WIND POWER GENERATION EXPANSION PLANNING BASED ON CAPACITY CREDIT MAXIMIZATION

BY

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Dedicated to my parents

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LIST OF ABBREVIATIONS

i, j	Indices of Areas
t	Indices of Hour
s	Indices for Scenario
I	Set of All Area of Wind Farm
S	Set of All Scenario
J	Set of All Area Receiving Power
T	Set of All Hours in the Study
x_i	Decision Variable of Wind Allocation
β_i	Upper Limitation of Wind Allocation In Area I
WC	Total Installation of Wind Capacity
CK_i	Capacity Outage Probability Table
q_i^t	Hourly Conventional Capacity of Area i
f_{ij}^t	Hourly Power Flow from Area i To Area j
D_i^t	Hourly Load Data for Area i
ω_i^t	Hourly Wind Data of Area i

CC_i	Capacity Credit of Area i
F_{ij}	Tie Line Capacity between Areas i and j (MW)
$C(.)$	Function Indicating Capacity Credit
Pr_s	Probability of Each Scenario
$\omega_i^{s,t}$	Hourly Wind Data of Area i for Scenario s
ωE_i^t	The Expected Value of Wind Data at Time t in Area i
$\mathbb{E}[.]$	The Expected Value
$f_{ij}^{s,t}$	Hourly Power Flow from Area i to Area J For Scenario s
CC_i^s	Capacity Credit of Area i for Scenario s
y_i^s	Incremental Load of Area i for Scenario s
$LOLE_{GEN(i)}$	Loss of Load Expectation for Conventional Capacity
$LOLP_{i\ WD}^t$	Loss of Load Probability after Adding Wind Power
$LOLE_{WD(i)}$	Loss of Load Expectation after Adding Wind Power
$LOLP_{i\ WDs}^t$	Loss of Load Probability after Adding Wind Power for Scenario s
$LOLE_{WDs(i)}$	Loss of Load Expectation after Adding Wind Power For Scenario s
PN	Pentation Level of Wind Power Plant

λ	The Membership Grade of the Solution
$\widetilde{CC}$	Fuzzy Sets for Capacity Credit
$\widetilde{W}$	Fuzzy Sets for Wind Power Parameter
$\underline{CC}$, $\overline{CC}$	Upper/Lower Limit for Capacity Credit
$\underline{W}$, $\overline{W}$	Upper/Lower Limit for Wind Parameter
u_{cc}	Membership Function of Capacity Credit
u_w	Membership Function of Wind Parameter

ABSTRACT

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This study develops a generation expansion model to find the optimal planning strategy of a new wind power generation. Generation expansion planning is the essential premise for the sustainable development of power system, especially with a high penetration of renewable energy generation. The proposed model specifies the size of wind power generation and finds out the optimal decision to allocate wind power among multi-area power system in order to maximize the capacity credit of a wind power plant.

Since the behavior of the wind speed is intermittent and variable, a fuzzy set has been developed to model the uncertainty of wind data by construction a membership function for each stochastic parameter. In addition, a stochastic model has been used to address the uncertainty of wind data by generating a number of scenarios. Among several methods of calculating the capacity credit of renewable power plant, Effective Load Carrying Capability (ELCC) has been used in this model as the objective function. ELCC represents the amount of additional load that can be served while maintaining the same reliability standard. The system under study is a multi-area power system in which each area has its own conventional capacity, its specific reliability data in addition to load profile as well as a specific wind data. A three interconnected power system example is studied to demonstrate the effectiveness of the proposed model to quantify the actual load carrying capacity of the intermittent power resources and to increase the reliability and the resilience of integrating new renewable power plant. This study is first stage analysis prior to economical analysis. It aims to evaluate the evaluable resources by increasing resources availability and reducing intermittency.

ملخص الرسالة

الاسم الكامل: حمود محمد غزال الشمري

عنوان الرسالة: نمذجة اعتمادية لرفع السعة الفعلية والتخطيط المثالي لمحطات توليد الكهرباء باستخدام طاقة الرياح

التخصص: الهندسة الكهربائية

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هدفت هذه الدراسة الى تطوير نموذج حتمي تزامني يساعد مهندسي ومخططي أنظمة الطاقة الكهربائية على وضع خطط توسيع السعة الحالية لمحطات توليد الطاقة، من خلال توزيع طاقة الرياح بشكل مثالي على اكثر من منطقة، لرفع السعة الكهربائية الفعلية لطاقة الرياح لأعلى حد ممكن، مما يساعد على رفع كفاءة طاقة الرياح والحصول على أعلى استفادة ممكنه من مصادر الطاقة المتجددة. ونظرا لطبيعة الرياح المتغيرة والمتقلبة، والغير قابلة للتنبؤ، فقد تم تطوير نموذج عشوائي يأخذ بالاعتبار الطبية المتغيرة للرياح. كما تم ايضاً تطوير نموذج مضبب لتضمين طبيعة الرياح المتغيرة داخل النموذج. والنظام الكهربائي الذي اقترحته الدراسة هو نظام كهربائي متعدد المواقع، بحيث يحتوي كل موقع على حمل خاص به، ومحطة توليد كهرباء، بالإضافة الى بيانات لطاقة الرياح لكل ساعة. ويرتبط النظام ككل بمواقعه المختلفة بواسطة خطوط نقل الكهرباء. لذلك فان هذه الدراسة تقدم اداة تمكن مهندسي الطاقة من الحصول على اعلى استفادة من المصادر المتجددة، ومعرفة تأثير توزيع الرياح على السعة الفعلية لطاقة الرياح .

CHAPTER 1

INTRODUCTION

1.1 Motivation

Due to the increasing demand for electrical power worldwide along with the constant electrification and automation in various sectors, electrical power grids need to be upgraded and more energy resources must be used. One of the main alternatives of conventional power resources is the renewable energy. It is clean and environmentally friendly and can reduce CO2 emissions, global warming, extreme weather and sea level rise. Likewise, the increasing demand for electricity and the change in the policy of energy generation in the Kingdom of Saudi Arabia to comply with the vision 2030 have raised the interest to understand, propose, and introduce an efficient method to expand the capacity credit of renewable energy resources such as wind and solar powers and so forth.

Recently, the global demand for renewable resources has grown dramatically as a result of the rising demand for electric power and energy security. The Kingdom of Saudi Arabia is among serval countries that still depend on fossil fuel for power generation. Consequently, the domestic consumption of fossil fuels for generating electricity is escalating annually. What adds up to this demand is the population growth and the rapid progress in the industrial sector. The annual growth of power consumption is about 7.5% [1]. In order to meet the increasing demand for power, KSA has already started to exploit the potential of renewable energy resources such as wind power, solar power, nuclear power and geothermal power.

Calculating the capacity credit is a very strong tool that helps system planners overcome the important issue of electric power system in determining the contribution of renewable power plants to reliably meet demand[2]. Furthermore, capacity credit is suited for system operators to account for ability for wind power to meet peak demands.

1.2 The Objective

This study proposed a generation expansion planning model (GEP) for optimal allocation of wind power generation in a multi-area power system based on maximizing the capacity credit (CC). Unlike the traditional GEP model which considers the cost as an objective function, the proposed model considers the capacity credit as objective function instead. Among several methods of calculating the capacity credit of renewable power plant, Effective Load Carrying Capability (ELCC) has been used to assess the capacity credit. Some previous studies have discussed the impact of wind allocation on the capacity of the transmission line. On the other hand, the proposed model of this study investigates the impact of allocating wind power in wide range on CC. The proposed model seeks the highest capacity credit which is inversely proportional to the Loss Of Load Probability (LOLP) of the system considering both the hourly wind data as well as the available conventional generation. Furthermore, number of factors that may have impact on CC have been investigated such as tie line capacity and the Correlation of wind resources between the areas.

Besides, in this study, the wait-and-see approach and the expected value approach of stochastic programming (SP) are used to deal with the uncertainty parameter and to check the robustness of the model. Furthermore, a fuzzy optimization model is constructed to address the uncertainty of wind data.

1.3 Thesis Outline

The rest of this thesis is organized as follows:

- Chapter two displays the literature review. It presents the generation expansion planning (GEP) and the global wind power potential. Additionally, the approaches of capacity credit of wind power plant and some stochastic programming techniques are revised along with fuzzy optimization.
- Chapter three presents the chronological model of GEP and discusses the methodology of ELCC explaining the chronological model formulation and a case study.
- Chapter four introduces Stochastic Programming (SP) model of GEP. This chapter discusses two of the SP approaches: wait-and-see approach and expected value approach which are used to address the uncertainty of wind data.
- Chapter five represents fuzzy optimization technique modeling of the uncertainty of parameter of the proposed GEP model. Similarly, problem formulation and case study reflect the optimization model using fuzzy approach represented in this chapter
- Chapter six represents the conclusion.

CHAPTER 2

LITERATURE REVIEW

1.4 GEP Using Renewable Resources

The Generation Expansion Planning (GEP) addresses the problem of finding out where, which, and when an extra power unit should be installed to serve the predicted energy demand over a long-term planning horizon. Solving the GEP problem is thought to be difficult due to several reasons. The first is the uncertainty associated with the input data, such as the predicted demand , wind speed and force outage rates. The second is related to a number of conflicting objectives that must be considered such as minimizing the total cost of the system and maximizing the reliability of the system [3][4].

As a result of the worldwide constant increase in electrical power demand caused by continuous electrification and automation in different sectors, an electrical grid is required to be upgraded. Also, more energy resources need to be used as generation expansion. Renewable energy is one of the main alternatives to fossil fuel because it is clean and environmentally friendly. It can also reduce CO2 emissions level, global warming, extreme weather and sea level rise. One of the main challenges of integrating energy production from renewables into the power system is the fact that the amount of power fluctuates according to weather conditions. Therefore, planning to integrate renewable resources requires accurate forecasting of the output power generated from different types of renewable resources [5][6].

Nowadays, wind power generation (WPG) is commonly utilized; and it is the fastest growing sector for electric generation among other renewable resources in the world [7]-[9]. The global wind power potentially utilizes 1.5 MW wind turbines at 80m of a hub height and projected a worldwide potential of 72000 GW [10][11]. The global capacity installation of wind turbines at the end of 2017 touched 539 GW, according to preliminary statistics published by World Wind Energy Association (WWEA)[12]. Where a 52 GW were installed in the year 2017, slightly more than in 2016 when 51.402 GW went online with the annual growth rate of only 10,8 %. When a 64 GW of wind power was installed in 2015 with a global growth rate of 17.2% that is more increasing than in 2014 (16.4%). World wind power generation reached 950 (TWh) in 2015 which amounts to approximately 4% of power generation in the world. The percentages of wind power in some countries have been amounted to much higher. Denmark generated electricity from wind power as 42% of its total electric generation in 2015 which is the reference load record worldwide. In Germany, a new record of 13% of wind power has been provided to serve the country's power demand in 2015 [13] [14]. In 2017, Europe installed 16.8 GW of wind power, and Germany has installed the highest capacity of wind power generation with 6581 MW. The total wind power installation in Europe has reached 177506 MW in 2017[15]. Also, Denmark has a new record by supplying 43.6 percent of Denmark's electricity consumption from wind energy resources in 2017, according to Denmark energy website [16].

There are several studies that discuss difficulties of large-scale wind energy integration from planning and operation perspective. Wind power generation is a challenging problem to overcome since wind power is known to be variable, intermittent and not dispatchable compared to conventional generators. Since, wind resources has limited predictability because of variable nature of these resources, This capitalized the boundaries between unit commitment (UC) functions, as well as the economic dispatch (ED) of committed units. Therefore, scientists proposed a new method of managing high variability by combining possible forecasts with the look-ahead scheduling to account for inter-temporal dependencies utilizing a small power system example. For operational challenges, some proposed a way to overcome these challenges by incorporating short-term wind prediction and by using more advanced hardware/software control of wind generators and operators. This way can modify the predictable element of wind energy supply more reliably and more efficiently or by storing portions of wind power locally [17].

Finding out the optimal allocation of wind power generation is crucial to the long-run operation of the electric power system [9]. In the past, installation of wind allocation was based on maximizing the expected annual energy production of a single turbine. Therefore, the wind farm installation was concentrated in high average wind speed locations. This way is valuable for a single investor to raise the return on investment. However, the case is different for energy supplier with high scale of wind installation due to the amount of power fluctuations in the total wind power output. The previous study has investigated the effect of wind allocation on the fluctuation of wind power in Germany. It concluded that the allocation of wind power optimally will stabilize the overall wind energy supply and will find out that the wind farm distribution in Germany is not optimal at all. [18]. Increase the transmission line capacity to send more power is another solution to extract the maximum benefit of renewability and overcome the operational problems of the increase in penetration that lead to unused power capacity[19].

Maintaining the power system reliability within technically acceptable bounds has continuously carried a significant priority to the policy makers. According to the above mentioned definition, one possible assumption is to give a zero value of capacity credit of WECS. According to this assumption, the renewable resources will be used to save fossil fuel and to reduce CO2 emissions, but this assumption will violate the economic constraint of the power system. The practical approach implies assigning a value for the WECS that represents its contribution to the power system adequacy. In other words, we assess the capacity credit of wind power plant according to lower operational cost of WECSs as these systems come first in the electricity market. Therefore, considering the capacity credit of wind energy conversion system (WECSs) shows a notable impact on the economics of the commercial scheme-based projects because greater capacity credit values lead to an enhanced economically such kind of projects [20].

Planning for future energy systems is a much harder and challenging issue because of the intermittent behavior of these resources, the difficulty of the long-term demand forecast in addition to the fact that the long-term forecast of wind power to the level of granularity is not possible. Capacity credit is an important aspect of long-term system planning. Since generators of renewable resources serve a lesser load than the rated capacity, therefore, the capacity credit of renewable power plants has been studied intensively recently.

One of these studies provides a probabilistic technique to assess the capacity credit of distributed generators (DGs) of renewable power using reliability aspect of the power system in the UK as they are targeting the supply of 20% electricity generation from renewable resources by 2020. It was concluded that the capacity credit changes according to various voltage levels to which wind generator turbines are connected to. In contrary to the different base case of LOLP, that does not affect CC [21]. Increasing the penetration level of the renewable energy will minimize the capacity credit of renewable power plant, but adding Battery Energy Storage System (BESS) enhances the ability to increase the penetration of the renewable energy to a specified level within the same CC. In contrast, the diversification of the renewable energy sources in the electric power system has a positive effect on the power system reliability. Also, there will be more enhancement with slight correlation among the output profiles of the renewable resources [22] [23].

There are several approaches to calculate the capacity credit of renewable power plant. One of them is the Effective Load Carrying Capability (ELCC). It is defined as the increase of the system load carrying capability at a fixed (LOLE) level due to the extension of a new generator, where the loss of load expectation (LOLE) and its reliability index measures the system adequacy and specifies the expectation of a loss of load events [24]. The ELCC technique is constructed to serve the reference load on the power system in order to maintain the same reliability standard of the power system. The primary ideas of effective load carrying capability have been well defined in [24] – [26]. First, the reliability level of the original system has been assessed without the renewable power resources. After renewable power resources have been added to the system, the system's reliability was calculated. Furthermore, an additional amount of load was added gradually so that the same reliability level of the original system is obtained. In the end, the additional amount of load that has been added represented the ELCC of the renewable power plant. Accordingly, we can define the capacity credit of any renewable power plant as the ELCC of that power plant.

Calculating capacity credit utilizing the ELCC can be a challenging process because the additional load has to be adjusted iteratively to obtain equality between the two LOLEs. These difficulties have directed the engineers to develop easier approximation methods to assess the capacity credit. These approximation methods decrease the computational difficulty by concentrating on the hours during which the power system is not likely able to meet the demand—typically hours with high loads or LOLPs [27]. One of them is The high-load hours' approximation approach which is the easiest method which can be utilized to achieve an approximation for a power plant’s capacity credit. This technique utilizes the average value of capacity factor of the renewable power plant through the highest load hours as an estimation of the capacity credit. The number of hours studied is important because the capacity factor calculated can be extremely sensitive to this parameter. This method gives a good approximation of capacity credit of renewable power plant that is close to the ELCC metric [28] [29].

The aim of the generation expansion problem (GEP) requires a minimum-cost capacity additional plan that meets the forecasted demand within a reliable criterion [30]. Therefore, a planning model that introduces the optimal strategy to plan the construction of a new generation while satisfying the technical and economical considerations is needed. A number of factors must be considered for any power system planning, either on the long term or short-term planning. These factors include the capacity credit of renewable power plant, optimal wind power allocation, and the size of renewable power needed to satisfy the additional amount of load. Unlike traditional power system expansion model that considers minimizing the overall cost, the proposed model considers CC as the objective function. It takes into account all the important factors which include finding out the optimal allocation of wind power generation in a multi-area power system and deciding the size of new power generation. This thesis proposes chronological model of GEP. Among several methods of calculating the capacity credit of renewable power plant, Effective Load Carrying Capability (ELCC) has been used in this model as the objective function This model seeks the highest capacity credit, which is inversely proportional to the loss of load probability (LOLP) of the system, considering the hourly wind data as well as the available conventional generation.

1.5 Stochastic Optimization

Linear programming optimization has a major contribution to several real-life applications with all robustness of LP in handling deterministic problems. However, it is still unable to accommodate solutions to problems that have some degree of uncertainty. The early method that can deal with uncertainty in LP was a sensitivity analysis which is not an efficient method for incorporating uncertainty in the model.

Nowadays, competitive and global business is intensely challenged. Making decisions that involve a percentage of uncertainty along with having the ability to deal and optimize such decisions is extremely important. Stochastic or probabilistic programming works with such kind of problems that have parameters which are described by stochastic or random variables of the optimization problem. The existence of variability is related to a number of reasons depending on the nature of the problem. It may have simple measurement errors and some data display information about future but the certainty cannot be known simply. Therefore, there was a necessity to find a new way that can sufficiently deal with uncertainty. At that time, stochastic programming (SP) emerged due to the issue of uncertainty which cannot be formulated in linear programming (LP) [31].The basic idea is how to derive an equivalent deterministic problem from a stochastic problem and to solve it by using familiar techniques. The ability of modeling SP is the main difficulty. The variability of SP can be counted for by using scenario tree. In this method, probability distribution function (pdf) of a stochastic parameter needs to be approximated by a discrete distribution of a specified number of outcomes. SP problem can be divided into three categories: the first one is distribution problems, the second one is recourse problems and the third is the chanced constraint problems[32]. The distribution in the category of distribution problem is related to that of the SP solution or objective function outcomes as the input varied. There is no relation between the distribution here and pdf that works with scenario generation.

SP distribution problem could be defined as the equivalent of sensitivity analysis in LP problem by varying the input to find out the variation in the output. There are two approaches to compute the objective function's distribution: the first one is the expected value and the second one is wait-and-see approach[32]. For expected value approach, the expected value of random variable takes place instead of all random variable, and so SP is reduced into LP. This method brings some intuitive insight into the model. Regarding wait-and-see approach, the objective function is calculated when there is no uncertainty. Then, the expected value of the objective function for a specified number of a realization is found out. This method is utilized to build up a picture of the objective function's distribution [33]-[39].

This thesis utilizes wait and see approach as well as expected value approach of SP to deal with the uncertainty of wind data and compare them with other optimization techniques.

2.3 Fuzzy Optimization

In many systems, the criteria of the performance, decision variable and parameter are not precise all the time. When the values of variables are difficult to be specified accurately, these variables are said to be uncertain or fuzzy. Probability distributions can be assigned to quantify the values that are uncertain. Alternatively, when it is better to describe the variables by qualitative adjectives such as clean or dirty, dry or wet and hot or cold, fuzzy membership functions can be used to quantify them.

Fuzzy set theory has been widely applied in the field of decision-making process in fuzzy environment. Many mathematical models utilizing fuzzy approaches have been developed to mitigate fuzziness problems. In 1965, Zadeh [40] introduced and established the concept fuzzy set theory in which membership functions have been used for describing and processing uncertain information.

Fuzzy optimization is well-known in decision-making process. Therefore, founding general and operable fuzzy optimization methods are important in both theory and application.

Fuzzy optimization has been used effectively to a number of power system operation applications. It has been used to model the uncertainties associated with the optimization of virtual power plant (VPP) operation before it bids into the external markets [41]. Also, the uncertainties of bidding V2G into markets are modeled using fuzzy optimization [42]. The advantage of fuzzy optimization among all optimization techniques is that the problem size does not increase significantly as the number of uncertain parameters increases because there is no need to generate number scenarios for each stochastic parameter.

This thesis proposes fuzzy model of GEP to deal with the uncertainty by generating a member ship function for each stochastic parameter in the model.

CHAPTER 3

CHRONOLOGICAL MODEL OF GEP

This study aims to develop a chronological expansion planning model in order to determine the size of a new generation capacity of wind power plant to meet demand and reliability level requirements. It also aims to find the optimal decisions to allocate wind power among multi area so that Capacity credit is maximized.

3.1 Capacity Credit

It is a critical part of long-term system planning. the idea of it fills the gap between the conventional system supply adequacy analysis and the variable behavior of renewable power. CC was first introduced to assess the load carrying capabilities of traditional power generation [24].

Methods for calculating CC can be categorized as reliability-based and approximation based methods. The first category comprises the Equivalent Firm Capacity (EFC) [43], Equivalent Conventional Capacity (ECC)[44] and Effective Load Carrying Capability (ELCC). The second category contains an Average capacity factor, Capacity factor during the peak-LOLP hours and Weighted capacity factor[45].

The reliability-based methods utilize the reliability indices of the power system which are in terms of loss of load probability (LOLP) and loss of load expectation (LOLE). one of the main advantages of the approximation technique is the simplicity but they vary in accuracy. Reliability based methods are widely accepted and considered accurate methods for calculating capacity credit [46].Table 3.1 shows Comparison Between Reliability-Based Methods and Approximation Techniques in terms of computational burden and data requirements[47].

Table 3. 1:Comparison Between Reliability-Based Methods and Approximation Techniques

Method	Type	Computational Burden	Data Requirements
Reliability-Based Methods	Equivalent Conventional Power (ECP)	High—LOLPs have to be iteratively computed to achieve equality between LOLEs when wind and benchmark units are added	Load and generator capacities and EFORs
	Equivalent Firm Capacity (EFC)		Load and generator capacities and EFORs
	Effective Load Carrying Capability (ELCC)	High—LOLPs have to be iteratively computed to achieve equality between LOLEs when wind and load are added	Load and generator capacities and EFORs
Approximation Methods	Average capacity factor	Low—At most, LOLPs must be computed once, if peak-LOLP or weighted capacity factor methods are used	Loads and generator capacities and EFORs
	Capacity factor during the peak-LOLP hours.		
	Weighted capacity factor		

3.2 ELCC Methodology

Generation system reliability is a critical part of making plan for generation expansion to sufficiently satisfy the extra load demand in the future. Therefore, some reliability indices will be introduced here as they are necessary to evaluate the ELCC.

3.2.1 Force Outage Rate (FOR)

The most common quantities in power system reliability assessments are the generation capacity and the failure probabilities of each power units. For two states model in unit operation, the failure probability of the unit can be expressed by unavailability U that can be written in terms of the unit failure rate λ and repair rate μ in given equation.

$$U = \frac{\lambda}{\lambda + \mu} \tag{3.1}$$

Where, λ is unit failure rate, μ is unit repair rate and U is unit unavailability

In general, the unavailability of generation unit is well known as Force Outage Rate (FOR). FOR is defined below:

$$FOR = \frac{Force\ outage\ hours}{In\ service\ hours + Forced\ outage\ hours} \tag{3.2}$$

The FOR is calculated for a long period of time (e.g. 365 days). It is the same index as the unavailability. force outage rate (FOR) of conventional power generation tends to range between 2% and 20%. This implies the availability of a conventional generator between 80% and 98% whereas the availability of wind energy varies in an average between 30% and 45%.

3.2.2 Capacity Outage Probability Table (COPT)

A power system typically comprises of a big number of generating units of various types, capacity, and reliability in parallel operations. Every unit is accepted to have two states a system with n units has 2n capacity state. COPT is a table that contains generation outage states and the corresponding probability of each state. Table 3.2 presents simple COPT of a power system that has only one power unit that has to state either up - generating C (with capacity outage 0) at probability A- or down -generating 0 (with capacity outage C) at probability-U.

Table 3. 2:COPT

Capacity Outage	Probability
0	A
C	U

3.2.3 Loss Of Load Probability (LOLP)

A power system is constructed to meet the power demand of the consumer momently, but failures still appear in the system when demand exceeds supply. In general, demand can exceed the generation for many reasons. One of these happens due to the random deviations of the load especially at peak load that exceeds the installed capacity of a power system. Generally, power system planners avoid such unexpected variations in demand by means of reserve margin of the capacity. When a power system is unable to meet the peak load, this means the demand exceeds the available generation capacity of a power system. Consequently, when there is a shortage of power, the overall probability is called a loss of load probability (LOLP).

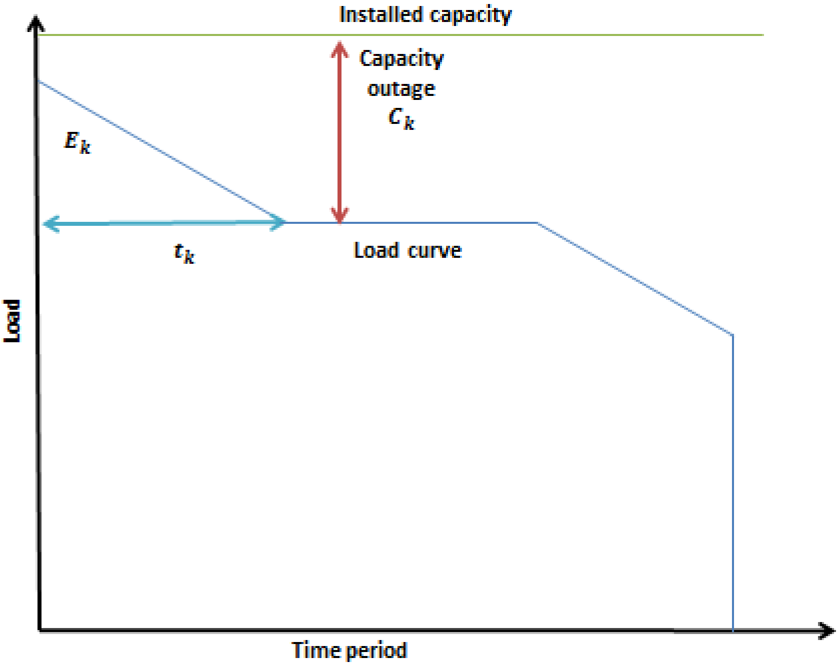

Figure 3. 1:Graph illustrate LOLP Concept

LOLP is expressed in terms of percentage of time, or as a day per year or an hour per day in case of the loss of load expectation (LOLE) which is the accumulated amount of time during which a shortage of power is experienced. LOLP equation can be presented in equation (3.3).

$$LOLP = \sum P_k \, (D_{\max.} > IC) \tag{3.3}$$

For the LOLE index, it is widely used as probabilistic approach in system reliability assessment for power generation. It required two kind of models, first one is Load model, and the other one is COPT. These models are combined together in the process to evaluate LOLE of the system.

The units of the LOLE are calculated in days per year (d/y). The LOLE evaluation method is expressed in the following mathematical formula:

$$LOLE = \sum t_k P_k \left(D_{\max.} > IC\right) \tag{3.4}$$

It is clear from the load characteristics explained in Figure 3.1 that if the capacity outages are less than the reserve, this will not cause a loss of load. Consider now: C_k is the k_{th} outage state in the COPT, P_k is the probability of this k_{th} outage and t_k is the number of time units for which this outage cause loss of load.

3.2.4 ELCC Calculation

To calculate ELCC, the needed data has to contain hourly load as well as hourly wind data. For a conventional generator, the installed capacity and the force outage rate are required so that the LOLE and capacity outages probability table (COPT) can be calculated.

Steps to calculate ELCC of renewable power plant are described below:

First, $\mathrm{LOLE_{GEN}}$ for conventional generator of original system without wind plant is calculated using the following formula:

$$LOLE_{GEN} = \sum_{t=1}^{T} LOLP(t)_{GEN} \tag{3.5}$$

Where T is the number of hours of the study, and $LOLP(t)_{GEN}$ represents the hourly loss of load probability. Then, wind power plant is added to the system and $LOLE_{WD}$ is calculated as:

$$LOLE_{WD} = \sum_{t=1}^{T} LOLP(t)_{WD} \tag{3.6}$$

After that, additional load (∇D) is added to the system, then $LOLE_{(NEW)}$ is calculated. We keep incrementing this load (∇D) until the LOLE of the system with wind equal to the standard LOLE of the original system and finally, the determined value of CC = ∇D .

3.3 System Configuration

The system under study is a multi-area power system where each area has conventional power plant and a specific load profile. All areas are interconnected together by tie lines so that it is possible to send power among them. Also, distinct wind profile for different location is assigned to each area. This system will be under study as generation expansion plans to see the impact of allocation of wind power among multi-area on the capacity credit, to construct a planning model that can determine the size of wind generation as well as finding out an optimal allocation of wind power targeting maximum capacity credit. An example of a multi-area power system is illustrated in Figure 3.2.

3.3.1 Load Model

The load is a main component of a power system that is a stochastic process in any time which is difficult to describe with a simple mathematical formula. For this study, a chronological load profile on an annual basis is utilized. The hourly load is developed by multiplying the per unit values by the annual peak load. Since multi-area power system is under study, different hourly chronological load profiles will be assigned for each area. The hourly chronological load profile for one area will be derived from RTS load data. This data consists of the percentage of maximum weekly load in a year, the load in 24 hours in a typical day in each season and the maximum load in each day in a week. The hourly chronological load model of 52*7 = 364 days can be established. The loads data for the other areas have been taken from Belgium Electricity Operator which is available on their website (ELIA)[48].

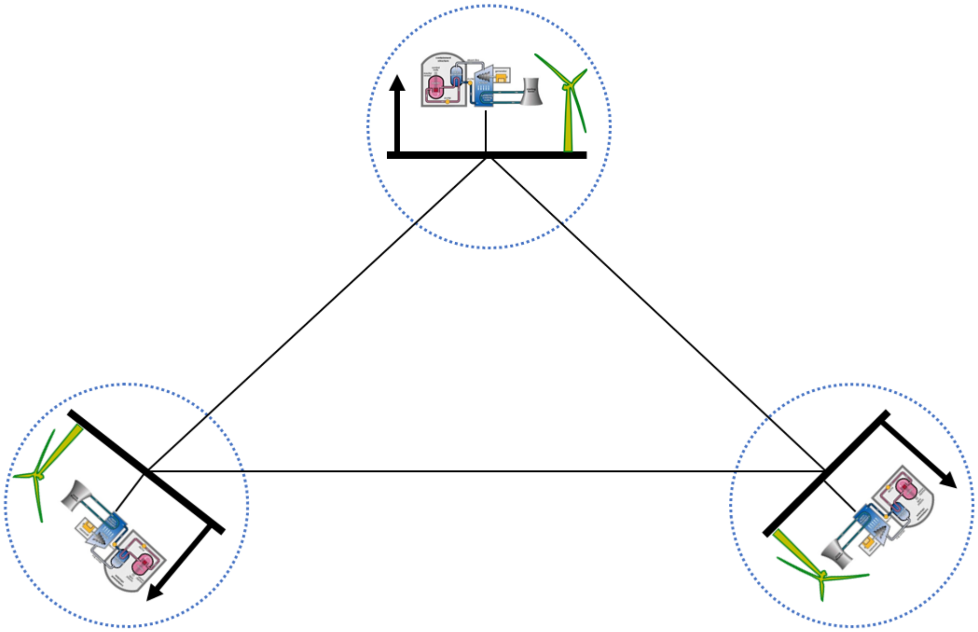

Figure 3. 2:Multi Area Power System Example

3.3.2 Wind Model

The chronological model requires hourly chronological load data as well as wind data. For that reason, the wind samples used in this study were taken from NREL website for different locations[49]. These data sets have hourly measurements of wind power for several stations across the USA. Distinct wind profile of 8736 hours has been assigned for each area in the study.

3.4 Problem Formulation

Generation planning faces the problem of finding the optimal strategy to plan the construction of a new generation while satisfying technical and economic constraints. Renewable energy is the most promising sector in power generation since it is sustainable and will never run out. Hence, renewable energy projects can bring economic benefits to many regional areas. A renewable energy generator has recognizable properties compared to a conventional power generator, and since renewable one has special impacts on the functional properties and operation of a power system. Power system planner must guarantee that a reliable supply of power is maintained even with the increasing share of renewable energy in a system. Considering CC is useful to Any renewable energy planning because it is the effective capacity that ensures meeting the demand. This concept is important for the plans for the expansion of electricity generation. In general, any effective planning of new generation units is an optimization problem that includes answering of the associated three questions to guarantee that installed generation capacity sufficiently serves the predicted growth demand over a medium to long-term planning horizon:

- What kind of generation technology should be used?
- How much is the size of a new generators (MW)?
- Where should these generators be allocated?

The proposed model specifies the size of a new wind generation designed to meet demand and reliability level requirement as a generation expansion planning. It decides the optimal allocation of wind generation among multi-area based on the maximum capacity credit.

I. Objective Function

Unlike traditional objective function of generation expansion planning that focuses on minimizing cost, the capacity credit is taken as an objective function. Therefore, the objective function to be maximized is the capacity credit of wind power plant.

$$\mathrm{MAX}\ (\textstyle\sum_{i\in I} CC_i) \tag{3.7}$$

II. S.T

$$0 \le x_i \le \beta_i \tag{3.8}$$

$$\sum_{i\in I} x_i = WC \tag{3.9}$$

$$LOLP_{i\ WD}^{t} = \Pr\left(C_K > \left(\omega_i^t * x_i q_i^t - \sum f_{ij}^t + \sum f_{ji}^t\right) - \ (D_i^t\ + \nabla D_i\ )\right)$$

$$\forall i \in I, \forall t \in T, \forall j \in J \tag{3.10}$$

$$LOLE_{WD\,(i)} = \textstyle\sum_{t=0}^{T} LOLP_{i\ WD}^{t}$$

$$\forall i \in I, \forall t \in T \tag{3.11}$$

$$LOLE_{WD\,(i)} = LOLE_{GEN\,(i)} \qquad \forall i \in I, \forall t \in T \tag{3.12}$$

$$CC_{i=} \frac{\nabla D_i}{WC} * 10 \qquad\qquad \forall i \in I \tag{3.13}$$

$$-F_{ij} \le f_{ij}^t \le F_{ij} \qquad \forall j \in J\ , \forall i \in I, \forall t \in T \tag{3.14}$$

$$0 \le q_i^t \le IC \qquad \forall i \in I, \forall t \in T \tag{3.15}$$

$$0 \le WC \le \text{PN} \tag{3.16}$$

∇D_i Stands for the additional amount of load that must be met after n year in an area where

$\nabla D_i = D_{peak}^{i}*\text{A}*\text{Y}$ where

A stands for percent of annual increase in demand

Y stands for the number of planning year

The first equation represents the objective function that maximizes the sum of capacity credit (CC) in all areas, where i is the index of area that belongs to the set of all area denoted by I. x_i is the decision variable which represents the installed capacity of wind power in area i. The constraints (3.8) show that the wind capacity x_i in each area is limited to an upper limitation β_i due to several conditions such as the environmental condition or social concerns. Equation (3.9) introduces the size of wind generation needed to expand the existing power plant to meet the increasing amount of load where WC is the decision variable of the size of the wind generation installation. $LOLP_{i\,WD}^{t}$ in equation (3.10) shows the hourly loss of load probability of the system after adding the wind power plant in area i where $LOLE_{WD\,(i)}$ indicates the loss of load expectation of the system that contains both types of generation: the conventional and the wind. The constraint (3.12) emphasizes the reliability level requirement by serving the additional amount of load by new wind generation. The constraint (3.13) represents the capacity credit formulation whereas the constraint (3.14) imposes the power flow for each area with tie line capacity. In equation (3.15), the hourly conventional power is limited to the capacity of the conventional capacity of each area. However, the constraint (3.16) is necessary to keep the penetration of wind power capacity at an acceptable level of the existing conventional power capacity. This is because the increasing of the penetration level of renewable power will decrease the capacity credit of the renewable power plant. Figure 3.3 shows algorithm framework of the proposed model.

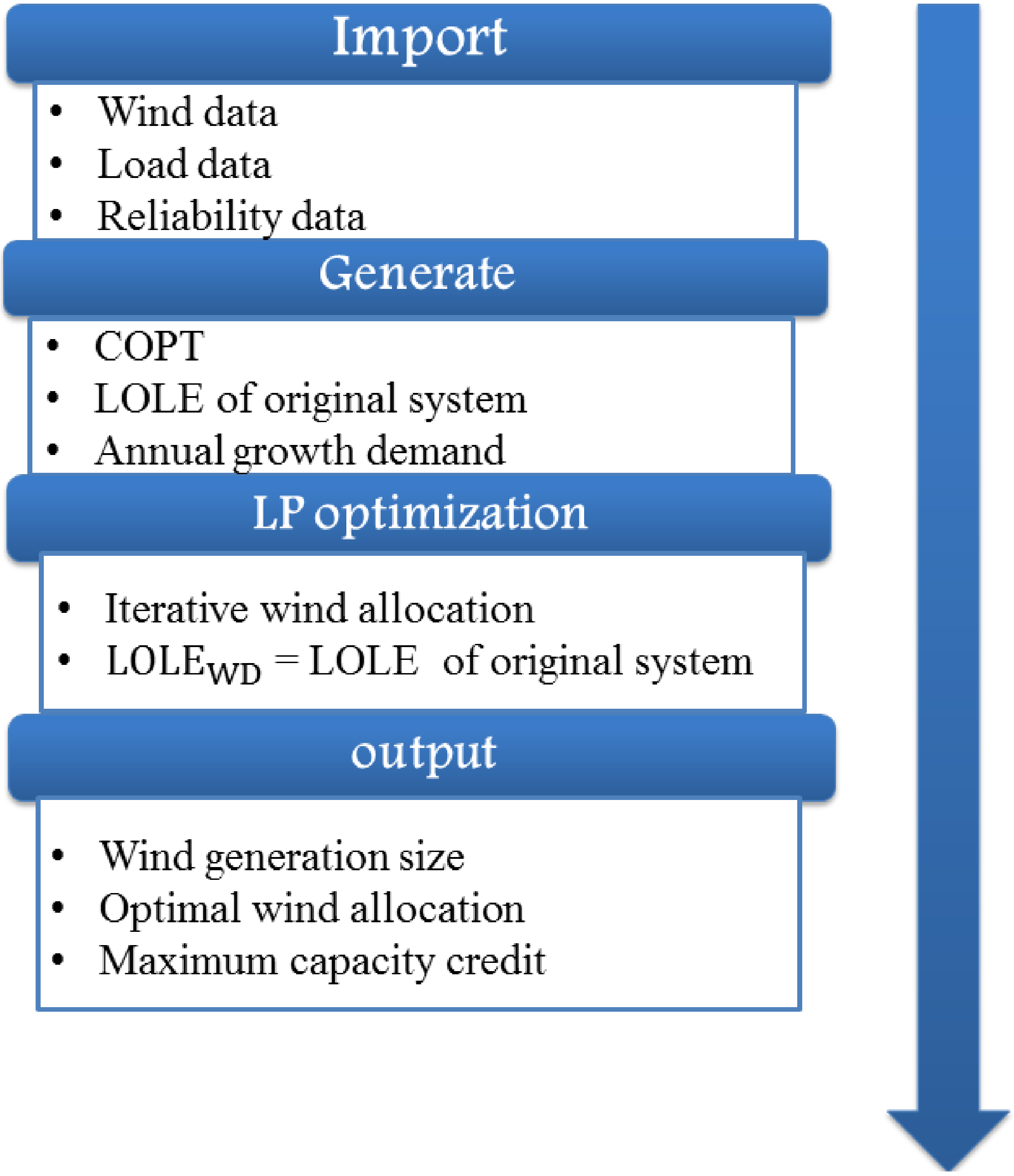

Figure 3. 3:Algorithm framework

3.5 Case study

A case study is used to investigate the chronological model that has been developed to expand the generation capacity of the existing power system and to investigate the impact of wind power allocation among multi-area on the capacity credit of wind power. Therefore, three areas of power system have been considered and all are connected by tie lines as it is shown in Figure 3.4. Each area has its own conventional power capacity and its specific wind profile and load. Both the conventional capacity and the peak load for each area are listed in Table 3.3. The load data for area one has been taken from RTS system whereas the load data for other areas have been taken from Belgium electricity operators that are available on their website (ELIA). The generating unit reliability data for all areas have been arranged and listed in Table 3.4, Table 3.5 and Table 3.6.

Table 3. 3:Power System data For original System

Area i	Load base case MW	Conventional capacity MW
1	445	560
2	550	696
3	600	751

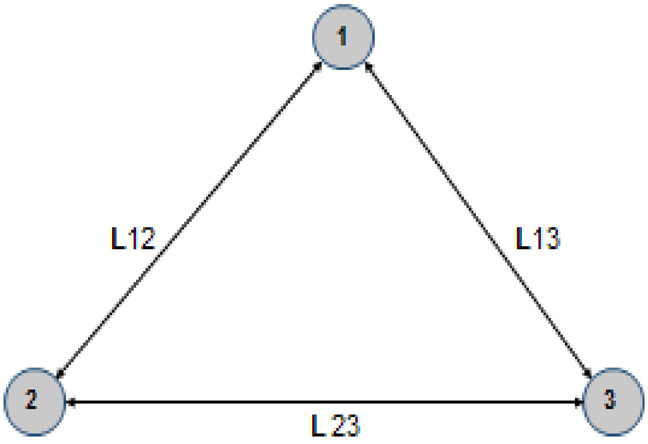

Figure 3. 4:Power System Configuration

The Generating unit reliability data has been taken from IEEE_RTS system which states: unit size, number of units and Forced outage rate. Accordingly, the capacity outage probability table (COPT) is calculated.

Table 3. 4:Reliability Data For Area 1

Unit size (MW)	NO# unit	FORs
12	5	0.02
50	4	0.01
100	3	0.04

Table 3. 5:Reliability Data For Area 2

Unit size MW	NO# unit	FORs
12	3	0.02
20	2	0.1
155	4	0.04

Table 3. 6:Reliability Data For Area 2

Unit size MW	NO# unit	FORs
20	3	0.1
50	2	0.02
197	3	0.05

The wind data has been taken from NREL website. The available data measures wind power generation every hour for one year for three distinct locations. The line capacity has been listed in Table 3.7.

Table 3. 7:Line Capacity

Line NO#	Capacity
L12	80 MW
L12	70 MW
L23	120 MW

I. Methodology

Since demand of power system increases annually, the percentage of annual demand increases and the number of years in the study for expansion power generation needs to be defined. First, the reliability data of the original system is calculated before generation expansion takes place. Then, 6% of annual demand growth will be considered as ∇D_i which defines the incremental load added to each area for one year as the period allocated to this study. After that, the reliability data of the system will be calculated after one year when the load is increased by 6%. So, the load data will be $(D_i^t + \nabla D_i)$. Finally, CVX solver will be used to solve the optimization problem to find out the size of the new wind generation to satisfy demand and to enhance the reliability to reach the standard level. Also, the optimal allocation of wind power among three areas will be found based on maximum capacity credit.

II. Result and analysis

The Reliability Assessment of the existing power system for each area as loss of load expectation (LOLE) in (hour/year) unit is calculated and listed in Table 3.8. Figure 3.5 shows the original reliability curve.

Table 3. 8:Reliability Assessment Of Original System

Area *i*	LOLE Base case(h/y)
1	5.58
2	18
3	41

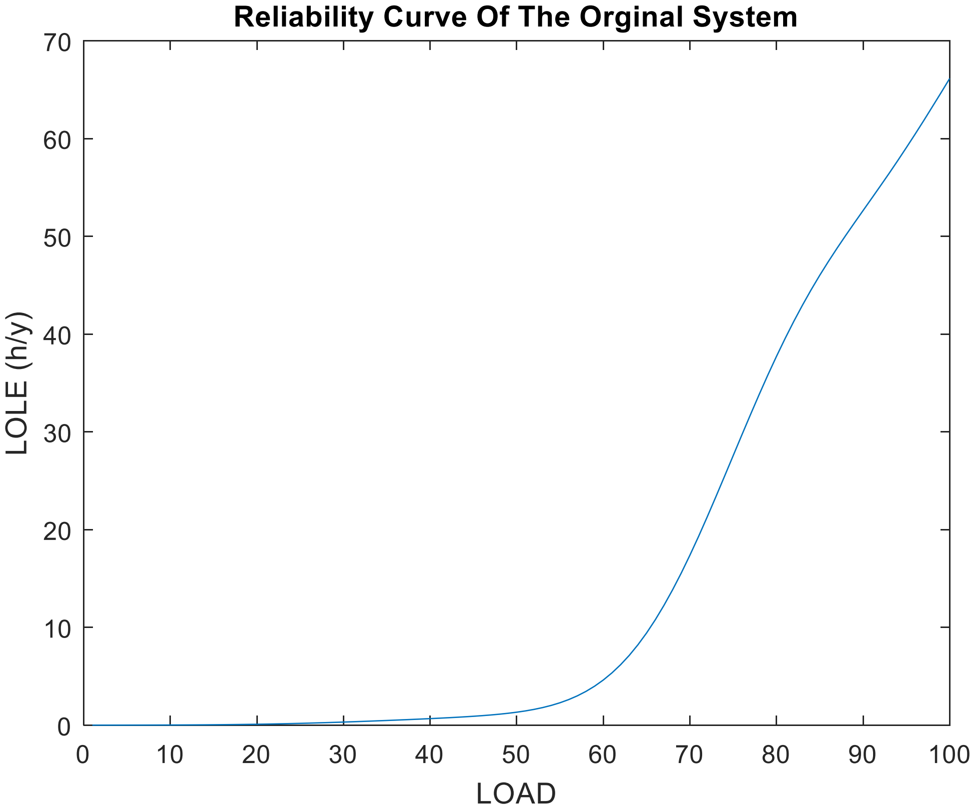

Figure 3. 5:Reliability Curve of the original System

Due to the annual growth rate that is assigned to be 6% of peak load of each area for one year as the allotted period for this study, this implies that the total increasing amount after one year is 6% of each peak load for each area. New peak load for each area due to additional amount of load ∇D_i is listed in Table 3.9.

Table 3. 9:New Peak Demand

Area i	Peak Load after 1 year (MW)
1	471.7
2	583
3	636

The LOLE of the power system after one year will be increased due to the annual growth rate. The Reliability assessment of the new system is listed in Table 3.10. Figure 3.6 shows the reliability curve for the system after one year with new peak load.

Table 3. 10:Reliability Assessment After One Year

Area *i*	LOLE(6%) after 1 year
1	10.57
2	32.9
3	57

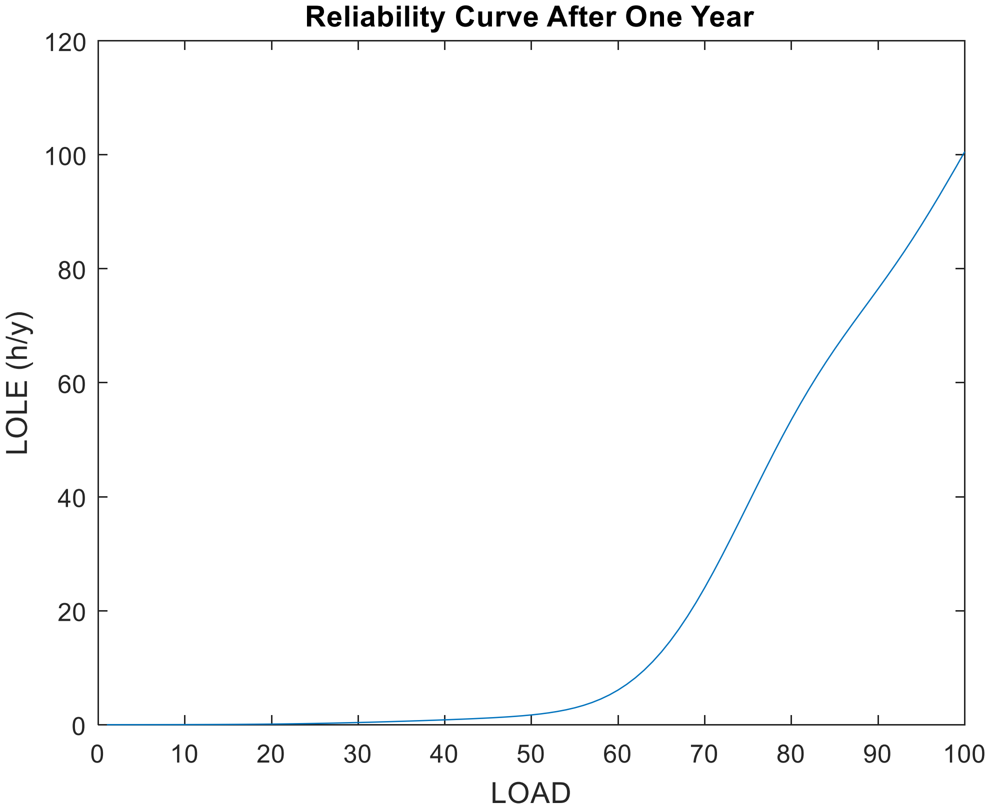

Figure 3. 6:Reliability Curve After One Year

It is obvious that the system after one year has more LOLE compared to the LOLE a year before. This is due to the annual growth demand as it is shown in Figure 3.7. The objective of power system planner is to decide how to maintain the reliability level to the standard level exploiting the resources in optimal manner.

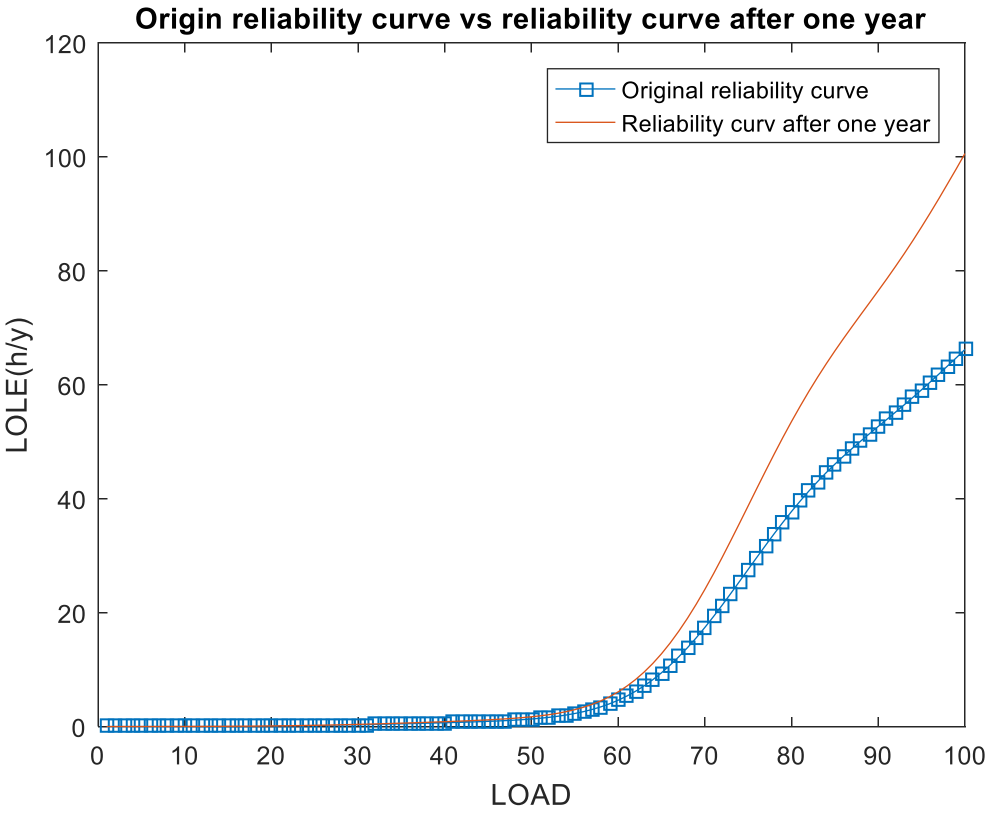

Figure 3. 7:Original Reliability Curve Vs Reliability After One Year

The optimization problem was solved and The wind generation expansion capacity and the optimal allocation are found. This serves the demand after one year and meets the reliability standard. The result of the optimization problems is listed in Table 3.11.

A number of cases were generated and tested in order to compare them with the optimal wind power allocation. For the optimal case, the wind power size is 326 MW and the CC of 29.3% with the optimal decision of wind allocation is 44 MW in area1, 147 MW in area 2, and 135 MW in area 3.

Table 3. 11:Result

Area i	Wind allocation x_i	Wind Generation Capacity (WC)	Capacity credit (CC)
1	44 MW	326 MW	29.3%
2	147 MW		
3	135 MW		

In this way, we can see the impact of each scenario on the capacity credit and the superiority of allocating wind power among multi-area. For the first case, we install all wind power in area 1 and we run the power flow. Then, the capacity credit is calculated. For the second and third case, all the wind power is installed in area 2 and area 3 respectively. The optimization problem was solved, and the results of all the cases are listed in Table 3.12 and Table 3.13.

Table 3. 12:Result of CC For All Cases

Area i	Wind Power Allocation (MW)			
	Case 1	Case 2	Case 3	Optimal wind Allocation
1	326	0	0	44
2	0	326	0	147
3	0	0	326	135
CC	12%	18%	22%	29.3%

The capacity credit for the first case is 1 is 12%, for case 2 is 18% and for case 3 is 22%. It is obvious that among the three scenarios, the third case is the best while the first one is the worst.

Regarding the optimal wind allocation, we can conclude that the distribution of wind among multi-area will maximize the capacity credit which is around 29.3%. Consequently, power system planner will have a clear vision of the best use of renewable resources and is able to obtain the maximum benefit of these resources.

Table 3.13 shows the loss of load expectation is reduced due to the wind installation. Since the capacity credit is proportional to the reduction of LOLE, it is expected that the optimal wind case has the least LOLE.

Table 3. 13:LOLE For All Cases

Area *i*	LOLE (h/y)			
	Case 1	Case 2	Case 3	Optimal Wind Allocation
1	4	8.9	6.4	5.2
2	28.35	16	27.7	17.6
3	52.3	49.7	35	41.28
Total	84.65	74.6	69.1	64.1

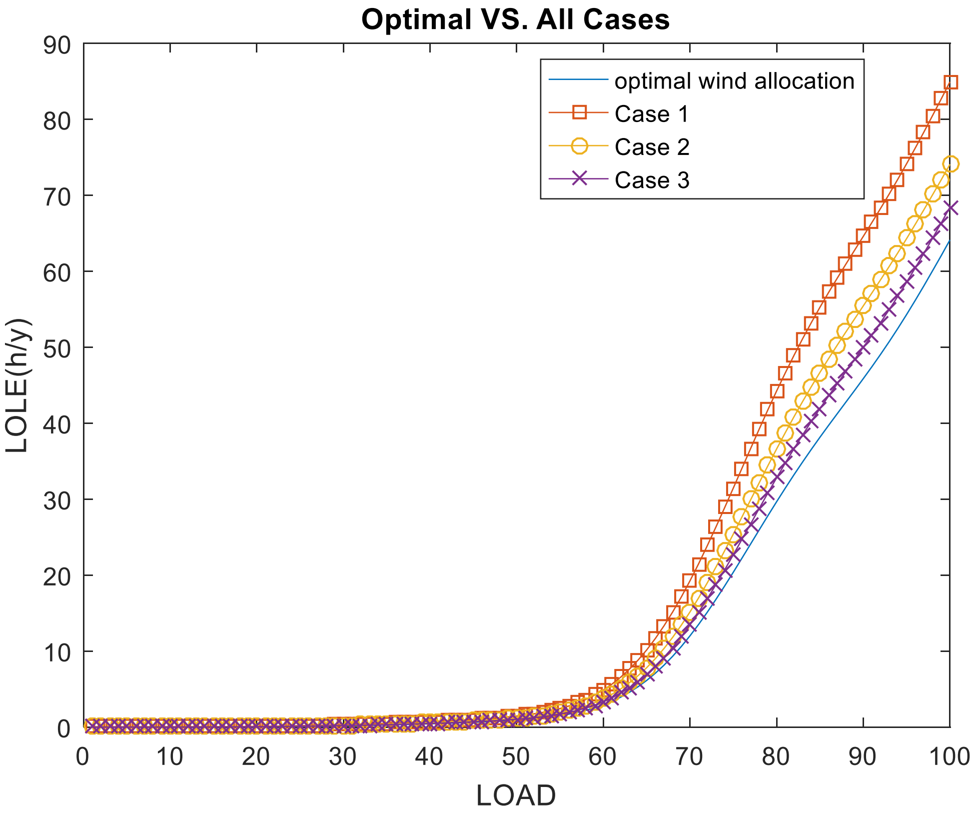

Figure 3. 8:Optimal Case vs Study Cases

Figure 3.8 illustrates the enhancement of the reliability curve for the optimal wind distribution compared to the other scenarios with the same wind power installation. Figure 3.9 shows CC in % of WC for all cases.

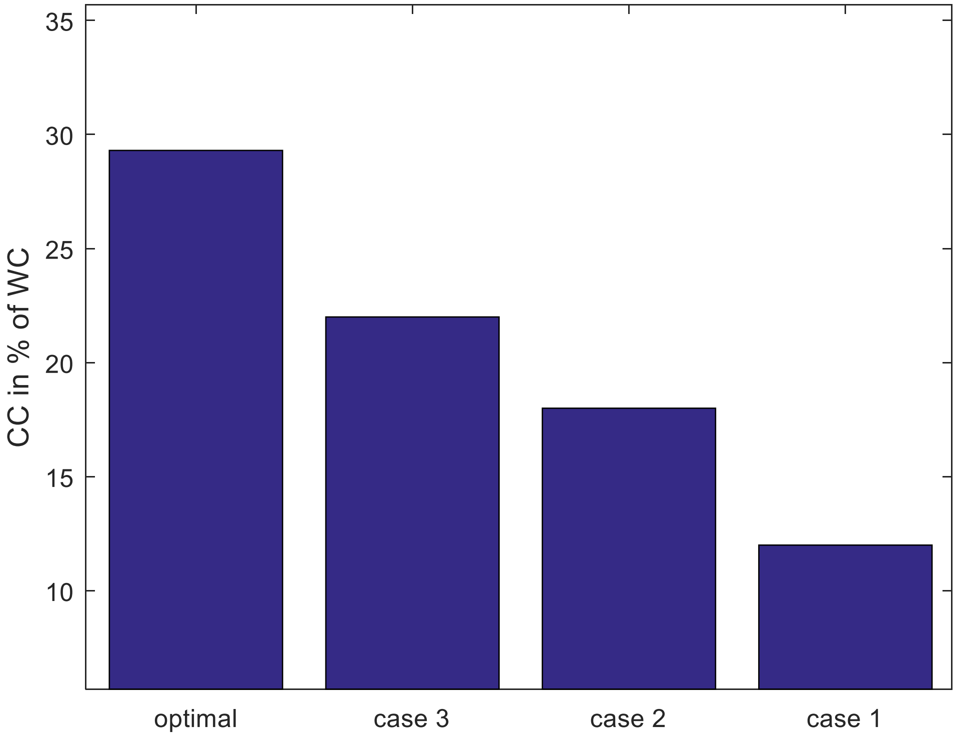

Figure 3. 9:CC in Percentage of Total Wind Installation

The size of wind power plant that satisfies the reliability requirement if expansion planning made based on case 3 which is the best among the 3 cases is listed in Table 3.14.

Table 3. 14:Size Of Wind Power Plant For Case 3

Case	Size of Wind Power Plant (MW)
3	442

If the power system planner has proposed case 3 as an expansion planning, the question will be how much is the loss of the utility?

The capital cost will be calculated for case 3, and then, it will be compared to the optimal one to find out how much the cost of a bad decision is.

There are several different methods to calculate the cost of the renewable energy. On the other hand, each way of calculating the cost of power generation brings its own insights. The costs that can be tested involve the financing costs, equipment costs (e.g. wind turbines), fixed and variable operating, total installation cost, maintenance costs (O&M) as well as fuel costs. The analysis of costs can be very detailed, so for this study, the capital cost will be considered for a brief comparison among cases.

According to [50], a Global weighted average total installed cost 1500 USD/kW. Hence, 1500 USD/kW will be considered as capital cost of wind power plant. The cost of case 3 as expansion planning and optimal one is represented in Table 3.15.

Table 3. 15:A capital Cost of Optimal Case And Case 3

Case	Size of power plant (MW)	Capital cost (MUSD)
3	442	663
optimal	326	489

The cost of a bad decision only for one project of generation expansion will be 174 MUSD.

III. Sensitivity analysis

In this part the Impact of tie line capacity on CC as well as the correlation of wind resources between the areas will be investigated.

line capacity has a major impact on the capacity credit, therefore, the line capacity of the system has been taken as base case to test the effectiveness of changing the transmission line capacity on the capacity credit of wind power plant. Therefore, the sensitivity result of line capacity has been shown in Figure 3.10.

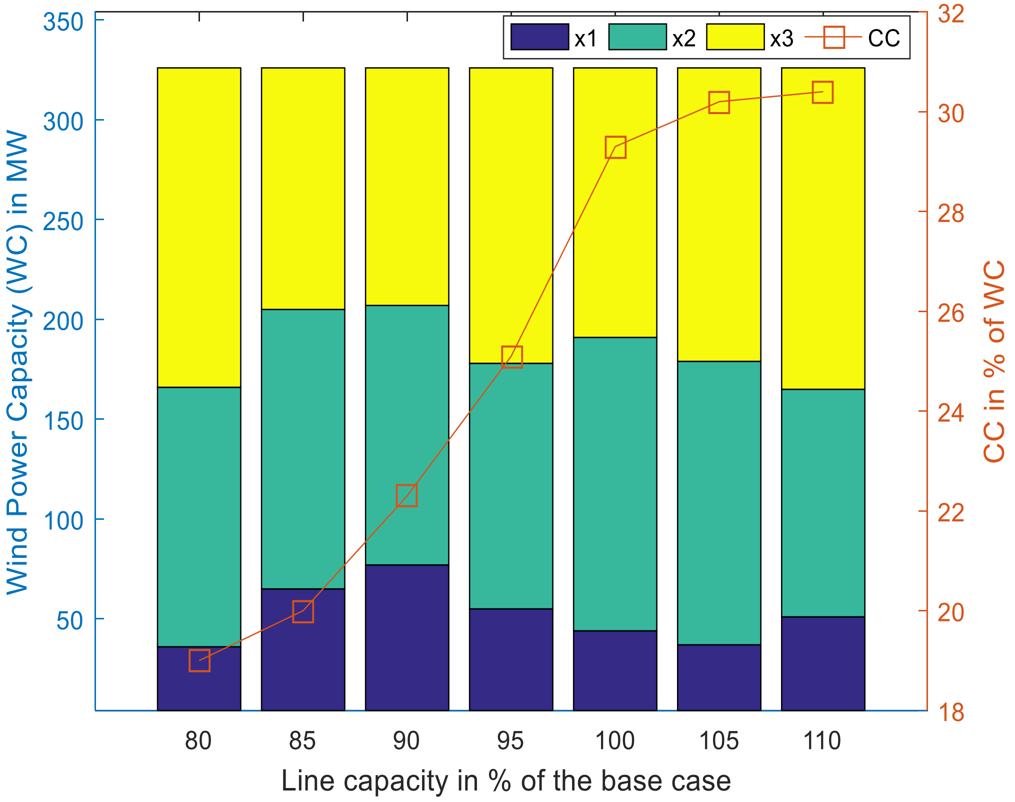

Figure 3. 10:Tie Line Sensitivity Result

As result of this, we conclude that increasing the capacity of transmission lines will maximize the capacity credit. This is due to the flexibility of the power flow since there is ability to send more power from any area that has excess wind power or at low power demand.

The sensitivity analysis has been studied by changing the correlation factor between area 1 and 2 and fixing area 3.Result for different correlation value shown in Figure 3.11.

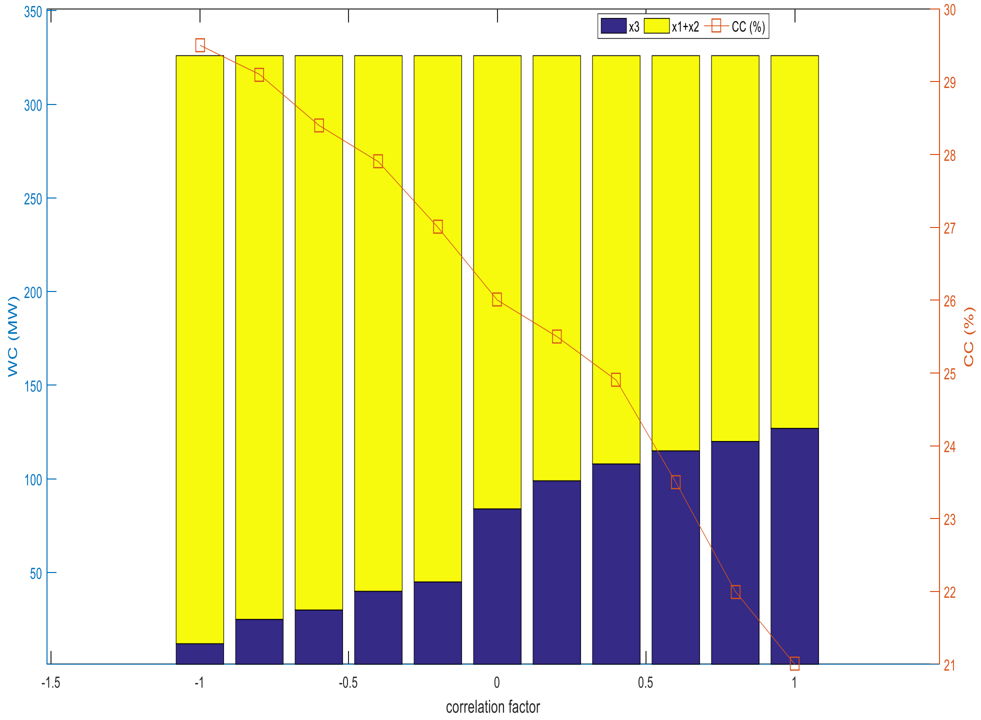

Figure 3. 11:Correlation Sensitivity Result

Figure 3.11 shows that choosing wind areas with negatively correlated will maximize CC.

CHAPTER 4

STOCHASTIC MODEL OF GEP

4.1 Introduction

Nowadays, competitive and global business is usually challenged, with the situation of making decisions that involve a percentage of uncertainty, the ability to deal and optimize such decisions is important. Stochastic or probabilistic programming works with such a kind of problem that has parameters are described by stochastic or random variables of the optimization problem. Therefore, the deterministic model will be reformulated considering the uncertainty of the wind power data (ω_i^t). The number of wind power scenarios will be generated and two approaches of (SP) will be utilized to construct the deterministic equivalent of SP. The first method is a wait-and-see approach [51] while the second one is an expected value approach[52].

4.2 Stochastic Model

I. Wait-and-see approach

In this method, the objective function is calculated when there is no uncertainty to find out decision variables x_i. Then, the expected value of the objective function for a specified number of a realization is found out. The number of scenarios will be generated for wind data. $\omega_i^{s,t}$ represents wind data in area i at time t for scenario s.

Where Pr_s is the probability of each scenario such that

$$\sum_{s \in S} Pr_s = 1 \tag{4.1}$$

Equation (4.1) means that the summation of probability of all scenarios is equal to 1.

Now we reformulate SP problem into deterministic equivalent SP after we generate the number of realizations of wind data ($\omega_i^{s,t}$). Therefore, the model is constructed as a two-stage problem. For the first stage, wind power allocation decisions are found and then the operation decisions are determined as $\tilde{\omega}$ is realized. The first-stage wind power planning problem is expressed as follows:

$$C(x, \tilde{\omega}) = MAX \sum_{i \in I} CC_i \tag{4.2}$$

$$0 \le x_i \le \beta_i \tag{4.3}$$

Second-stage

$$C(x, \tilde{\omega}_s) = \mathbb{E}[C(x, \tilde{\omega})] = \sum_{s \in S} Pr_s * C(x, \tilde{\omega}) \tag{4.4}$$

$$M_i = x_i * WC_s \tag{4.5}$$

$$LOLP_{i\ WDs}^{t} = \Pr(CK_i > \left(\omega_i^{s,t} * M_i + q_i^t - \sum f_{ij}^{s,t} + \sum f_{ji}^{s,t}\right) - (D_i^t + y_i^s)) \quad \forall i \in I, \forall t \in T, \forall s \in S \tag{4.6}$$

$$LOLE_{WDs(i)}\ \sum_{t=0}^{T} LOLP_{i\ WDs}^{t} \quad (4.7)$$

$$CC_i^s = \frac{\nabla D_i}{WC_s} * 100 \quad (4.8)$$

$$0 \leq WC_s \leq \mathrm{PN} \quad (4.9)$$

$$-F_{ij} \leq f_{ij}^{s,t} \leq F_{ij} \qquad \forall j \in J\ , \forall i \in I, \forall t \in T, \forall s \in \quad (4.10)$$

$$0 \leq q_i^{s,t} \leq IC \qquad \forall i \in I, \forall t \in T \quad (4.11)$$

In the second stage, the operational variable will be found such as optimal power flow among the areas in each hour for all scenarios. Also the wind size will be found for each scenario to satisfy the load and maintain reliability standard. Finally the objective value obtained from scenario 1,2,..,n will be multiplied by the probability distribution to get the expected objective function as shown in constraint (4.4). Flowchart represents the mechanism of wait and see approach is shown in Figure 4.1 .

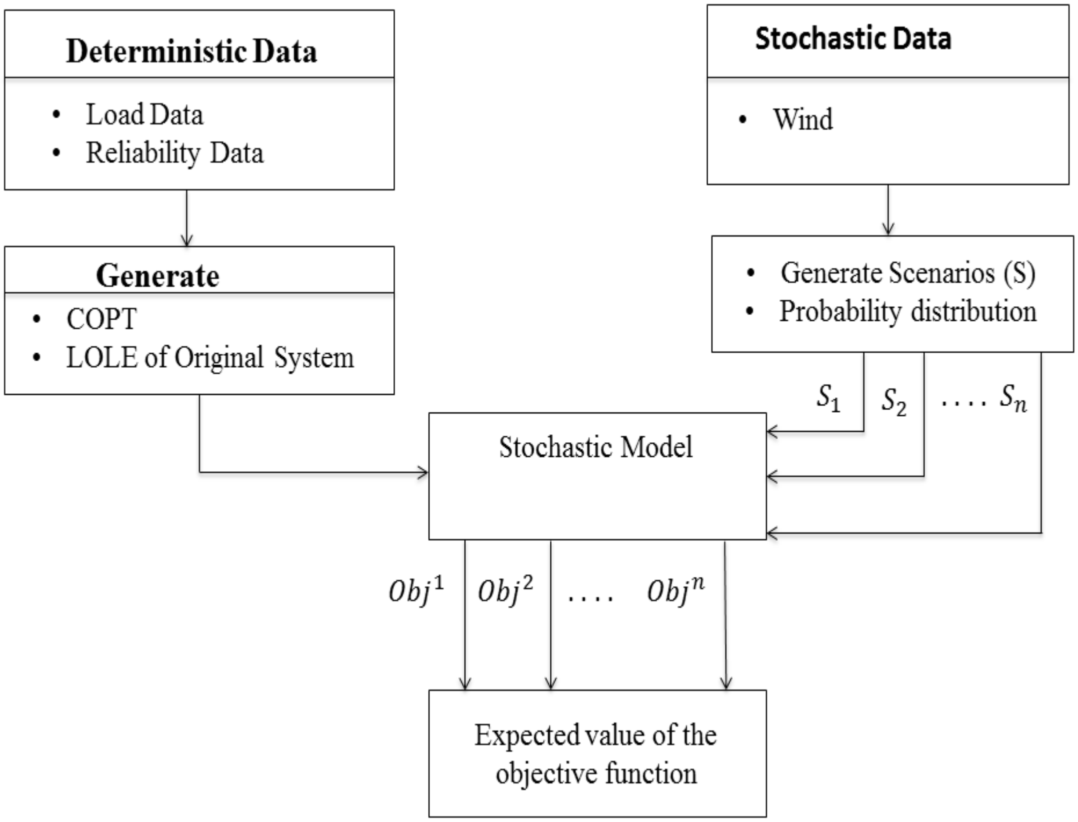

Figure 4. 1:Flowchart of wait-and-see approach

II. Expected value approach

In expected value method, the expected value of random parameter takes place instead of all random variable. So, SP is reduced into LP. This method provides some intuitive insight into the model.

$$\omega E_i^t = \sum_{s \in S} Pr_s * \omega_i^{s,t} \tag{4.12}$$

ωE_i^t represents the expected value of random variable of wind data ($\omega_i^{s,t}$) and index s represents the number of scenarios of wind data.

After the ωE_i^t is calculated, it will be embedded into the model to form a deterministic equivalent of SP. Flowchart represent the mechanism of expected value approach is shown in Figure 4.2.

$$\text{MAX} \left(\sum_{i \in I} CC_i\right) \tag{4.13}$$

S.T

$$0 \le x_i \le \beta_i \tag{4.14}$$

$$\sum_{i \in I} x_i = WC \tag{4.15}$$

$$LOLP_{i\ WD}^{t} = \Pr\left(C_K > \left(\omega E_i^t * x_i + q_i^t - \sum f_{ij}^t + \sum f_{ji}^t\right) - \left(D_i^t + \nabla D_i\right)\right)$$
$$\forall i \in I, \forall t \in T, \forall j \in J \tag{4.16}$$

$$LOLE_{WD(i)} = \sum_{t=0}^{T} LOLP_{i\ WD}^{t}$$
$$\forall i \in I, \forall t \in T \tag{4.17}$$

$$LOLE_{WD(i)} = LOLE_{GEN(i)} \tag{4.18}$$
$$\forall i \in I, \forall t \in T$$

$$CC_{i=} \frac{\nabla D_i}{WC} * 100 \qquad \forall i \in I \tag{4.19}$$

$$-F_{ij} \leq f_{ij}^{t} \leq F_{ij} \qquad \forall j \in J, \forall i \in I, \forall t \in T \tag{4.20}$$

$$0 \leq q_i^t \leq IC \qquad \forall i \in I, \forall t \in T \tag{4.21}$$

$$0 \leq WC \leq \mathrm{PN} \tag{4.22}$$

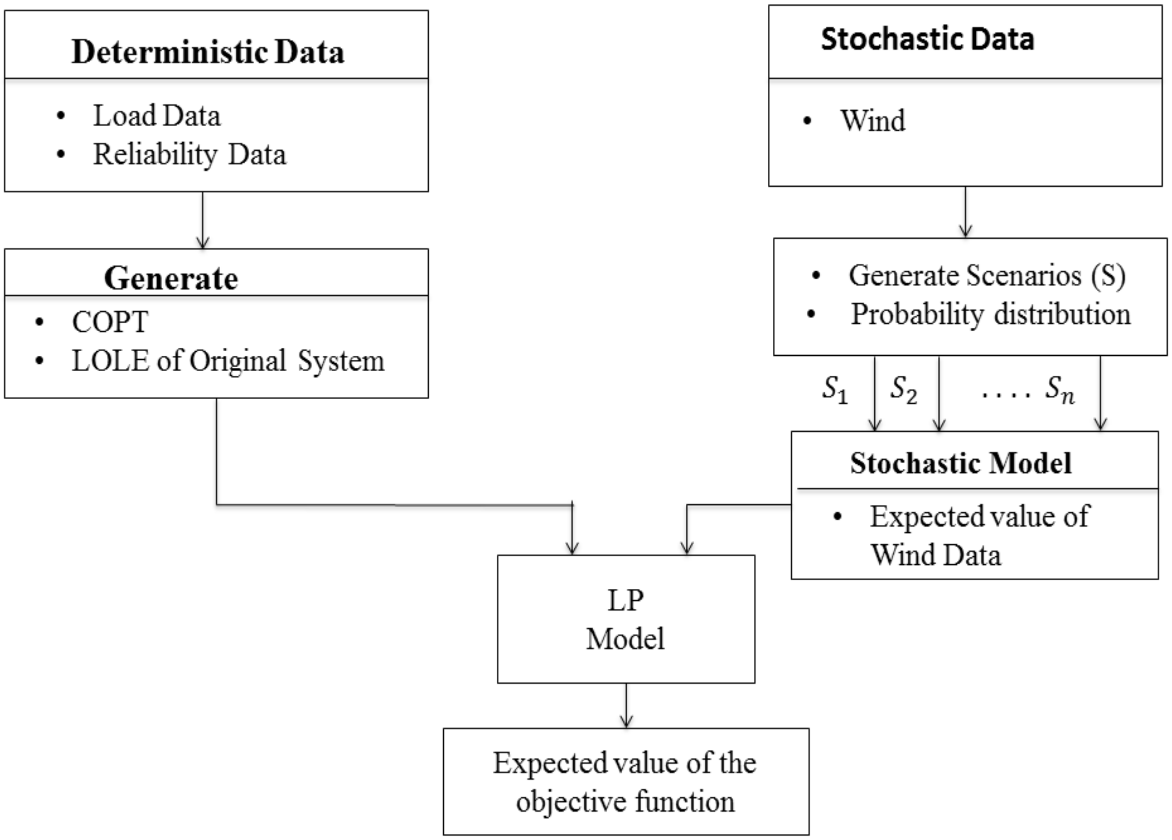

Figure 4. 2:Flowchart of expected value approach

4.3 Case Study

In this case study, the stochastic model is investigated after considering the uncertainty of wind data. Five scenarios were generated as a realization of the uncertainty parameter. The same power data is considered as it is the in case study 1. The wind data has been taken from NREL website. We have five years wind data for each area in order to assign three wind data for each year for three area power system as one scenario. Also, we have assigned a probability for each scenario which is illustrated in TABLE 4.1. The variability of two years wind data of area 3 is shown in Figure 4.3 as it demonstrates the uncertainty problem in wind behavior.

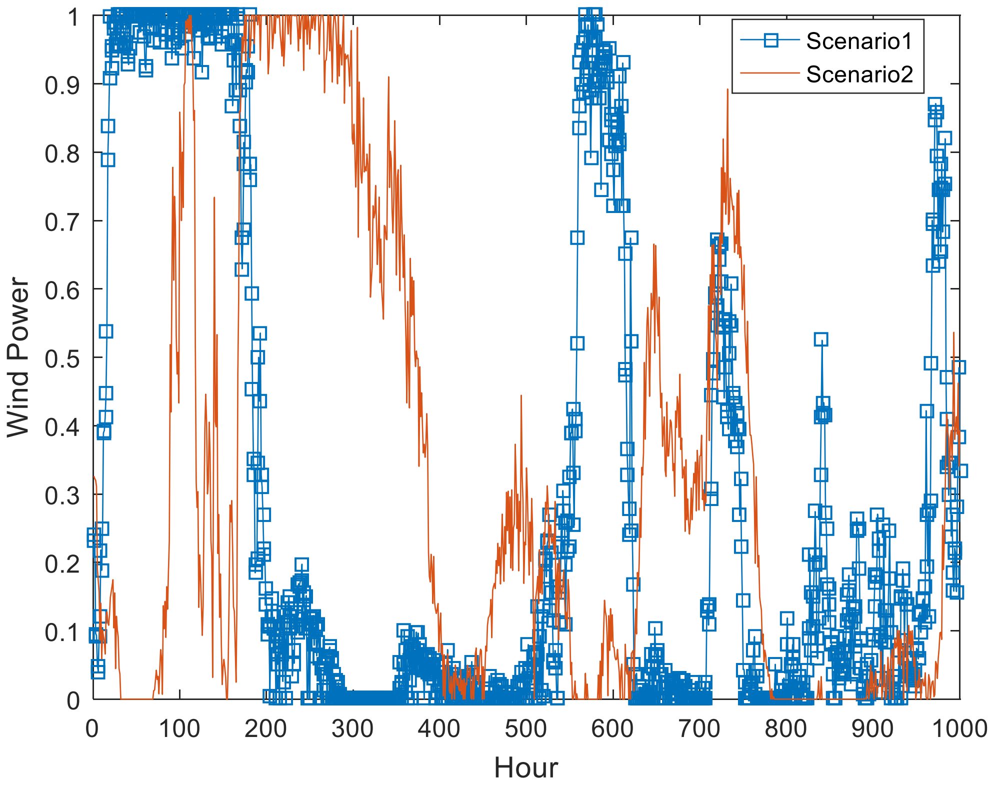

Figure 4. 3:Wind Variability For One Location

Table 4. 1:Probability distribution for SP Model

Scenario	1	2	3	4	5
Probability	0.2	0.2	0.2	0.2	0.2

For a wait-and-see method, a two-stage model has been solved. In the first stage, the decision variable of wind power allocation has been found out before the realization of wind data took place. Therefore, the first stage Decision variables are shown in Table 4.2. In the second stage, the operational variable has been solved as it is illustrated in Figure 4.4. The expected value of the objective function has been obtained as shown in Table 4.3.

Table 4. 2:Result Of First Stage Decision Variable

Area i	x_i
1	70
2	109
3	124

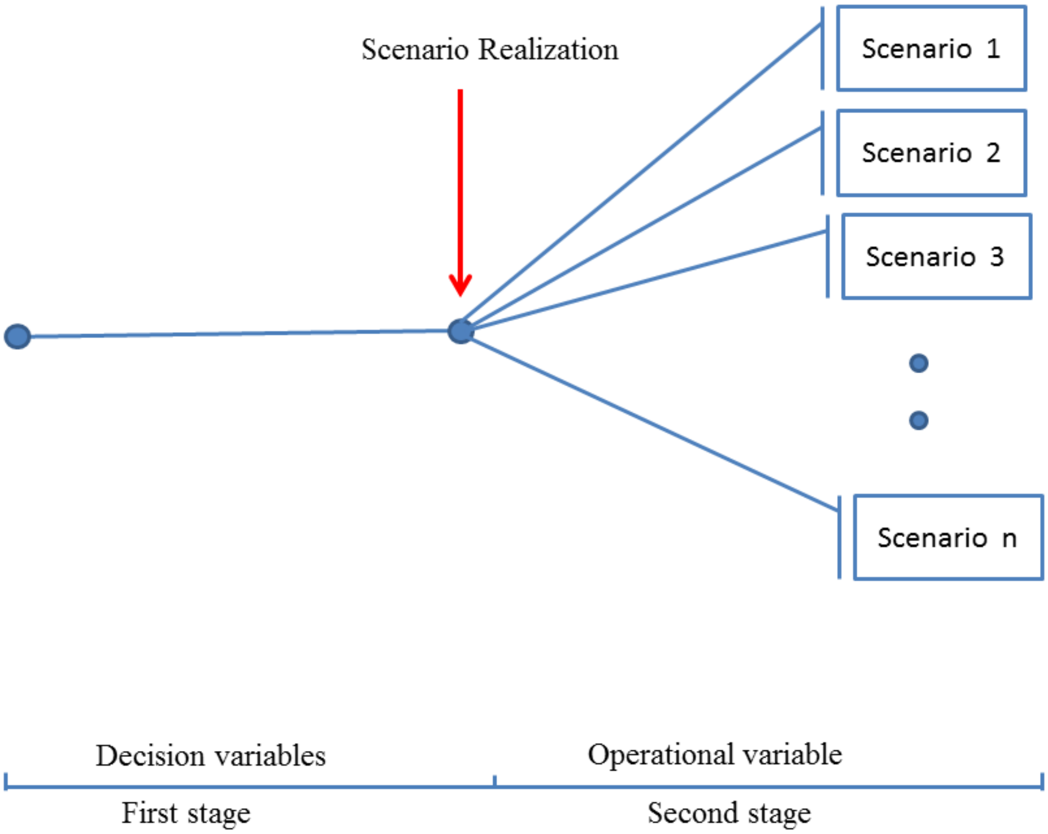

Figure 4. 4:Two Stage Stochastic Model

Table 4. 3:Result of The expected Value of CC

	SCENARIOS					Expected Value
	1	2	3	4	5	
CC (%)	31.6	29.1	24.4	23	22.5	26.12
WC (MW)	303	329	392	416	425	_
PR	0.2	0.2	0.2	0.2	0.2	_

As it can be seen from Table 4.3, the expected value of the capacity credit has decreased in comparison to the deterministic approach. For a power system planner, a probabilistic approach is more practical than a chronological one since the uncertainty of wind data has been taken into account which is the case in reality due to the variability of wind. However, the chronological approach is valuable from an operation point of view.

For the expected value method, the expected value of a random parameter of wind data for the five scenarios is calculated. Then, the uncertainty parameter of wind data is replaced with their expectation. So, SP is reduced into LP. The result of this method is illustrated in Table 4.4.

Table 4. 4:Result Of Expected Value Model

Area i	Wind allocation x_i	Wind Generation Capacity (WC)	Capacity credit (CC)
1	82 MW	397 MW	24.1 %
2	151 MW		
3	164 MW		

This method is a single stage approach; therefore, the decision variable is found up at the same time. The result of this approach is slightly less than other approaches. The reduction of the capacity credit occurs due to the drawback of taking the expected value of the realization of wind data since we found out the average of the wind data for five years. Consequently, every single hour of wind data (ω_i^t) will be affected by the five hours of the corresponding scenario. Then, if any hour of these is zero, this will reduce the amount of the expected wind data of that hour which results in less power that can serve the load. This implies that there is less load carrying capability which results in less capacity credit in return.

CHAPTER 5

FUZZY OPTIMIZATION MODEL OF GEP

5.1 Introduction

Most of optimization problems contain uncertainty parameter, so the number of mathematical techniques has been introduced to address the uncertainty data. The fuzzy set theory is one these techniques that deals with uncertainty of the optimization problem. Fuzzy optimization transforms the objectives and constraints into satisfaction functions of fuzzy sets. The standard form of optimization problem is written as follow:

Maximize $f(x, \varepsilon, \alpha)$ (5.1)

Subjected to $g_i(x, \varepsilon, \alpha) \leq 0,$ $i = 1, \ldots, m$ (5.2)

$h_j(x, \varepsilon) \leq 0,$ $j = 1, \ldots, p$

Where $f(x, \varepsilon, \alpha)$ is the objective function, and $g_i(x, \varepsilon, \alpha)$ is the constrain function with the uncertainty parameters denoted by the vector α, and crisp parameters denoted by ε, Where $h_j(x, \varepsilon)$ is constraints function with only crisp parameter. In deterministic optimization problem, the degree of uncertainty is neglected and the data is considered to be certain in optimization problem. The problem above can be reformulated in fuzzy optimization as follow:

Maximize λ

Where

$\lambda = \min\,(u_f, u_{g1}, \dots \dots., u_m)$

Where the new variable λ denotes the membership grade of the solution. The min function finds out the minimum of the satisfaction values, where u_f and u_{gi} are the membership function of the objective function f and the jth fuzzy constraint respectively.

5.2 Problem Formulation

I. Fuzzy Objective Model

For proposed GEP optimization problem, the objective function maximized the sum of capacity credit (CC). Therefore, the fuzzy set of CC will be written as follow:

$$\widetilde{CC} = \left\{[CC, u_{cc}]\,,\quad \underline{CC} \le CC \le \overline{CC}\right\} \tag{5.3}$$

The membership function of the objective function CC is formulated as inequality constraint in (5.4)

$$u_{cc} = \begin{cases} 0 & CC \le \underline{CC} \\ \dfrac{CC - \underline{CC}}{\overline{CC} - \underline{CC}} & \underline{CC} \le CC \le \overline{CC} \\ 1 & CC \ge \overline{CC} \end{cases} \tag{5.4}$$

The possible value of CC is found out using the deterministic model. The upper limit $\overline{CC}$ and the lower limit of $\underline{CC}$ are specified by power system planner. in fuzzy model, the objective function is considered as constraint, therefore, the membership function of CC is converted to a fuzzy constrain in (5.5)

$$\lambda \le u_{cc} = \frac{CC - \underline{CC}}{\overline{CC} - \underline{CC}}$$

$$\lambda * (\overline{CC} - \underline{CC}) \le (CC - \underline{CC}) \tag{5.5}$$

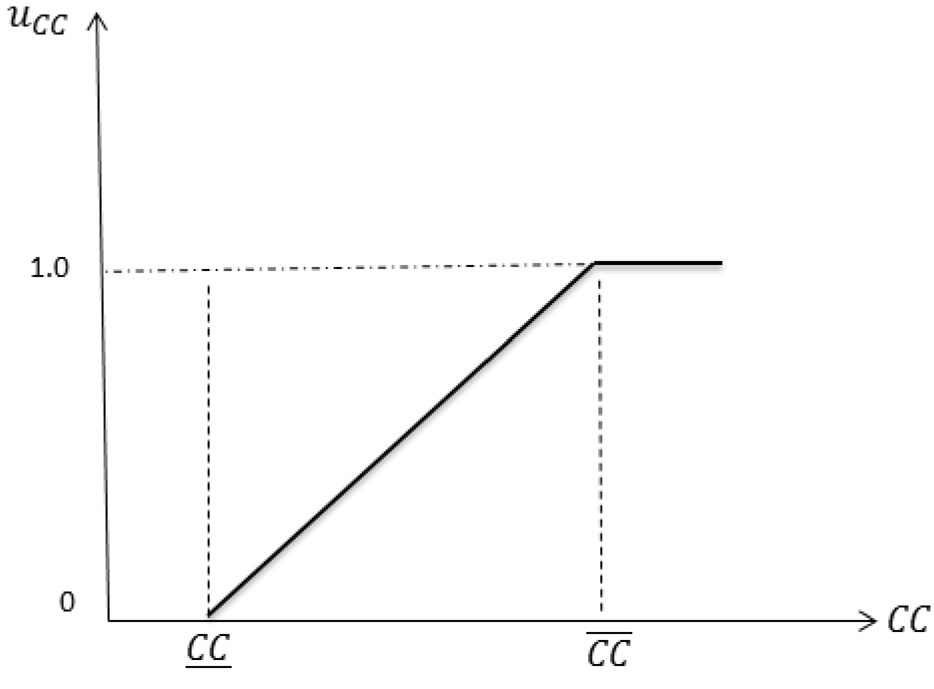

Figure 5. 1:Membership Function of Objective Function

II. Fuzzy Model of wind power

The uncertainty of wind power will be taken into account in fuzzy optimization model. The fuzzy model of wind power (W) is constructed and can be represented as follows:

$$\widetilde{W} = \left\{[W, u_w]\,, \quad \underline{W} \le W \le \overline{W}\right\} \tag{5.6}$$

The membership function for wind power data is shown in (5.7)

$$u_w = \begin{cases} 0 & W \le \underline{W} \\ \dfrac{W - \underline{W}}{\overline{W} - \underline{W}} & \underline{W} \le W \le \overline{W} \\ 1 & W \ge \overline{W} \end{cases} \tag{5.7}$$

The value of $\overline{W}$ and $\underline{W}$ is up to power system planner. The membership function is turned into fuzzy constraint as in (5.8)

$$\lambda * (\overline{W} - \underline{W}) \le (W - \underline{W}) \tag{5.8}$$

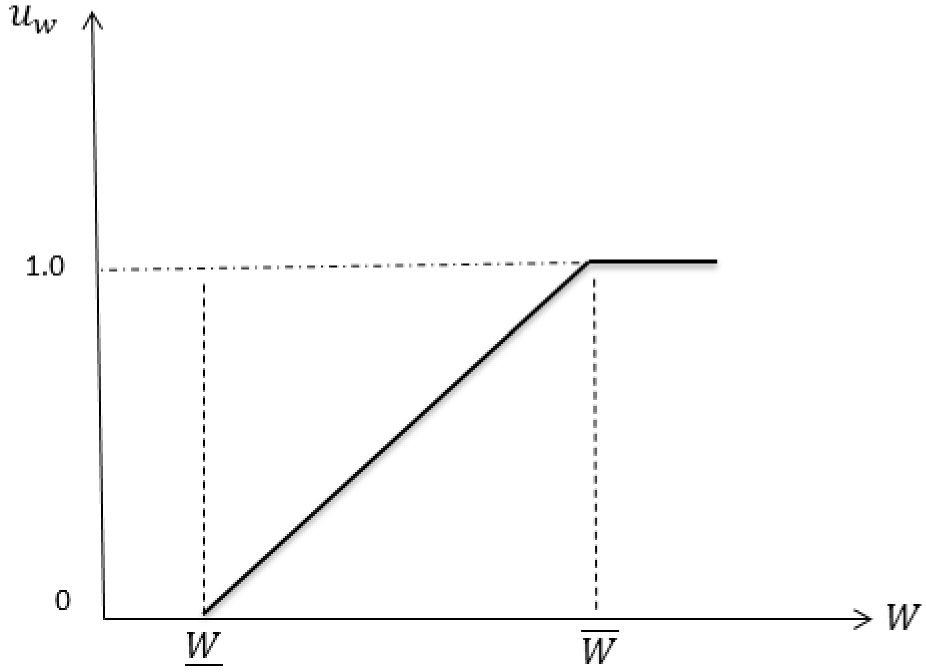

Figure 5. 2:Membership Function of Wind Data

III. Complete Fuzzy Model of Proposed GEP

$$\text{Maximize } \lambda \tag{5.9}$$

Subjected to

Relations (5.5), (5.8), (3.7) – (3.16)

Compared to the deterministic formulation, the fuzzy formulation comprises a redefined objective function and only two additional constraints.

5.3 Case Study

In this case study, we investigate the fuzzy model after considering the uncertainty of wind data. The mean absolute percentage error (MAPE) between two years of wind data for each location of the 3 area power system has been calculated as listed in Table 5.1.

Table 5. 1:MAPE Result

Area i	MAPE
1	13.3%
2	11.1%
3	15.21%
Average	13.2%

For simplicity, average of MAPE has been taken of the 3 areas and assigned for the wind maximum $\overline{W}$ and minimum $\underline{W}$ expected limits of the wind data for all areas. Also, the maximum Capacity Credit $\overline{CC}$ and the minimum $\underline{CC}$ limits for the fuzzy model have been predefined as percentages of deterministic Capacity Credit (CC). These limits have been set as ± 9 percent of deterministic CC. The optimization problem has been solved using CVX solver and the expected value of CC as well as all decision variables as it is shown in Table 5.2.

Table 5. 2:Result of Fuzzy Model

Area i	Wind allocation x_i (MW)	WC (MW)	Capacity credit (CC)
1	47	330	29 %
2	129		
3	154		

To simulate real time, Monte Carlo simulations are carried out. The actual value of CC for deterministic, SP and fuzzy approach has been found out by using realization of 52422 historical wind sample for each area. Then, the decision variables are set all for each approach as it is found out in Table 3.11 ,Table 4.2,Table 4.4 and Table 5.2. The result of actual (realized) CC is shown in Table 5.3.

Table 5. 3:Comparison Between Fuzzy And Deterministic CC

Optimization Technique	Deterministic	Fuzzy	Expected Value Approach of SP	Wait and See Approach
Expected CC	29.3 %	29 %	24.1%	26.12
Actual CC	21.1 %	22.8 %	20.2	21.9

Table 5.3 compares the capacity credit of wind generation using different approaches. In fuzzy optimization, the expected value of CC is found out as 29 % which is less than the CC in deterministic. However, the actual value of CC found out by fuzzy approach is higher than those

of deterministic and the SP technique. The actual value of expected value approach is the worst among others. Using fuzzy approach in finding CC shows the importance of involving the wind uncertainty in the optimization model. According to this result, neglecting the uncertainty of optimization problem could result in misleading the expected capacity credit.

The advantage of fuzzy optimization among all optimization techniques is that the problem size does not increase significantly as the number of uncertain parameters increases. This is because there is no need to generate number scenarios for each stochastic parameter. Figure 5.3 shows comparison among deterministic, fuzzy and SP approach.

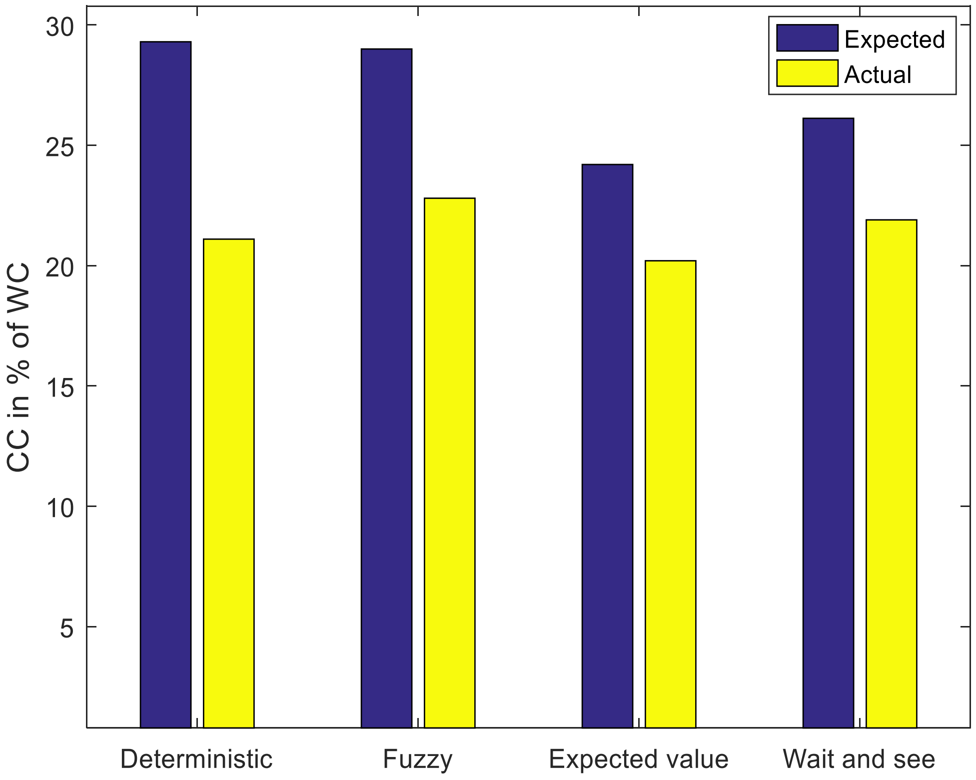

Figure 5. 3:Comparison among optimization techniques

Furthermore, changing the fuzzy capacity credit limit $\overline{CC}$ and $\underline{CC}$ for different level will result in different CC value. Two levels of fuzzy CC limits have been compared to the base case as shown in Table 5.4. As the result of this comparison, setting limits of CC to 9 % will maximize the CC.

Table 5. 4:Sensitivity of Capacity Credit to Fuzzy CC Limits

	Deterministic	Fuzzy		
		±5	±9	±13
Expected value of CC	29.3 %	28.7 %	29 %	28.4 %
Actual value of CC	21.1 %	22.63 %	22.8 %	22.5 %

CHAPTER 6

CONCLUSION

This report presents a chronological GEP model for multi-area wind power capacity allocation based on capacity credit maximization. Also, in this study, fuzzy optimization approach has been used to deal with the uncertainty of the proposed model. Similarly, the wait-and-see approach has been used in addition to expected value approach of stochastic programming (SP) to deal with the uncertainty of proposed model. A three-area power system that is interconnected together by tie lines is used as case study. The configuration of three-area power system follows IEEE-RTS system with different generation capacity and load profile. CVX solver has been used to solve the optimization problem by finding out the optimal decision to allocate wind power capacity in each area so that capacity credit is maximized.

This study concluded that allocating of wind power optimally has significant impact on CC. In addition, tie line capacity has a major effect on the capacity credit, therefore, increasing the capacity of tie lines will maximize the capacity credit. Furthermore, choosing wind resources with negatively correlated between the areas will capitalize CC. Also, using fuzzy approach in finding CC shows the importance of involving the wind uncertainty in the optimization model. Therefore, neglecting the uncertainty of optimization problem could result in misleading the expected capacity credit.

6.1 Future Work

This work can be extended by incorporating a Battery Storage System (BBS) to the model to see the impact of BSS on the capacity credit of renewable power plants.

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