40	0.29064	0.29189	0.29435	0.29229
50	0.9	0.1	20	0.2908	0.29114	0.29072	0.29088
			30	0.29095	0.29223	0.29082	0.29133
			40	0.29161	0.28973	0.28956	0.29030
	0.8	0.2	20	0.29065	0.29162	0.28978	0.29068
			30	0.28994	0.28973	0.29094	0.29020
			40	0.28967	0.28969	0.28987	0.23252

4.3.3 MODE

The algorithm of the MODE for finding the optimum capacity and place of a one and several DGs and DSTATCOMs in the radial distribution grid shown below. Moreover, Table 4.4 shows the parameters of the MODE, so that, the best parameters highlighted in the table.

Algorithm of MODE:

Step 1: Input the data of the grid.

Step 2: Initialize the population within the bond.

Step 3: Run the radial power flow and evaluate the objective functions.

Step 4: Assign rank based on Pareto dominance.

Step 5: While not terminal condition.

Step 6: For every agent.

Step 7: Find the perturbation vector U .

Step 8: Find the perturbed vector y through the crossover of x and U .

Step 9: Run the radial load flow and calculate the objective function.

Step 10: Change x to y if y dominated x .

Step 11: End for.

Step 12: Plot the Pareto front.

Step 13: End while.

Step 14: Display the solutions.

Step 15: Plot the Pareto front.

Table 4.4: MODE Parameters

Population size	Crossover percentage	Scaling factor	Maximum iteration	The result			
				1st run normalized vector results	2nd run normalized vector results	3rd run normalized vector results	Avarage of the results
50	0.1	0.3	30	0.29155	0.29155	0.29521	0.29277
			40	0.29055	0.28974	0.30818	0.29615
		0.5	30	0.28958	0.29288	0.29354	0.29200
			40	0.29087	0.29209	0.29069	0.29121
		0.7	30	0.29132	0.29123	0.29051	0.29102
			40	0.2906	0.29202	0.29061	0.29107
	0.2	0.3	30	0.28978	0.29398	0.29024	0.29133
			40	0.29196	0.29061	0.29239	0.29165
		0.5	30	0.29024	0.28966	0.29175	0.29055
			40	0.29134	0.291	0.28974	0.29069
		0.7	30	0.29081	0.28969	0.29544	0.29198
			40	0.29734	0.2896	0.29079	0.29257

Chapter 5

RESULTS AND DISCUSSION

5.1 General Description

The suggested methods were examined on IEEE 33 nodes radial distribution grid with two different loading levels as light (62.5%), nominal (100%), and heavy (125%). The codes of the GA, DE, MOGA, MODE, and the radial power flow have programmed and implemented in MATLAB 2016 on window 10 Pro Intel® Core™ i3 Processor, 2.27 GHz, RAM 3 GB.

In this thesis, a constant power load model has considered for modelling the behavior of loads of the power system grid. The cost of DG generated power and DSTATCOM has neglected for this study. The energy loss cost of 0.05 \$ per unit has taken for analysis of the cost-benefit Shukla, T et al [48]. The savings calculated as the difference in energy dissipation cost without DG and DSTATCOM, the sum of energy dissipation cost with DG and DSTATCOM.

5.2 IEEE 33-bus system

This is a medium scale radial distribution grid with 33 buses and 32 branches. The line and bus data taken from [47]. This system fed on one side, and it has serially connected loads, while the load is assumed to be constant as shown in Figure 2.3. The line voltage and real and reactive power loads of the radial distribution grid are 12.66 kV, 2.3219 MW and 1.4375 MVAR respectively, while the base MVA is 100MVA.

5.3 Case Studies

Three cases have considered for the investigation of the optimal operation of the IEEE 33 nodes radial distribution grid with three different loading level for analysis:

- Case 1: Single DG
- Case 2: Single DSTATCOM
- Case 3: Single DSTATCOM and Single DG

5.2.1 Single DG

In this case, a single DG has been optimally sited into the network to improve its performance by using GA, DE, MOGA, and MODE as shown in chapter 4. To analyze the performance of each one of these algorithms three loading levels were used as follow. It assumed, the DG supplies only real power to the grid.

- Light Load:

The total real and reactive load power connected to the grid are 3343.5 kW and 2070 kVAr which represent 62.5% of the nominal system loading. First, a simple load flow has performed. After that, the DG has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.1 shows the comparison of the real power dissipation, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.2 displays the results of the MOGA and Table 5.3 displays the results of the MODE.

In the GA, the real power dissipation have decreased to 42.15 kW (i.e. the ratio of the decrease is 45.71%) after placing a DG into the network at bus 5 with a size of 1697.055 kW. From the results, it is obvious that GA is better than DE in all the aspects. To compare the results of MOGA and MODE with the GA and DE, first, the

objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which shaded in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.1 and Figure 5.2 in that order. Overall, the minimum power loss and the annual energy cost obtained when GA has used which is not very different from the one obtained when MODE has used. The minimum CPU time needed is 8.64 sec which achieved when GA has used while the minimum voltage deviation found when MODE has used. Finally, the best overall performance obtained by MODE. Figure 5.3 shows the Pareto front when MOGA has used, and Figure 5.4 shows the Pareto front when MODE has used. Figure 5.5 and Figure 5.6 show the weight vector results and time in that order for each algorithm.

Table 5.1: Results of GA and DE case of a single DG at a light Load

	Base	GA	DE
Power Loss (kW)	77.6558	42.1570	42.7343
Voltage Deviation (V)	0.0581424	0.033967	0.037669
Energy Cost (\$)	34013.28	18464.78	18717.64
DG Location	-	Bus 5	Bus 25
DG Size (kW)	-	1697.055	1431.185
Comp. Time (sec)	-	8.64	13.37
Minimum Voltage (V)	0.94185	0.96603	0.96233
$\sum_{i=1}^n k_i f_i$	1	0.559403	0.589332

Table 5.2: Results of MOGE case of a Single DG at a Light Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 7	1246.9054	45.0450	0.032902	19729.71	0.574390
Bus 7	1228.3279	44.9148	0.033154	19672.68	0.575118
Bus 6	1228.3279	43.4423	0.038996	19027.74	0.603931
Bus 7	2352.5969	82.6133	0.018459	36184.66	0.765295
Bus 7	1561.495	49.8587	0.028680	21838.14	0.582537
Bus 7	1275.9023	45.2830	0.032508	19833.98	0.573518
Bus 7	2143.7871	71.2146	0.021104	31192.01	0.6954209
Bus 7	1263.1238	45.1729	0.032682	19785.74	0.5738650
Bus 7	1414.1774	46.9967	0.030645	20584.58	0.5739426
Bus 7	1797.3522	56.6118	0.025575	24795.97	0.6133528
Bus 7	1918.3290	61.0882	0.024002	26756.66	0.6371176
Time	12.31 sec				

Table 5.3: Results of MODE Case of a Single DG at Light Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 6	1684.3497	42.7856	0.032139	18740.12	0.5516842
Bus 6	1564.7289	42.3566	0.033926	18552.19	0.5606634
Bus 6	2291.0121	51.3454	0.023213	22489.29	0.5564127
Bus 5	1464.5949	42.1612	0.037195	18466.62	0.5816433
Bus 7	2183.7093	73.2455	0.020596	32081.54	0.7076176
Bus 6	1670.3381	42.7135	0.032348	18708.55	0.5525650
Bus 6	1875.5208	44.3424	0.029303	19422.00	0.5442019
Bus 6	1671.9765	42.7217	0.032324	18712.11	0.5524631
Bus 6	1635.6598	42.5600	0.032865	18641.29	0.554935
Bus 6	2090.5527	47.3549	0.026139	20741.45	0.545710
Bus 6	1897.0264	44.5840	0.028985	19527.79	0.543880

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 5	1870.7819	43.1093	0.031571	18881.89	0.550277
Time	12.92 sec				

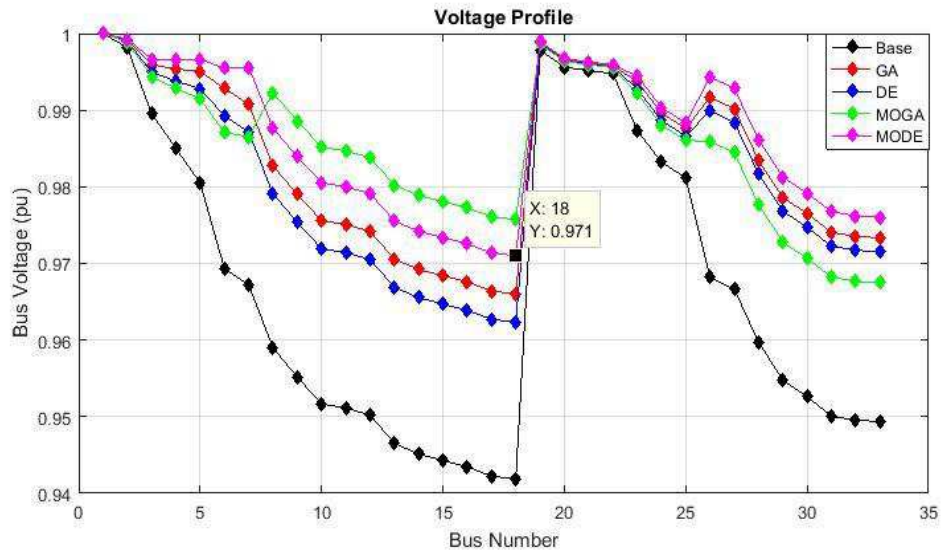


Figure 5.1: Voltage Profile (Single DG - Light Load)

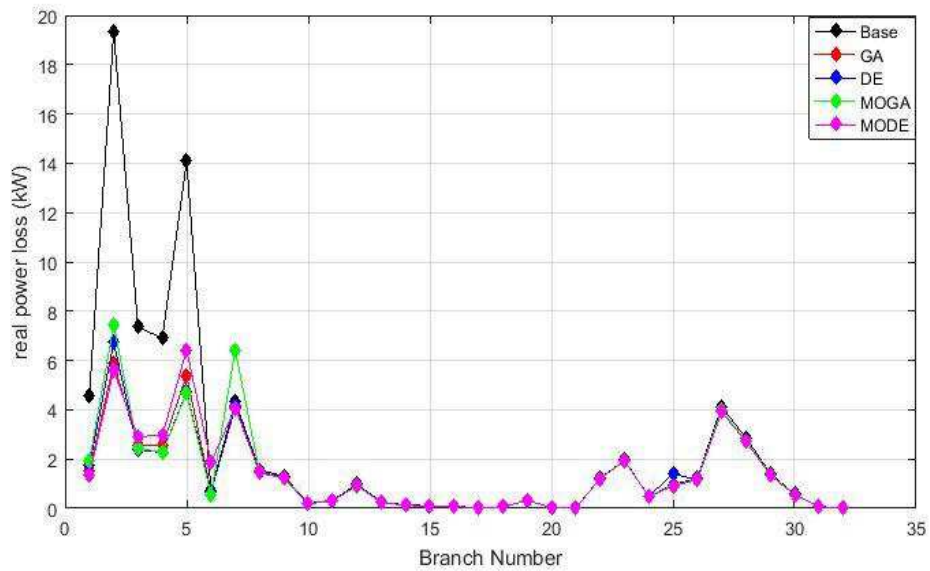


Figure 5.2: Active Power Loss (Single DG - Light Load)

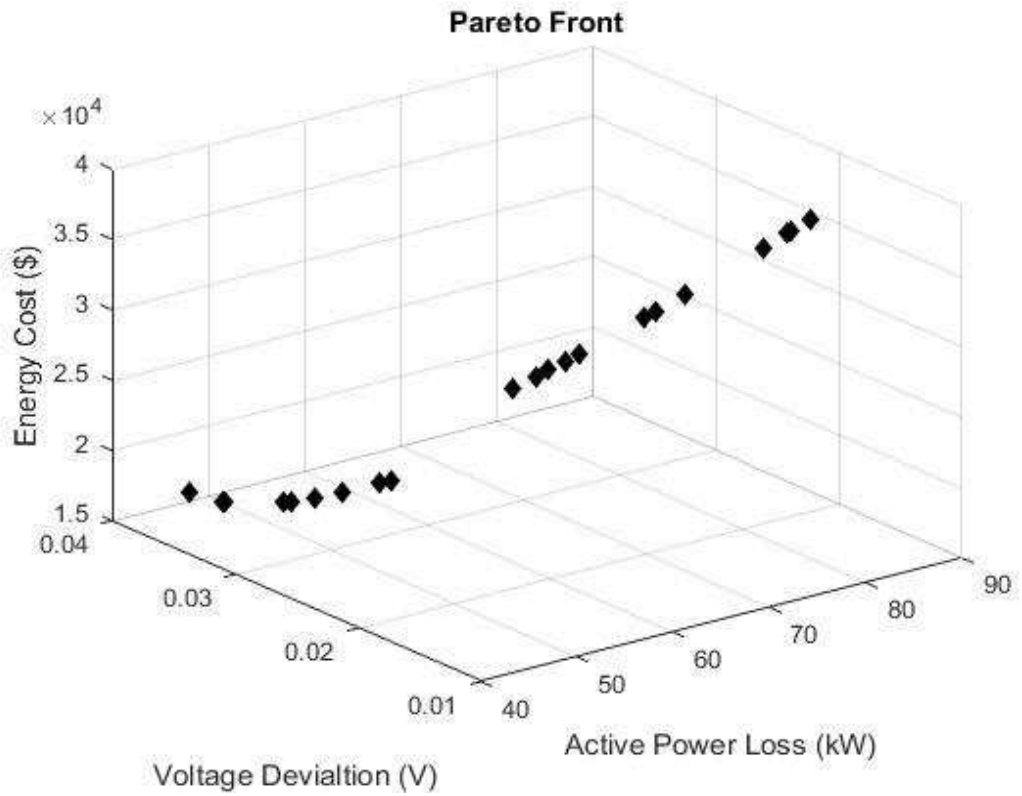


Figure 5.3: Pareto Front for MOGA (Single DG at Light Load)

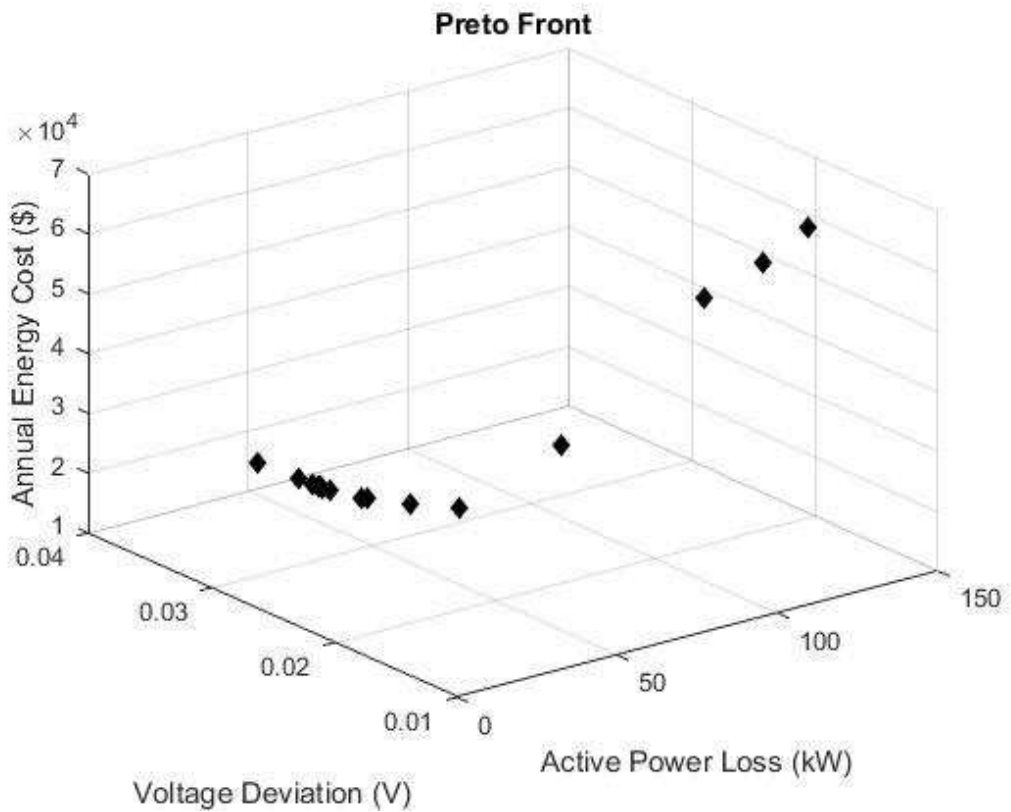


Figure 5.4: Pareto Front for MODE (Single DG - Light Load)

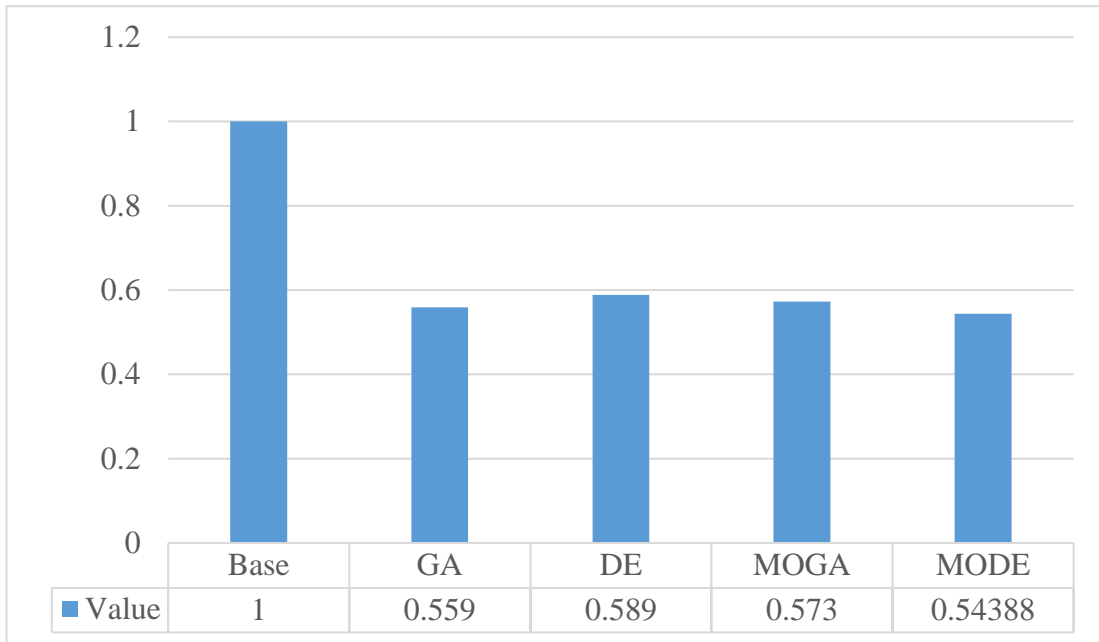


Figure 5.5: Weight Vector Results (Single DG – Light Load)

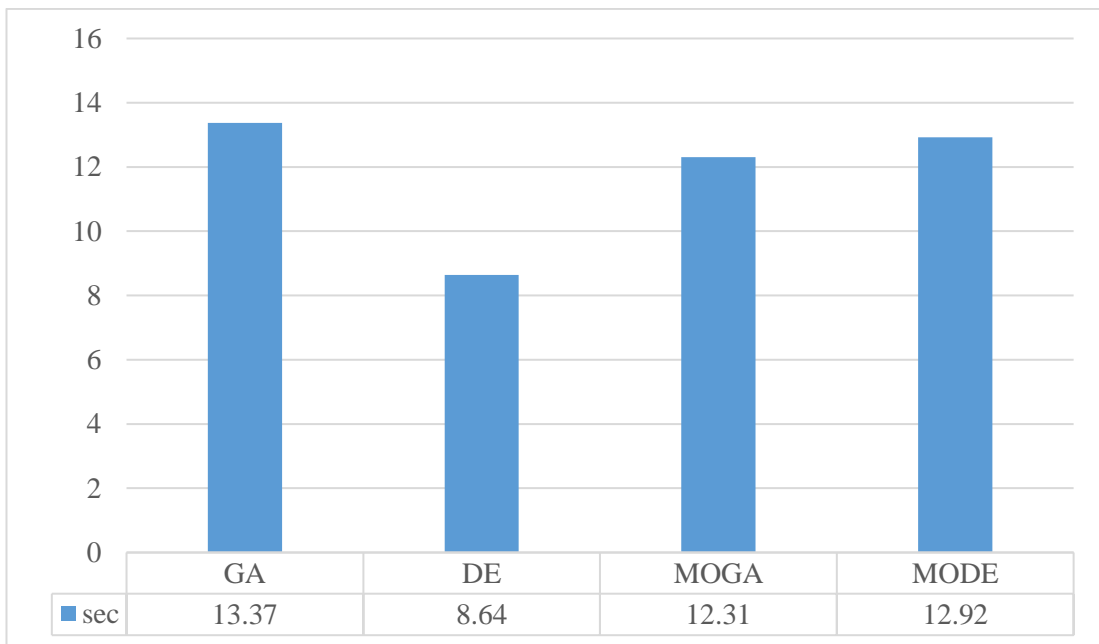


Figure 5.6: Computation Time (Single DG – Light Load)

- Nominal Load

The total real and reactive load power connected to the grid are 3715 KW and 2300 KVAR which represent 100% of the normal system loading. First, a simple load flow has performed. After that, the DG has optimally placed with the help of GA, DE,

MOGA, and MODE. Table 5.4 shows the comparison of the real power losses, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.5 shows the results of the MOGA and Table 5.6 displays the results of the MODE.

In the GA, the real power dissipation have decreased to 111.6599 kW (i.e. the ratio of the decrease is 47.07%) after placing a DG in the network at bus 5 with a size of 2375.37 kW. From the results, it is obvious that GA performs very similar to DE in all the aspects. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which shaded in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.7 and Figure 5.8 in that order. Overall, the minimum power loss and annual energy cost obtained when GA has used which is not very different with the one obtained when MODE has used. The minimum CPU time needed is 9.03 sec which achieved when GA has used, while the minimum voltage deviation found when MODE has used. Finally, the best overall performance obtain by MODE. Figure 5.9 shows the Pareto front when MOGA has used, and Figure 5.10 shows the Pareto front when MODE has used. Figure 5.11 and Figure 5.12 show the overall performance and time in that order for each algorithm.

Table 5.4: Results of GA and DE case of a single DG at a Nominal Load

	Base	GA	DE
Power Loss (kW)	210.9875	111.6599	111.7027

Voltage Deviation (V)	0.096222	0.060691	0.060792
Energy Cost (\$)	92412.54	48907.06	48925.80
DG Location	-	Bus 5	Bus 5
DG Size (kW)	-	2375.37	2368.33
Comp. Time (sec)	-	9.03	17.28
Minimum Voltage (V)	0.903777	0.939308	0.939207
$\sum_{i=1}^n k_i f_i$	1	0.569830	0.570372

Table 5.5: Results of MOGE case of a Single DG at a Nominal Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 8	2214.4755	134.7461	0.051287	59018.80	0.5963897
Bus 26	2438.9611	115.7464	0.059863	50696.95	0.5780098
Bus 8	2044.3193	128.7460	0.053536	56390.78	0.5886760
Bus 26	2214.4755	115.4245	0.063045	50555.97	0.5903222
Bus 8	2478.7683	147.4020	0.047858	64562.07	0.6181256
Bus 8	1957.5992	126.3550	0.054695	55343.51	0.5866946
Bus 5	2035.1186	115.3400	0.065590	50518.93	0.6006616
Bus 8	2436.9353	145.1343	0.048396	63568.83	0.6139133
Bus 8	2035.1186	128.4708	0.053658	56270.22	0.5884006
Bus 8	2082.5835	129.9453	0.053027	56916.07	0.5899706
Time	14.74 sec				

Table 5.6: Results of MODE case of a Single DG at a Nominal Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 8	2431.9824	144.8723	0.048460	63454.08	0.6134343
Bus 7	1961.9514	118.8823	0.054484	52070.48	0.5645668

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 5	2435.0510	111.3526	0.059838	48772.46	0.5654110
Bus 7	1856.9653	118.2367	0.055932	51787.70	0.5687503
Bus 7	1878.0595	118.3208	0.055640	51824.53	0.5677756
Bus 7	2058.1926	119.9690	0.053166	52546.43	0.5621781
Bus 8	2408.0350	143.6251	0.048768	62907.82	0.6111680
Bus 7	2176.8016	121.9490	0.051554	53413.69	0.5611077
Bus 7	1961.3941	118.8774	0.054492	52068.32	0.5645861
Bus 7	2015.2230	119.4258	0.053753	52308.51	0.5630736
Bus 6	2487.1639	112.0106	0.056050	49060.67	0.5515352
Bus 7	2290.0533	124.4896	0.050027	54526.45	0.5619847
Bus 7	2052.0434	119.8855	0.053250	52509.88	0.5622899
Time	13.13 sec				

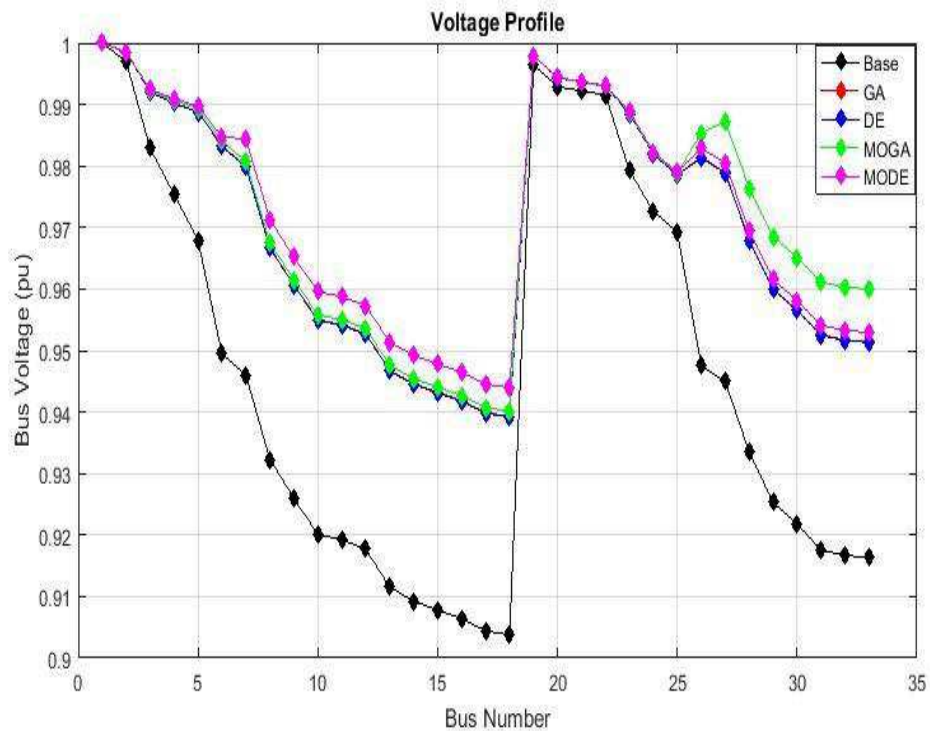


Figure 5.7: Voltage Profile (Single DG - Nominal Load)

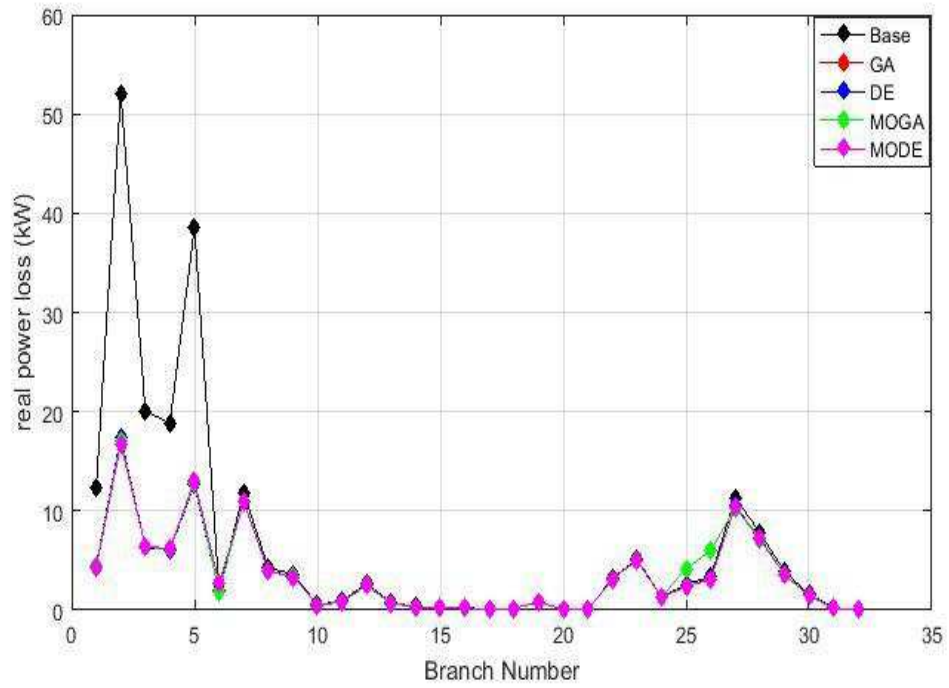


Figure 5.8: Active Power Loss (Single DG - Nominal Load)

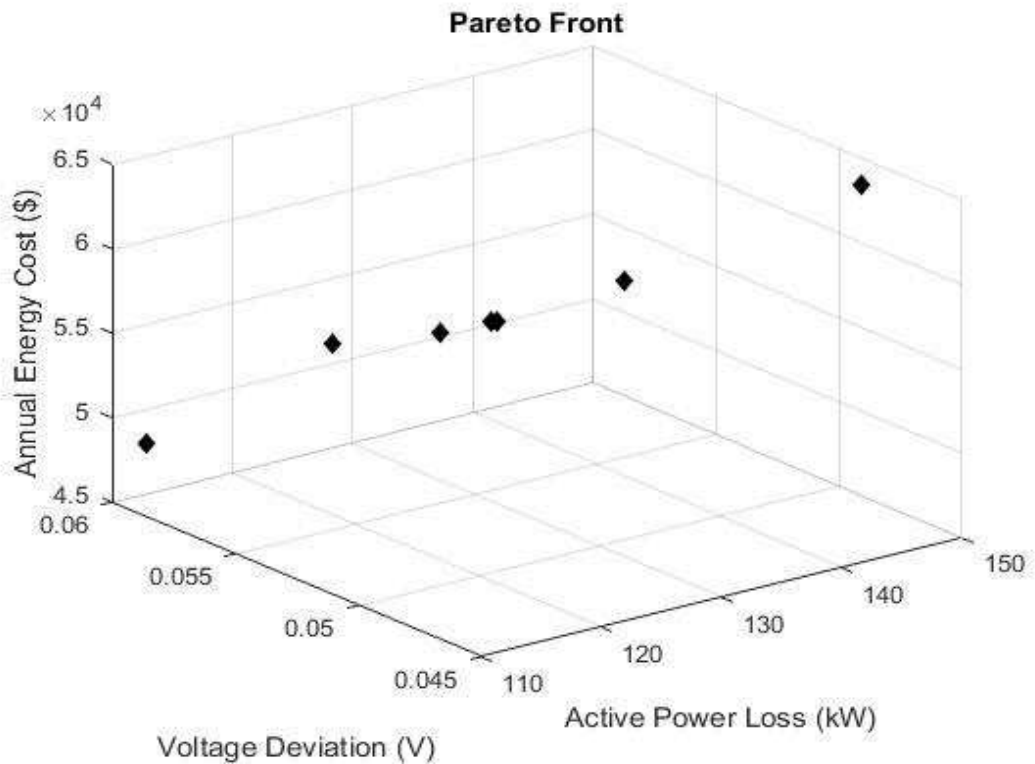


Figure 5.9: Pareto Front for MOGA (Single DG - Nominal Load)

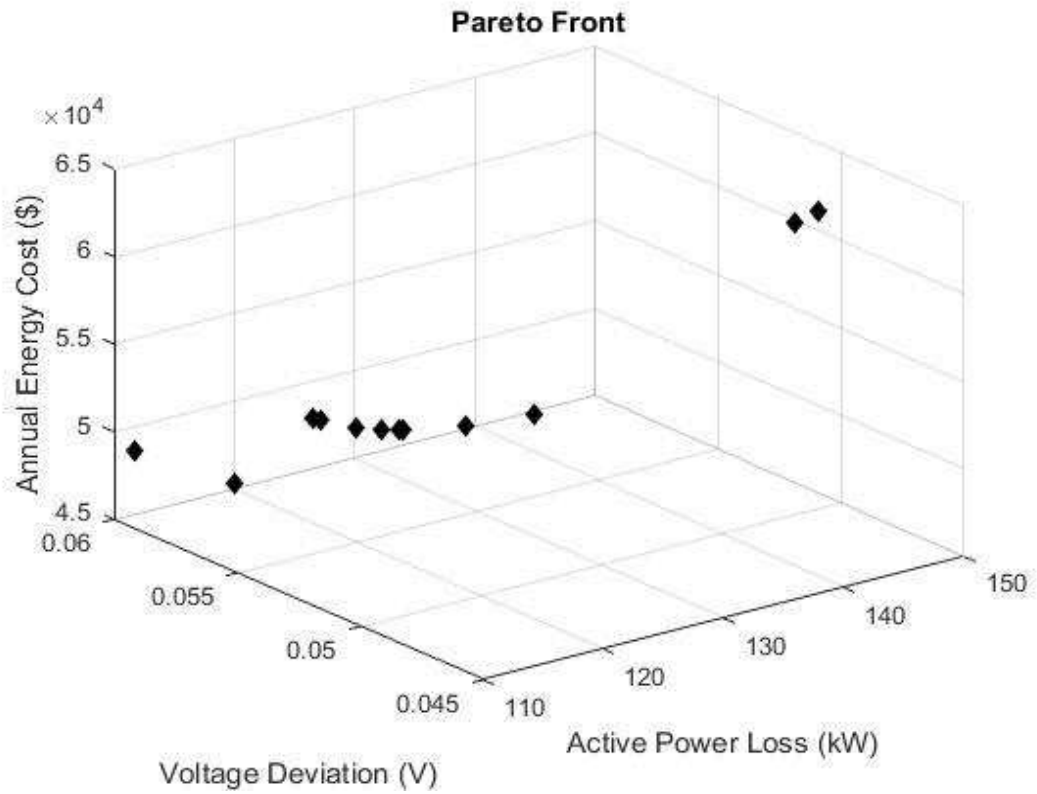


Figure 5.10: Pareto Front for MOGA (Single DG - Nominal Load)

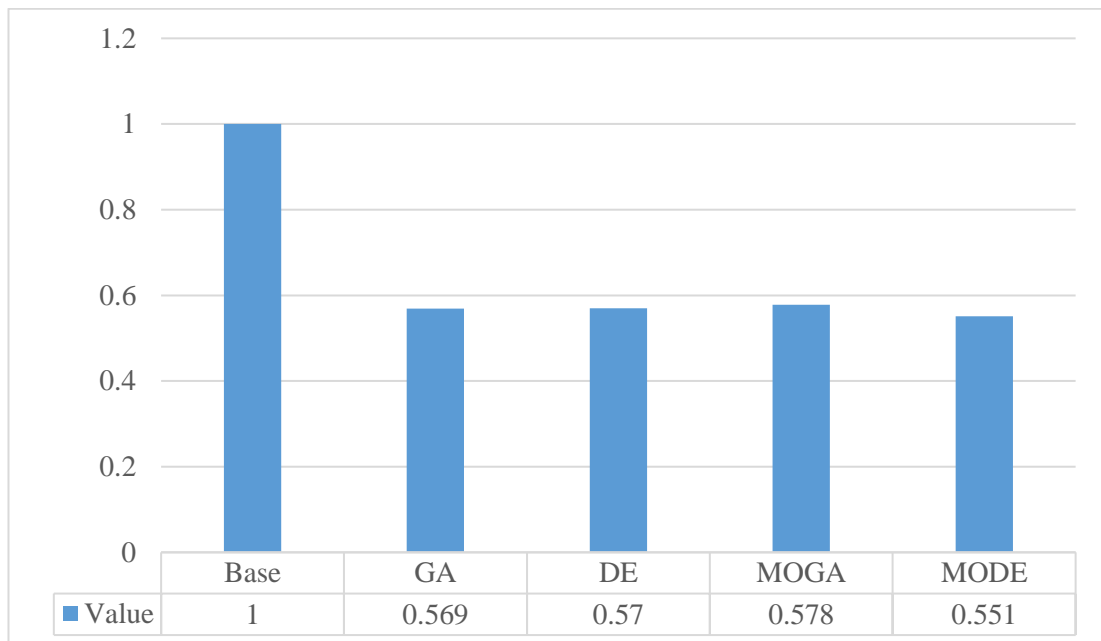


Figure 5.11: Weight Vector Results (Single DG – Nominal Load)

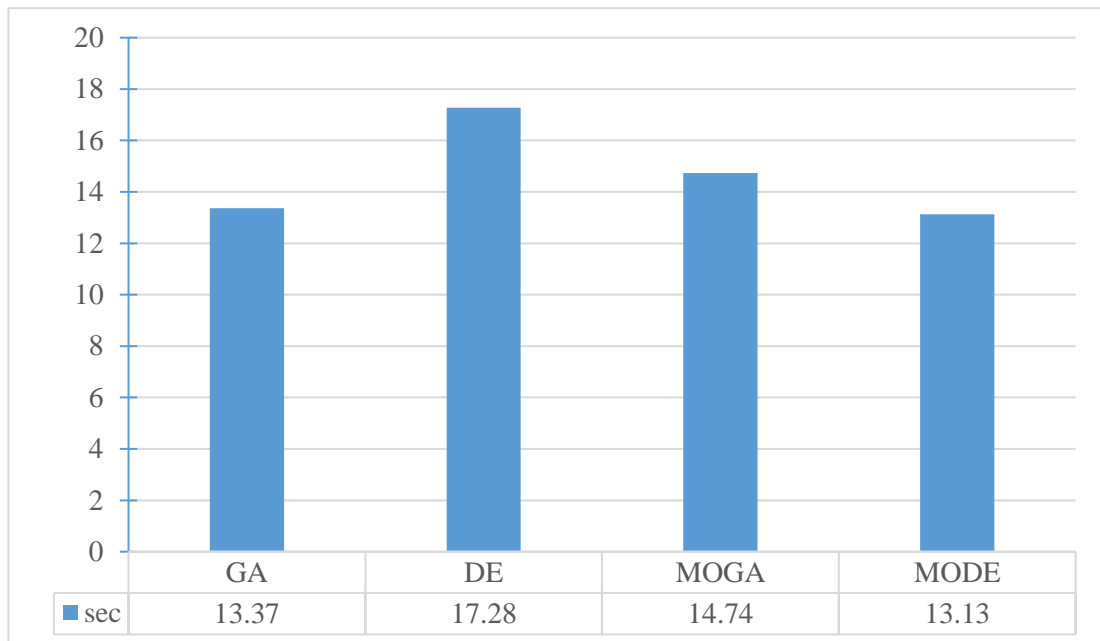


Figure 5.12: Computation Time (Single DG – Nominal Load)

- Heavy Load

The total real and reactive load power connected to the grid are 4643.75 kW and 2875 kVAr which represent 125% of the nominal system loading. First, a simple load flow has performed. After that, the DG has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.7 shows the comparison of the real power dissipation, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.8 displays the results of the MOGA and Table 5.9 displays the results of the MODE.

In the DE, the real power dissipation have decreased to 189.35 kW (i.e. the ratio of the decrease is 45%) after placing a DG in the network at bus 7 with a size of 2239.72 kW. From the results, it is obvious that DE is better than GA in the reduction of the power loss and the annual energy cost. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each

objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.13 and Figure 5.14 in that order. Overall, the minimum power loss and the annual loss cost obtained when DE has used which is not very different with the one obtained when MOGA and MODE have used. The minimum CPU time needed is 14.99 sec which achieved when MODE has used while the minimum voltage deviation found when GA has used. Finally, the best overall performance obtained by MODE. Figure 5.15 shows the Pareto front when MOGA has used, and Figure 5.16 shows the Pareto front when MODE has used. Figure 5.17 and Figure 5.18 show the overall performance and time in that order for each algorithm.

Table 5.7: Results of GA and DE case of a single DG at a Heavy Load

	Base	GA	DE
Power Loss (kW)	344.3189	200.5266	189.3565
Voltage Deviation (V)	0.123288	0.070318	0.072328
Energy Cost (\$)	150811.71	87830.65	82938.16
DG Location	-	Bus 8	Bus 7
DG Size (kW)	-	2398.7311	2239.7289
Comp. Time (sec)	-	25.84	39.07
Minimum Voltage (V)	0.876711	0.929681	0.927671
$\sum_{i=1}^n k_i f_i$	1	0.57757	0.56463

Table 5.8: Results of MOGA case of a Single DG at a Heavy Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 9	247.4709	217.6469	0.069595	95329.35	0.60506
Bus 8	236.1286	199.5607	0.070825	87407.59	0.57753
Bus 8	242.8061	201.3433	0.069921	88188.40	0.57770

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 7	2315.4560	189.4011	0.071263	82957.71	0.56125
Bus 6	2474.7093	185.5738	0.081407	81281.35	0.58749
Bus 10	2495.2299	221.9579	0.069382	97217.57	0.61188
Time	65.34 sec				

Table 5.9: Results of MODE case of a Single DG at a Heavy Load

DG location	DG size (kW)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 7	2335.1316	189.4622	0.070988	82984.46	0.56046
Bus 8	2360.4730	199.5407	0.070836	87398.82	0.57753
Bus 5	2474.1388	186.9957	0.084632	81904.13	0.60043
Time	14.99 sec				

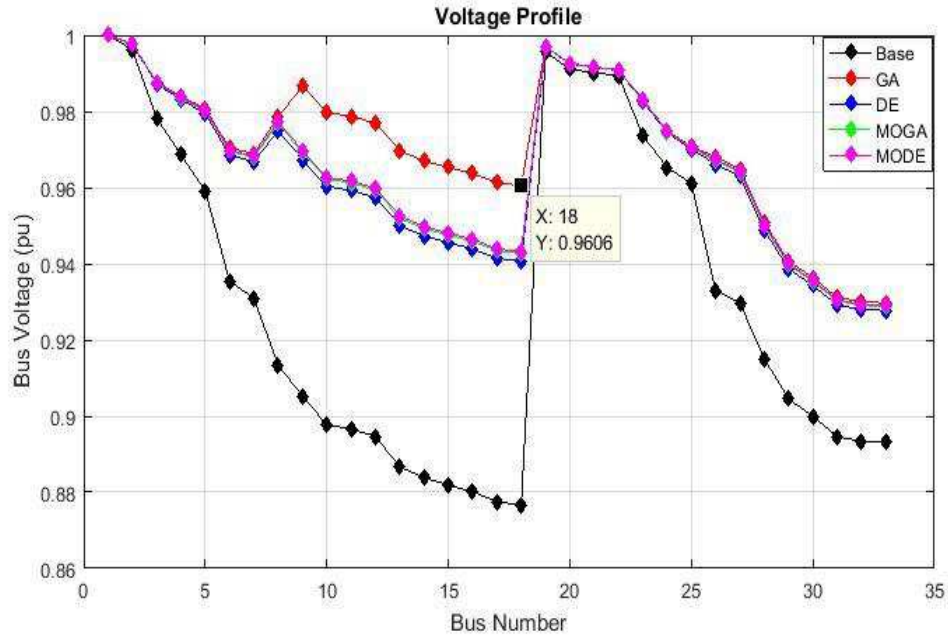


Figure 5.13: Voltage Profiles (Single DG - Heavy Load)

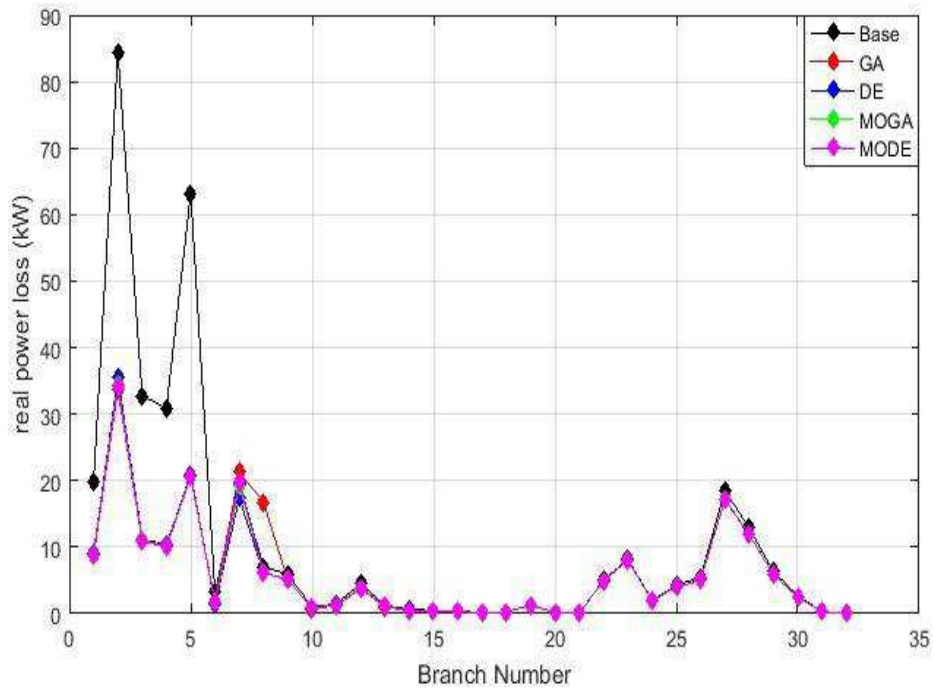


Figure 5.14: Active Power Loss (Single DG - Heavy Load)

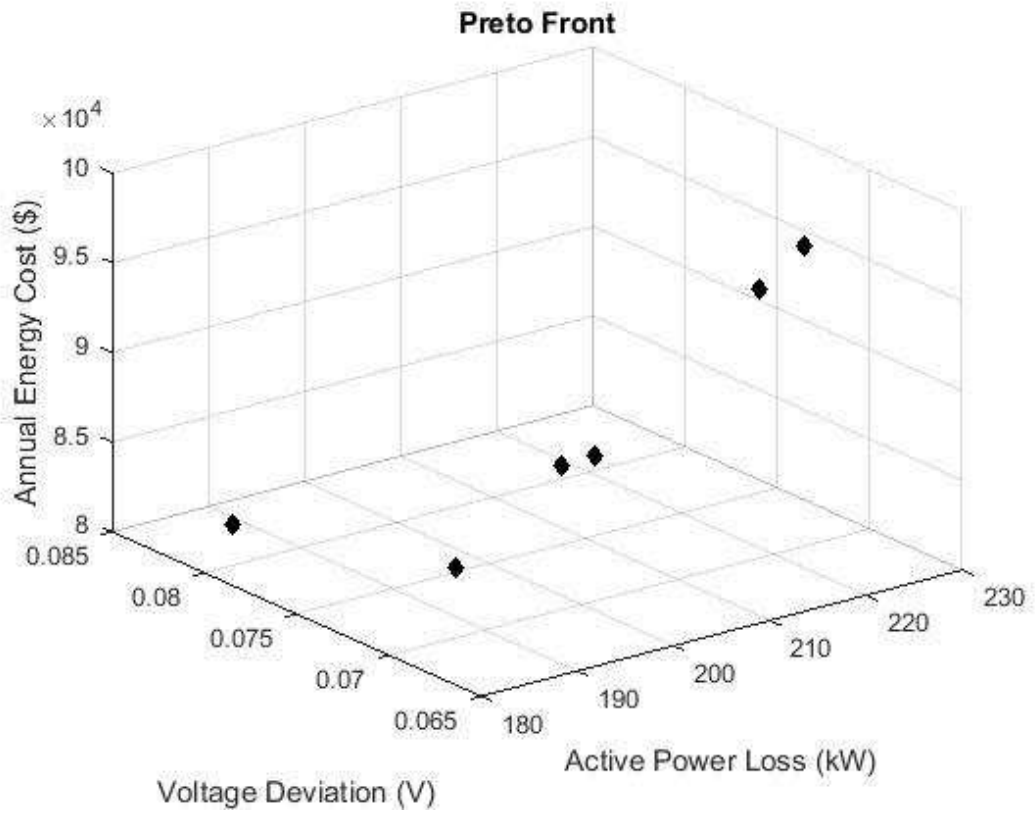


Figure 5.15: Pareto Front for MOGA (Single DG - Heavy Load)

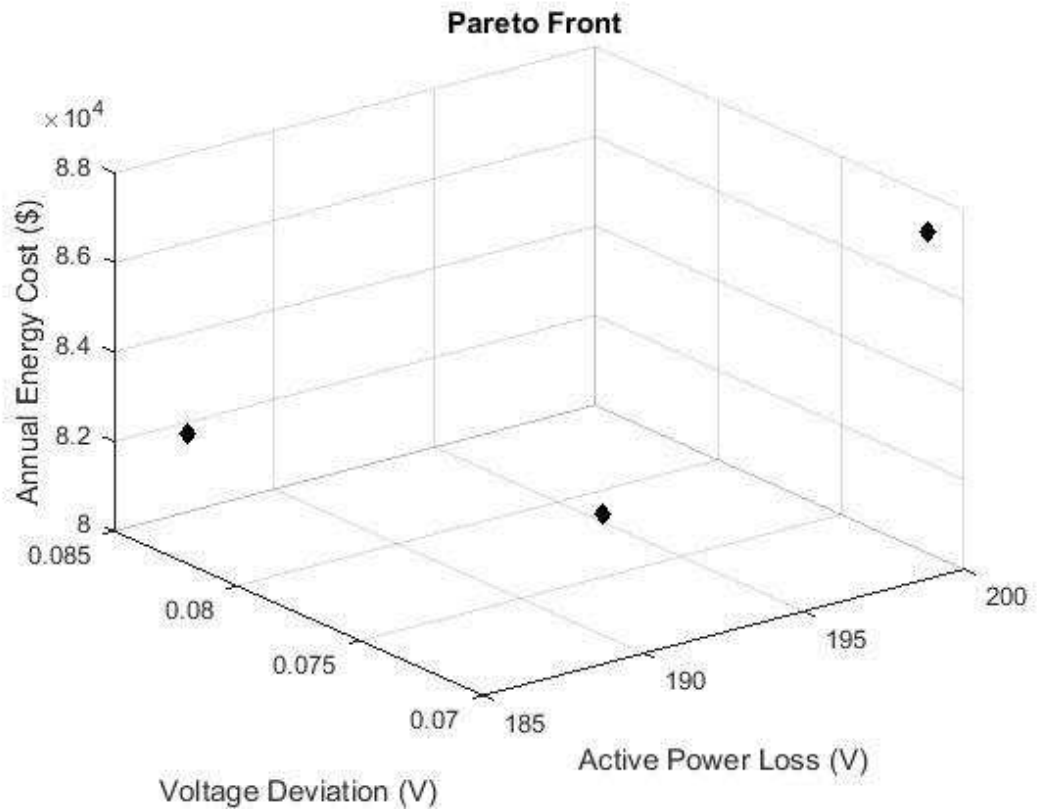


Figure 5.16: Pareto Front for MODE (Single DG - Heavy Load)

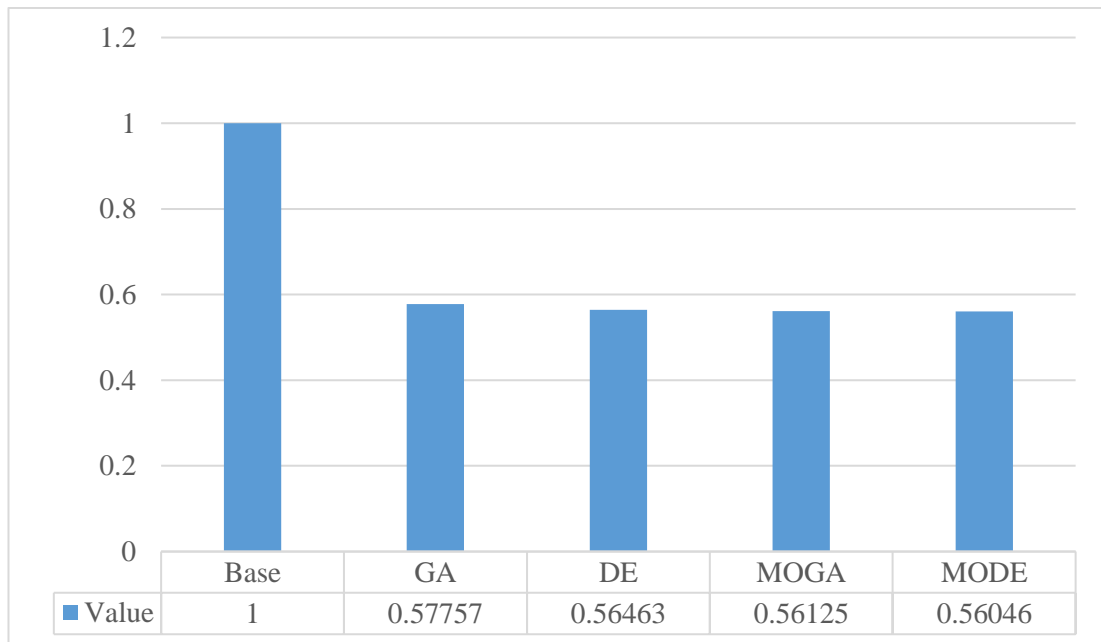


Figure 5.17: Weight Vector Results (Single DG – Heavy Load)

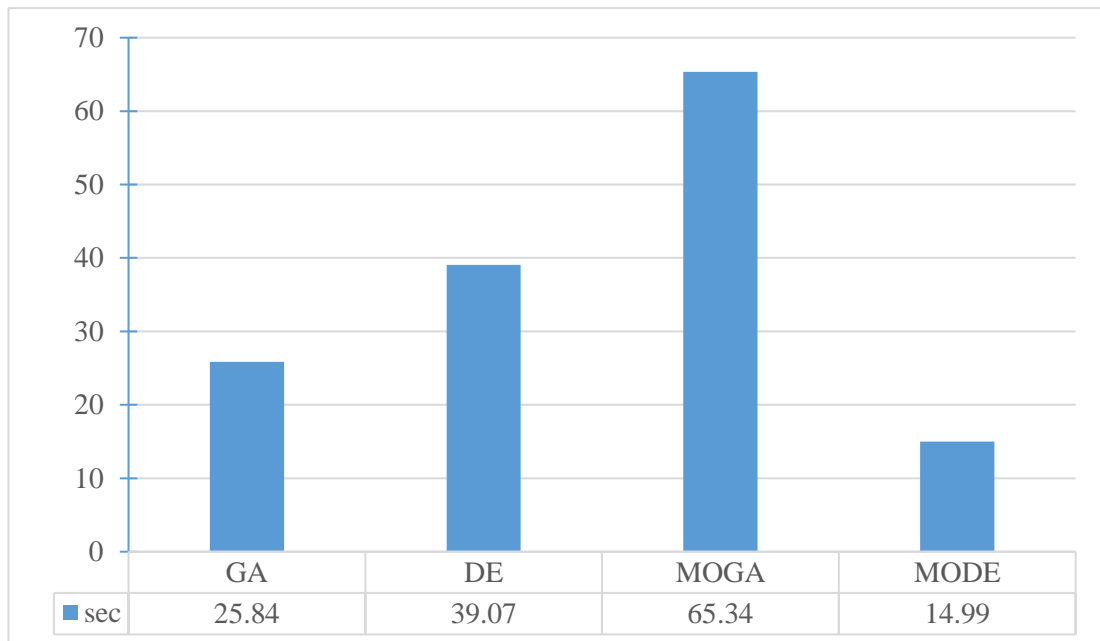


Figure 5.18: Computation Time (Single DG – Heavy Load)

5.2.2 Single DSTATCOM

Here, only a one DSTATCOM has been optimally sited into the radial electrical distribution grid to improve its performance by using GA, DE, MOGA, and MODE as shown in chapter 4. To analyze the performance of each one of these algorithms three loading levels were used as follow. It assumed that, DSTATCOM injects only reactive power into the network.

- Light Load:

The total real and reactive load power connected to the grid are 3343.5 kW and 2070 kVAr which represent 62.5% of the nominal system loading. First, a simple load flow has performed. After that, the DSTATCOM has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.10 shows the comparison of the real power losses, voltage deviation, annual energy cost, computation time, locations, and size of the DSTATCOM for GA and DE. Table 5.11 displays the results of the MOGA and Table 5.12 displays the results of the MODE.

In the DE, the real power dissipation have decreased to 65.10 kW (i.e. the percentage of the decrease is 16.16%) after placing a DSTATCOM into the network at bus 7 with a size of 902.169 kVAr. From the results, it is obvious that DE is better than GA in the lessening of the power dissipation and the cost. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which shaded in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.19 and Figure 5.20 in that order. Overall, the minimum power loss and the annual energy cost obtained when MOGA has used which is not very different from the one obtained when DE and MODE have used. The minimum CPU time needed is 16.44 sec which achieved when MODE has used while the minimum voltage deviation found when GA has used. Finally, the best overall performance obtained by MOGA. Figure 5.21 shows the Pareto front when MOGA has used, and Figure 5.22 shows the Pareto front when MODE has used. Figure 5.23 and Figure 5.24 show the weight vector results and time in that order for each algorithm.

Table 5.10: Results of GA and DE case of a single DSTATCOM at a light Load

	Base	GA	DE
Power Loss (kW)	77.6558	67.5131	65.1005
Voltage Deviation (V)	0.058142	0.035838	0.042388
Energy Cost (\$)	34013.28	29570.75	28514.02
DSTATCOM Location	-	Bus 6	Bus 7
DSTATCOM Size (kVAr)	-	1699.6031	902.169
Comp. Time (sec)	-	23.34	30.91

	Base	GA	DE
Minimum Voltage (V)	0.94185	0.96416	0.95761
$\sum_{i=1}^n k_i f_i$	1	0.76818	0.79460

Table 5.11: Results of MOGE case of a Single DSTATCOM at a Light Load

location	Size (kVAr)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 29	911.8999	57.1391	0.049573	25026.96	0.78253
Bus 27	1121.2017	59.9696	0.047737	26266.71	0.79176
Bus 6	1551.6919	64.9203	0.037713	28435.11	0.76105
Bus 29	852.8172	56.7264	0.050098	24846.19	0.78295
Bus 6	2137.2637	78.8617	0.031527	34541.42	0.82621
Bus 7	789.0301	64.2371	0.043380	28135.89	0.79476
Bus 29	854.659	56.7358	0.050082	24850.29	0.78291
Bus 27	1174.5117	60.6846	0.047267	26579.86	0.79406
Bus 6	1594.7946	65.6102	0.037165	28737.29	0.76262
Bus 7	854.6596	64.6558	0.042803	28319.27	0.79403
Bus 6	2010.7744	75.0233	0.032601	32860.24	0.80394
Bus 29	789.0301	56.5417	0.050670	24765.30	0.78546
Bus 6	2153.3137	79.3808	0.031391	34768.81	0.82929
Bus 7	2353.6585	132.6426	0.030628	58097.46	1.23556
Bus 29	797.1566	56.5501	0.050597	24768.97	0.78502
Bus 7	731.6823	64.0583	0.043887	28057.55	0.79687
Bus 6	1010.2494	60.9341	0.044681	26689.14	0.77819
Bus 27	1134.9085	60.1405	0.047616	26341.54	0.79225
Time	68.18 sec				

Table 5.12: Results of MODE Case of a Single DSTATCOM at Light Load

Location	Size (kVAr)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 6	2304.3284	84.6172	0.030119	37062.34	0.86100
Bus 6	1685.2818	67.2343	0.036019	29448.64	0.76728
Bus 6	1558.6630	65.0282	0.037624	28482.37	0.76128
Bus 6	1041.7553	60.9251	0.044271	26685.22	0.77530
Bus 6	2271.1756	83.4133	0.030398	36535.05	0.85361
Bus 6	1078.0217	60.9521	0.043800	26697.04	0.77227
Bus 26	1087.4907	60.0663	0.048045	26309.07	0.79463
Bus 7	882.6733	64.9037	0.042558	28427.83	0.79426
Bus 5	1274.5438	60.9084	0.046361	26677.90	0.78955
Bus 27	1166.5894	60.5697	0.047337	26529.56	0.79365
Bus 27	823.2419	58.5019	0.050402	25623.83	0.79876
Bus 6	2067.1760	76.6792	0.032121	33585.52	0.81344
Time	16.44 sec				

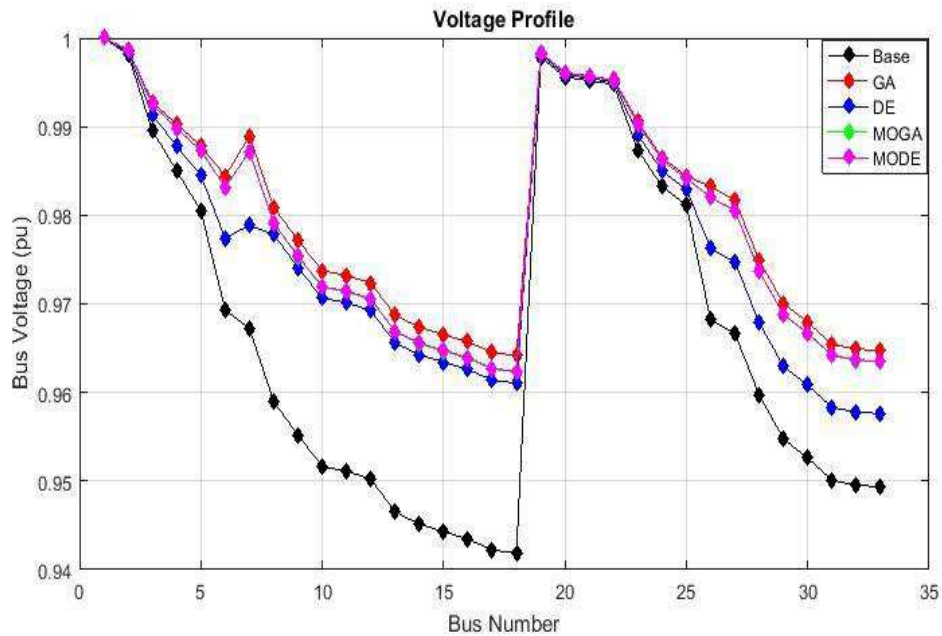


Figure 5.19: Voltage Profile (Single DSTATCOM - Light Load)

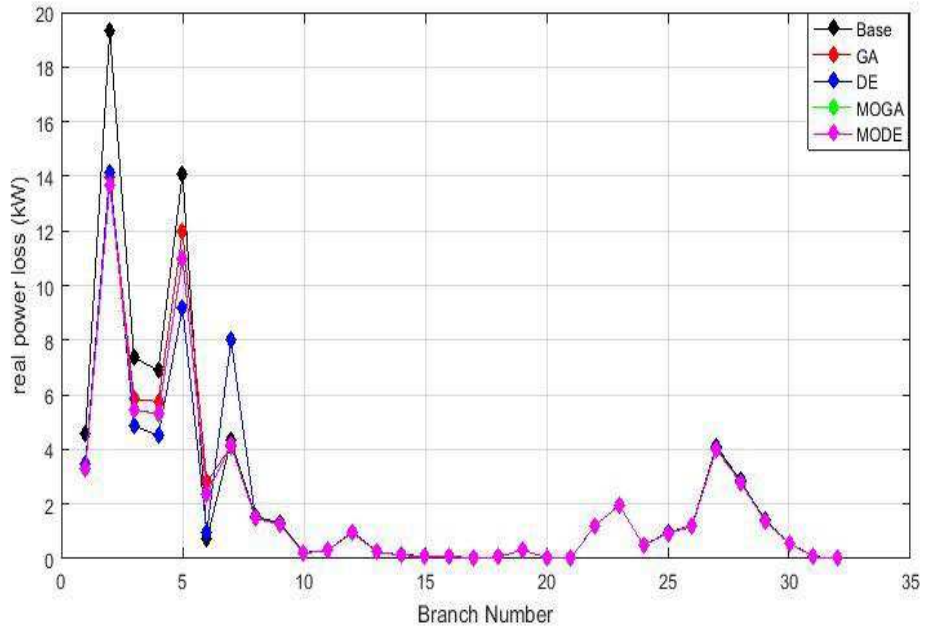


Figure 5.20: Active Power Loss (Single DSTATCOM - Light Load)

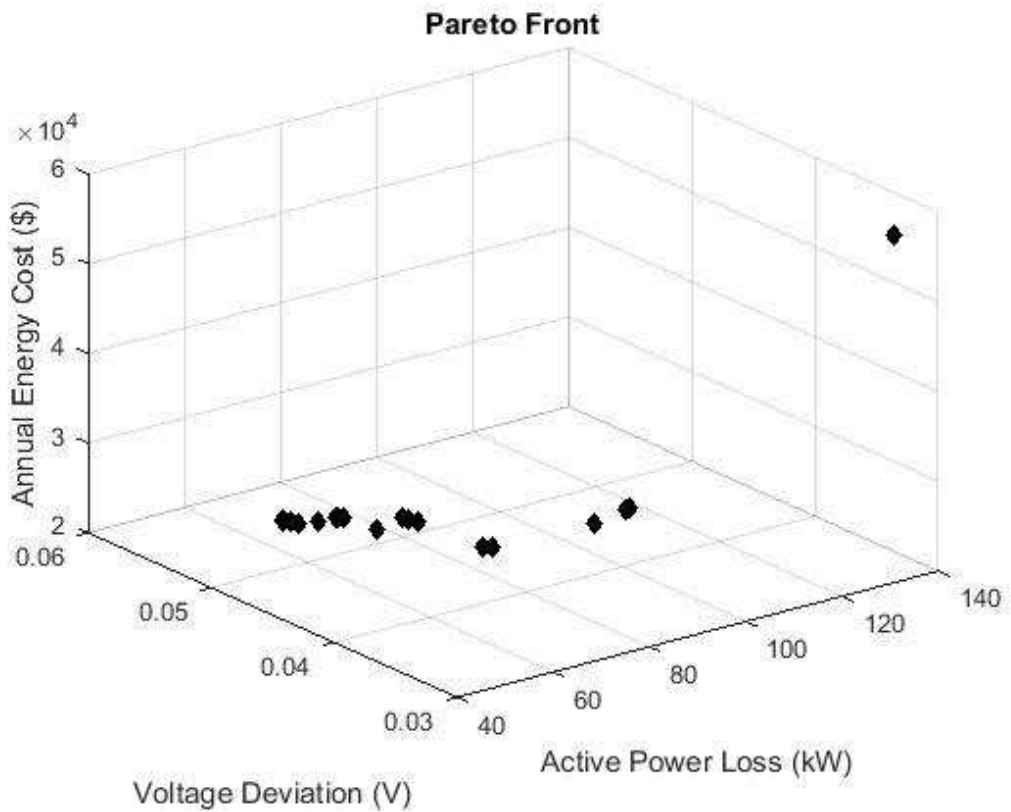


Figure 5.21: Pareto Front for MOGA (Single DSTATCOM - Light Load)

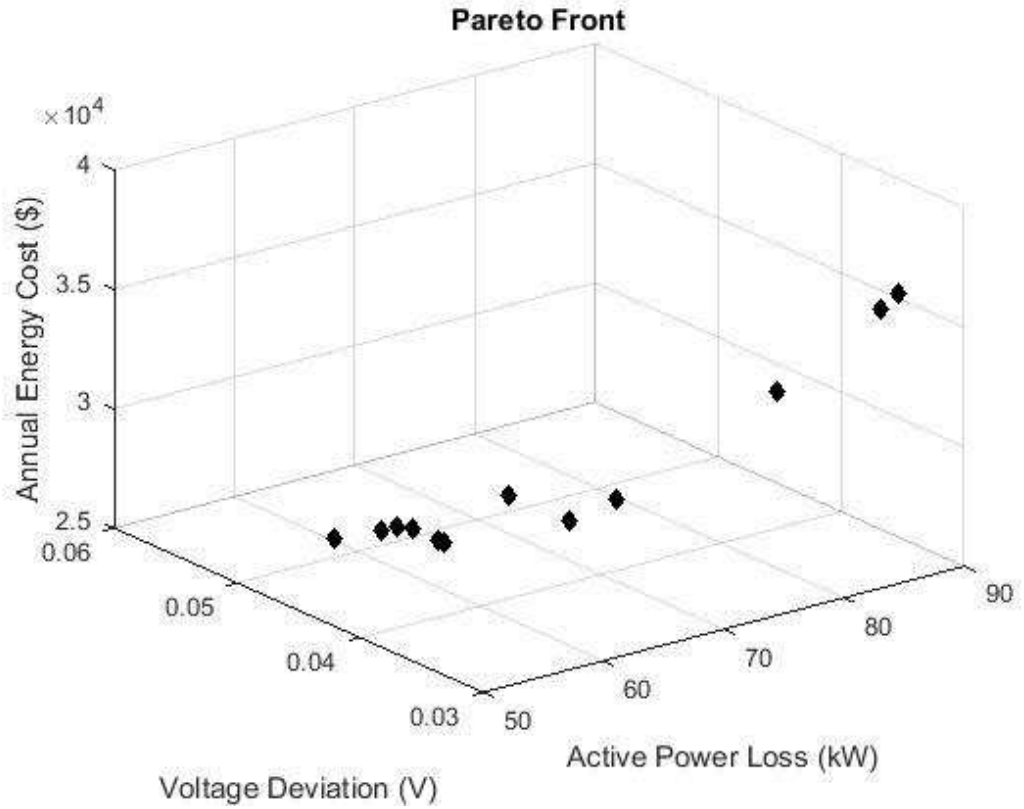


Figure 5.22: Pareto Front for MODE (Single DSTATCOM - Light Load)

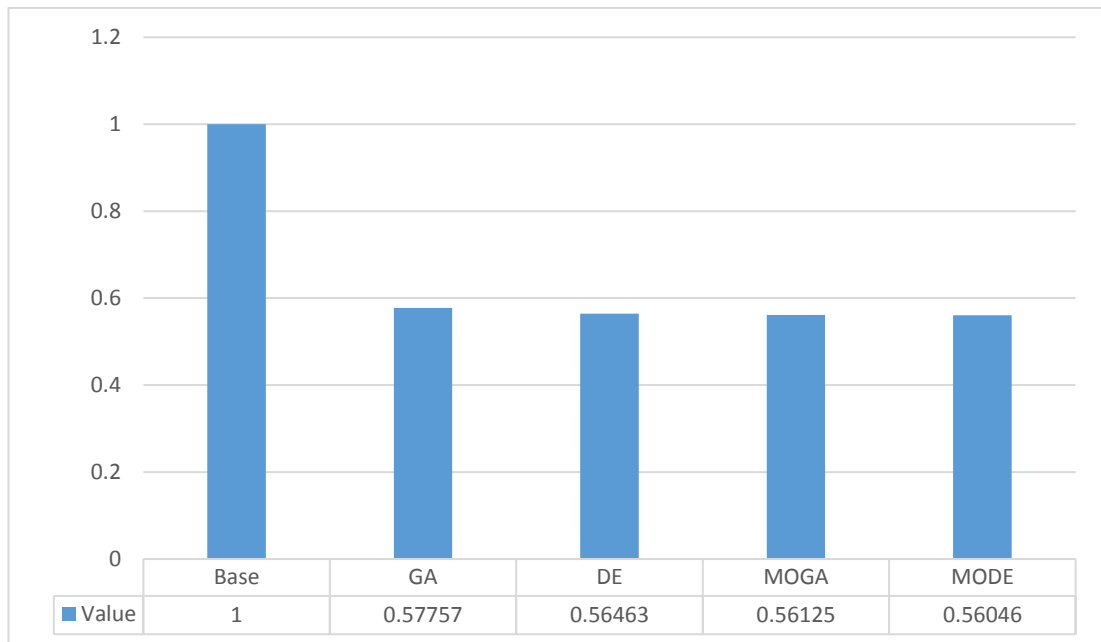


Figure 5.23: Weight Vector Results (Single DSTATCOM – Light Load)

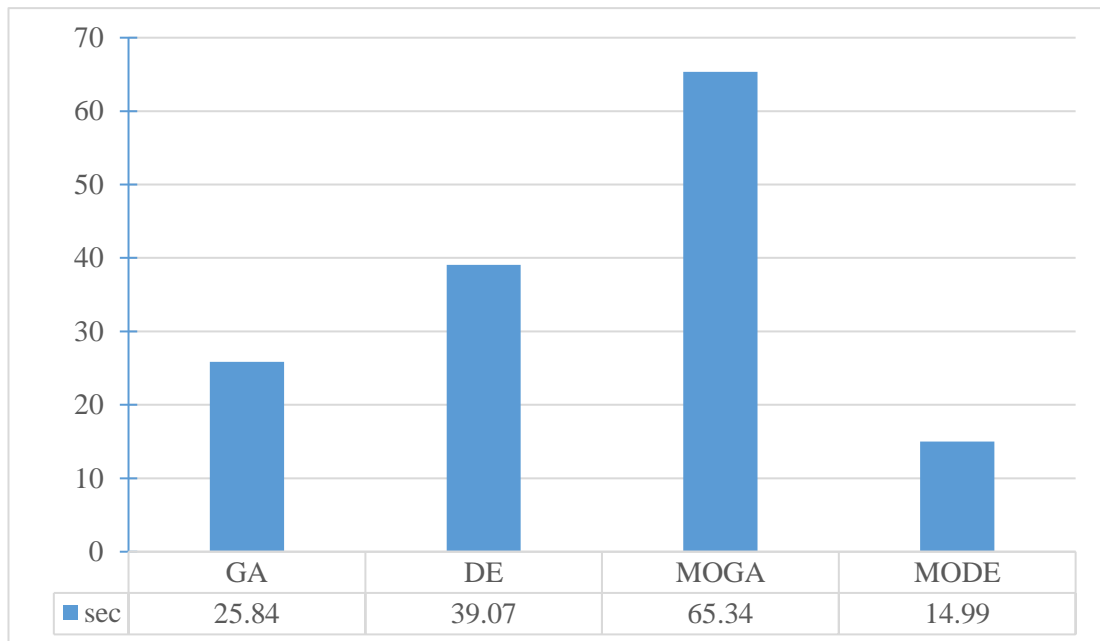


Figure 5.24: Computation Time (Single DSTATCOM – Light Load)

- Nominal Load:

The total real and reactive load power connected to the grid are 3715 kW and 2300 kVAr which represent 100% of the normal system loading. First, a simple load flow has performed. After that, the DSTATCOM has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.13 shows the comparison of the real power losses, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.14 displays the results of the MOGA and Table 5.15 displays the results of the MODE.

In the DE, the real power dissipation have decreased to 163.63 kW (i.e. the percentage of the decrease is 22.44%) after placing a DSTATCOM into the network at bus 6 with a size of 1875.80 kVAr. From the results, it is obvious that DE is better than GA in the lessening of the power dissipation and the cost. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor

for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which shaded in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.25 and Figure 5.26 in that order. Overall, the minimum power loss and the annual energy cost obtained when MODE has used. The minimum CPU time needed is 16.02 sec which achieved when MODE has used while the minimum voltage deviation found when GA has used. Finally, the best overall performance obtained by GA. Figure 5.27 shows the Pareto front when MOGA has used, and Figure 5.28 shows the Pareto front when MODE has used. Figure 5.29 and Figure 5.30 show the weight vector results and time in that order for each algorithm.

Table 5.13: Results of GA and DE case of a single DSTATCOM at a nominal Load

	Base	GA	DE
Power Loss (kW)	210.9875	170.2084	163.6385
Voltage Deviation (V)	0.096222	0.063551	0.070222
Energy Cost (\$)	92412.54	74551.30	71673.68
DSTATCOM Location	-	Bus 6	Bus 6
DSTATCOM Size (kVAr)	-	2384.719	1875.8019
Comp. Time (sec)	-	41.77	76.97
Minimum Voltage (V)	0.903777	0.93644	0.92977
$\sum_{i=1}^n k_i f_i$	1	0.74821	0.75726

Table 5.14: Results of MOGA case of a Single DSTATCOM at a nominal Load

DSTATCOM		Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location	Size (kVAr)				
Bus 25	1910.6355	161.9770	0.077635	70945.94	0.78336

DSTATCOM		Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location	Size (kVAr)				
Bus 6	1711.9016	163.2061	0.072403	71484.30	0.76510
Bus 27	1825.8700	160.7366	0.078406	70402.64	0.78303
Bus 28	1747.1780	158.8537	0.079104	69577.93	0.78058
Bus 28	1684.9666	157.3205	0.079653	68906.39	0.77850
Bus 28	1390.8833	153.2509	0.082307	67123.89	0.77796
Bus 6	1747.1780	163.2288	0.071932	71494.22	0.76321
Bus 25	1835.5682	161.6341	0.078334	70795.76	0.78528
Bus 8	1972.8403	209.3679	0.065718	91703.18	0.86858
Bus 8	2058.7836	215.2772	0.065047	94291.43	0.88260
Bus 27	1809.8546	160.4165	0.078550	70262.44	0.78272
Bus 8	2498.8004	252.4742	0.061734	110583.7 3	0.97461
Bus 29	1547.2771	154.2794	0.080875	67574.41	0.77493
Bus 6	2130.2897	165.9459	0.066867	72684.32	0.74988
Time	68.18 sec				

Table 5.15: Results of MODE Case of a Single DSTATCOM at nominal Load

Location	Size (kVAr)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
29	1384.1563	151.9233	0.082344	66542.44	0.77434
11	2424.6664	294.6337	0.063210	129049.58	1.10063
7	1970.7687	190.4085	0.065354	83398.95	0.81315
28	1500.1715	154.1443	0.081310	67515.23	0.77636
6	1706.3120	163.2061	0.072478	71484.29	0.76541
8	1451.1338	183.4495	0.069971	80350.89	0.81256
29	1715.8120	158.6093	0.079391	69470.88	0.78108
7	1278.6973	172.6345	0.071323	75613.94	0.78742

Location	Size (kVAr)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
29	1782.1140	160.8314	0.078816	70444.17	0.78501
8	1318.1997	179.6720	0.071106	78696.36	0.80653
8	1336.1185	180.1122	0.070951	78889.17	0.80714
Time	16.02 sec				

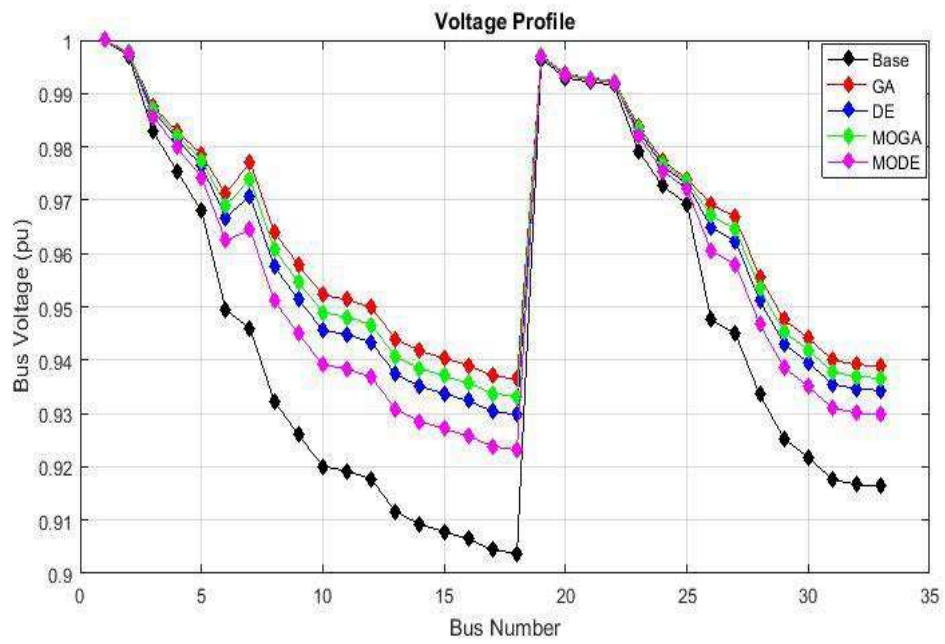


Figure 5.25: Voltage Profile (Single DSTATCOM - Nominal Load)

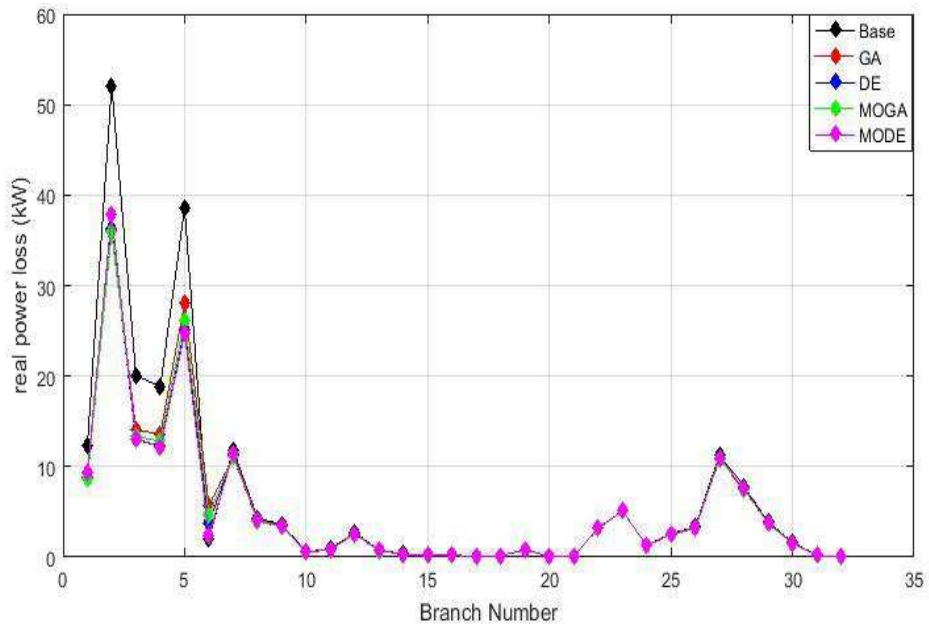


Figure 5.26: Active Power Loss (Single DSTATCOM - Nominal Load)

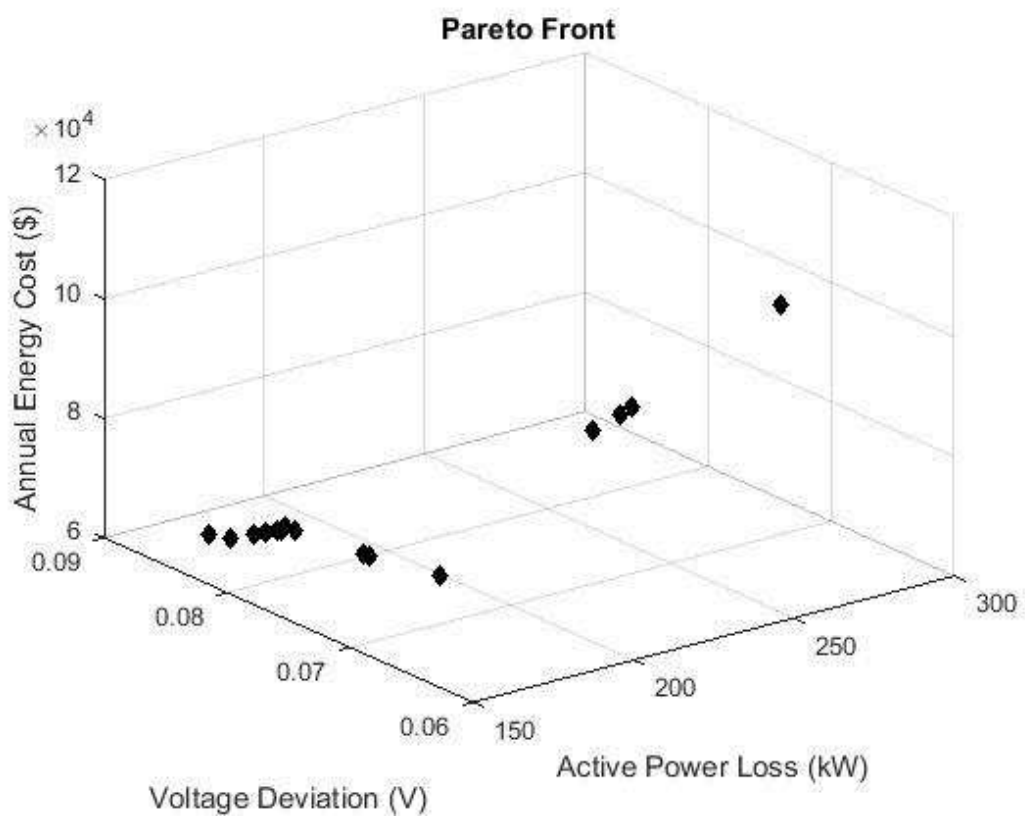


Figure 5.27: Pareto Front for MOGA (Single DSTATCOM - Nominal Load)

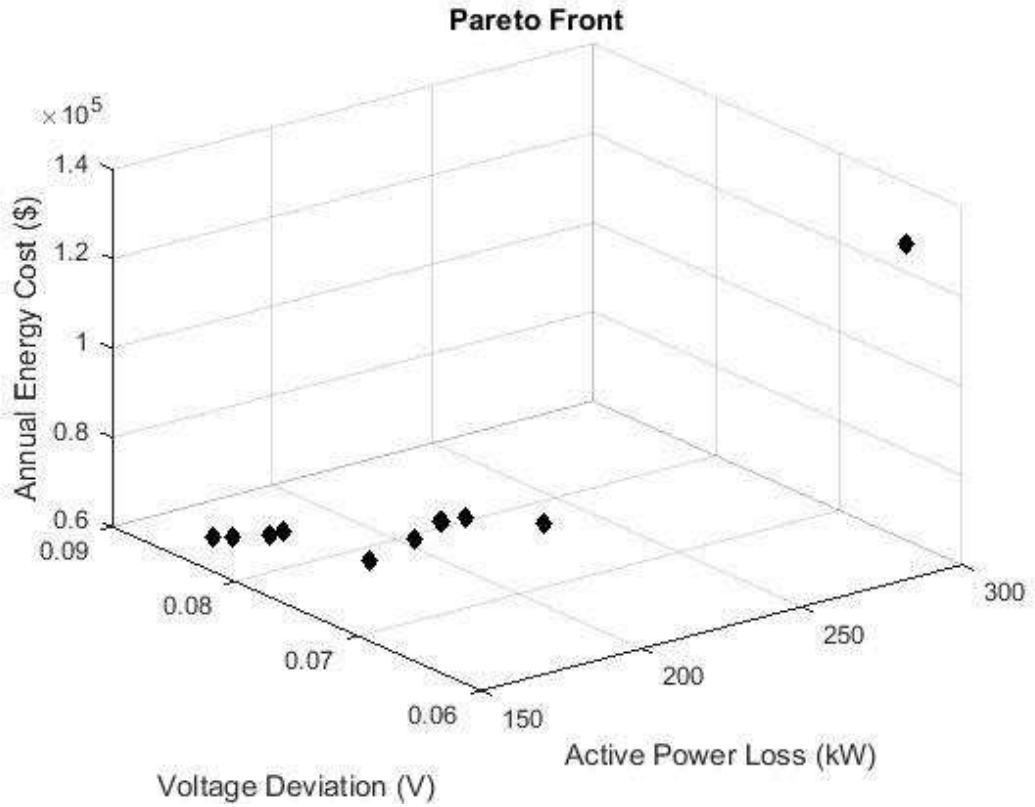


Figure 5.28: Pareto Front for MODE (Single DSTATCOM - Nominal Load)

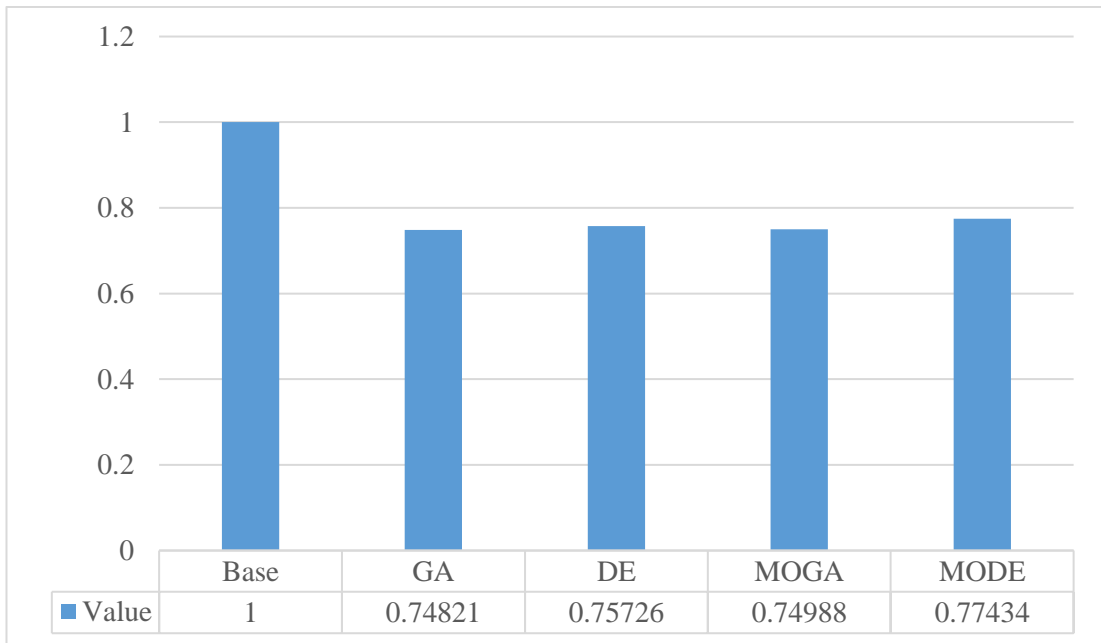


Figure 5.29: Weight Vector Results (Single DSTATCOM – Nominal Load)

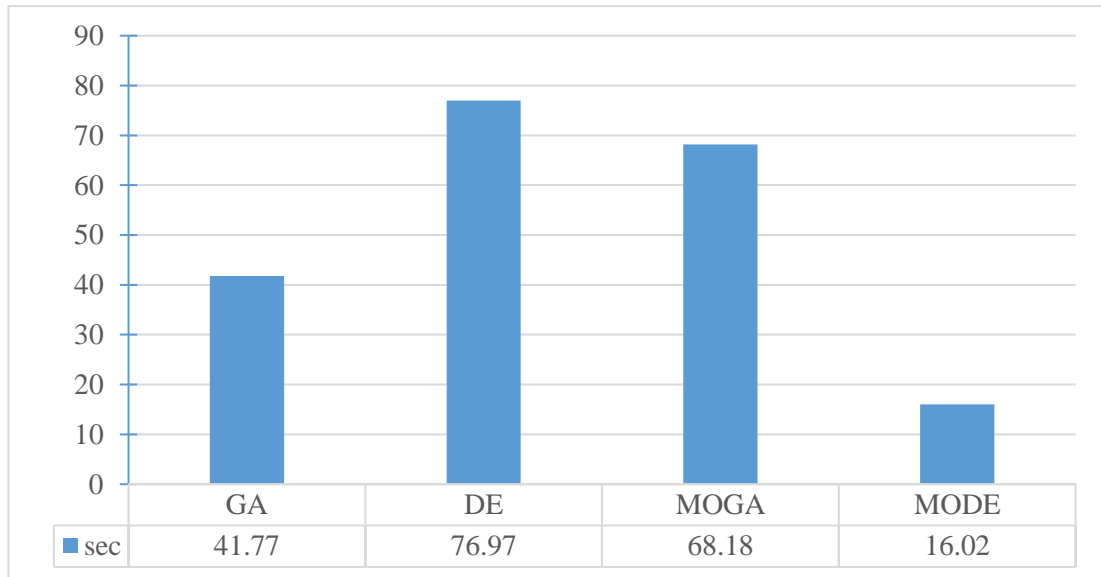


Figure 5.30: Computation Time (Single DSTATCOM – Nominal Load)

- Heavy Load

The total real and reactive load power connected to the grid are 4643.75 kW and 2875 kVAr which represent 125% of the nominal system loading. First, a simple load flow has performed. After that, the DG has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.16 shows the comparison of the real power dissipation, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.17 displays the results of the MOGA and Table 5.18 displays the results of the MODE.

In the DE, the real power dissipation have decreased to 246.98 kW (i.e. the percentage of the decrease is 28.26%) after placing a DSTATCOM in the grid at bus 28 with a size of 1645.35 kW. From the results, it is obvious that DE is better than GA in the lessening of the power dissipation and the annual energy cost. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and

$k_3 = 0.1$) [30]. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.31 and Figure 5.32 in that order. Overall, the minimum power loss and the annual loss cost obtained when DE has used. The minimum CPU time needed is 15.31 sec which achieved when MODE has used while the minimum voltage deviation found when MODE has used. Finally, the best overall performance obtained by MODE. Figure 5.33 shows the Pareto front when MOGA has used, and Figure 5.34 shows the Pareto front when MODE has used. Figure 5.35 and Figure 5.36 show the overall performance and time in that order for each algorithm.

Table 5.16: Results of GA and DE case of a single DSTATCOM at a Heavy Load

	Base	GA	DE
Power Loss (kW)	344.3189	263.6174	246.9878
Voltage Deviation (V)	0.123288	0.090198	0.105946
Energy Cost (\$)	150811.71	115464.43	108180.67
Location	-	Bus 6	Bus 28
Size (kVAr)	-	2308.1165	1645.3501
Comp. Time (sec)	-	31.57	68.14
Minimum Voltage (V)	0.876711	0.90980	0.89405
$\sum_{i=1}^n k_i f_i$	1	0.75201	0.77412

Table 5.17: Results of MOGA case of a Single DSTATCOM at a Heavy Load

Location	Size (kVar)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 27	2306.6364	259.4005	0.09990	113617.44	0.77617
Bus 27	2188.1638	256.6600	0.10098	112417.09	0.77489
Bus 6	2492.8236	264.8700	0.08770	116013.06	0.74611
Bus 6	2306.6364	263.6117	0.09021	115461.93	0.75206

Location	Size (kVar)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 8	2465.6301	336.9779	0.08416	147596.32	0.86028
Bus 28	1783.1448	247.4752	0.10465	108394.14	0.77077
Bus 28	1832.4349	247.9459	0.10419	108600.31	0.77011
Bus 29	1496.2047	244.5061	0.10730	107093.69	0.77422
Bus 6	2295.7779	263.5719	0.09036	115444.49	0.75247
Bus 6	2454.2773	264.5205	0.08822	115860.01	0.74718
Bus 25	2454.2773	261.6551	0.09853	114604.97	0.77564
Bus 25	2473.9410	261.8194	0.09834	114676.90	0.77532
Bus 8	2392.1301	331.0483	0.08473	144999.17	0.85178
Bus 6	2473.9410	264.6930	0.08796	115935.56	0.74662
Bus 28	2044.6967	251.7264	0.10225	110256.20	0.77040
Bus 28	1803.5238	247.6510	0.10446	108471.15	0.77047
Bus 8	2473.9410	337.6694	0.08410	147899.20	0.86128
Bus 8	2380.4331	330.1356	0.08482	144599.41	0.85049
Bus 29	2012.0731	250.7465	0.10254	109826.98	0.76964
Bus 27	2249.5335	257.9912	0.10042	113000.17	0.77539
Bus 7	2260.4639	296.4591	0.08525	129849.12	0.79321
Time	66.68 sec				

Table 5.18: Results of MODE case of a Single DSTATCOM at a Heavy Load

Location	Size (kVar)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 6	2419.6761	264.2463	0.08869	115739.89	0.74822
Bus 7	2405.0394	303.3357	0.08404	132861.07	0.80127
Bus 27	2203.3229	256.9711	0.10084	112553.35	0.77498
Bus 5	2452.6871	261.8059	0.09855	114671.02	0.77596
Bus 29	1586.2461	244.2156	0.10645	106966.44	0.77094

Location	Size (kVAr)	Active power loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Bus 26	2360.6294	260.7253	0.09941	114197.68	0.77688
Bus 7	2169.2843	292.6815	0.08602	128194.51	0.78913
Bus 28	1878.4481	248.5248	0.10376	108853.88	0.76974
Bus 26	2492.4799	262.3511	0.09817	114909.79	0.77570
Bus 6	2073.9587	263.5776	0.09338	115446.98	0.76229
Bus 6	2375.5968	263.9511	0.08928	115610.61	0.74963
Bus 28	2137.5935	254.2630	0.10142	111367.20	0.77212
Bus 29	1730.7025	244.9847	0.10510	107303.33	0.76789
Bus 27	2296.3122	259.1336	0.10000	113500.53	0.77601
Bus 6	2499.8661	264.9388	0.08761	116043.21	0.74592
Time	15.31 sec				

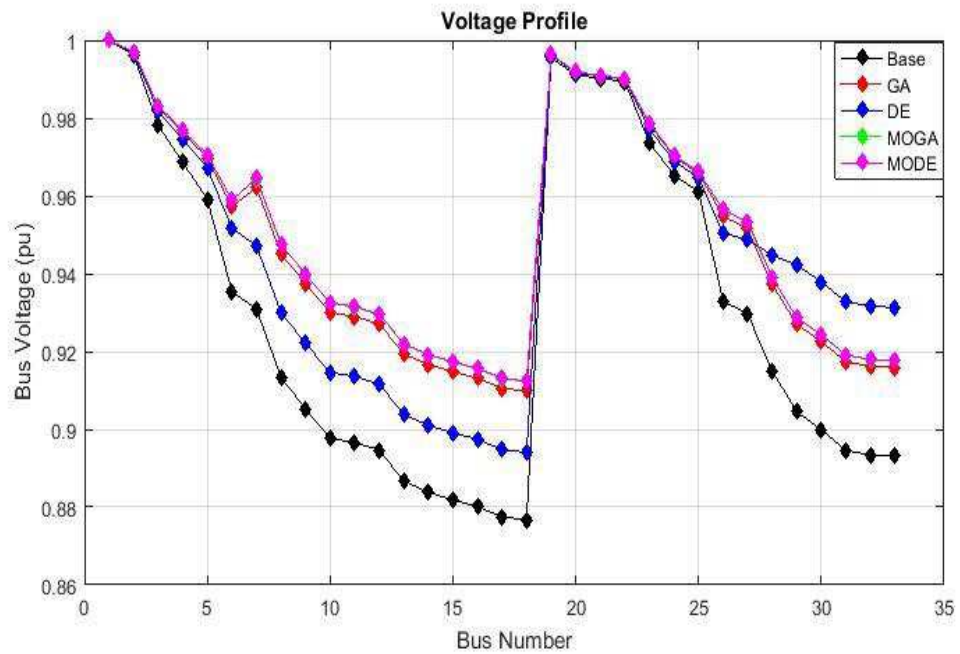


Figure 5.31: Voltage Profile (Single DG - Heavy Load)

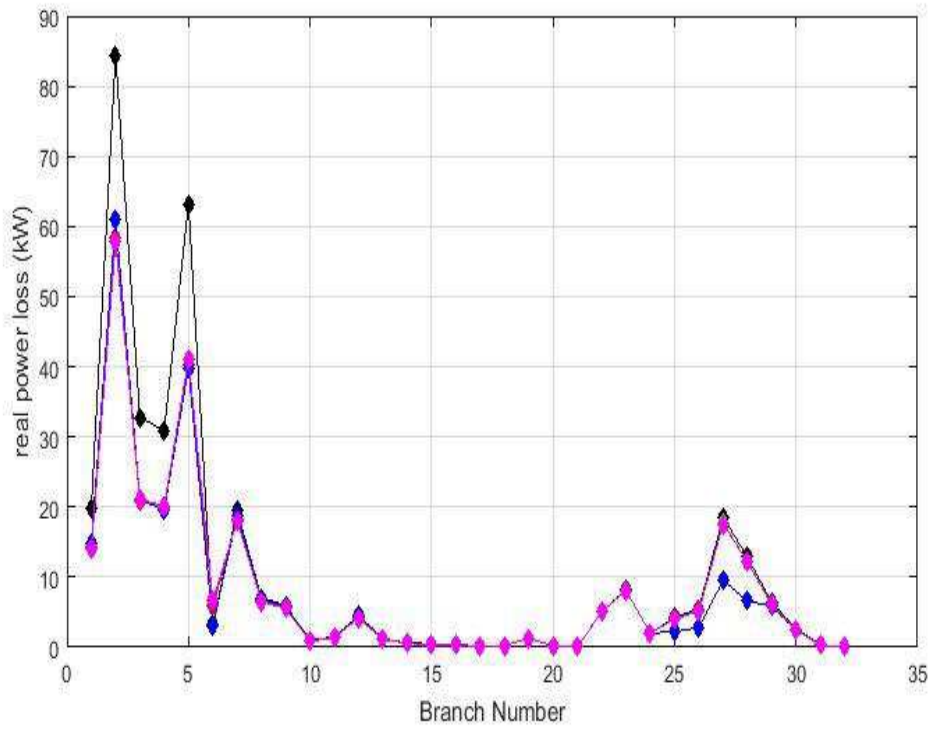


Figure 5.32: Active Power Loss (Single DG - Heavy Load)

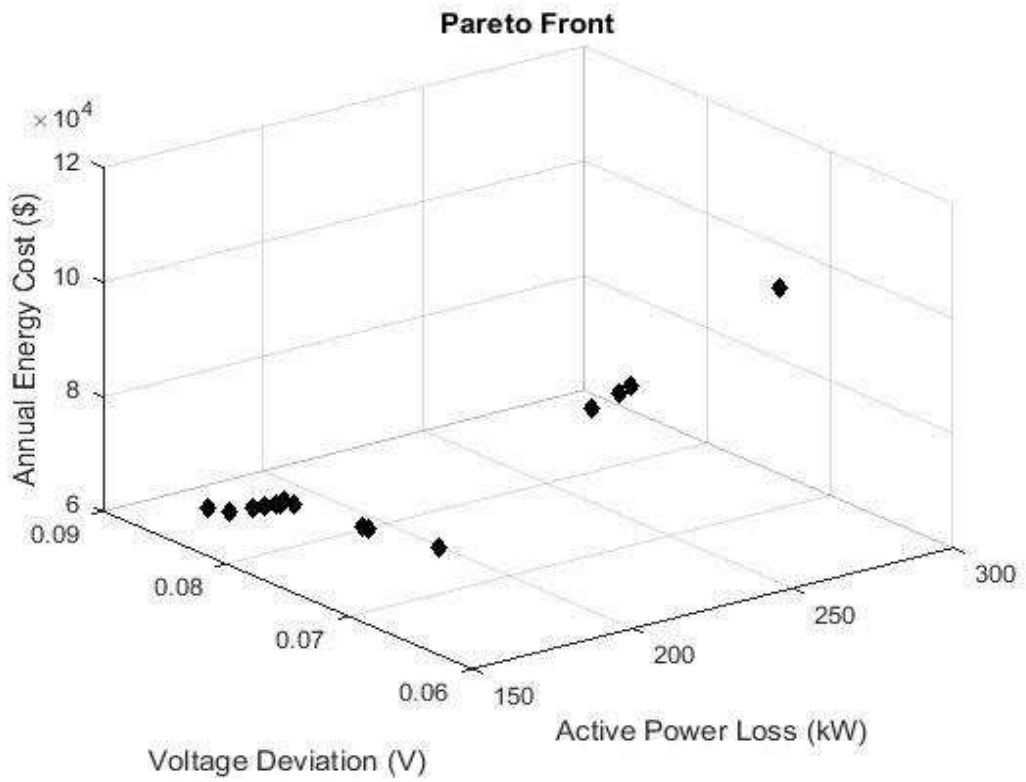


Figure 5.33: Pareto Front for MOGA (Single DSTATCOM - Heavy Load)

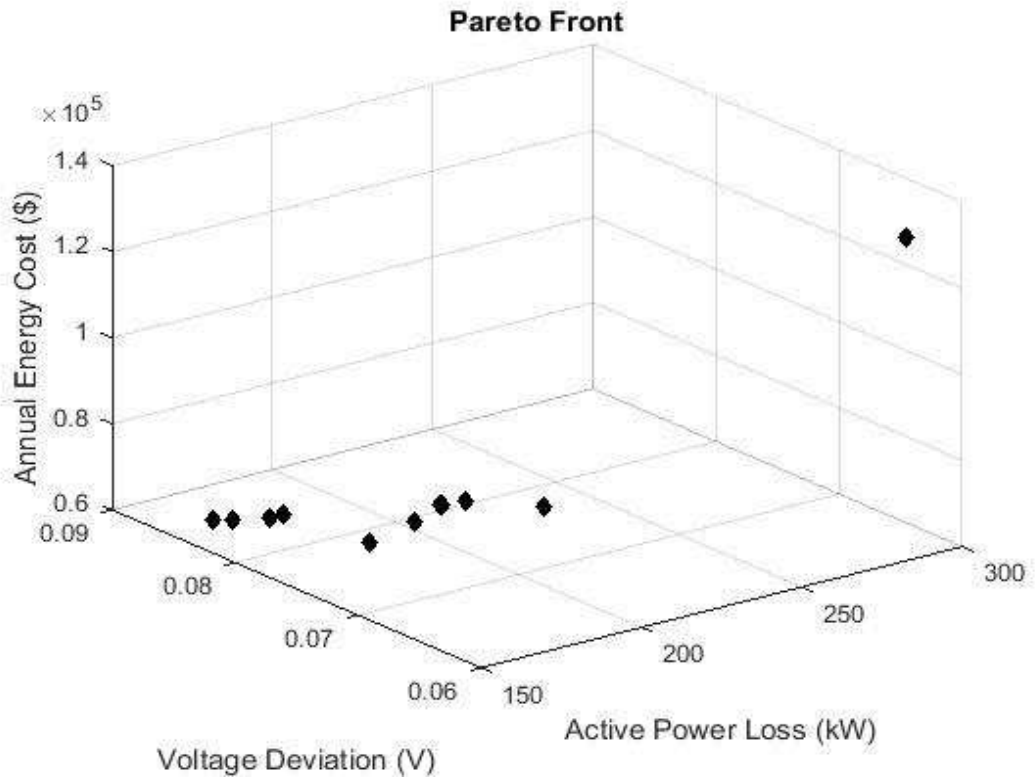


Figure 5.34: Pareto Front for MODE (Single DSTATCOM - Heavy Load)

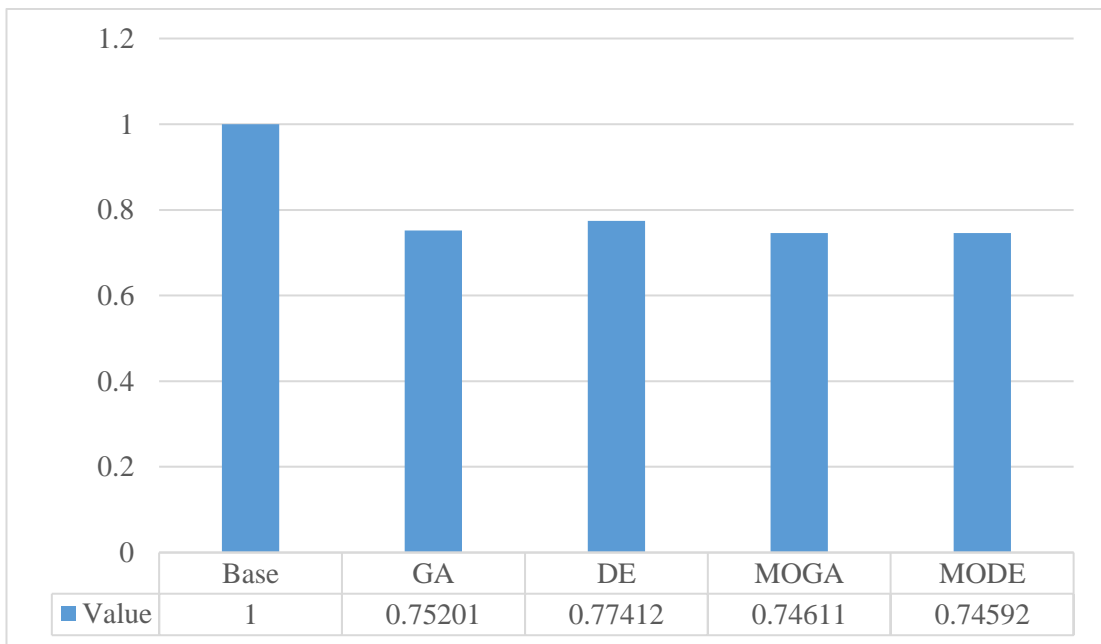


Figure 5.35: Weight Vector Results (Single DSTATCOM – Heavy Load)

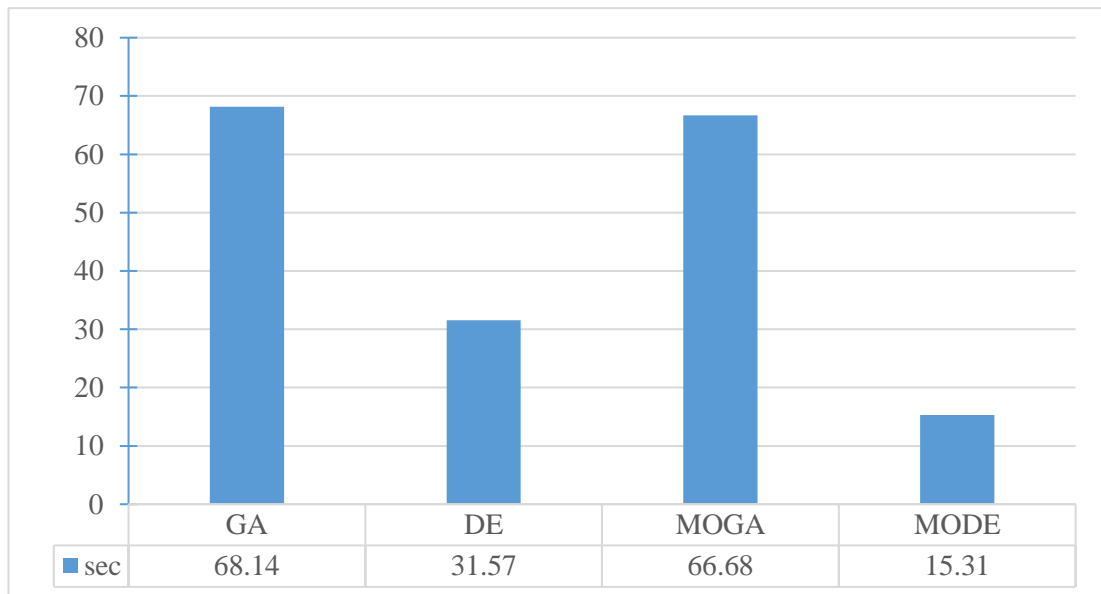


Figure 5.36: Computation Time (Single DSTATCOM – Heavy Load)

5.2.3 Single DG and Single DSTATCOM

In this case, a single DG and a single DSTATCOM have been optimally sited into the grid to improve its performance by using GA, DE, MOGA, and MODE as shown in chapter 4. To analyze the performance of each one of these algorithms three loading levels were used as follow. It assumed, the DG supplies only real power to the network while the DSTATCOM supplies only reactive power to the network.

- Light Load:

The total real and reactive load power connected to the grid are 3343.5 kW and 2070 kVAR which represent 62.5% of the nominal system loading. First, a simple load flow has performed. After that, the DSTATCOM and DG have optimally sited with the help of GA, DE, MOGA, and MODE. Table 5.19 shows the comparison of the real power losses, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.20 displays the results of the MOGA and Table 5.21 displays the results of the MODE.

In the GA, the real power dissipation have decreased to 33.92 kW (i.e. the percentage of the decrease is 56.30%) after placing a DG into the network at bus 9 with a size of 1233.206 kW and A DSTATCOM at bus 30 with a capacity of 744.3288 kVAr. From the results, it is obvious that GA is better than DE in all the aspects. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which highlighted in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.37 and Figure 5.38 respectively. Overall, the minimum power dissipation and the annual energy cost obtained when MODE has used. The minimum CPU time needed is 15.53 sec which achieved when MODE has used while the minimum voltage deviation found when GA has used. Finally, the best overall performance obtained by MODE. Figure 5.39 shows the Pareto front when MOGA has used, and Figure 5.40 shows the Pareto front when MODE has used. Figure 5.41 and Figure 5.42 show the weight vector results and time respectively for each algorithm.

Table 5.19: Results of GA and DE case of a DG and DSTATCOM at a light Load

	Base	GA	DE
Power Loss (kW)	77.6558	33.9297	35.5328
Voltage Deviation (V)	0.0581424	0.013118	0.017838
Energy Cost (\$)	34013.28	14861.21	15563.37
DG Location	-	Bus 9	Bus 13
DG Size (kW)	-	1233.2063	815.1286
DSTATCOM Location	-	Bus 30	Bus 27
DSTATCOM Size (kVAr)	-	744.3288	1272.9716

	Base	GA	DE
Comp. Time (sec)	-	22.50	29.47
Minimum Voltage (V)	0.94185	0.98688	0.98216
$\sum_{i=1}^n k_i f_i$	1	0.35240	0.39726

Table 5.20: Results of MOGA case of a DG and DSTATCOM at a Light Load

DG – DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location		Size					
Bus		kW	kVAr				
27	6	2219.3138	2063.2130	69.3306	0.00675	30366.84	0.58218
6	6	1729.1903	1105.6111	26.7097	0.02150	11698.85	0.35429
6	6	1573.8756	1095.8099	26.8162	0.01958	11745.52	0.34195
6	6	1957.4502	1694.0638	35.8368	0.00826	15696.54	0.33373
27	6	2219.3138	2022.3961	68.2276	0.00683	29883.70	0.57414
6	6	2256.4524	1095.8099	34.8410	0.00965	15260.36	0.33562
6	6	1868.4889	1095.8099	28.6754	0.01526	12559.83	0.32660
6	6	1957.4502	1095.8099	29.7197	0.01397	13017.27	0.32576
6	6	1868.4889	1105.6111	28.6951	0.01514	12568.47	0.32590
29	6	2439.6160	2455.6038	119.1750	0.00546	52198.68	0.95840
Time		65.63 sec					

Table 5.21: Results of MODE Case of a DG and DSTATCOM at Light Load

DG – DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location		Size					
Bus		kW	kVAr				
10	5	2347.6077	1332.2070	109.0972	0.00785	47784.59	0.89697
8	31	2478.5823	2193.5043	175.4436	0.00611	76844.32	1.39759
7	27	1379.6946	933.8297	28.4716	0.01558	12470.59	0.32723
10	29	846.5568	1144.7629	31.0117	0.01332	13583.14	0.33129
7	31	1464.8986	2087.8943	106.636	0.00967	46706.91	0.89047
5	6	2196.0116	1160.8858	31.7866	0.01220	13922.55	0.32954

DG – DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size					
		kW	kVAr				
27	9	1921.9124	909.339	53.3913	0.00993	23385.41	0.48084
25	9	2298.3367	562.9358	41.1299	0.01056	18014.93	0.39044
10	28	1358.2815	1111.8991	39.6104	0.01155	17349.39	0.38552
Time				15.53 sec			

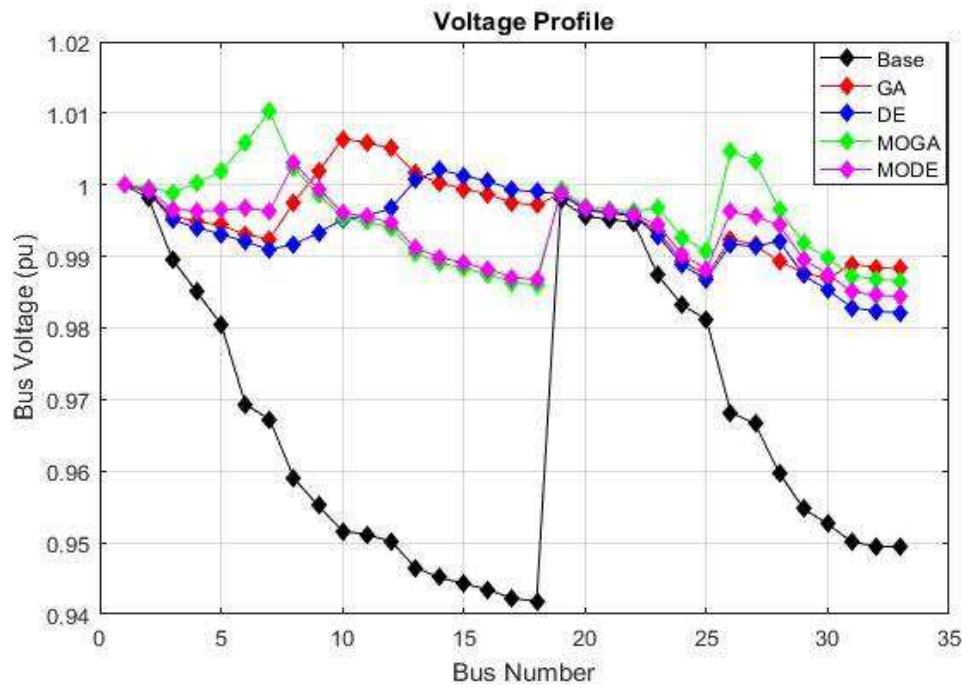


Figure 5.37: Voltage Profile (Single DG and DSTATCOM - Light Load)

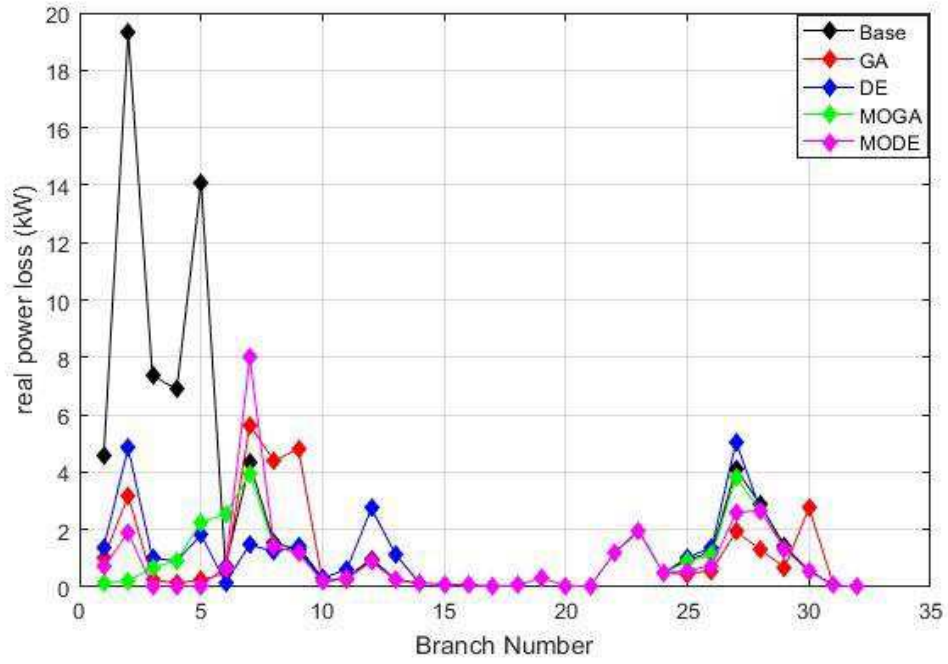


Figure 5.38: Active Power Loss (Single DG and DSTATCOM - Light Load)

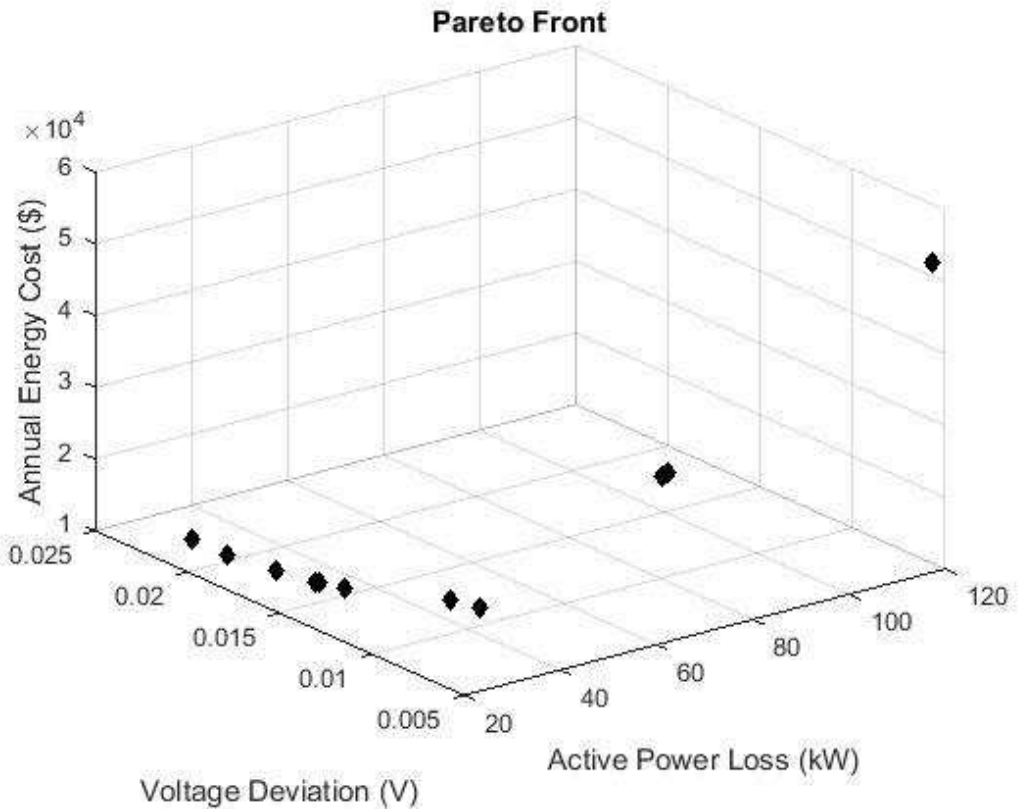


Figure 5.39: Pareto Front for MOGA (Single DG and DSTATCOM - Light Load)

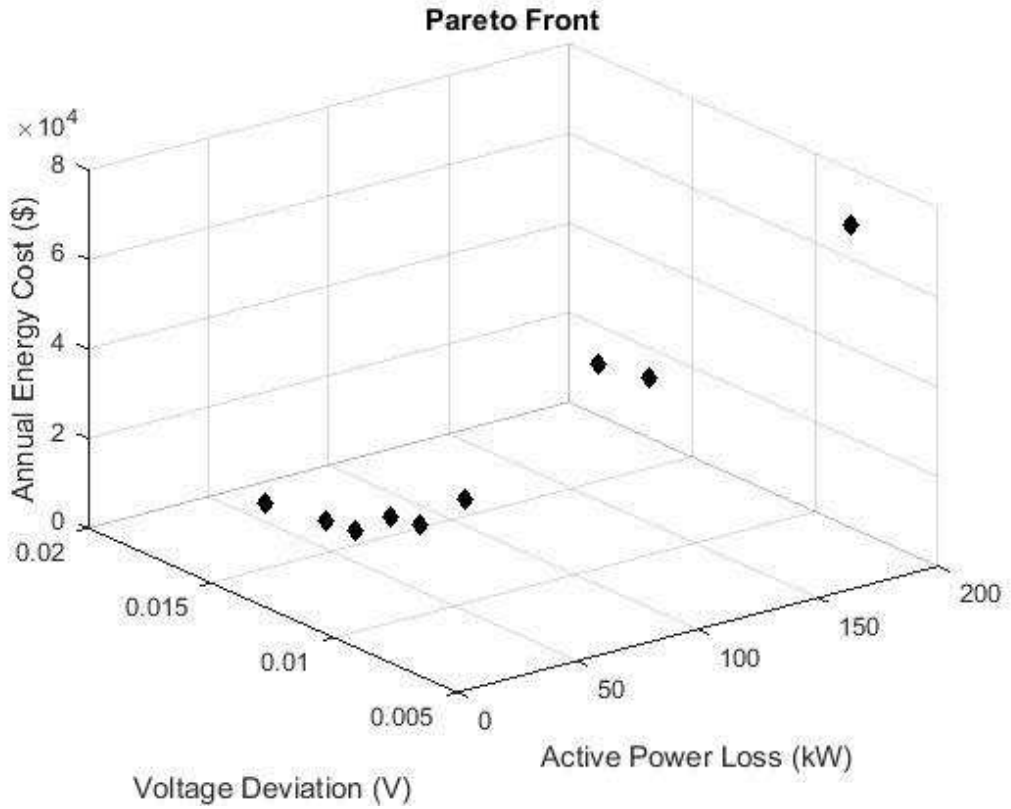


Figure 5.40: Pareto Front for MODE (Single DG and DSTATCOM - Light Load)

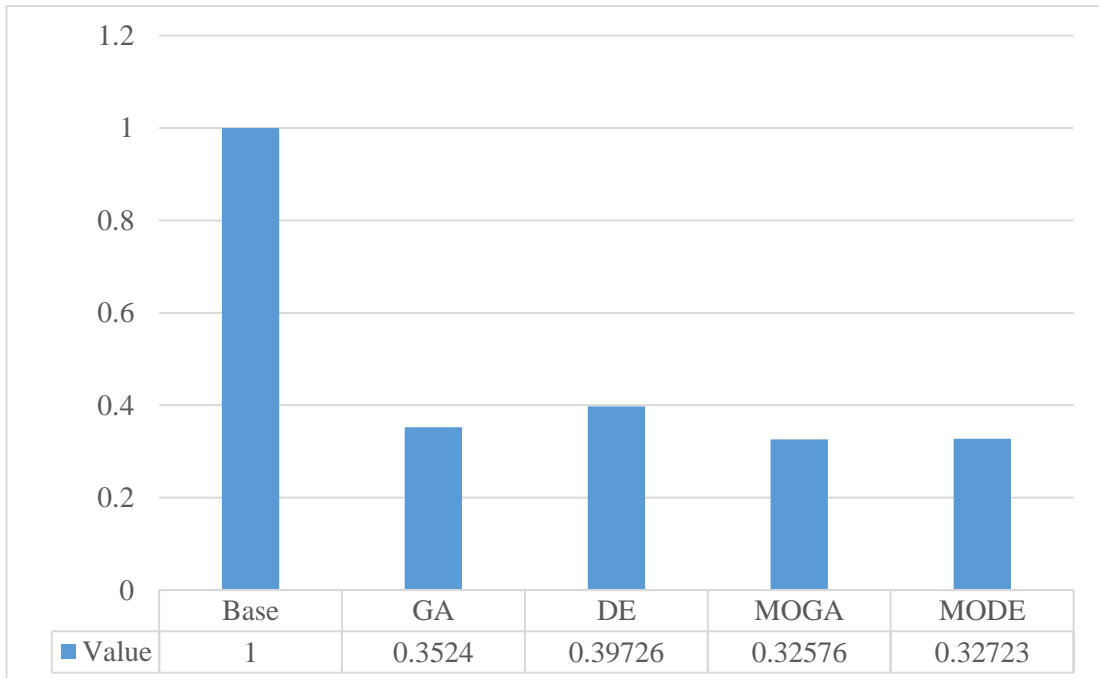


Figure 5.41: Weight Vector Results (Single DG and DSTATCOM – Light Load)

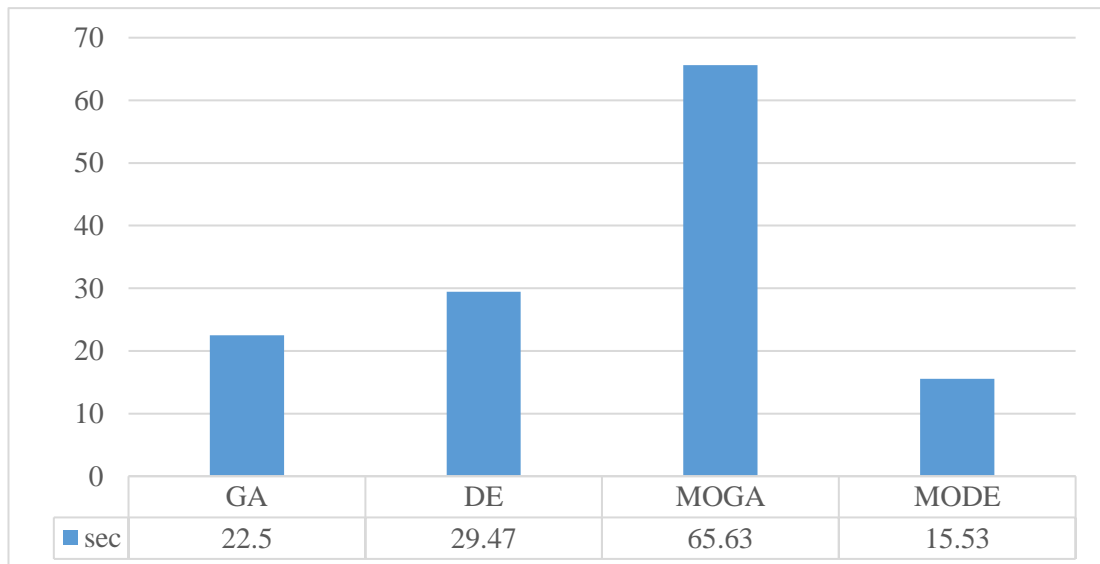


Figure 5.42: Computation Time (Single DG and DSTATCOM – Light Load)

- Nominal Load

The total real and reactive load power connected to the grid are 3715 kW and 2300 kVAr which represent 100% of the normal system loading. First, a simple load flow has performed. After that, the DG and DSTATCOM have optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.22 shows the comparison of the real power dissipation, voltage deviation, annual energy cost, computation time, locations, and size of the DG for GA and DE. Table 5.23 displays the results of the MOGA and Table 5.24 displays the results of the MODE.

In the GA, the real power dissipation have decreased to 80.4864 kW (i.e. the percentage of the decrease is 61.85%) after placing a DG in the network at bus 7 with a capacity of 2327.57 kW and a DSTATCOM at bus 26 with a capacity of 1446.45 kVAr. From the results, it is obvious that GA performs very similar to DE in all the aspects. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen

as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. After that, the best solution selected for the cases of the MOGA and MODE which shaded in the tables. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.43 and Figure 5.44 respectively. Overall, the minimum power dissipation and annual energy cost obtained when MOGA has used. The minimum CPU time needed is 15.53 sec which achieved when MODE has used, while the minimum voltage deviation found when MODE has used. Finally, the best overall performance obtain by MOGA. Figure 5.45 shows the Pareto front when MOGA has used, and Figure 5.46 shows the Pareto front when MODE has used. Figure 5.47 and Figure 5.48 show the overall performance and time in that order for each algorithm.

Table 5.22: Results of GA and DE case of a DG and DSTATCOM at nominal Load

	Base	GA	DE
Power Loss (kW)	210.9875	80.4864	91.9015
Voltage Deviation (V)	0.096222	0.033689	0.043910
Energy Cost (\$)	92412.54	35253.06	40252.89
DG Location	-	Bus 7	Bus 29
DG Size (kW)	-	2327.5718	2119.0243
DSTATCOM Location	-	Bus 26	Bus 6
DSTATCOM Size (kW)	-	1446.4543	1550.4759
Comp. Time (sec)	-	18.94	29.86
Minimum Voltage (V)	0.903777	0.96631	0.96340
$\sum_{i=1}^n k_i f_i$	1	0.36893	0.44388

Table 5.23: Results of MOGA case of a DG and DSTATCOM at a Nominal Load

DG - DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size (kW)					
26	29	2474.5591	1469.3218	64.7012	0.04535	28339.13	0.37255

DG - DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size (kW)					
7	29	1649.7590	1111.7032	65.2712	0.03947	28588.81	0.34971
7	30	2293.1004	2280.0647	127.1414	0.01751	55687.95	0.43439
8	29	2474.5591	1288.2567	92.7055	0.01853	40605.04	0.34069
7	29	2293.1004	1111.7032	71.6648	0.02372	31389.21	0.30244
26	29	2293.1004	1469.3218	63.8771	0.04788	27978.18	0.38071
6	29	2474.5591	861.56040	64.1868	0.04774	28113.85	0.38102
8	29	1589.6420	1470.1714	68.8655	0.02741	30163.10	0.30978
8	32	2474.5591	1618.3736	117.5506	0.01805	51487.16	0.40936
Time		65.32 sec					

Table 5.24: Results of MODE case of a DG and DSTATCOM at a Nominal Load

DG – DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size (kW)					
7	30	2092.8101	1373.7875	75.6969	0.02606	33155.25	0.32361
8	30	1920.5189	1268.0142	78.4817	0.02062	34375.02	0.30891
8	30	1652.9592	1168.7247	73.6224	0.02814	32246.63	0.32636
8	27	1911.8739	2419.9151	99.3379	0.01850	43510.01	0.35941
8	28	1627.2639	1128.3027	69.8545	0.03426	30596.30	0.34109
8	28	1681.9759	1820.5426	76.9742	0.02156	33714.72	0.30853
25	27	2218.4436	1555.8406	65.7364	0.04819	28792.55	0.38728
8	29	1519.0861	1557.5727	70.3832	0.02891	30827.87	0.32035
7	28	2012.0148	2284.9721	93.7304	0.02039	41053.95	0.35133
8	27	1604.0409	2435.6646	96.9703	0.01959	42473.02	0.35721
7	30	2092.8101	1373.7875	75.6969	0.02606	33155.25	0.32361
Time		15.53 sec					

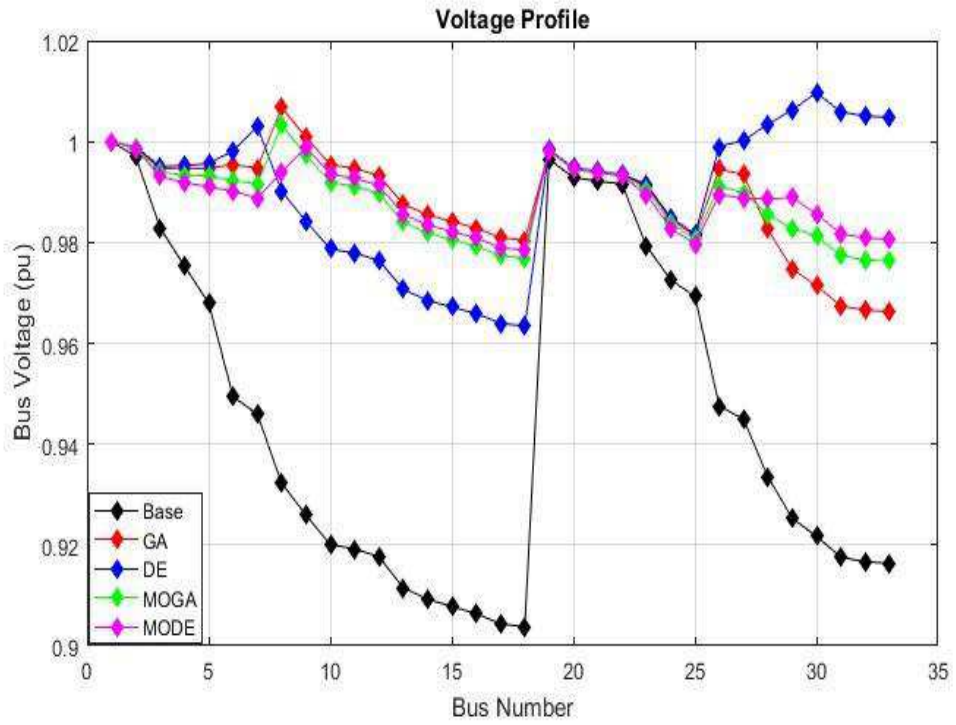


Figure 5.43: Voltage Profile (Single DG and DSTATCOM - Nominal Load)

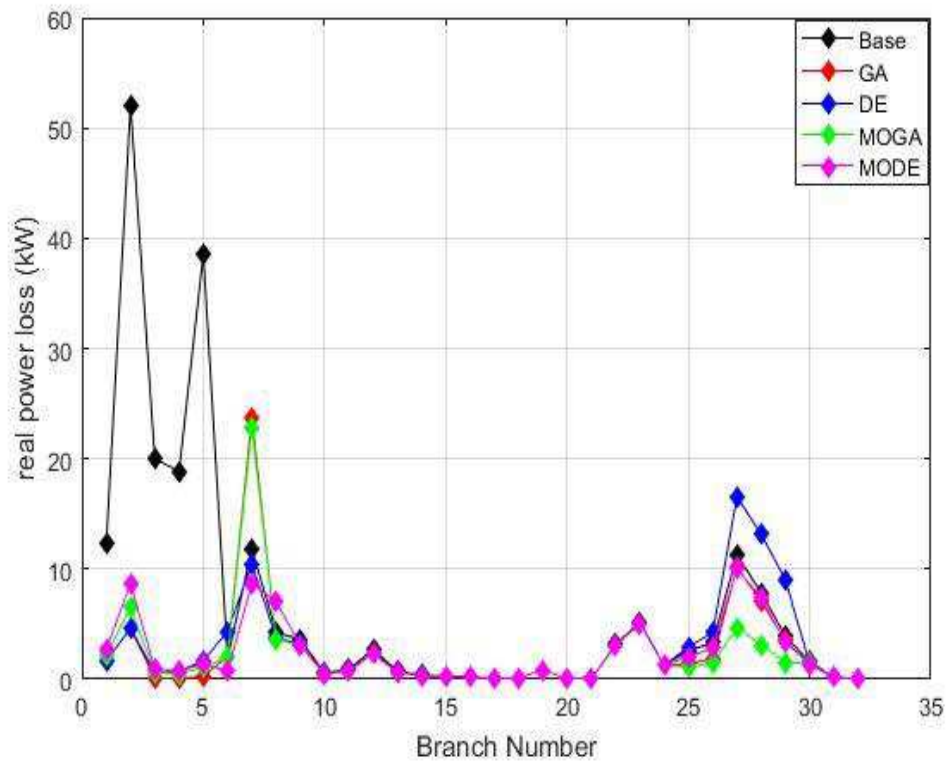


Figure 5.44: Active Power Loss (Single DG and DSTATCOM - Nominal Load)

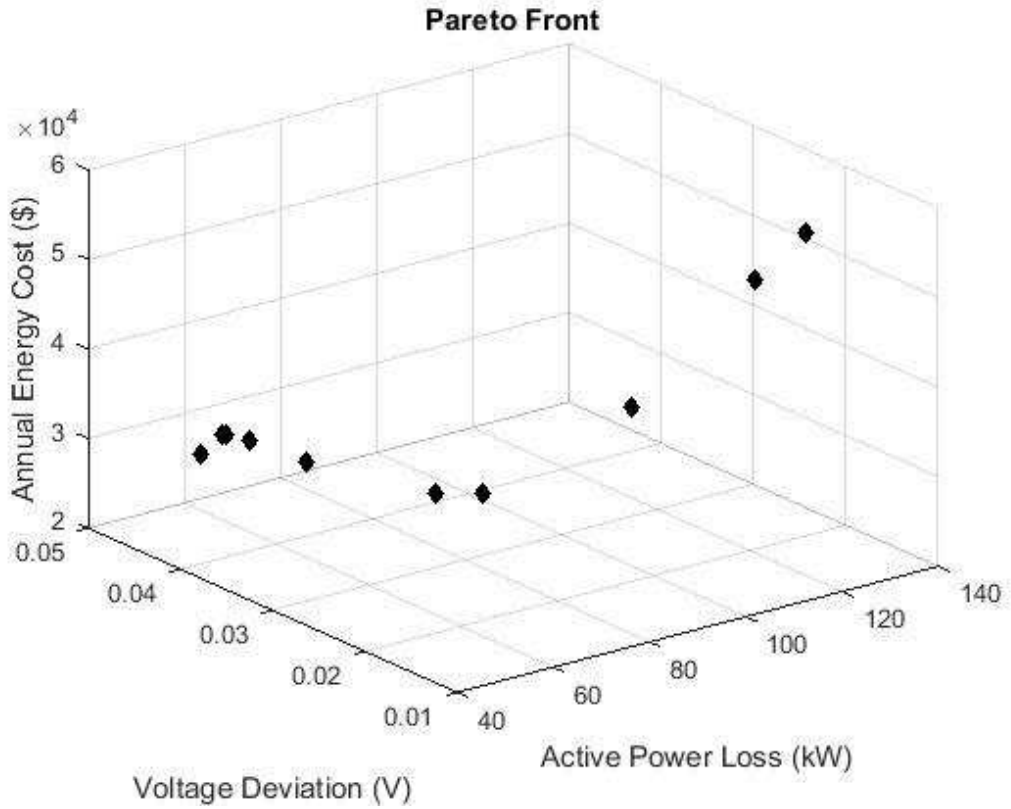


Figure 5.45: Pareto Front for MOGA (Single DG and DSTATCOM - Nominal Load)

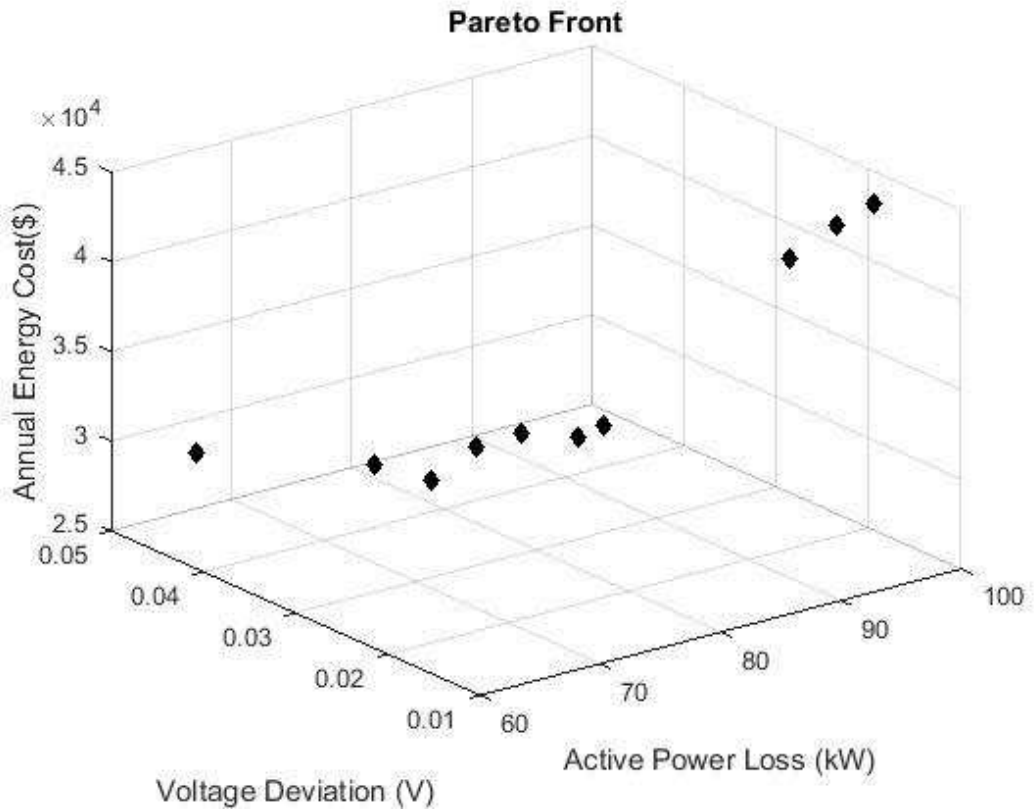


Figure 5.46: Pareto Front for MOGA (Single DG and DSTATCOM - Nominal Load)

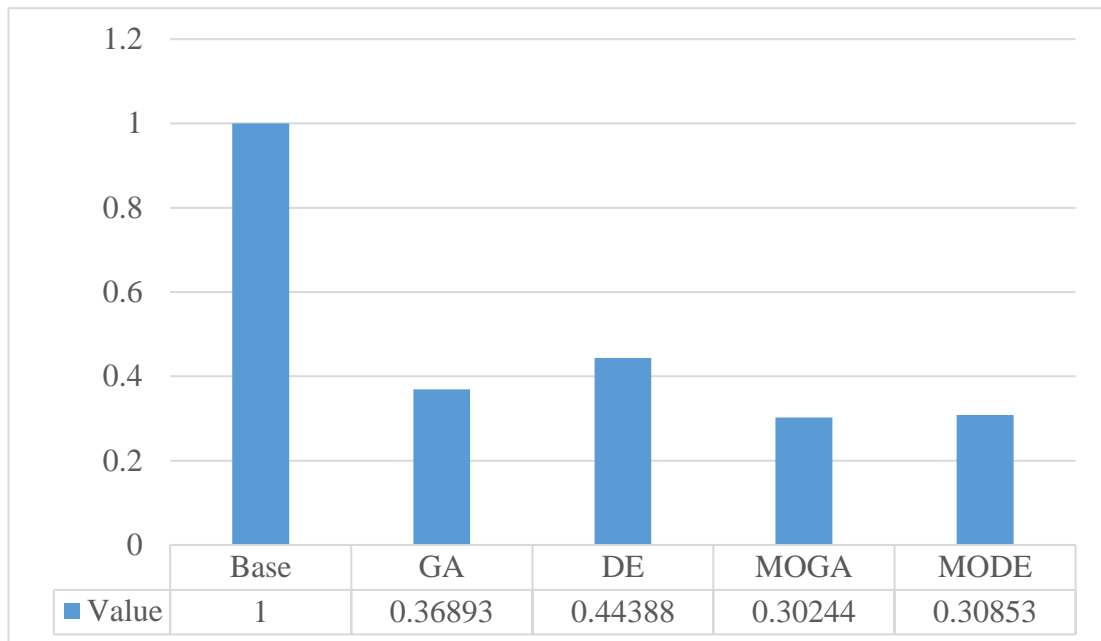


Figure 5.47: Weight Vector Results (Single DG and DSTATCOM – Nominal Load)

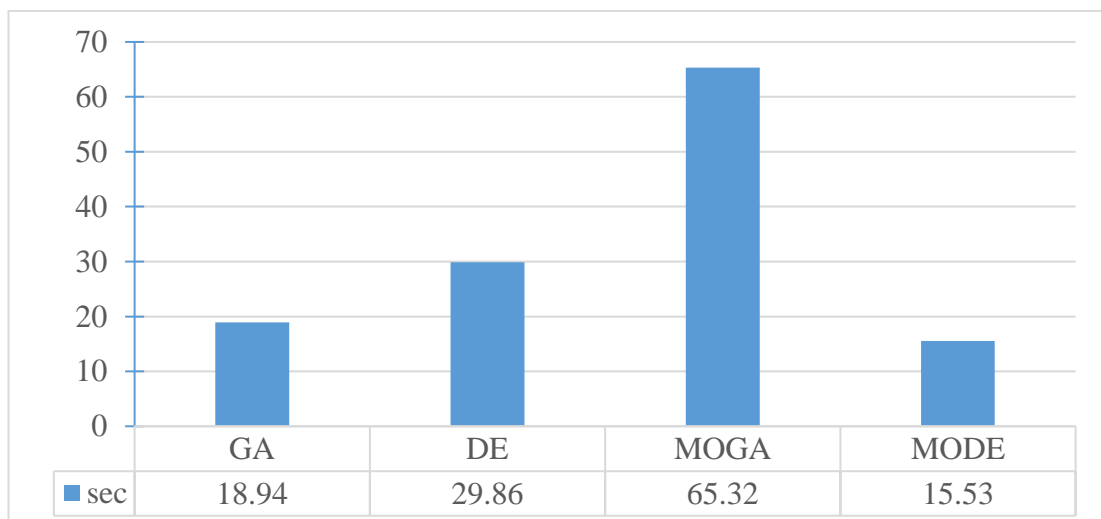


Figure 5.48: Computation Time (Single DG and DSTATCOM – Nominal Load)

- Heavy Load

The total real and reactive load power connected to the grid are 4643.75 kW and 2875 kVAr which represent 125% of the nominal system loading. First, a simple load flow has performed. After that, the DG has optimally placed with the help of GA, DE, MOGA, and MODE. Table 5.25 shows the comparison of the real power dissipation, voltage deviation, annual energy cost, computation time, locations, and size of the DG

for GA and DE. Table 5.26 displays the results of the MOGA and Table 5.27 displays the results of the MODE.

In the GA, the real power dissipation have decreased to 122.807 kW (i.e. the percentage of the decrease is 64.33%) after placing a DG in the grid at bus 10 with a capacity of 2253.55 kW and a DSTATCOM at bus 29 with a capacity of 1779.82 kVAr. From the results, it is obvious that DE performs better than GA in all the aspects. To compare the results of MOGA and MODE with the GA and DE, first, the objective functions normalized by dividing each objective with its base value. Then, equation (4.2) used, so that, the importance factor for each objective function is chosen as ($k_1 = 0.5$, $k_2 = 0.4$, and $k_3 = 0.1$) [30]. The voltage profile and the branches loss for the base case, GA, DE, MOGA, and MODE are shown in Figure 5.49 and Figure 5.50 in that order. Overall, the minimum power dissipation and the annual loss cost obtained when MODE has used. The minimum CPU time needed is 14.65 sec which achieved when MODE has used while the minimum voltage deviation obtained when MOGA has used. Finally, the best overall performance obtained by MODE. Figure 5.51 shows the Pareto front when MOGA has used, and Figure 5.52 shows the Pareto front when MODE has used. Figure 5.53 and Figure 5.54 show the overall performance and time in that order for each algorithm.

Table 5.25: Results of GA and DE case of a DG and DSTATCOM at a Heavy Load

	Base	GA	DE
Power Loss (kW)	344.3189	122.8073	134.5095
Voltage Deviation (V)	0.123288	0.030006	0.063493
Energy Cost (\$)	150811.71	53789.61	58915.17
DG Location	-	Bus 10	Bus 29
DG Size (kW)	-	2253.5584	2317.9899

	Base	GA	DE
DSTATCOM Location	-	Bus 29	Bus 27
DSTATCOM Size (kW)	-	1779.8226	2466.3738
Comp. Time (sec)	-	19.02	31.63
Minimum Voltage (V)	0.876711	0.96999	0.93650
$\sum_{i=1}^n k_i f_i$	1	0.31135	0.44039

Table 5.26: Results of MOGA case of a DG and DSTATCOM at a Heavy Load

DG - DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size (kW)					
10	28	1538.2476	1753.1334	115.0496	0.04306	50391.73	0.34019
10	28	1676.1779	1950.7703	116.3856	0.03711	50976.91	0.32323
10	29	1997.5061	2436.2680	137.7143	0.02584	60318.88	0.32381
10	28	1676.1779	1887.2441	115.3041	0.03841	50503.22	0.32555
10	28	1750.1235	2372.9516	129.2503	0.02766	56611.64	0.31500
10	28	1750.1235	2393.1492	130.1187	0.02727	56992.01	0.31522
10	28	2432.1749	2393.1492	147.2938	0.02436	64514.68	0.33572
5	30	2432.1749	1007.9280	114.9560	0.07479	50350.75	0.44299
Time				65.03 sec			

Table 5.27: Results of MODE case of a DG and DSTATCOM at a Heavy Load

DG - DSTATCOM				Active Loss (kW)	Voltage deviation (V)	Energy cost (\$)	$\sum_{i=1}^n k_i f_i$
Location Bus		Size (kW)					
7	29	2252.1144	1985.9803	107.5346	0.03999	47100.18	0.31713
8	29	1943.1782	1764.4715	107.9254	0.03694	47271.33	0.30794
10	28	1896.3313	2029.8538	118.9957	0.03257	52120.13	0.31304
29	12	2198.3051	1928.1918	216.4067	0.02647	94786.15	0.46300
9	31	1801.9158	1842.4295	134.7746	0.02934	59031.31	0.33004
Time				14.65 sec			

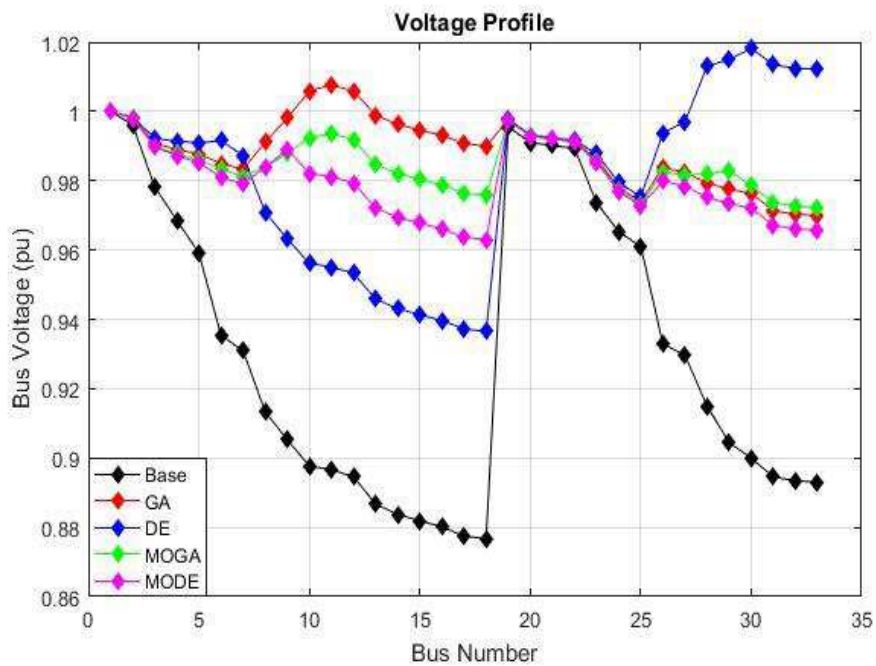


Figure 5.49: Voltage Profile (Single DG and DSTATCOM - Heavy Load)

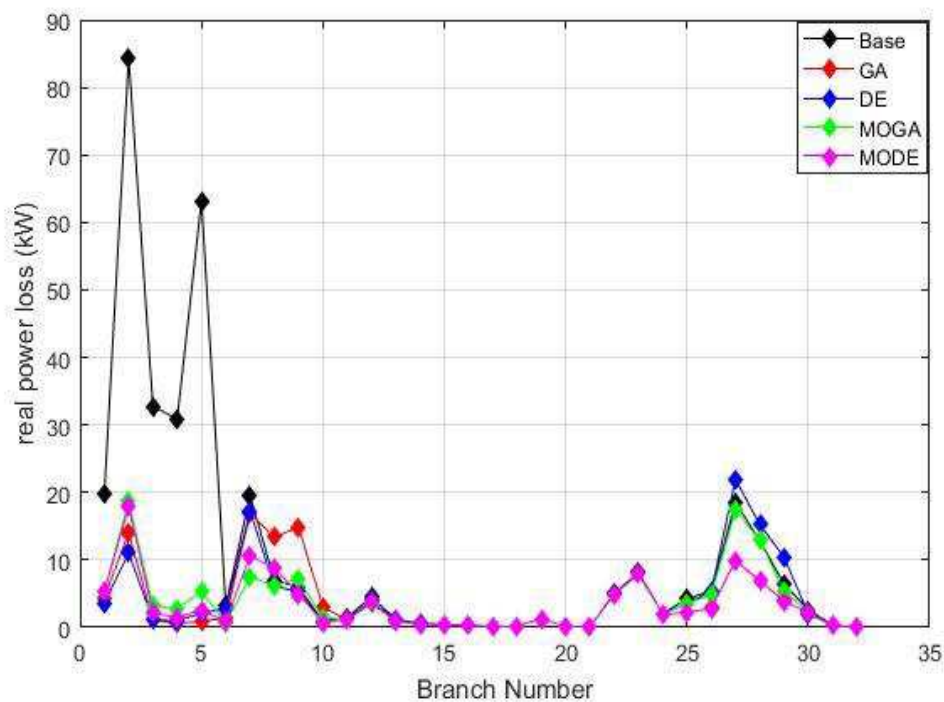


Figure 5.50: Active Power Loss (Single DG and DSTATCOM- Heavy Load)

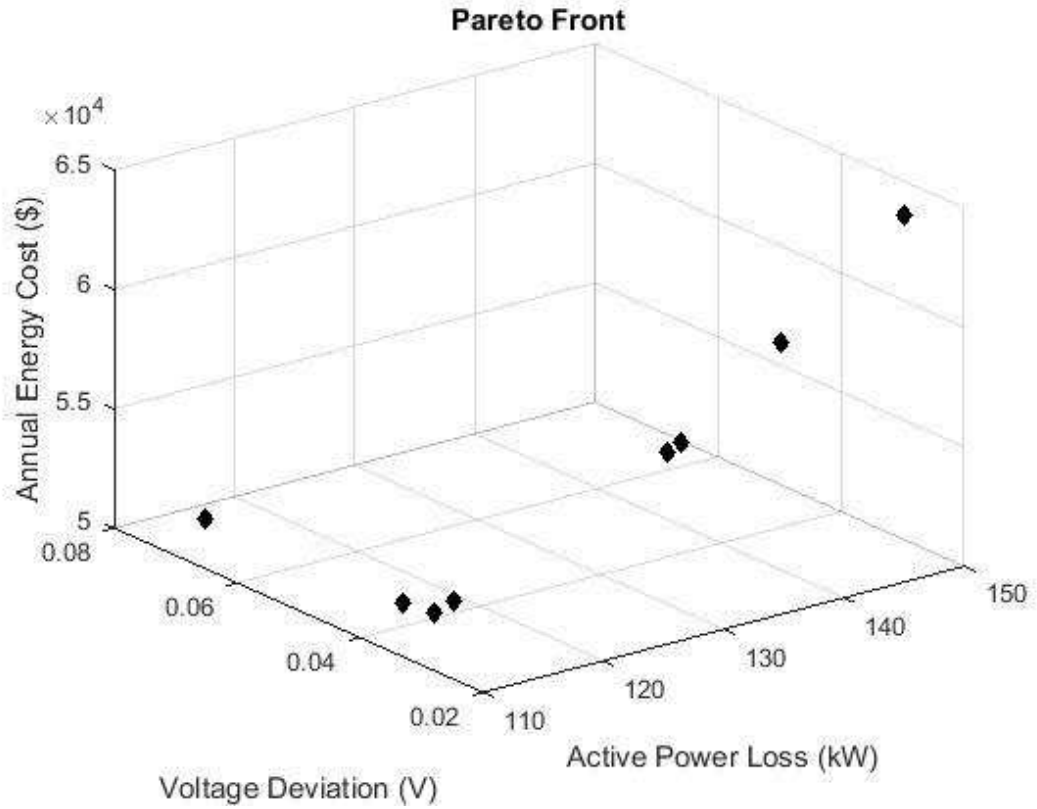


Figure 5.51: Pareto Front for MOGA (Single DG and DSTATCOM - Heavy Load)

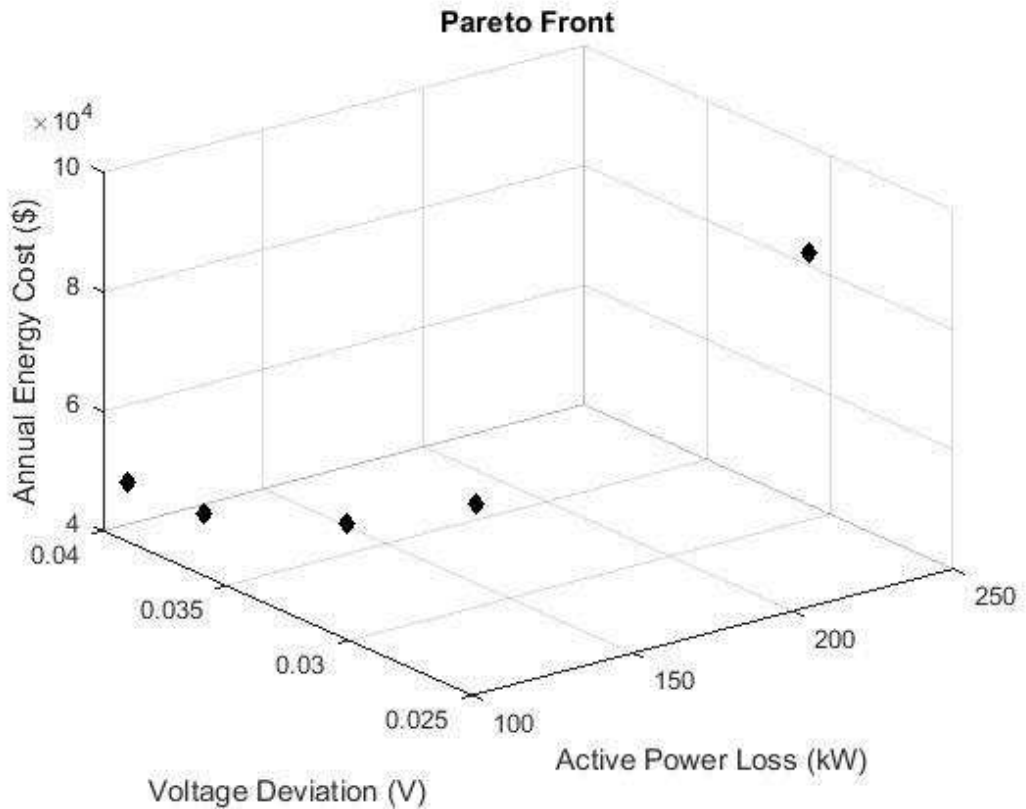


Figure 5.52: Pareto Front for MODE (Single DG and DSTATCOM - Heavy Load)

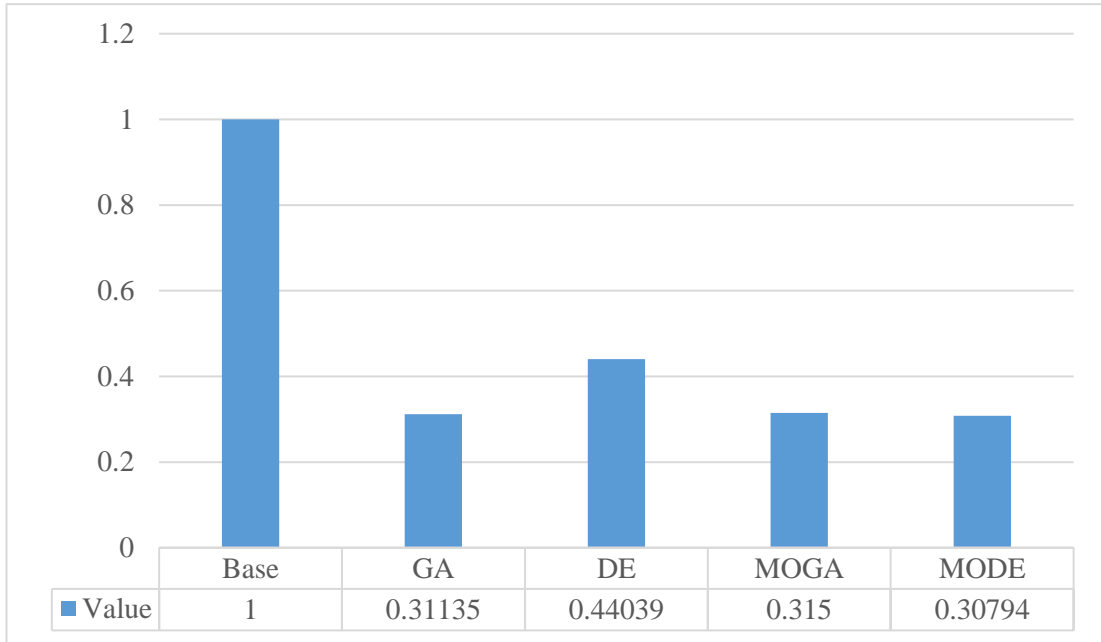


Figure 5.53: Weight Vector Results (Single DG and DSTATCOM – Heavy Load)

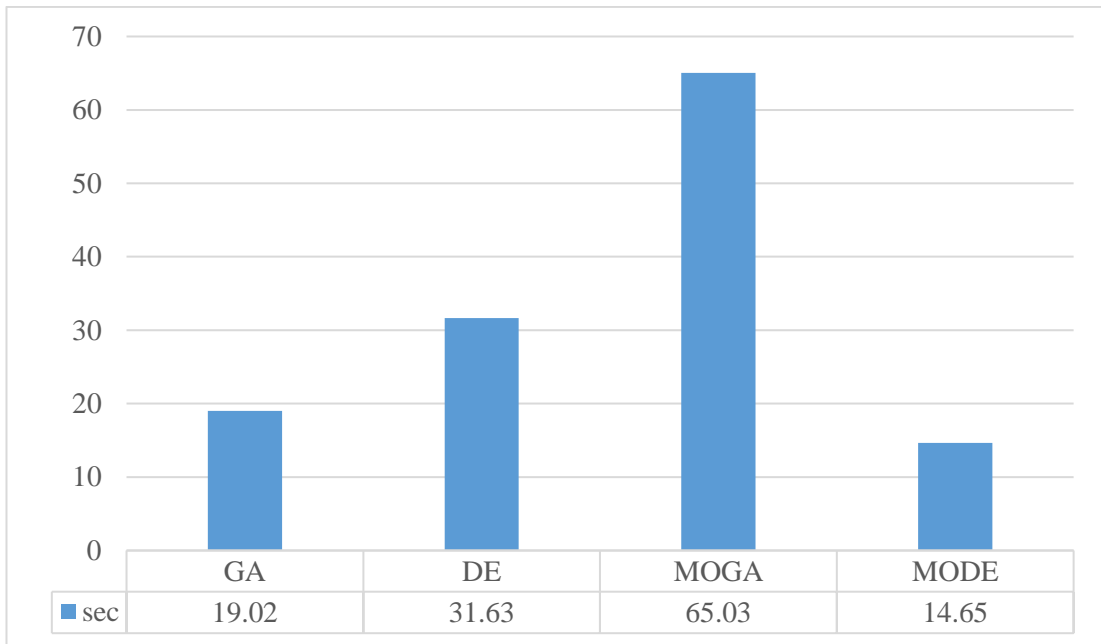


Figure 5.54: Computation Time (Single DG and DSTATCOM - Heavy Load)

5.4 Comparative Analysis

To confirm the performance of the suggested algorithms on IEEE 33-bus system the results achieved are compared with the previous work results like Shukla et al [48], Taher, S. A., & Afsari, S. A. [49], and Iqbal et al [50] and it is summarized in Table

5.34. Table 5.34 shows a comparison of the location and size of the DG and DSTATCOM, power dissipation lessening, minimum voltage, and the cost of the losses obtained by the proposed methods and other methods in the literature.

Table 5.28: Comparative Analysis of the 33-bus system at a Nominal Load

The Cases	Objectives	Proposed Methods				Previous Work		
		GA	DE	MOGA	MODE	[48]	[49]	[50]
Single DG	Base Loss (kW)	210.9	210.9	210.98	210.98	216	202	201
	Location	5	5	26	6	6	-	30
	Size (kW)	2375	2368	2438	2487	2380	-	1000
	Active Loss (kW)	111.6	111.7	115.7	112	132	-	113
	Minimum Voltage (pu)	0.939	0.939	0.94	0.943	-	-	-
	Energy Saving (\$)	43505	43487	41716	43352	36511	-	-
Single DSTATCOM	Location	6	6	6	29	-	12	30
	Size (kVAr)	2384	1875	2130	1384	-	962.49	3200
	Active Loss (kW)	170	163	165	151	-	171	198
	Minimum Voltage (pu)	0.936	0.929	0.933	0.917	-	0.925	-
	Time (sec)	41.7	76.9	68	16.44	-	-	-
DG and DSTATCOM	Location DG	7	29	7	8	-	-	30
	Size DG (kW)	2327	2119	2293	1681	-	-	1000
	Location DSTATCOM	26	6	29	28	-	-	30
	Size DSTATCOM (kVAr)	1446	1550	1111	1820	-	-	1500
	Active Loss (kW)	80	91	71	76	-	-	86
	Minimum Voltage (pu)	0.966	0.963	0.976	0.978	-	-	-
	Energy Cost (\$)	35253	40252	31389	33714	-	-	-

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In conclusion, this research work showed the formulation and implementation of a single objective optimizer GA, DE and the ideal multi-objective optimizer MOGA and MODE to help in reducing system real power losses, minimizing the voltage deviation, and reducing the annual operation cost by optimizing the location and size of a single DG, a single DSTATCOM, and the combination of a single DG and a single DSTATCOM. As seen from the results for the minimum active power loss, the minimum voltage deviation, and maximum energy cost saving are achieved when both DG and DSTATCOM are used. The maximum reduction in real power loss for the case of the light and the heavy load were 63.34% and 68.66% obtained by MODE while for the case of nominal was 66.03% obtained by MOGA. The voltage profile was generally improved and the best voltage profile obtained by using the ideal multi-objective optimizer with lowest bus voltages of 0.986 pu, 0.978 pu, 0.972 pu for the the case of the light load, nominal load, and heavy load respectively.

The MODE and MOGA method also performed well in reducing the losses and improving the voltage profile of the IEEE 33-bus test system. However, MODE has the minimum computation time. Thus the ideal multi-objective methods especially MODE proved more suited for this optimization as compared to the single one such as GA and DE methods. After using the MODE method to study the effects of DG and

DSTATCOM allocation on power losses, voltage profile, and the cost it was clearly shown that the system power losses and the voltage deviation reduced with the optimal allocation of the DG and DSTATCOM in to the network but the unsuitable location or size of the DG and DSTATCOM resulted to an increase in system power losses, voltage profile and the cost.

6.2 Future Work

In this thesis, some factors were not considered and could be considered in the future. The first of these factors, the total harmonic distortion which leads to several problems like the heating in machines. On the other hands, it is necessary to take into account the load variations with the time.

REFERENCES

- [1] Molzahn, D. K., Dörfler, F., Sandberg, H., Low, S. H., Chakrabarti, S., Baldick, R., & Lavaei, J. (2017). A survey of distributed optimization and control algorithms for electric power systems. *IEEE Transactions on Smart Grid*, 8(6), 2941-2962.
- [2] Prakash, P., & Khatod, D. K. (2016). Optimal sizing and siting techniques for distributed generation in distribution systems: A review. *Renewable and Sustainable Energy Reviews*, 57, 111-130.
- [3] Jordehi, A. R. (2015). Brainstorm optimisation algorithm (BSOA): An efficient algorithm for finding optimal location and setting of FACTS devices in electric power systems. *International Journal of Electrical Power & Energy Systems*, 69, 48-57.
- [4] Lomi, A., Hien, N. C., & Mithulananthan, N. (2009, September). Application of distributed generation to enhance loadability of distribution system, a case study. In *Sustainable Alternative Energy (SAE), 2009 IEEE PES/IAS Conference on*(pp. 1-7). IEEE.
- [5] Jazebi, S., Hosseinian, S. H., & Vahidi, B. (2011). DSTATCOM allocation in distribution networks considering reconfiguration using differential evolution algorithm. *Energy Conversion and Management*, 52(7), 2777-2783.
- [6] Sirjani, R., & Jordehi, A. R. (2017). Optimal placement and sizing of

distribution static compensator (D-STATCOM) in electric distribution networks: A review. *Renewable and Sustainable Energy Reviews*, 77, 688-694.

- [7] Osman, I. H., & Kelly, J. P. (1996). Meta-heuristics: an overview. In *Meta-heuristics* (pp. 1-21). Springer, Boston, MA.

- [8] Bin Humayd, A. (2011). *Distribution system planning with distributed generation: Optimal versus heuristic approach* (Master's thesis, University of Waterloo).

- [9] Jegadeesan, M., & Venkatasubbu, S. (2017). Minimization of Cost by Simultaneous Placement of Multi-DGs and Capacitors in Distribution System Using Hybrid Optimization”. *International Journal of Advances in Computer and Electronics Engineering*, 2(06), 8-14.

- [10] Lehn, P. W. (2002). A Benchmark System for Simulation of the D-STATCOM. In *Power Engineering Society Winter Meeting, 2002. IEEE* (Vol. 1, pp. 496-498). IEEE.

- [11] Mahela, O. P., & Shaik, A. G. (2015). A review of distribution static compensator. *Renewable and Sustainable Energy Reviews*, 50, 531-546.

- [12] Kishore, P. V., & Reddy, S. R. (2014). Compensation of Reactive Power Using D-STATCOM. *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 9(1), 17-27.

- [13] Sultana, S., & Roy, P. K. (2016). Krill herd algorithm for optimal location of distributed generator in radial distribution system. *Applied Soft Computing*, 40, 391-404.
- [14] Gupta, A. R., & Kumar, A. (2016). Optimal placement of D-STATCOM using sensitivity approaches in mesh distribution system with time variant load models under load growth. *Ain Shams Engineering Journal*.
- [15] Injeti, S. K., & Kumar, N. P. (2013). A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems. *International Journal of Electrical Power & Energy Systems*, 45(1), 142-151.
- [16] Sultana, S., & Roy, P. K. (2014). Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems. *International Journal of Electrical Power & Energy Systems*, 63, 534-545.
- [17] Sultana, S., & Roy, P. K. (2015). Oppositional krill herd algorithm for optimal location of distributed generator in radial distribution system. *International Journal of Electrical Power & Energy Systems*, 73, 182-191.
- [18] Gupta, A. R., & Kumar, A. (2015). Energy savings using D-STATCOM placement in radial distribution system. *Procedia Computer Science*, 70, 558-564.

- [19] Prabha, D. R., & Jayabarathi, T. (2016). Optimal placement and sizing of multiple distributed generating units in distribution networks by invasive weed optimization algorithm. *Ain Shams Engineering Journal*, 7(2), 683-694.
- [20] Ali, E. S., Elazim, S. A., & Abdelaziz, A. Y. (2017). Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations. *Renewable Energy*, 101, 1311-1324.
- [21] Van Dao, T., Chaitusaney, S., & Nguyen, H. T. N. (2017). Linear least-squares method for conservation voltage reduction in distribution systems with photovoltaic inverters. *IEEE Transactions on Smart Grid*, 8(3), 1252-1263.
- [22] Yuvaraj, T., Ravi, K., & Devabalaji, K. R. (2015). DSTATCOM allocation in distribution networks considering load variations using bat algorithm. *Ain Shams Engineering Journal*.
- [23] Biswas, P. P., Mallipeddi, R., Suganthan, P. N., & Amaratunga, G. A. (2017). A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network. *Applied Soft Computing*, 60, 268-280.
- [24] Kumar, M., Nallagownden, P., & Elamvazuthi, I. (2017). Optimal placement and sizing of distributed generators for voltage-dependent load model in radial distribution system. *Renewable Energy Focus*, 19, 23-37.
- [25] Tang, J., Wang, D., Wang, X., Jia, H., Wang, C., Huang, R., ... & Fan, M.

- (2017). Study on day-ahead optimal economic operation of active distribution networks based on Kriging model assisted particle swarm optimization with constraint handling techniques. *Applied Energy*, 204, 143-162.
- [26] Sadanandan, S., & Natarajan, B. (2017, March). Power system optimization with an inertia study on the IEEE 30-bus test system. In *SoutheastCon, 2017* (pp. 1-6). IEEE.
- [27] Lee, C. S., Ayala, H. V. H., & dos Santos Coelho, L. (2015). Capacitor placement of distribution systems using particle swarm optimization approaches. *International Journal of Electrical Power & Energy Systems*, 64, 839-851.
- [28] Hussain, S. S., & Subbaramiah, M. (2013, April). An analytical approach for optimal location of DSTATCOM in radial distribution system. In *Energy Efficient Technologies for Sustainability (ICEETS), 2013 International Conference on*(pp. 1365-1369). IEEE.
- [29] Kanwar, N., Gupta, N., Niazi, K. R., & Swarnkar, A. (2015). Improved cat swarm optimization for simultaneous allocation of DSTATCOM and DGs in distribution systems. *Journal of Renewable Energy*, 2015.
- [30] Devabalaji, K. R., & Ravi, K. (2016). Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using bacterial foraging optimization algorithm. *Ain Shams Engineering Journal*, 7(3), 959-971.

- [31] Gandomi, A. H., & Alavi, A. H. (2012). Krill herd: a new bio-inspired optimization algorithm. *Communications in Nonlinear Science and Numerical Simulation*, 17(12), 4831-4845.
- [32] Mirjalili, S. (2015). The ant lion optimizer. *Advances in Engineering Software*, 83, 80-98.
- [33] Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *science*, 220(4598), 671-680.
- [34] Roa-Sepulveda, C. A., & Pavez-Lazo, B. J. (2003). A solution to the optimal power flow using simulated annealing. *International journal of electrical power & energy systems*, 25(1), 47-57.
- [35] Ali, A., Padmanaban, S., Twala, B., & Marwala, T. (2017). Electric Power Grids Distribution Generation System for Optimal Location and Sizing—A Case Study Investigation by Various Optimization Algorithms. *Energies*, 10(7), 960.
- [36] Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. *IEEE control systems*, 22(3), 52-67.
- [37] Yang, X. S. (2010). A new metaheuristic bat-inspired algorithm. In *Nature inspired cooperative strategies for optimization (NICSO 2010)* (pp. 65-74). Springer, Berlin, Heidelberg.
- [38] Devi, S., & Geethanjali, M. (2014). Optimal location and sizing of distribution

static synchronous series compensator using particle swarm optimization. *International Journal of Electrical Power & Energy Systems*, 62, 646-653.

- [39] Sultana, U., Khairuddin, A. B., Mokhtar, A. S., Zareen, N., & Sultana, B. (2016). Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system. *Energy*, 111, 525-536.
- [40] Sharma, S., Bhattacharjee, S., & Bhattacharya, A. (2016). Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for optimal allocation of DG in radial distribution network. *International Journal of Electrical Power & Energy Systems*, 74, 348-373.
- [41] Kowsalya, S. K. S. M. (2016). Optimal Allocation of Solar based Distributed. *system*, 1(2), 3.
- [42] Srinivasan, G., & Visalakshi, S. (2017). Application of AGPSO for Power loss minimization in Radial Distribution Network via DG units, Capacitors and NR. *Energy Procedia*, 117, 190-200.
- [43] Luo, L., Gu, W., Zhang, X. P., Cao, G., Wang, W., Zhu, G., ... & Wu, Z. (2018). Optimal siting and sizing of distributed generation in distribution systems with PV solar farm utilized as STATCOM (PV-STATCOM). *Applied Energy*, 210, 1092-1100.
- [44] Sharma, A., Sharma, H., Bhargava, A., Sharma, N., & Bansal, J. C. (2017).

- Optimal placement and sizing of capacitor using limaçon inspired spider monkey optimization algorithm. *Memetic Computing*, 9(4), 311-331.
- [45] Ramadan, H. S., Bendary, A. F., & Nagy, S. (2017). Particle swarm optimization algorithm for capacitor allocation problem in distribution systems with wind turbine generators. *International Journal of Electrical Power & Energy Systems*, 84, 143-152.
- [46] Manafi, H., Ghadimi, N., Ojaroudi, M., & Farhadi, P. (2013). Optimal placement of distributed generations in radial distribution systems using various PSO and DE algorithms. *Elektronika ir Elektrotechnika*, 19(10), 53-57.
- [47] Sanam, J., Ganguly, S., Panda, A. K., & Hemanth, C. (2017). Optimization of Energy Loss Cost of Distribution Networks with the Optimal Placement and Sizing of DSTATCOM Using Differential Evolution Algorithm. *Arabian Journal for Science and Engineering*, 42(7), 2851-2865.
- [48] Shukla, T. N., Singh, S. P., Srinivasarao, V., & Naik, K. B. (2010). Optimal sizing of distributed generation placed on radial distribution systems. *Electric power components and systems*, 38(3), 260-274.
- [49] Taher, S. A., & Afsari, S. A. (2014). Optimal location and sizing of DSTATCOM in distribution systems by immune algorithm. *International Journal of Electrical Power & Energy Systems*, 60, 34-44.
- [50] Iqbal, F., Khan, M. T., & Siddiqui, A. S. (2017). Optimal placement of DG and

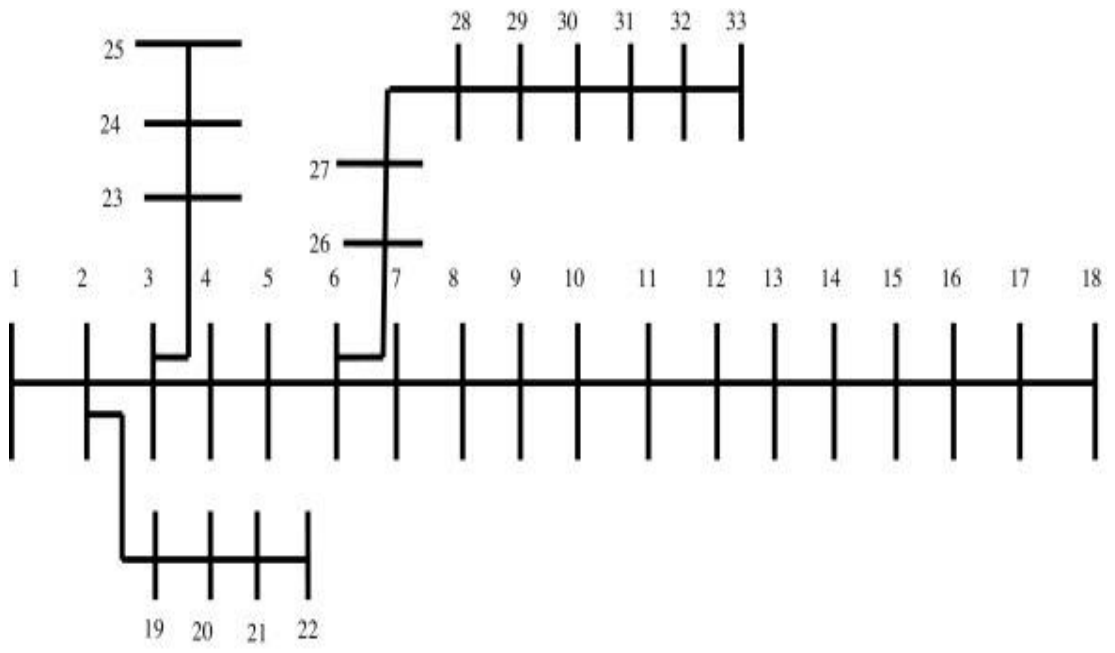
DSTATCOM for loss reduction and voltage profile improvement. *Alexandria Engineering Journal*.

APPENDIX

Table A: System data for 33-bus radial distribution network

Branch Number	Sending Bus	Receiving Bus	Resistance Ω	Reactance Ω	Nominal Load at Receiving Bus	
					P (kW)	Q (kVAr)
1	1	2	0.0922	0.0470	100	60
2	2	3	0.4930	0.2511	90	40
3	3	4	0.3660	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.8190	0.7070	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	0.7114	0.2351	200	100
8	8	9	1.0300	0.7400	60	20
9	9	10	1.0440	0.7400	60	20
10	10	11	0.1966	0.0650	45	30
11	11	12	0.3744	0.1238	60	35
12	12	13	1.4680	1.1550	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.5910	0.5260	60	10
15	15	16	0.7463	0.5450	60	20
16	16	17	1.2890	1.7210	60	20
17	17	18	0.7320	0.5740	90	40
18	2	19	0.1640	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	50
23	23	24	0.8980	0.7091	420	200
24	24	25	0.8960	0.7011	420	200
25	6	26	0.2030	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.0590	0.9337	60	20
28	28	29	0.8042	0.7006	120	70
29	29	30	0.5075	0.2585	200	600
30	30	31	0.9744	0.9630	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.3410	0.5302	60	40

33 BUS RADIAL DISTRIBUTION NETWORK



33 - Bus Radial Distribution Network