Optimal Allocation of Reactive Power Compensators in Transmission Networks Considering Wind Energy Uncertainty

Numan Khan

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Approval of the Institute of Graduate Studies and Research

Prof. Dr. Ali Hakan Ulusoy
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 Kukrer
2. Assoc. Prof. Dr. Reza Sirjani
3. Asst. Prof. Dr. Muhammad Abid

ABSTRACT

This thesis addresses the problem of finding the optimal configuration (location and size) of static var compensator (SVC) considering the intermittent nature of wind power in the transmission system. A probabilistic load flow (PLF) integrated with a five-point estimation method is used to model the wind power uncertainties by discretizing wind power distribution into five discrete points. Consolidating PLF with multi-objective non-dominated sorting genetic algorithm (NSGA-II), location and size of SVC can be optimally allocated considering the impacts of wind power uncertainties. This method aims to minimize system operating cost, power loss reduction and voltage profile enhancement. The viability of the applied method is validated on the IEEE 30 bus system. Simulation outcomes demonstrate the viability of the applied method in minimizing different objective functions under the vague nature of wind power. The total voltage profile is improved by 33.2%, while the total power loss of the mentioned power system is reduced by almost 40% after installation of SVCs and wind turbine.

Keywords: Static Var Compensator, Wind Power Uncertainty, 5-Points Estimation Method, NSGA-II.

ÖZ

Bu tez, iletim sisteminde rüzgar enerjisinin aralıklı doğası göz önünde bulundurularak Statik Var Kompansatör (SVC) en uygun yapılandırmasını (konum, boyut ve sayı) bulma sorununu ele almaktadır. Olasılıksal yük akışı (PLF) tabanlı beş nokta tahmin yöntemi beş ayrı nokta içine rüzgar gücü dağılımı ayrıştırarak rüzgar gücü belirsizlikleri modellemek için kullanılır. PLF'nin çok nesnel olmayan hakim olmayan genetik algoritma (NSGA-II) ile birleştirilmesi, SVC'nin konumu ve boyutlandırılması, rüzgar enerjisi belirsizliklerinin etkileri göz önünde bulundurularak en iyi şekilde tahsis edilebilir. Bu yöntem, sistem işletme maliyetini, güç kaybını azaltmayı ve voltaj profili iyileştirmeyi en aza indirmeyi amaçlamaktadır. Uygulanan yöntemin uygulanabilirliğini göstermek için IEEE 30 veri yolunda doğrulanır. Simülasyon sonuçları, rüzgar enerjisinin belirsiz doğası altında farklı nesnel fonksiyonlarıen en aza indirmede uygulanan yöntemin etkinliğini kanıtlamaktadır. Bahsedilen güç sisteminin toplam voltaj sapması% 33.2 oranında artarken, güç sisteminin toplam güç kaybı, SVC'lerin ve rüzgar türbininin takılmasından sonra neredeyse% 40 oranında azalır.

Anahtar kelimeler: Statik Var Kompansatör, Rüzgar Energisi Belirsizlikleri, 5-Nokta Tahmin Yöntemi, NSGA-II.

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony Algorithm
CSA	Cukoo Search Algorithm
DA	Drogonfly Algorithm
FACTS	Flexible AC transmission systems
GA	Genetic Algorithm
IHS	Improved Harmony Search Algorithm
MCS	Monte Carlo Simulation
NSGA	Non-dominated Sorting Genetic Search Algorithm
PDF	Probability Density function
PEM	Point Estimation Method
PV	Photovoltaic
RES	Renewable Energy Sources
STATCOM	Static Compensator
SVC	Static Var Compensator
TCSC	Thyristor Controlled Series Compensator
WT	Wind Turbine

Chapter 1

INTRODUCTION

1.1 Overview

Electrical energy has significant effects on technological and economic developments. Most of the conventional electricity consumption requests can be supplied by non-renewable sources of energy; considering fossil fuel, diesel, and natural gas. Due to the economic upswing and demographic development electricity demand has surged and is expected to continue to incline double the demand rate in the next decade. In addition to this, these conventional energy systems have a bad effect on the environment caused by the emission of CO_2 gas during combustion. Thus, fulfilling the demand from the non-renewable sources of energy is problematic. Alternatively, renewable energy sources like wind and solar are a good way to overcome these problems [1].

As the energy crises arose in the 1970s, many researchers and the world society had to make a changeover to alternative power generation methods using renewable energy sources (RES) like solar and wind. Many countries adopted strict environmental and sustainable policies to start generating electricity using RES [2].

The shift of RESs can be clarified by numerous matters such as economic (decreased dependency to natural gas), environs (by keeping the environment safe and green) and social (e.g. energy approachability in rural areas). Despite, these advantages of RESs, they do have their disadvantages such as difficult operation and policy challenges. Wind generation is a standout amongst the most broadly acknowledged renewable generation, thus the concentration of this thesis is on this specific type of RESs [3].

Higher penetration of wind power brings uncertainty and variability in the power system network, in regards to the non-linear and unpredictable behavior of wind speed. For instance, changing in weather lead to variation in wind speed due to which the generated power of Wind Generators (WGs) fluctuate which occur technical issues, including power quality and reliability in the power system. To avoid this problem, the integration of Flexible AC transmission system (FACTs) devices in the power system is considered a standout among the solutions to assure the system stability and power quality. As they prove beneficial to the system's transmission capacity and load flow control in terms of flexibility and rapidity [4].

The FACTS are electronic control converters equipped for controlling different electrical parameters in both steady state power flow and dynamic stability control, consisting of the thyristor-controlled series compensator, Static Compensator (STATCOM), Static Var Compensator (SVC). SVC is a shunt connected static Var generator or absorber with its output being adjusted to exchange capacitive or inductive currents to provide voltage support, and can also minimize power losses if placed correctly. Besides, it has the highest usability in power networks as a result of its lowest cost and high performance [5].

As of late, specific consideration has been given to the use of SVC to reduce the system unbalances. In recent literature, it was demonstrated that the utilization of SVC can turn out to be increasingly appealing when they are optimally placed and sized in the power system. Studies show that misusing and miss placement of SVC in power systems can affect many aspects of power systems such as system performance, voltage regulation, power quality, reliability and system operation cost [6].

Recently, numerous optimization techniques including Genetic Algorithm (GA) [7], Cuckoo Search Algorithm (CS) [8], Improved Harmony Search Algorithm (HS) [5] and many more have been applied to locate the optimal location and size of SVC in power system with the end goal of many objectives, such as energy cost minimization, reduction of system losses, frequency, power quality enhancement and many more.

1.2 Problem Statement

Due to increase in the demand of energy and environmental contamination, enthusiasm for wind power has been expanded, although integrating wind generation raises an issue of system uncertainty, brought about by the stochastic nature of wind energy. The integration of SVC in power system is one of the good solutions to guarantee the stability and power quality enhancement.

With the increasing usage of SVC in the power system, it became crucial to decide the optimal sizes and locations to ensure operational security and system economy. The improper sizing and placement of these devices may prompt numerous issues such as an increasing the cost rate of the power system network and the risk of voltage stability.

Finding the best location of SVC is a complex problem which has attracted many investigators and designers. The solution methods for optimal sitting and capacity of SVC in power systems can get by using different optimization techniques. The most common of these techniques are GA, CS, and PSO which are being simple and robust. Furthermore, for reliability and better decision-making purpose modeling of wind uncertainty is important which should be taken into account of the optimization process.

1.3 Objectives

The focus of this work is to provide an efficient algorithm of optimization to place the most suitable size of SVC at the most appropriate location considering wind uncertainty in the power system. The following three objectives have been taken into account in this thesis:

- To minimize the total operational cost of the power system by considering the optimal location of static var compensator (SVC) to develop the system economically.
- To lower the power losses of the power system due to which load demand should be satisfied.
- To control the voltage at each bus to enhances the voltage profile of the power system.

1.4 Thesis Framework

The remaining part of this thesis is organized as:

- Chapter 2 is consisting of three sections. Section 1, presents different issues of power system caused by wind power integration, uncertainty handling techniques and a literature review on different kinds of uncertainty handling techniques. Section 2, discussed FACTS, different categories of FACTS devices, and their applications. In the last section of this chapter, a literature review of the optimal sitting and sizing problem of SVC is presented.
- Chapter 3, presents optimization terminology and different optimization algorithm which can be utilized to find out the best placement and size of SVC.

- Chapter 4, discussed probabilistic modeling of wind power, problem formulation, and solution method.
- In chapter 5, the simulation results are presented and comparative analysis of the power system with and without SVC is presented.
- Chapter 6, composed over conclusion and future recommendations.

Chapter 2

LITERATURE REVIEW

2.1 Challenges with Wind Power Penetration

Power systems based on wind power integration faces issues with reliability, power quality, stability, and planning because of characteristic fluctuation and vulnerability, highly dependent on the penetration level [9].

2.1.1 Impact on System Reliability

Since it is a well-known fact that there cannot be a 100% reliable system, wind power generation faces reliability issues with the generation, planning and scheduling power supply, as the intermittent wind factor will build the level of generation uncertainty and lower the operating reserve capacity, which will increase the generation cost. At lower penetration level. The submitted Conventional Generators (CGs, for example, diesel or hydro units, have sufficient burden following ability without extra working store. However, it becomes challenging at high penetration level. The reaction time of CGs isn't quick enough during abrupt and huge changes in wind control because of irregular failures or gust of wind. Besides, the extra operating reserve is required.

2.1.2 Effect on Power Quality

Power quality crucially relies on the location and the irregular nature of wind turbines, these factors can result in lower power quality in terms of voltage dips, and harmonic distortions.

Wind turbines, particularly inductive machines, in general, absorbs reactive power from the system and which lower the power factor. Poor power quality can cause operational insufficiency for the end client which affects the system stability.

2.1.3 Impact on System Planning

Due to the often-remote locations of wind resources far from load centers. It is crucial to develop efficient transmission between wind turbines and load centers. Furthermore, transmission planning influenced by regional policies. Moreover, generation capacity, load size, and transmission locations are diverse in each territory, these make a need to develop new technical requirements for transmission technology.

2.2 Uncertainty Handling Techniques

Along with increasing usage of renewable energy resources and rebuilding power systems, new inconstancies rise in the operation and investment decision-making process. Thus, the consideration of the significant amount of uncertain details is required as a characteristic feature of a wind power system.

The most common methods and approaches designed to deal with such uncertainties that ensure a realistic model and better decision making in electric power systems are [10]:

- Probabilistic techniques
- Possibilistic techniques
- Hybrid probabilistic-possibilistic-approach

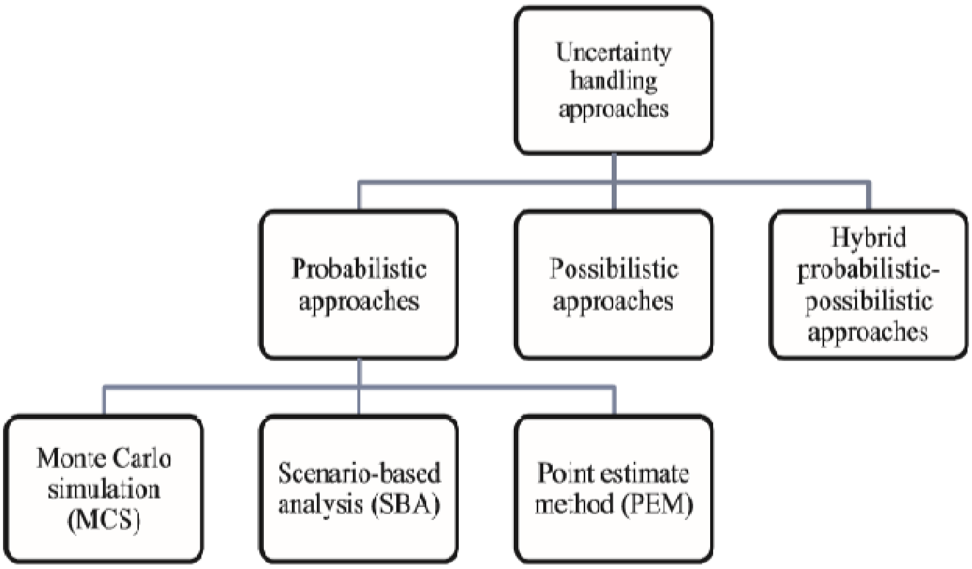

Figure 2.1: Classification of Uncertainty Handling Techniques [10]

2.2.1 Probabilistic Techniques

In these approaches, probability density function (PDF) is utilized for modeling of uncertain parameters, then some unique probabilistic strategies are used, which are described here:

2.2.1.1 Monte-Carlo-Simulation (MCS)

This is the most well-known and accurate technique which uses PDF of random variables to deal with uncertainty issues. MCS is normally utilized when the model is unpredictable, non-linear, or incorporate a few uncertain-parameters [11]. The fundamental concept of MCS is summarized in the following steps:

1. Set the MCS counter $C = 1$;
2. Create a parametric model $Y = h(x_1, x_2, \ldots, x_n)$;
3. Randomly create a set of inputs by using their PDF $X^i = (x_1^i, x_2^i, \ldots, x_n^i)$;
4. Estimate the model and compute the Y^i;
5. Perform again steps 3 and 4 for $i = 1$ to n;

6. Analyze the outcome utilizing histograms, summary statics, confidence-intervals, and others.

2.2.1.2 Understanding of Scenario-Based Analysis

This is another common probabilistic approach which uses to deal with uncertainties. The PDF curve of uncertain variables in this strategy is subdivided into numerous areas, and the probability of indeterminate variables in each region is obtained using the PDF curve. Each area corresponds to a scenario, for example, there are scenarios $i = 2,3\ \dots, i, \dots, k$ with probabilities $P_2, P_3 \dots, P_i \dots, P_k$. The average of upper and lower limits of region i, denoted as X_i, which represents the rate of uncertainties in that area. At that point, the normal estimation of yield variable y is resolved as pursues. At that point the normal estimation of the output variable 'y' is determined as:

$$y = \sum_{i=1}^{k} P_i X_i \tag{2.1}$$

It should be noted that the result's accuracy is proportional to the number of scenarios.

Scenario-based analysis was utilized [12] to handle uncertainties in unit commitment problem of microgrids based on sustainable and unsustainable generation units and storage units. Researchers have considered variations in load demand, PV and wind generation uncertainties, as well as an economic point of view in their research. With different scenarios being generated, a scenario reduction technique has been implemented to reduce the computational load. With this technique, 20 scenarios were selected out of 2000. Weibull PDF was used to model the wind speed, whereas Photovoltaic generation, electricity price and load profile were modeled as normal PDF's.

Furthermore, in [13] scenario-based analysis was used to handle scheduling problems regarding vulnerabilities of wind and solar output power of distributed generators. They modeled wind speed in terms of Rayleigh PDF, while Beta PDF has modeled solar irradiance. While solar irradiance and wind speed were modeled in Beta distribution. Three different scenarios were taken into account for every uncertain parameter such as solar irradiance and wind speed.

2.2.1.3 Point-Estimate-Method (PES)

Another kind of probabilistic method which is used most often for uncertain parameters of an electrical power system is point estimate method (PES). The idea behind PES is that generate some moments of uncertain input parameters that characterize the output variables in the form of Gaussian PDF. For instants, assume there are 'm' uncertain variables the PES works as:

1. Set $E(Y) = 0,\ E(Y^2) = 0$ and $k = 1$
2. The point and probability of the concentration $\varepsilon_{k,i}$ and $P_{k,i}$ are calculated as:

$$\varepsilon_{k,i} = \frac{M_3(X_k)}{2\sigma_{X_k}^3} + (-1)^{i+1}\sqrt{n} + 0.5(\frac{M_3(X_k)}{\sigma_{X_k}^3}) \tag{2.2}$$

$$P_{k,i} = \frac{(-1)^i \varepsilon_{k,3-i}}{2n\sqrt{n}+0.5\left(\frac{M_3(X_K)}{\sigma_{X_k}^3}\right)^2} \tag{2.3}$$

Where M_3 is the third moment of X_k

3. Derive the concentration points as:

$$X_{k,i} = \mu_{X_k} + \varepsilon_{k,i}\sigma_{x_k}\ for\ i = 1,2. \tag{2.4}$$

Where μ_{X_k} and σ_{x_k} are the average and standard deviation of X_k

Then, compute f for $X_{k,i}$

$$X = (X_0, X_1, \dots, X_j, \dots, X_n)\ (j = 0,1) \tag{2.5}$$

Where n shows the number of uncertain variables

4. The mean and variance of uncertainty i.e. $E(Y)$ and $E(Y^2)$ can be computed from the following equations:

   $$E(Y) = E(Y) + \sum_{i=1}^{2} P_{k,i} f(X_1, X_2, \dots, X_i, \dots, X_n) \tag{2.6}$$

   $$E(Y^2) = E(Y^2) + \sum_{i=1}^{2} P_{k,i} f^2(X_1, X_2, \dots, X_i, \dots, X_n) \tag{2.7}$$

5. $k = k + 1$ if $k \geq n$ continue, else go to step 2.
6. Average and standard deviation can be obtained by the following equation:

   $$\mu_y = E(Y) \tag{2.8}$$

   $$\sigma_y = \sqrt{E(Y^2) - E(Y)} \tag{2.9}$$

Alireza et al. [11] have been utilized an unsymmetrical two point-estimate strategy for handling uncertain nature of Wind generation, PV generation and the electric load of distribution network. The electric load of each bus has been modeled by normal distribution function; wind speed was modeled while utilizing the Weibull PDF. Whereas solar-irradiance was modeled as Beta PDF. For checking the performance of the proposed method, they compare their results with MCS results.

2.2.2 Possibilistic Techniques

In these approaches, the uncertain variables are expressed in a fuzzy-membership function. This study used the α-cut method, which has the characteristic in which the membership-function of input variables is used for finding the membership-function of yield variables. Subsequently, a defuzzify technique is utilized for defuzzification of output variables due to which a uniform output value is come out. The common strategy for defuzzification is the Centroid method.

In [14], possibilistic methods have been used for handling the uncertainties of environmental-economic dispatch in a microgrid system based on different generating units. In their research they modeled the uncertainty of the price of electricity using a triangular-fuzzy-membership-function along with the total present values, containing various objectives, which have been modeled as the objective function.

2.2.3 Hybrid Probabilistic-Possibilistic Techniques

In this technique, many of the parameters PDF are known while others which are not known, the unknown parameters can be modeled in the form of fuzzy membership function. This leads to the formation of the hybrid model which is capable to deal with the uncertain parameters of the model.

To sum up, SBA and MCS are the easiest techniques for dealing with uncertainties. They are easier than other methods i.e. PEM and Possibilistic techniques. But they are computationally costly. Suppose that, if there are n uncertain parameters in a problem, then for each uncertain parameter k sample are created. In that point, in SBA and MCS, k_n function assessments are necessary. But in the case of PEM only a few functions are required.

2.3 FACTS Devices

Recently, FACTS became a symbolic term for high controllability in power electronic devices systems. Many of which were introduced internationally for various applications. The main application FACTS devices are that which easily control power flow, improve the transmission capability and voltage profile, stability and power quality improvement and reactive power compensation. Despite all the benefits it provides, it is important to minimize FACTS devices implemented in a system and locate them in their optimal locations, because of the considerable cost of it [4].

FACTS controller categorizes in two main types:

- **Series FACTS**

An example of series FACTS is Thyristor Controlled Series Capacitor (TCSC), which uses an extremely simple main chip composed of; a capacitor attached in series with the transmission line for compensation and a thyristor-controlled inductor associated in shunt with the capacitor. Thus, there would be no need for interfacing equipment, and that makes the TCSC one of the most economic FACTS technologies.

In [15], the TCSC has one of two characteristics generator or absorber, increasing or decreasing the total reactance of the X_L line. The capacitor and inductor in TCSC are variables, and dependent on the reactance and power capability of the line in which the device is inserted in series. To avoid resonance, one if the components can be switched one at a time, and to keep away from overcompensation of the line -0.8X_L is fixed as the maximum value of the capacitance, and 0.2 X_L for inductance.

- **Shunt devices**

Most common FACTS controllers are SVC and STATCOM. These operate as reactive power compensators. Mainly used for:

• Minimization of undesirable reactive power which minimized network power losses.

• Preserving of contractual exchange power with adjusted reactive power.

• Recovery of static or transient stability.

2.3.1 Static Var Compensator

Static Var Compensator (SVC) is a static generator or absorber with varied generated power to control the voltage of the electric power systems. It can be installed at the high voltage side of transmission lines, and are used by utilities in transmission applications, mainly for controlling voltage at the network's weak points.

SVC has a very simple form, consisting of a thyristor-controlled reactor fixed capacitor (TCR-FC) connected to it, and the major components are, coupling transformer, thyristor valves, reactors, and capacitors. SVC's drawn current and reactive power can be described as [5]:

$$I_{svc} = jB_{SVC} \times V \quad (2.10)$$

$$Q_{SVC} = -jB_{SVC} \times V^2 \quad (2.11)$$

Where:

B_{SVC} : is the susceptance of SVC

I_{SVC} : is the current of SVC

Q_{SVC} : represents the reactive power of SVC

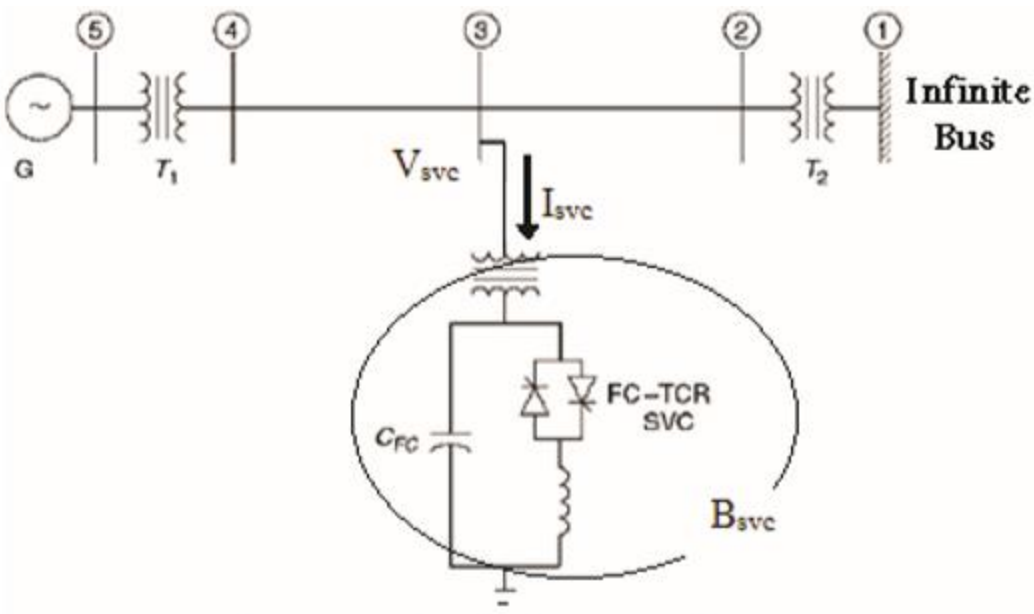

Figure 2.2: Circuit Diagram of SVC [5]

The reactive power injected to a bus whose voltage is one per unit is represented by the size of SVC. The SVC can work in a capacitive mode or inductive mode. In capacitive mode, SVC generates reactive power and supplied it into the system, while in inductive mode SVC retains reactive power from the network.

2.4 SVC Location and Sizing Optimization

Optimal sitting and size of SVC is a complex optimization issue considering the objectives of power loss, operation cost, and voltage deviation. Numerous investigators in this context presented numerous sorts of researches.

Vinod K. Shende et al. [6] Proposed PSO technique for searching the best location and size of the SVC with the ultimate objective of two goals, reduction of active power loss and voltage deviation. IEEE 14-bus system is used for test analysis, the outcome acquired from their work shows that the applied algorithm has given better results in term of voltage profile improvement and power loss minimization.

In [8], Cuckoo search (CS) optimization technique is applied to find out the optimal location of SVC in power system network. Multi-objective function is considered, defined minimization of various objectives, voltage deviation and the cost of SVC devices. Comparative analysis between the CS algorithm and some other methods has been done. Three different case studies are considered to check the accomplishment of the applied algorithm. From the outcomes of the simulation, it is observable that the CS algorithm calculation gives a more prominent decrease in voltage deviation and total cost contrasted with the other optimization strategy. In [16], all the types of FACTS devices, their functions, constructions and their optimal location and sizing strategies are reviewed in details.

F. Berrouk, B, et al. [17] analyzed the impact of FACTS devices including SVC and STATCOM with the end goal of control and improvement of voltage profile. Newton Rapson power flow algorithm is utilized for load flow analysis. IEEE 30-bus system is used for checking the performance of the proposed methodology. In [7], GA optimization technique is used to demonstrate the best location and size of SVCs in the IEEE-14 and 30 bus system in which multi-objective function is characterized minimization of voltage deviation, the total energy cost of the system and power loss.

An Improved Harmony Search (IHS) has been utilized in [5] for finding the optimal placement and size of SVC in power system. Three objectives have been considered including minimization of active power loss, improvement of the voltage profile and total cost of the system. The proposed algorithm has been examined on IEEE-57 bus system. Furthermore, the obtained results from the proposed algorithm is then compared with the outcomes of PSO algorithm. Comparative analysis shows IHS gives greater solution in terms of voltage fluctuation reduction and power loss minimization. In [18] , Non-dominated sorting GA (NSGA-II) is proposed to solve a multi-objective optimization problem of SVC placement and size. Enhancement of voltage profile and reduction of power loss are considered as objectives of the research. The performance of the applied approach is examined on IEEE-14 bus system.

The reviewing literature regarding the SVC location and sizing problem is summarized in table 2.1.

Table 2.1: Literature Review Summary

Ref	Objective functions	Constraints	Proposed approach	Case of study
[11]	1. Active power loss	1. Power flow equations 2. Voltage limits 3. Feeders and substation capacity limits	Unsymmetrical Two Point Estimation Method	1. 9 BUS DN 2. Realistic 574 BUS DN
[4]	1. Voltage deviation 2. Minimization of power loss	1. Power balance 2. voltage limitation 3. FACTS capacity limitation	GA	IEEE 39-bus
[5]	1.power loss 2. Improvement of voltage profile 3. Investment cost of SVC	1. Power flow limit 2. Bus voltage limit	HIS	57-bus transmission network
[6]	1.Minimization of voltage deviation 2.Reduction of power loss	1.Power flow limit 2.Voltage limit	PSO	IEEE 14-bus system
[8]	1.Reduction of voltage deviation 2.Power loss minimization 3.Minimization of investment cost	1.Power balance limitation 2.Voltage limitation 3.Limitation of SVC	CS	IEEE 30-bus
[17]	1.Improvement of voltage profile 2.Reduction of reactive power loss	1.Power balance limitation 2.Voltage limitation	-	IEEE 30-bus
[18]	1.Active power losses 2.Voltage deviation	1.Power flow limit 2. Voltage limit	NSGA-II	IEEE 14-bus

Chapter 3

OPTIMIZATION

The procedure of optimization can be outlined as the way toward looking through vector of decision factors which fulfill the restrictions or limitation in the issue which upgrade the objective function. Generally, the purpose of optimization is to gain the values of the design factors which minimize or maximize the objective function while considering the constraints.

3.1 Optimization Terminology

As it is referenced before the optimization issue is to look for the estimations of choice factors that fulfill the limitations and upgrading of the goal capacities.

3.1.1 Variables

Also known as choice factors or plan parameters, they are the values to be considered in the problem of optimization. Aims that the arrangement begins by defining the issue, which in return identifies the decision variables from the parameters that impact the objective function directly.

Mathematically, the vector of variables can be express as:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} \tag{3.1}$$

For the proposed problem of this work, the choice factors are the voltage of each bus, generated power of generators, SVC location, and size.

3.1.2 Boundaries

Some constraints or boundaries to give high regard to are environmental or other assets, for instance, physical constraints, time limitation, financial restrictions, etc. These constraints must be satisfied to validate a solution. The mathematical form of the constraints that define conditions in the decision variables has two algebraic expressions: It may have unequal expression such as:

$$g_i(x) \leq 10, \qquad i = 0,2, \dots, m \tag{3.2}$$

Or equal expression:

$$h_j(x) = 10, \quad j = 0,2, \dots, p \tag{3.3}$$

The solution of an optimization problem can be either feasible or infeasible according to its compatibility with constrains. The aim is to get a feasible solution. The scope of this thesis concerns the optimal sitting of SVCs, and many constraints are applied which are voltage limitation and the reactive power limit of SVC, etc.

3.1.3 Objective Function

The performance criteria of the problem can be gauged via the objective function which is a numerical expression. The problem of optimization can be divided into a single objective or multi-objective. Where the multi-objective problem deal with the enhancement of many targets and upgraded. Generally, most of the optimization problems deal with multi-objective optimization problems.

For instance; the optimal sitting and size of SVC is a multi-objective problem. The above-mentioned optimization problem tries to enhance numerous objectives such as to minimize the operating cost, reduction of voltage deviation and minimization of system losses.

There are different techniques which can be used for resolving optimal sitting and sizing optimization problem of SVC. There is a need to find the best improvement strategy to handle this issue accurately.

3.2 Genetic Algorithm (GA)

It is an optimization technique which mimics the process of natural evolution such as inheritance, mutation, and crossover. GA is commonly used to generate high-quality solution to optimization problems.

This can be achieved by generating random values for the objective function variables which are called the population of chromosomes. After creating the population of 'chromosomes' these are check for the solution of the problem considering some criteria the numbers which are matching with these criteria are kept while the others are neglected. The kept chromosomes are then stored some of them are taken and 'crossover' with other the new population can be created from that. The new population will take the place of the numbers which are neglected. With this, the population will decrease and the solution can be found easily.

Another essential perspective of genetics known as mutation also used in GA. Some of the population is mutated with each other in different ways which will be explained. This shows some changes especially when the parent chromosomes are commonly essentially comparative. The methodology of crossover and mutation is then repeated until either the pre-determined number of populace ages has been come to or until the moment some other stopping criteria is reached.

Genetic algorithm has the ability for solving discrete as well as continues problems, due to the way that there is a population of having the ability to look a wide variety of solutions in the meantime and ready to find the global optima rather than stuck in local optima.

Optimization toolbox can be used for genetic algorithm which is available in MATLAB. However, it does not represent all conditions and can along these lines be changed under the necessities of the user. The remainder of this area will deal with the diverse parts of GA, as shown in figure 3.1.

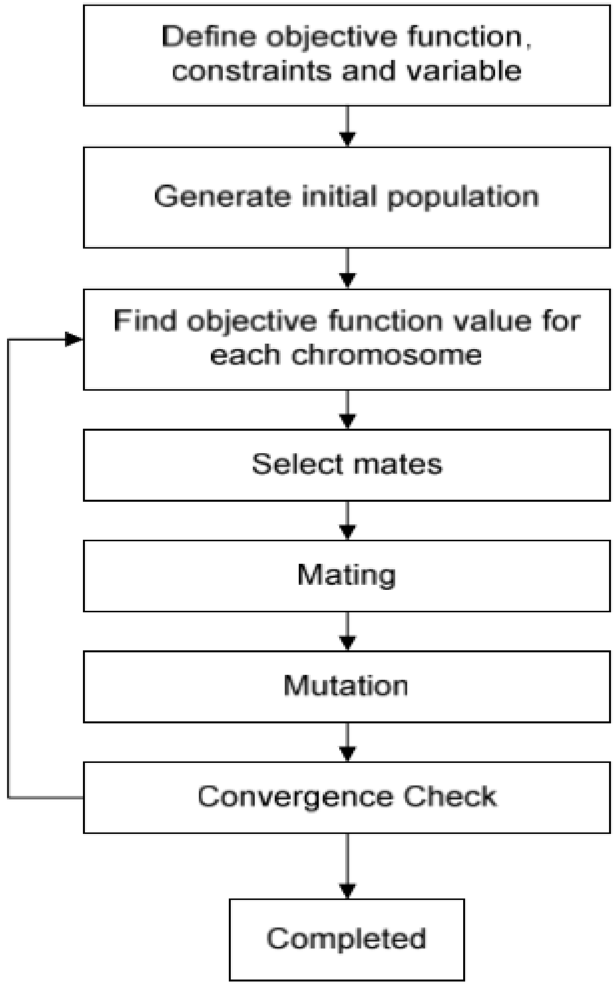

Figure 3.1: GA Flowchart [7]

3.2.1 Initial Population

As discussed previously, to solve a problem, genetic algorithm uses a population of chromosomes. In this kind of problem, the chromosome is made by variables that need to be optimized. In this thesis, the variables are the voltage of bus (v_i), generated power of the generators (P), location of SVC ($SVC_{location}$) and size of SVC ($SVC_{capacity}$). The following table 3.1 can represent the chromosome.

Table 3.1: Representation of Chromosome

v_i	P_{G_i}	$SVC_{location}$	$SVC_{capacity}$

It depends on the user to randomly generate the initial population size. In matrix form, the size of population can be represented using the number of variables. Unless constrained by upper and lower bounds, the chromosomes are created and normalized to be real numbers between 0 and 1.

3.2.2 Selection

The chromosomes values are calculated with the objective function later generation of the initial population. The chromosomes with the lowest values of the objective function are discarded and the ones with maximum values are added to the population. The following are the two ways this can be achieved.

The chromosomes are assorted and then ranked in increasing order concerning their objective function values. A percentage is specified by the user for the chromosomes to be kept.

The second method eliminates the need for ranking of the chromosomes with respect to their objective function. Instead, a threshold is set for the objective function. This threshold is then used to determine which chromosome will move to the upcoming generation. The ones with objective function value above the set threshold are removed and ones that fall below are kept. On the contrary, this method lacks the control of the number of chromosomes the go to the next generation.

3.2.3 Mating

Once the selection of chromosomes in done, these selected chromosomes are then crossover with each other. The new offspring is generated from the selected crossover of parents. For example, s1 and s2 are two different chromosomes the offspring s3 is generated after the crossover of s1 and s2 which can be shown in the following figure 3.2.

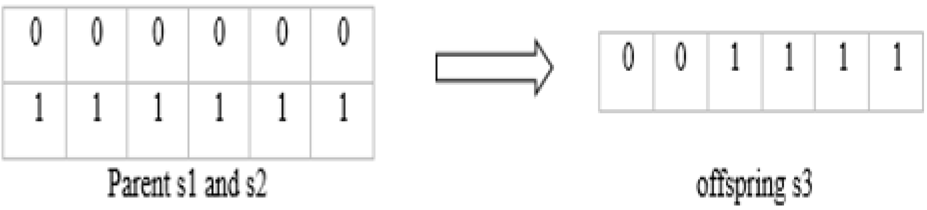

Figure 3.2: Mating Process

The generated new offspring are then put into the next generation and by injecting this into objective function new solution can be added to the algorithm.

3.2.4 Mutation

Using the strategies of selection and crossover leads to fast convergence to a minimum point. On the off chance that this combination happens too quickly, the system may meet to local minima instead of global minima. To stay away from this and to familiarize new arrangements with the estimation, mutation can happen.

In Mutation process, one or two gene value of chromosome is changed which bring diversity in the calculation. For instance, if A is a chromosome by flipping one of the bits the new chromosome B is generated representing in the following figure 3.3.

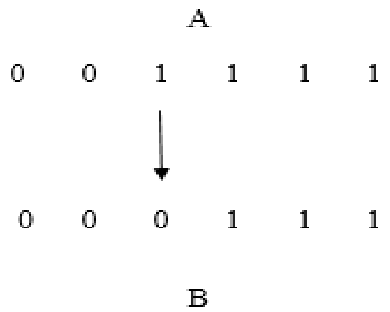

Figure 3.3: Mutation Process

Chapter 4

Problem Formulation

4.1 Introduction

The aim of this thesis is to optimize the system accurately such that, the total system cost is reduced and the load is satisfied with the generated power. For this purpose, obtaining or passing through different steps are important. Which are discussed here:

4.2 Uncertainty Modelling of Wind Energy System

There is fluctuation in the output power of wind farms because wind energy system is totally dependent on wind speed which is not constant. To have a precise and reliable wind energy system, modeling of the wind energy system is essential.

In order to have a precise wind speed data model or have detail wind speed information. Weibull distribution is commonly acknowledged as the most ideal method for wind speed probabilistic distribution. Due to incredible flexibility, Weibull distribution function (PDF) was used to present wind speed forecasting, which is characterized [11] as:

$$f(v) = \left(\frac{k}{\lambda}\right)\left(\frac{v}{\lambda}\right)^{k-1} \exp\, -\left(\frac{v}{\lambda}\right)^{k} \qquad (4.1)$$

Where, v in equation 4.1 represent the value of the wind speed in (m/s), k and λ represent the shape and scale parameters of Weibull PDF respectively. To derive the value of k and λ numerous methods have been presented by many investigators. A standout amongst the most well-known is the 'method of moments', described in the following equation:

$$\bar{v} = \lambda . \Gamma\left(1 + \frac{1}{k}\right) \ \& \ k = \left(\frac{0.9874}{\frac{\sigma}{\bar{v}}}\right)^{1.0983} \tag{4.2}$$

Where $\bar{v}$ and σ are the mean and standard deviation of wind speed data respectively.

After the proper distribution of wind speed data, output power distribution of WT is required. According to Vinay Thapar et al. [19] linear power curve model for wind power is presented based on predicting the performance of WT. Where assumed that output power of WT increases linearly with the wind speed from cut-in (v_{ci}) to the normal wind speed (v_{no}) and then it constant from normal wind speed to cut-out (v_{co}). Accordingly, following linear approximation equation have been proposed for modelling WT:

$$Y = \begin{cases} 0 & X \leq v_{ci} \ or \ X > v_{co} \\ \alpha + \beta X & v_{ci} \leq X \leq v_{no} \\ M & v_{no} \leq X \leq v_{co} \end{cases} \tag{4.3}$$

Where $\alpha = \frac{-MV_{ci}}{V_{no} - V_{ci}}$ & $\beta = \frac{M}{V_{no} - V_{ci}}$

In equation 4.3, Y is the generated power of WT, X represents the 'actual wind' speed, M the 'peak power' of WT, α and β are the coefficients, v_{ci}, v_{co} and v_{no} represents the cut-in, cut-out, and wind speed, respectively.

The following figure 4.1 shows the comparison between the actual power curve provided by manufacturer and the power curve obtained by using above model.

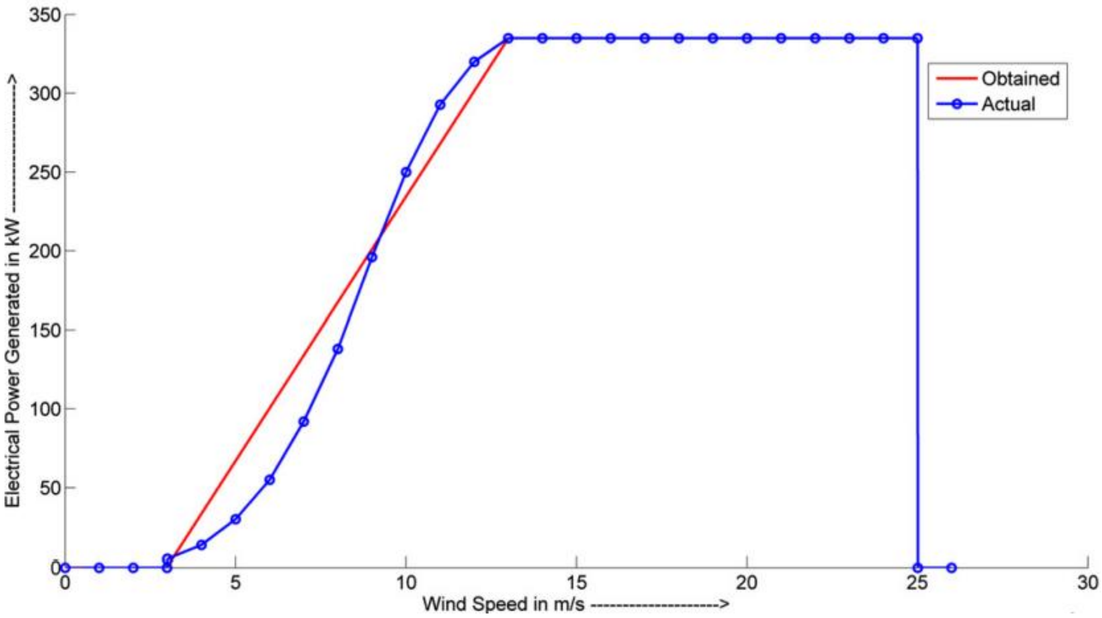

Figure 4.1: Comparison of Power Curve Obtained from the Linear Power Curve Model with the Actual Power Curve

4.3 Estimation Technique: The Five-Point Estimation Method

To reduce the computation efforts in optimal sitting and size of SVC problem, rather than using continues PDF, discrete PDF function with the help of a 5-point estimation algorithm [20] can be used. The basic concept of the 5-PEM algorithm is to discretize continues PDF of wind output power distribution into five points discrete probability mass function (PMF). The basic steps of 5-PEM are described as:

- Initially, the chances of ‘0’ and ‘max power’ can be obtained by using the following equations:

$$P_1 = \text{Prob}\{Y = 0\} = \text{Prob}(X \leq V_{ci}) + \text{Prob}(X > V_{co}) \tag{4.4}$$

$$P_5 = \text{Prob}(Y = M) = \text{Prob}(v_{no} \leq \text{X} \leq \text{v}_{co}) \tag{4.5}$$

- Then for $v_{ci} \leq X \geq v_{co}$, the PDF of Y is redefined as

$$\tilde{f}_Y(y|\lambda, k) = \frac{\frac{1}{\beta} f(\frac{y-\alpha}{\beta}|\lambda,k)}{1-P_1-P_5} \tag{4.6}$$

Notice that

$$\int_0^M \check{f}(y|\lambda, k)dy = 1 \tag{4.7}$$

This fact will be utilized in the discretizing of continuous form of Y.

$$\tilde{\mu}_Y = \int_0^M y\check{f}(y|\lambda, k)dy \tag{4.8}$$

$$\tilde{\sigma}_Y{}^2 = \int_0^M (y - \tilde{\mu}_Y)^2 \check{f}(y|\lambda, k)dy \tag{4.9}$$

$$\lambda_j = \int_0^M \left(\frac{y-\tilde{\mu}_Y}{\tilde{\sigma}_Y}\right)^j \check{f}(y|\lambda, k)dy \tag{4.10}$$

Where $\tilde{\mu}_Y$, $\tilde{\sigma}_Y$ and λ_j are the mean, standard deviation and jth central moment of Y.

Let $z = (\frac{y-\tilde{\mu}_Y}{\tilde{\sigma}_Y})$ the standardized value of$Y$.

The moment equations are given by

$$\sum_{i=2}^{4} p_i z_i = \lambda_j \qquad for\ j = 1,2,3,4 \tag{4.11}$$

Where p_i is the probability according to z_i.

Calculating for (4.10), we can obtain

$$\begin{cases} z_2 = \frac{\lambda_3}{2} - \sqrt{\lambda_4 - \frac{3\lambda_3^2}{4}} \\ z_3 = 0 \\ z_4 = \frac{\lambda_3}{2} - \sqrt{\lambda_4 - \frac{3\lambda_3^2}{4}} \end{cases} \tag{4.12}$$

$$\begin{cases} p_2 = \frac{-1}{z_2(z_4 - z_2)} \\ p_3 = 1 - p_2 - p_4 \\ p_4 = \frac{1}{z_4(z_4 - z_2)} \end{cases} \tag{4.13}$$

By using equations (4.11) and (4.12), 3 points discrete distribution p_2, p_3 and p_4 with respect to location z_2, z_3 and z_4 can be estimated for $\tilde{f}_y$. Then with the help of these estimated points Y_i and corresponding P_i can be calculated as:

$$\begin{cases} Y_2 = \tilde{\mu}_Y + \tilde{\sigma}_Y z_2 & \text{and} \quad P_2 = p_2(1 - P_1 - P_5) \\ Y_3 = \tilde{\mu}_Y & \text{and} \quad P_3 = p_3(1 - P_1 - P_5) \\ Y_4 = \tilde{\mu}_Y + \tilde{\sigma}_Y z_{24} & \text{and} \quad P_4 = p_4((1 - P_1 - P_5) \end{cases} \tag{4.14}$$

4.4 Methodology

The problem in this work is a minimization problem. It is crucial to formulate the problem accurately which satisfies the objective function considering constraints. This section of the thesis will discuss different formulation which is used for the optimization purpose.

4.4.1 Objective Function

The problem of best placement and size of SVC has been formulated as a constrained nonlinear optimization problem with the end goal of three objectives function in this work. These objectives are the minimization of total operational cost of the system, reduction of voltage deviation, and minimization of power losses.

$$\begin{cases} \min f_1 = \sum_{i=1}^{5} \mathrm{Prob}_i . \mathrm{Cost}_i \\ \min f_2 = \mathrm{Prob}_i . \left(\sum_{i=1}^{n} \left(\frac{v_{k.i} - v_{k,i}^{spec}}{\Delta v_{k,i}^{max}} \right)^2 \right) \\ \min f_3 = \sum_{i=1}^{5} \mathrm{Prob}_i . P_{loss_i} \end{cases} \tag{4.15}$$

Where Prob_i in equation (3.15) represents the probability of wind power in the ith scenario, n represents the total number of bus node, $v_{k,i}$ represent the voltage of bus k at scenario i, $v_{k,i}^{spec}$ represent the expected voltage at i scenario, and $Cost_i$ shows the total operation cost in ith scenario. Which unit is taken in dollars per hour ($/h).

$$Cost_i = \sum_{j=1}^{NG} C_i \left(P_{G_j}\right) + C_{i,w} + C_{i,svc} = \sum_{j=1}^{NG} (a_j + b_j . P_{G_j} + c_j . P_{G_j}^2)\, t_i + c^{opw.i} . P_{i,wind} . t_i + c^{opsvc,i} . Q_{i,svc} . t_i \tag{4.16}$$

Where:

NG: represent the number of total generators

$C_i \left(P_{G_j}\right)$: shows the fuel cost of conventional generator j at i scenario ($/h)

$C_{i,w}$ and $C_{i,svc}$: are the cost of ‘wind energy’ generation and SVC in scenario i ($/h)

a_j, b_j and c_j: represent the fuel cost coefficients of conventional generator j

$c^{opw,i}$ and $c^{opsvc,i}$: are the operation cost of wind power generator and SVC ($/MWh) in scenario i

$P_{i,wind}$: is the output power of wind turbine at scenario i

t_i: represent the time duration in scenario i (h)

By following [5], the total active power losses i.e. P_{loss_i} in the scenario i can be expressed as follows:

$$P_{loss_i} = \sum_{l=1}^{b} R_l I_l^2 = \sum_{l=1}^{b} \sum_{j=1, i \neq j}^{b} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j) Y_{ii} cos\varphi_{ij}] \quad (4.17)$$

Where:

b: represent the number of transmission line

R_l: represents the resistance of line l

I_l: represents the current passing through line l

V_k: represents the voltage of bus k

δ_k: is the angle at bus k

Y_{ii} *and* φ_{ij}: are the 'magnitude' and 'angle' of the line admittance.

4.4.2 Problem Constraints

The types of constraints which have been considered in this thesis are:

- **Equality Constraints**

The overall power generated by power generators should be equal to the total power losses and the total load demanded of the system, which can be shown as:

$$\sum_{j=1}^{NG} P_{i,j} + P_{i,wind} - P_D - P_{i,Loss} = 0 \quad (4.18)$$

Where:

P_D: represents the total load demand

P_{Loss}: is the total loss of the power system

- **Inequality Constraints**

The inequality constraints considered are bus voltages limitation and limitation of SVC reactive power:

$$V_{i,min} \leq V_i \leq V_{i,max} \tag{4.19}$$

$$Q_{i,min} \leq Q_i \leq Q_{i,max} \tag{4.20}$$

The range of reactive power of SVC is assumed $Q_{min} = 0$ and Q_{max}=20MVar in this thesis.

4.5 Proposed Method (NSGA-II)

NSGA-II is the advanced version of NSGA, which is a non-elitist and non-dominated Sorting Genetic Algorithm. The purpose of elitism means to keep the best solution in the next iteration. When the author of NSGA-II algorithm sees the algorithm in a multi-objective problem. So, there are very few algorithms available to which implement the elitism property of GA which is there in a single objective optimization problem. Deb et al. implemented a novel idea of making or having how to define the elitist solution in the multi-objective solution space. The property of elitism plays a key role in a single objective problem similarly plays a key role in a multi-objective optimization problem. The strength of NSGA-II is that, it has the elitist preserving property and also support the diversity in the population. There are various algorithms proposed in the literature which implement the elitism property but do not have the ability to maintain the diversity. Therefore, in NSGA-II, we have two prime consents to maintain the elite preserving property and to maintain the diversity in the population. The whole idea of NSGA-II is explained in the following steps:

Step 1: $R_t = P_t \cup Q_t$ (4.21)

It starts with the formation of R_t population size of $2N$, which is the union of parent population (P_t) of size N and offspring population (Q_t) of the same size N which comes after the cross-over and mutation operators on parent solution similar to GA. Then performing the non-dominating sorting on the whole set of R_t to obtained different fronts $(F_1, F_2, F_3, \ldots)$ in R_t which depends upon non-domination sorting that how many fronts are there.

Step 2: Initialize the population in the next iteration denoted by P_{t+1} and increment the counter i equal to 1 $(i = 1)$. Then check whether the size of P_{t+1}combine with first front (F_1) is less then N or not. If the size of P_{t+1} is less than N then we include this first front into the next iteration population P_{t+1} , then again check whether front 2 (F_2) combine with the existing size of population P_{t+1} in next iteration population is less then N or not. If yes, then again F_2 will be included in $P_{t=1}$. This process will continue until the size of P_{t+1} become equal to or greater than N.

Step 3: Lastly, if the size of P_{t+1} exceeds N then crowding sort will perform on the current front (F_i) which is not included in P_{t+1}. In that front (F_i) most widely spread solutions will include and the number of solutions which are included is $(N - |P_{t+1}|)$ means only the remaining solutions in P_{t+1} are selected from the front (F_i) which are not included and the selection is based on crowding distance.

Step 4: After including all the solutions and forming new population P_{t+1} of size N then a new population Q_{t+1} will create by applying the selection operator. Here the selection operator is different, we have the crowding distance tournaments selection operator by which we will form Q_{t+1}. After that, we will apply mutation and crossover which is similar to GA.

Crowding distance tournament selection depends on the crowded-comparison operator ($\prec_c$) between the two solution. The comparison is based on two attributes, first is the non-domination rank of the solution (i_{rank}) and second is the crowding distance ($i_{distance}$). The rank shows the fitness of solution and crowding distance shows that how much the solution is closed to its neighbor. For example, we have to compare two solutions $i\ (i_{rank}, i_{distance})$ and $j\ (j_{rank}, j_{distace})$ with the crowded-comparison operator ($\prec_n$). If the rank of i (i_{rank}) is lower (better) then rank of $j(j_{rank})$ then i will be selected in tournament selection as a better solution. If the rank of i (i_{rank}) is equal to the rank of j (j_{rank}) then the crowding distance will compare. The solution whose crowding distance is more will be selected. The high crowding distance means it is a widely spread solution and it will improve the diversity in the population. Figure 4.2 shows the main procedure of NSGA-II, moreover the parameter of NSGA-II used for the proposed problem is shown in table 4.1.

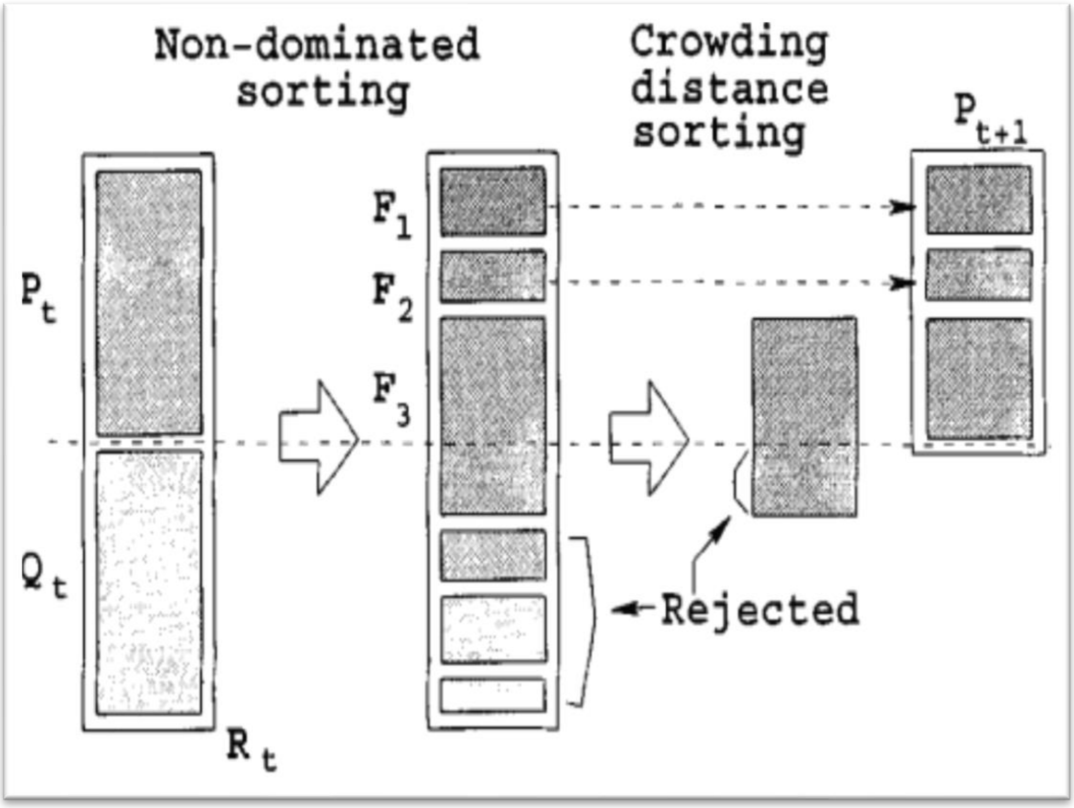

Figure 4.2: NSGA-II Procedure [21]

- Algorithm of NSGA-II for the proposed problem is explained in the following steps:

Step 1: Input the data of power system (IEEE 30-bus).

Step 2: Randomly generate the initial population P with N particles within the system: Comparative analysis of 30-bus system without SVCs and with SVCs limitation, number of 100 population has been taken in this work.

Step 3: Initialize the NSGA-II parameters and voltage of each bus, output power of generators, and possible location and possible size of SVC.

Step 4: Discretizing wind power generation with the help of a 5-point estimation method and create 5 scenarios.

Step 5: Run the power flow analysis by utilizing the Newton-Raphson method.

Step 6: Then sort the population based on the non-domination sorting concept, and evaluate the objective functions.

Step 7: If the algorithm has not yet found the lowest possible operation cost, power loss, and voltage deviation. Then new population $P_{t+1}$of size N will create for the new iteration, which is based on binary tournament selection.

Step 8: the end criteria will meet after searching all the scenarios.

Step 9: display the results.

Figure 4.3 represents the flowchart of the NSGA-II algorithm for the proposed problem. While the parameters of NSGA-II and choice factors for the proposed problem are recorded in table 4.1.

Table 4.1: NSGA-II Parameter and Decision Variables for Proposed Problem

Maximum iteration	100
Population size	100
Crossover rate	0.7
Mutation rate	0.4
Decision variables	Voltage of each bus, output power of generators, SVC location and size

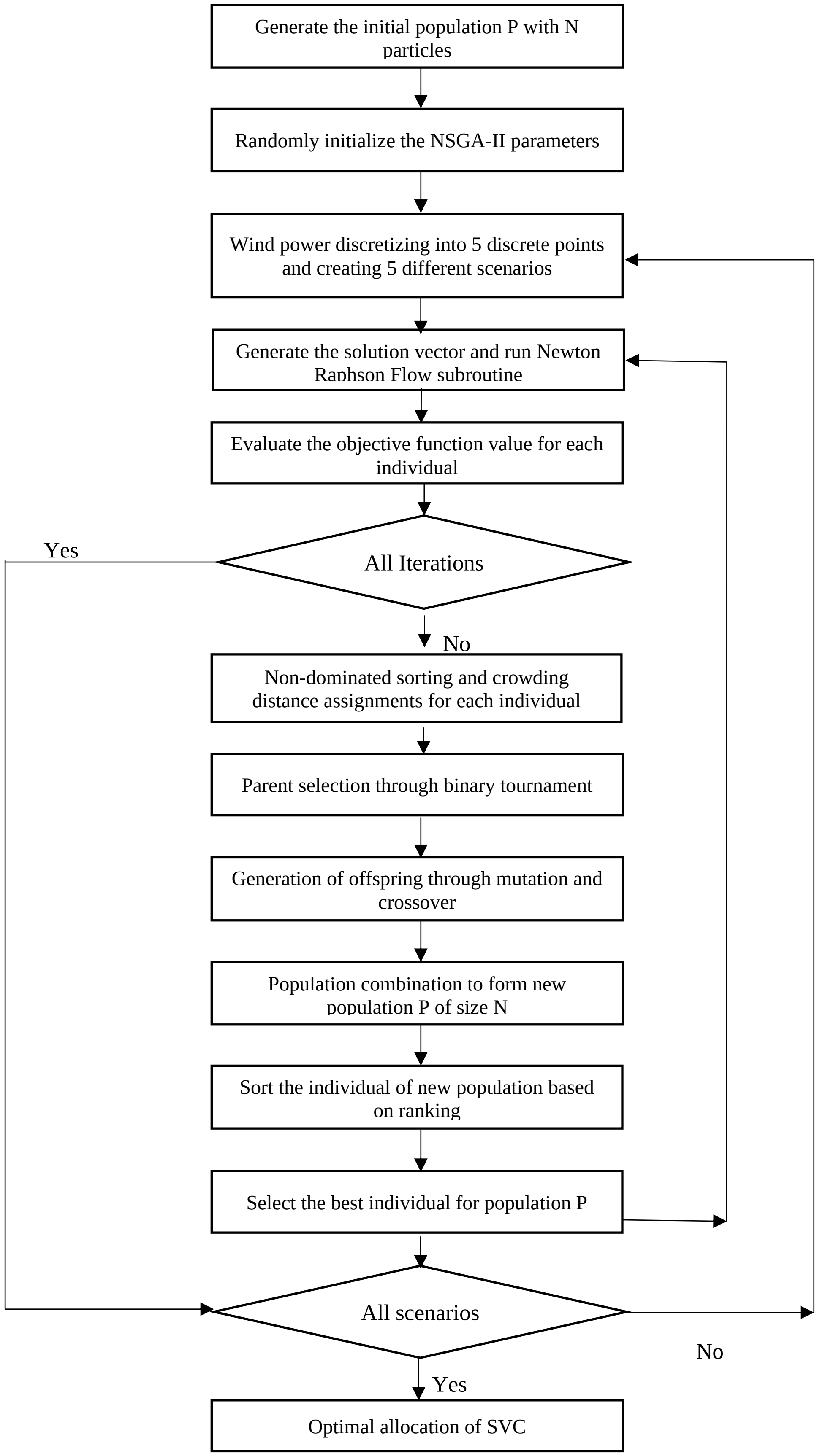

Figure 4.3: Flowchart of NSGA-II for the Proposed Problem

Chapter 5

RESULTS AND DISCUSSION

The applied method NSGA-II was examined on the IEEE 30-bus system in order to check its quality and strength. The code of NSGA-II has been programmed and executed in MATLAB 2018 environment on windows 10 Intel Core™ i3 Processor, 1.70 (GHz), 4.00 (GB) RAM.

5.2 Case Study

Here, standard IEEE 30-bus system is utilized for simulation purposes. The system consists of five generator units at buses 1, 5, 8, 11 and 13. Bus number 1 is refer as swing bus, buses 5, 8, 11, 13 are voltage control (PV) nodes, while the others are defined as load buses (PQ) nodes. Furthermore, the rated power of 113 MW a WT is connected to bus 2. The one-line diagram of modified IEEE 30-bus, which includes wind generation at bus 2 is shown in figure 5.1. The general network data is taken from [20].

For the load demand data, a case of daily load demand profile for a system in the city of 'Madison' is taken. The peak load demand of 283 MW has been picked as a max load condition to execute NSGA-II in the proposed case study.

According to the reference [22], the total operation cost of WT (c^{opw}) is taken as 30 ($/MWh) incorporate both the operation and maintenance cost.

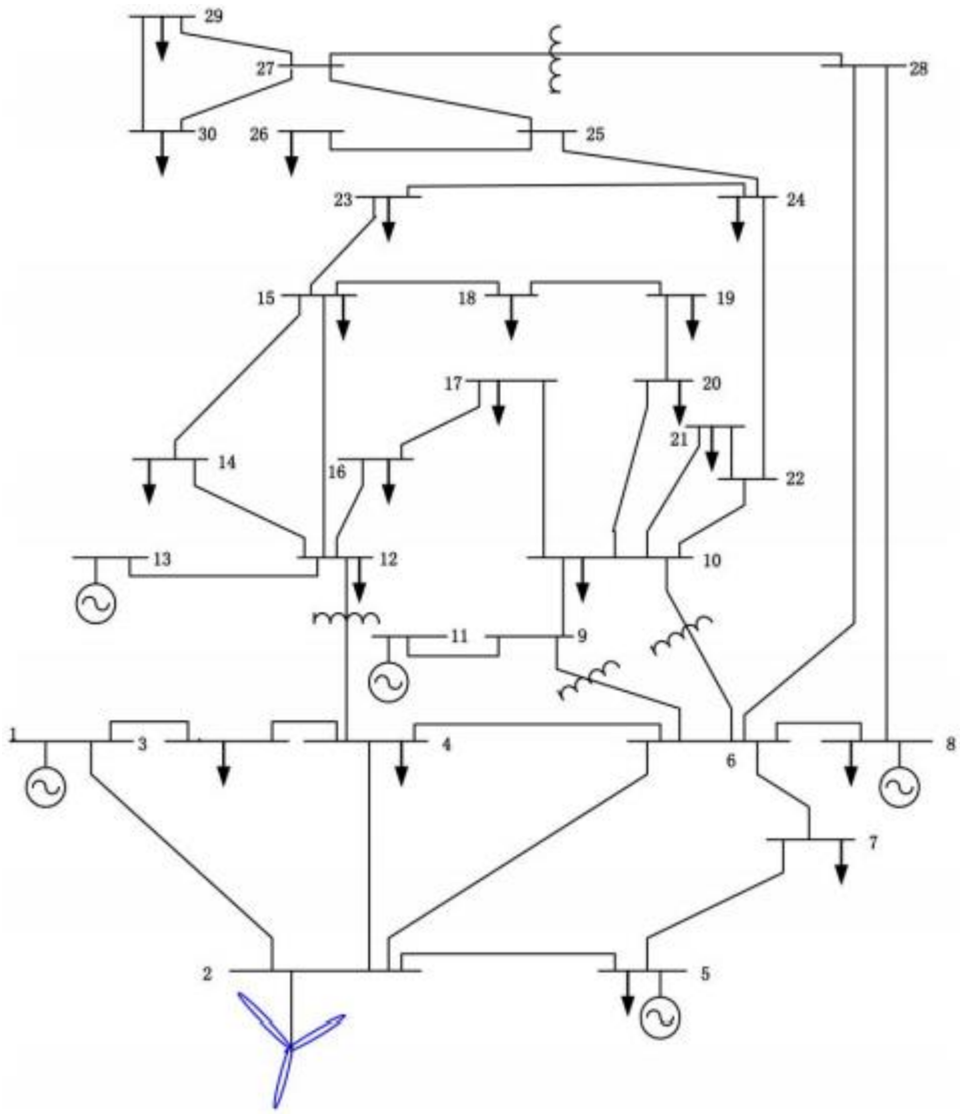

Figure 5.1: Modified IEEE-30 Bus System [20]

5.3 Simulation Results

Multi-objective evolutionary optimization NSGA-II algorithm is developed for determining the best allocation and sizing of SVC in the proposed test system. The algorithm is programmed and implemented in MATLAB environment. As a part of power flow analysis, Newton-Raphson technique is utilized which solved both equality and inequality constraints of the proposed problem.

In NSGA-II, considering the total wind generation, for each population, size of the SVCs for each bus are randomly initialized and with each iteration, the size at each bus is updated. Finally, the size of SVCs at certain buses becomes zero, which implies that there is no need to install SVCs in those certain buses. The capacity of SVCs at the remaining buses will converge to their ideal value. Furthermore, the network with the got capacity of SVCs is analyzed with the five scenarios of wind distribution which is discussed in the previous chapter. Tables 5.1 and 5.2 represent the estimated results. However, some of the different non-dominated solutions which are obtained in different iteration are shown in figure 5.2, figure 5.3 and 5.4.

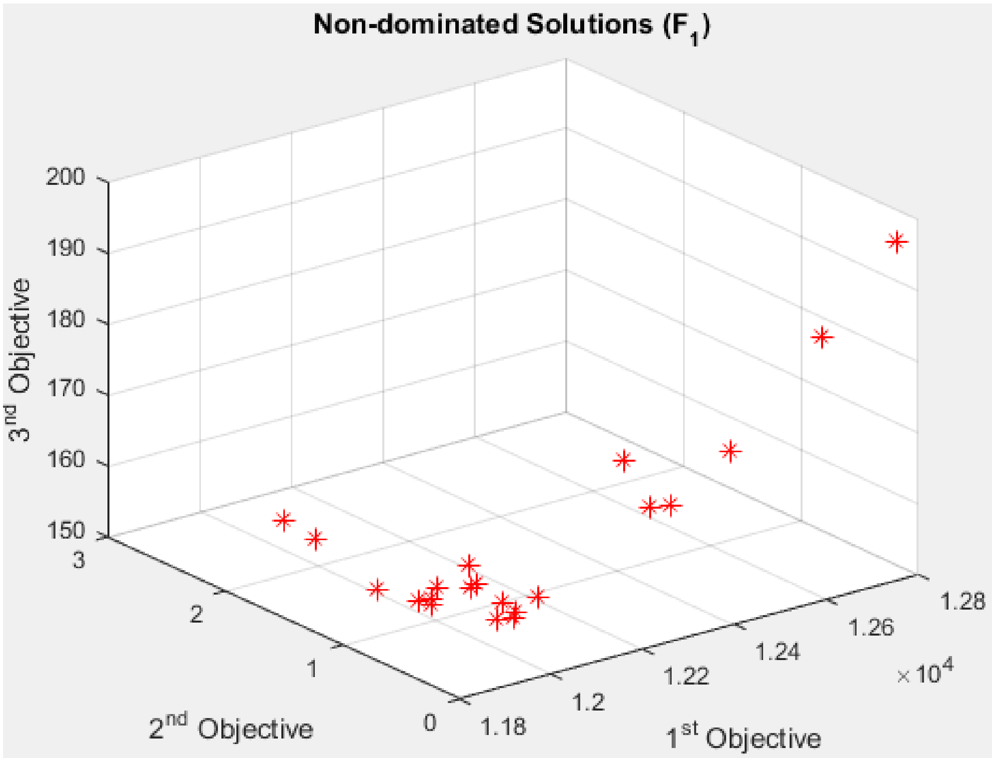

Figure 5.2: Non-dominated Solution at Iteration 10

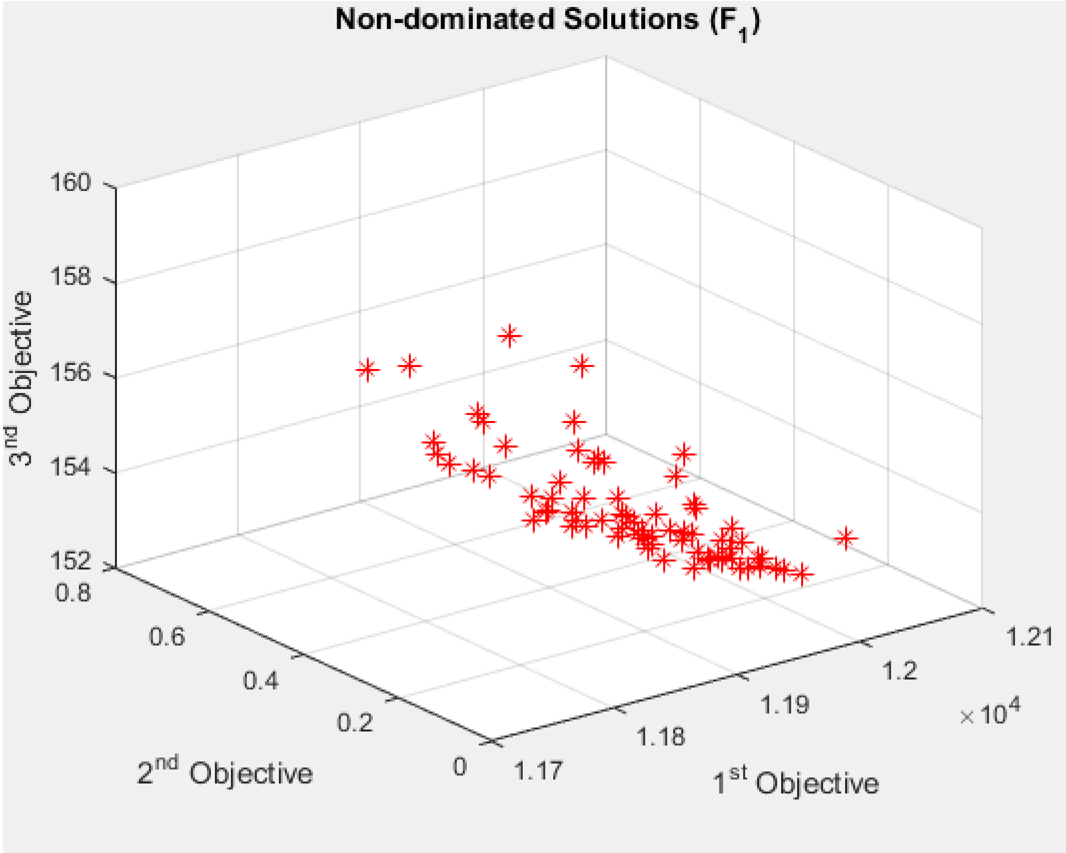

Figure 5.3: Non-dominated Solution at Iteration 30

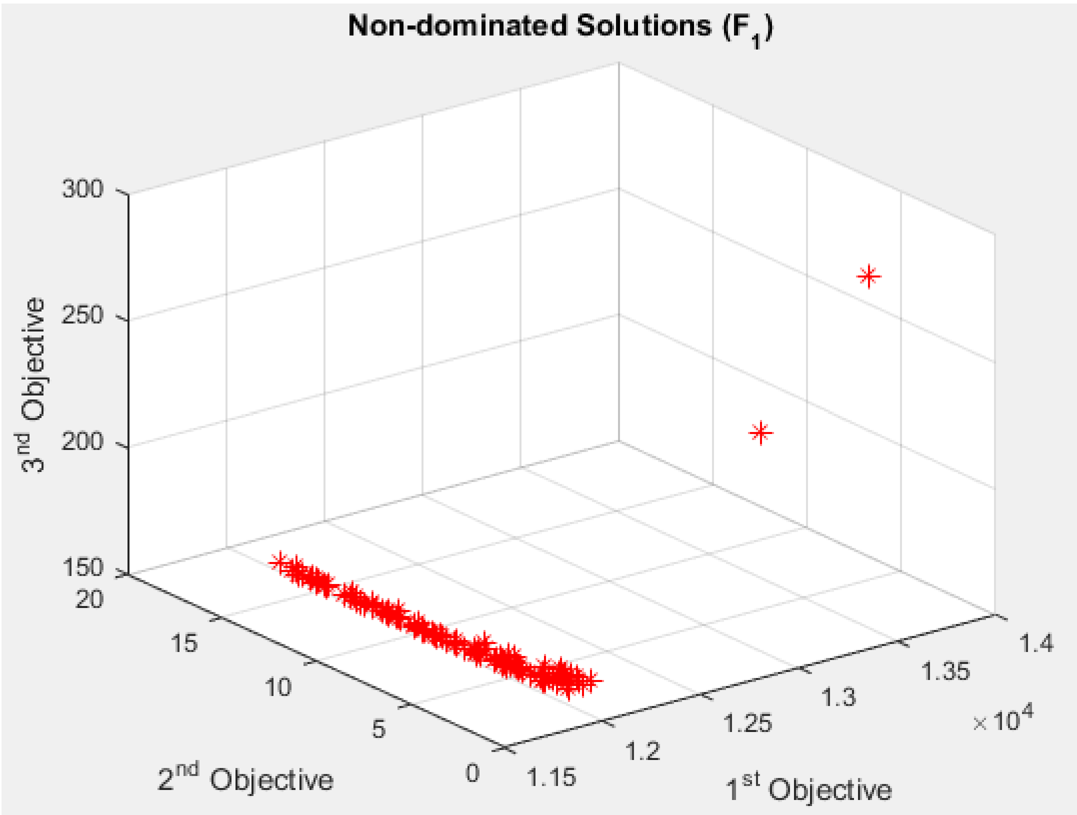

Figure 5.4: Non-dominated Solution at Iteration 100

Table 5.1: Optimal Generation Values of Different Generators Including Wind Turbine in 5 Scenarios.

Bus No	Generators	Scenario1	Scenario2	Scenario3	Scenario4	Scenario5
1	PG1(MW)	115.2152	100.2531	57.86646	15.20562	0.230497
2	Wind(MW)	0	14.50916	56.04459	98.36086	113.36
5	PG2(MW)	30.06893	30.06893	30.06893	30.06893	30.06893
8	PG3(MW)	20.31466	20.31466	20.31466	20.31466	20.31466
11	PG4(MW)	30	30	30	30	30
13	PG5(MW)	29.52778	29.52778	29.52778	29.52778	29.52778

The resultant best location of SVCs, the operational cost of generation, power losses, and voltage deviation are recorded in table 5.2. The rows which are highlighted in table 5.2 represent the main objectives of this work. Buses 5, 13, 16, 21, 27 are found to the best location for SVC with the sizes of 3.0780 MVar, 0.6051 MVar, 4.5427 MVar, 4.4846 MVar, 3.2279 MVar. It is clear from table 5.2 that system operation cost, power loss, voltage deviation, and power loss are reduced with an increment of wind generation, respectively. The total operating cost is reduced from 12041 to 11522 with the increase of wind power from 0 (MW) to 113 (MW). In addition, the power loss reduced from 9.050 MW to 6.66 MW with an increase in wind power contribution. The total voltage deviation and total operation cost function are represented in figure 5.5 and figure 5.6.

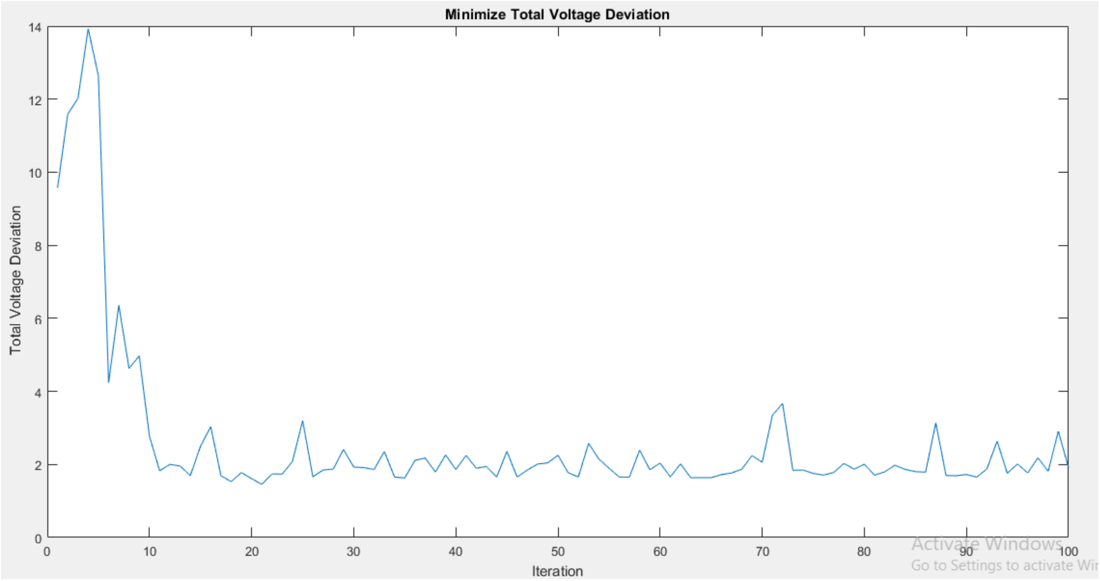

Figure 5.5: Total Voltage Deviation Function

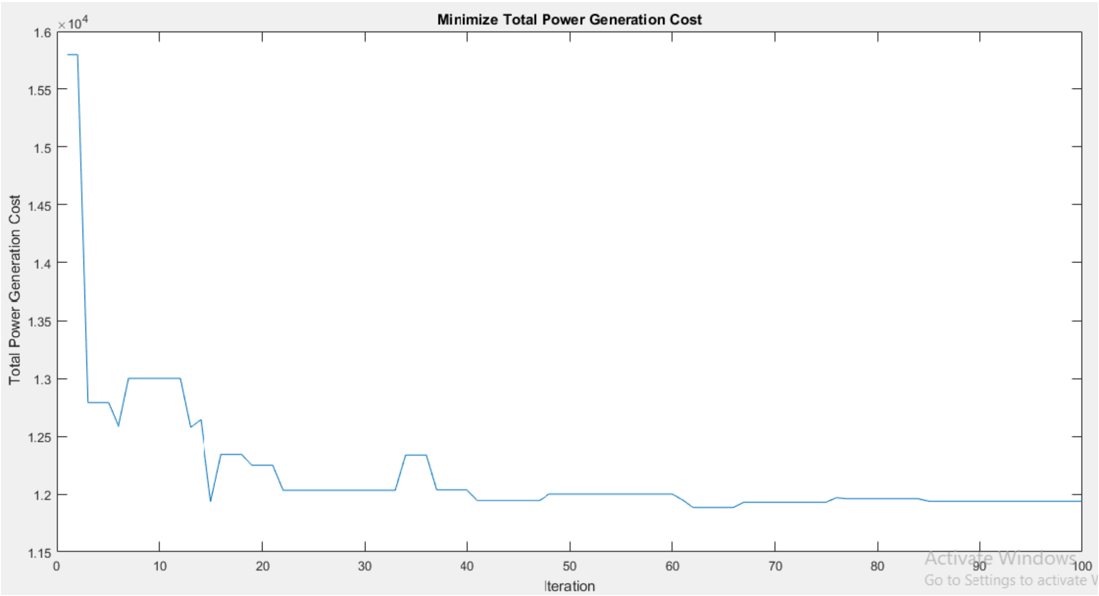

Figure 5.6: Total Power Generation Cost Function

Table 5.2: Results of NSGA-II Case of IEEE-30 Bus System

Wind Power (MW)	0	14.509	56.044	98.360	113.36
Probabilities	0.068	0.203	0.404	0.199	0.122
Power loss (MW)	9.050	8.571	7.250	6.766	6.666
Voltage Deviation (%)	1.735	1.823	1.829	1.831	1.833
Generation Cost($/h)	12041.06	11913.35	11650.56	11529.87	11522.40
Total Voltage Deviation (%)	1.810				
Total Generation Cost($/h)	11691.00				
Optimal Size (MVar)	3.078, 0.60, 4.54, 4.48, 2.22				

5.4 Comparative Analysis

Three case studies are considered for comparative analysis which are:

- Normal power flow analysis, considering wind penetration, without SVCs.
- Implement the NSGA-II algorithm, with SVCs but not considering wind power
- Implement the NSGA-II algorithm, considering total wind power, with SVCs.

Results achieved from the above case studies are recorded in table 5.3 and figure 5.7. From table 5.3 it is clear that after installing SVCs and wind power total voltage deviation, total system power loss and operation cost is minimized respectively.

Table 5.3: Comparative Analysis of 30-Bus System without SVCs and with SVCs

Objectives	Without SVCs considering wind power	With SVCs but not considering wind power	With SVCs considering wind power
Total voltage deviation (%)	2.74	1.735	1.810
Total operation cost ($/h)	12325	12041	11691
Total power loss (MW)	12.428	9.050	7.073

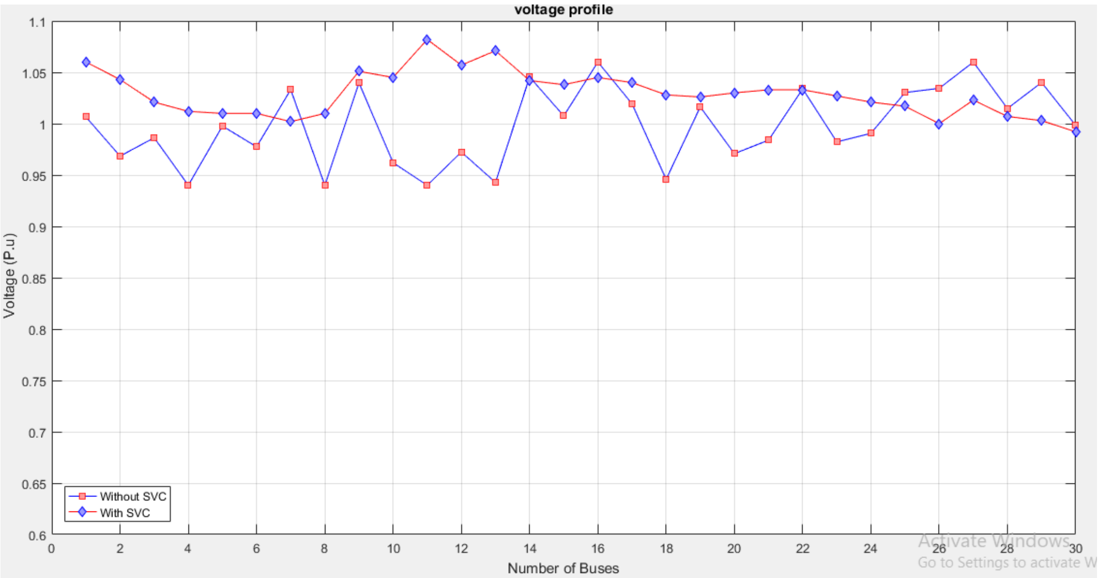

Figure 5.7: Voltage Profile of Modified IEEE 30-Bus System with SVC and without SVC

To validate the performance of the applied method NSGA-II, the present simulation results of this study are compared with previous work results like K.Jyotshna Devi et al. [23] and J.Vanishree et al. [24] and it is summarize in table 5.4. Table 5.4 shows the location and size of SVC, total voltage deviation and total power losses results obtained from the applied method and other methods in the literature.

Table 5.4: Comparison of IEEE 30-Bus System Results with other Algorithms

Methodology	Objectives			SVC location	SVC size (MVar)
	Total power loss (MW)	Total voltage deviation (%)	Total operational cost ($)		
Applied method (NSGA-II)	9.05	1.735	12041	5 13 16 21 27	3.08 0.60 4.54 4.48 2.22
HSA [23]	17.52	-	-	7 26	28.37 4.12
DA [24]	9.553	0.86	-	19	26.46

Chapter 6

CONCLUSION AND POTENTIAL DIRECTION

6.1 Summary

A multi-objective evolutionary optimization algorithm NSGA-II is applied in this thesis for determining the best allocation and size of SVC considering wind power uncertainty to minimize three objectives including total operation cost of a power system, total voltage deviation, and total power loss minimization. Newton-Raphson method is utilized for load flow analysis. Furthermore, a 5-point estimation method is used for discretizing the continuous power distribution of wind turbine. Five different scenarios are created to observe the effect of wind power penetration at a different level on power system network.

To confirm the performance of the proposed method IEEE-30 bus system is tested. SVCs are placed at the best location in the power system due to which the voltage profile of the power system is improved by 33.3% while total power loss is reduced from 12.428 MW to 7.073 MW.

6.2 Potential Direction

Future work may include the consideration of some other factors, which are not considered in this thesis. These factors are the selection of different FACTS technology and the investigation of their operation. There are various kinds of FACTs technology, it is important to select the right technology before optimizing the location and size of FACTs. In addition, analysis of FACTs operation is crucial to improve the system stability. Furthermore, FACTs controllers can be installed on wind farms for power quality improvement purposes.

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