DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

COORDINATED TRANSMISSION EXPANSION PLANNING WITH WIND POWER GENERATION AND FACTS DEVICES

by
Güneş BECERİK MİR

October, 2022
IZMIR

COORDINATED TRANSMISSION EXPANSION PLANNING WITH WIND POWER GENERATION AND FACTS DEVICES

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Doctor of
Philosophy in Electrical and Electronics Engineering Program

by
Güneş BECERİK MİR

October, 2022
IZMIR

Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled "**COORDINATED TRANSMISSION EXPANSION PLANNING WITH WIND POWER GENERATION AND FACTS DEVICES**" completed by **GÜNEŞ BECERİK MİR** under supervision of **PROF. DR. ENGİN KARATEPE** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

....

Prof. Dr. Engin KARATEPE

Supervisor

....

Prof. Dr. Metin H. SABUNCU

Thesis Committee Member

....

Asst. Prof. Dr. Emrah BIYIK

Thesis Committee Member

....

Prof. Dr. Mutlu BOZTEPE

Examining Committee Member

....

Assoc. Prof. Dr. Engin ÇETİN

Examining Committee Member

Prof. Dr. Okan FISTIKOĞLU

Director

Graduate School of Natural and Applied Sciences

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my advisor Prof. Dr. Engin Karatepe for his continuous encouragement as well as for his patience, guidance, and unlimited motivation throughout this Ph.D. study. I can't thank him enough for his constructive feedbacks that has a perfect blend of insight and humor, kind support and as his comments that broaden my perspective not only on academic life but also on outlook on life in general.

I would like to extend my sincere thanks to the rest of my thesis committee members Asst. Prof. Dr. Emrah Bıyık and Asst. Prof. Dr. Abdül Balıkçı, for their insightful comments and encouragement which incented me to widen my research from various perspectives. I would also like to thank the members of Yaşar University, Faculty of Engineering and Department of Electrical and Electronics Engineering for allowing me to continue my thesis and research studies along with my research assistant duties. Also, many thanks to all my colleagues at both Yaşar University and Dokuz Eylül University for their continuous encouragement as well as their time, advice, and moral support.

Last but not the least, I would like to thank my family and my husband who endured this long process with me, always offering support and love.

Güneş Becerik Mir

COORDINATED TRANSMISSION EXPANSION PLANNING WITH WIND POWER GENERATION AND FACTS DEVICES

ABSTRACT

Today, the electricity grid turns into an even more complex structure with the integration of renewable energy sources. Maintaining the adequacy of the power system is a primary role for system planners, but it is complex to deliver a reliable supply due to the uncertain nature of these resources. The effective use of available renewable generation only makes sense if the grid is not congested, which once again underlines the importance of the transmission infrastructure. In this context, this thesis presents a probabilistic AC power flow-based transmission expansion planning model that handles load, wind, and N-1 contingency uncertainties. Transmission expansion planning model is handled with a chance-constrained optimization structure using probability distribution functions. The economic load distribution problem is adapted to planning optimization formulations by using distributed slack bus and participation factor approaches to reduce the computational burden due to the AC power flow equations. In that manner, it is aimed to use the probability distribution functions of the network constraints and the AC power flow equations without linearization, and the transmission expansion planning is analyzed in terms of risk. In the first stage, the applicability of probability distributions in planning problem using DC power flow equations are examined, then AC probabilistic power flow is modeled using a distributed slack bus approach and compared with the classical power flow. In the last stage, chance constrained transmission investments are obtained and tested with different scenarios, then risk-oriented investment plans are examined by including FACTS devices in the proposed AC planning model. Consequently, a coordinated stochastic transmission expansion planning with FACTS devices is developed by providing direct use of probability distribution functions of voltage, reactive power in addition to active power and resulting investment decisions are examined in terms of economic, technical and flexibility standpoints.

Keywords: Chance constrained programming, distributed slack bus, participation factor, transmission expansion planning, wind power, flexible AC transmission systems.

RÜZGÂR ENERJİSİ VE FACTS CİHAZLARI İLE KOORDİNELİ İLETİM HATTI PLANLANMASI

ÖZ

Günümüzde elektrik şebekesi yenilenebilir enerji kaynakları ile birlikte daha da karmaşık bir yapıya dönüşmektedir. Sistem planlayıcıları için en önemli görev, elektrik üretimi ve tüketimi arasında denge kurmaktır; ancak bu kaynakların değişken doğası güvenilir bir tedarik sağlamayı zorlaştırmaktadır. Yenilenebilir üretimin mevcut gücünün etkin kullanımı şebekenin altyapısının yeterli olduğu durumlarda anlamlıdır, bu da iletim planlamasının önemini bir kez daha vurgulamaktadır. Bu tez çalışmasında rüzgar, yük ve N-1 kısıtlılık durumlarındaki belirsizlikleri dikkate alan AC güç akış tabanlı olasılıksal iletim hattı planlama yöntemleri geliştirilmiştir. İletim hattı planlama modelleri olasılık dağılım fonksiyonları kullanılarak şans kısıtlı optimizasyon yapısıyla ele alınmıştır. AC doğrusal olmayan denklemler kullanılarak oluşturulan optimizasyon çalışmalarında, hesaplama yükünü azaltmak için dağıtık salınım barası ve katılım faktörü yaklaşımları kullanılarak ekonomik yük dağıtımı problemi iletim hattı planlama formülasyonlarına adapte edilmiştir. Tez kapsamında geliştirilen modellerde şebeke kısıtlarının olasılık dağılım fonksiyonlarının ve AC güç akış denklemlerinin doğrusallaştırma işlemi yapılmadan kullanılabilmesi amaçlanmış ve iletim hattı planlamaları risk açısından analiz edilmiştir. Tez çalışmasının ilk aşamasında, iletim hattı planlamasında olasılık dağılım fonksiyonlarının DC güç akışı denklemleri kullanılarak uygulanabilirliği irdelenmiş, ardından AC olasılıksal güç akışı dağıtık salınım barası yaklaşımı kullanılarak modellenmiş ve klasik güç akışı yöntemi ile kıyaslanmıştır. Daha sonra, şans kısıt programlaması ile iletim hattı planlamaları elde edilerek farklı senaryolar altında güvenilirliği test edilmiş, ve son bölümde geliştirilen AC iletim hattı planlamasına FACTS cihazları dahil edilerek risk odaklı yatırım planları irdelenmiştir. Sonuç olarak, iletim hattı ve FACTS cihazlarının koordineli planlamasında aktif gücün yanında gerilimin, reaktif gücün ve olasılık dağılım fonksiyonlarının doğrudan kullanılması sağlanarak, iletim hattı planlama modeli ekonomik, teknik ve esneklik açısından stokastik bakış açısı ile ele alınmıştır.

Anahtar kelimeler: Şans kısıtlı programlama, dağıtılmış salınım barası, katılım faktörü, iletim hattı planlaması, rüzgâr enerjisi, esnek AC iletim sistemi cihazları.

CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

LIST OF SYMBOLS

i, k	: Bus no
c	: Contingency
β	: Not overload probability
N	: Total number of buses
Ω	: Total set of candidate lines
Ω^C	: Total set of contingency
P_{Gi}	: Real power output of a generator at bus i
P_{Di}	: Load at bus i
P_{IMB}	: Imbalance power
C_i	: Quadratic cost function of generator at bus i
$C_i(P_{Gi})$	: Total generation cost
a_i, b_i, c_i	: Cost coefficients of generator at bus i
P_{Gi_sch}	: Scheduled real power output of a generator at bus i
P_{Gi_upd}	: Updated real power output of a generator at bus i
Pf_i	: Participation factor of generator at bus i
P_i	: Injected active power at bus i
Q_i	: Injected reactive power at bus i
$P_{sp,i}$	: Specified (known) active power at bus i
$Q_{sp,i}$	: Specified (known) reactive power at bus i
ΔP	: Mismatch active power vector
ΔQ	: Mismatch reactive power vector
V_i	: Voltage magnitude at bus i
θ_i	: Voltage angle at bus i
${V_i}^c$	: Voltage magnitude at bus i at contingency operating condition c
${\theta_i}^c$	: Voltage angle at bus i at contingency operating condition c
g_{ik}	: Conductance of line i-k
b_{ik}	: Susceptance of line i-k
b_{ik}^{sh}	: Shunt susceptance of line i-k

g_{ik}^{c} : Conductance of line i-k at contingency operating condition c

b_{ik}^{c} : Susceptance of line i-k at contingency operating condition c

$b_{ik}^{c,sh}$: Shunt susceptance of line i-k at contingency operating condition c

P_{ik}^{from} : Active power flow of line i-k

Q_{ik}^{from} : Reactive power flow of line i-k

S_{ik}^{from} : Complex power flow of line i-k

P_{ik}^{to} : Active power flow of line k-i

Q_{ik}^{to} : Reactive power flow of line k-i

S_{ik}^{to} : Complex power flow of line k-i

$P_{ik}^{c,from}$: Active power flow of line i-k at contingency operating condition c

$Q_{ik}^{c,from}$: Reactive power flow of line i-k at contingency operating condition c

$S_{ik}^{c,from}$: Complex power flow of line i-k at contingency operating condition c

$P_{ik}^{c,to}$: Active power flow of line k-i at contingency operating condition c

$Q_{ik}^{c,to}$: Reactive power flow of line k-i at contingency operating condition c

$S_{ik}^{c,to}$: Complex power flow of line k-i at contingency operating condition c

$\overline{S_{ik}}$: Complex power flow limit of line i-k

$\underline{V_i}$: Minimum voltage magnitude limit at bus i

$\overline{V_i}$: Maximum voltage magnitude limit at bus i

$Cost_{ik}$: Cost of line i-k

n_{ik}^{0} : Initial number of lines between buses i and k

n_{ik} : Integer number of new lines added between buses i and k

$\overline{n_{ik}}$: Maximum number of added lines between buses i and k

ABBREVIATIONS

AC	: Alternative Current
DC	: Direct Current
CCP	: Chance Constraint Programming
CDF	: Cumulative Distribution Function
CVaR	: Conditional Value at Risk
EENS	: Expected Energy Not Supplied
IEA	: International Energy Agency
FACTS	: Flexible AC Transmission Systems
FOR	: Forced Outage Rate
KKT	: Karush-Kuhn Tucker
MCS	: Monte Carlo Simulation
MILP	: Mixed Integer Linear Programming
MINLP	: Mixed Integer Nonlinear Programming
OPF	: Optimal Power Flow
PDF	: Probability Distribution Function
PEM	: Point Estimation Method
RES	: Renewable Energy Sources
RTS	: Reliability Test Systems
SVC	: Static VAR Compensator
TCSC	: Thyristor Controlled Series Compensator
TEP	: Transmission Expansion Planning

CHAPTER ONE
INTRODUCTION

1.1 Background

The infrastructure of the power grid has undergone a significant transition with the introduction of renewable energy sources (RES) into the power system. Considering increasing demand for electricity and the impact of fossil fuels on reaching environmental targets, the effective and reliable use of these sustainable, clean energy sources has been gradually increasing. In this context, many nations prioritize promoting policies that enhance deregulation, renewable penetration, market integration, regional planning, and the development of new technologies for the efficient use of power network (Lumbreras & Ramos, 2016). For instance, as part of an ambitious effort to reduce greenhouse gas emissions, advance clean energy technology, and to meet rising electricity demand with other objectives, a large-scale RES program is being developed in Europe over the next few decades (Skea, 2012). In this context, it is necessary to enhance the transmission system to connect renewable sources as much as possible. However, transmission expansion is a multi-stage problem where the planner takes various decisions at several time horizons. Therefore, the computational complexity of the stochastic transmission expansion planning (TEP) problem increases dramatically with the uncertainty and the size of the power network. These uncertainties not only impact on the system operation but also the behavior of the network and market conditions. For this reason, long-term transmission expansion problem under uncertainty should be handled systematically at both investment and operational levels.

Replacing conventional generators with clean energy combinations will support economic, technical, societal, and environmental benefits. Therefore, considerable utilization of RES power in the power grid is anticipated. Lately, it is observed that wind energy has the highest participation rate in the grid. According to the study of the Global Wind Energy Council, it has been announced that with the installation of 21.1 GW of offshore wind energy in 2021, three times more wind energy investments were made than the energy industry compared to 2020 (Council G.W.E., 2022). About half of the world's renewable energy installed power comes from Europe, which is the biggest proponent of this technology. European (EU) countries have set challenging targets for RES integration and carbon reduction. According to Eurostat data, the EU met its stated goal of consuming 20% renewable energy by 2020 by consuming 22.1 percent of its energy from renewable sources (Eurostat, 2022). Additionally, recent studies from the International Energy Agency (IEA) show that new wind installations in Europe totaled 17.4 GW (14 GW onshore and 3.4 GW offshore) in 2021 (IEA World Energy Outlook, 2021). As shown in Figure 1.1, the investment capacity for wind power increases gradually. The EU countries have set the goal of ensuring 32% of their gross final energy consumption comes from renewable sources by 2030. However, to reach the present objective of 30% renewable energy by 2030, an enormous change in the energy sector would still be required.

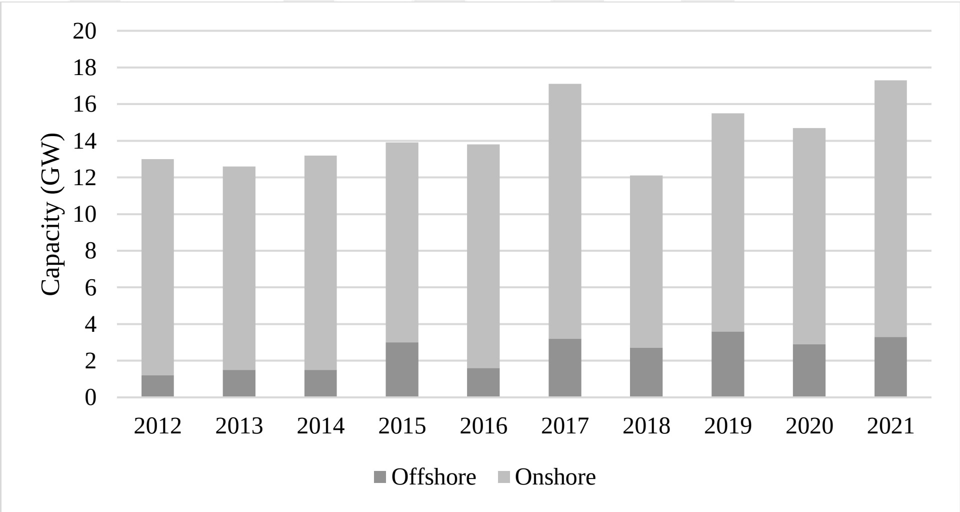

Figure 1.1 Annual new wind installations in Europe, 2012-21

The vast market opportunity for clean technologies coordinated with the modern energy economy translates into a new sector for investment and competition. As shown in Figure 1.2, the United Kingdom, Sweden, Germany, Turkey, and the Netherlands have the highest share of new installed capacity (Wind Energy in Europe, 2021). A modern energy system with higher share of renewable sources comes with benefits, such as improved energy security, economic growth, more employment opportunities and reaching environmental targets. Economic and political support for RES development increases the utilization of these sources continuously, which contributes long-term sustainability targets and reduces the negative environmental impact of conventional sources.

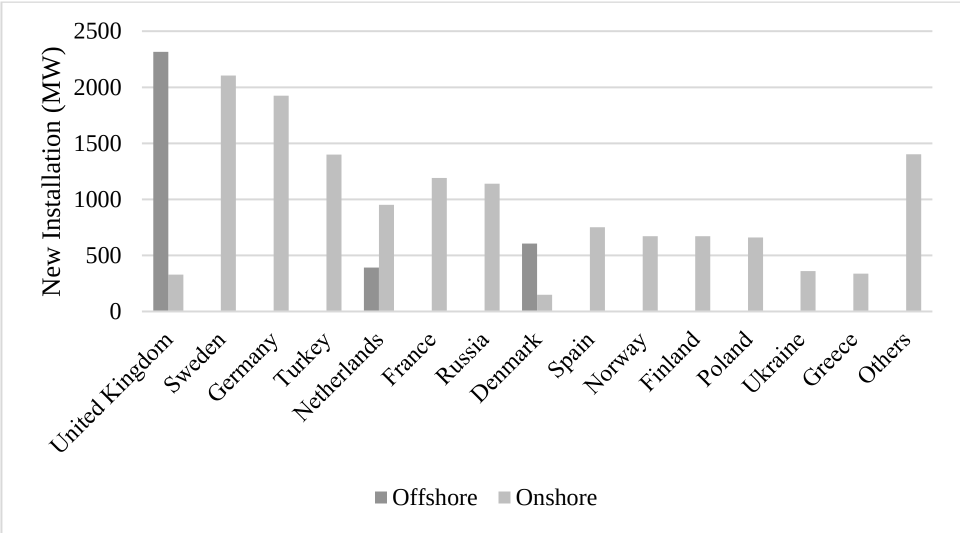

Figure 1.2 New wind installations (offshore and onshore) in Europe 2021

It is evident that the global target for high-level integration of RES power can be achieved by making significant investments in transmission network, which serves to balance out the adverse effects of RES integration. From the planning perspective, there is a trade-off between the effective utilization of renewable sources and the cost of transmission. Transmission facilities are used by all producers and consumers to exchange electric energy. Although it has a low relative cost compared to the price of a generation plant, it has a significant impact on how much the system operates. In that manner, there are two main approaches adopted for transmission expansion planning with renewable capacity additions. A resource-driven approach allocates renewable investment where the resource quality is best. This often results with more investment than anticipated and can cause over design for transmission network due to high generation costs for renewable sources. Alternatively, system-driven approach which distributes capacity investments with demand centers as well as local grid capacity into account. This will lower the cost of renewable energy and provide more efficient use of transmission network (Godron et al.,2018). In the modernized grid the effective use of transmission network is a key to alleviate congestion and curtailment which are the main barriers for a reliable planning decision. Besides, increasing share of renewable sources necessitates a more flexible decision due to the uncertainty in the output power it brings. Therefore, transmission topology and variability of system operational behavior must be handled thoroughly from technical and economical perspectives. Considering uncertainty, triggers the use of probabilistic techniques in the decision-making process at different levels of power system planning (Velasquez et al.,2016; Conejo et al., 2016).

The intermittent nature of RES power adds great variability to the system operation that introduce considerable concerns in both operation and planning of power network. Network is in fact subject to many uncertainties such as expansion and retirement of generation, fuel pricing, rising demand, component failures, carbon emissions, demand response and a host of other sources of uncertainty that can affect its structure to varying degrees (Seifi & Sepasian, 2011). With higher levels of RES integration, the cumulative effect of these uncertainties presents a complex problem which is difficult to solve. Moreover, the main barriers for large scale wind integration can be seen on operating cost, power quality, power imbalances, power system dynamics, and transmission planning (Georgilakis, 2008). Therefore, the main problem explored in the power system planning is how to manage the transmission and generation potential adequately and securely for increased variability on both the supply and demand sides.

In the modern power system planning, the trend for high share integration of RES power for long term horizons can be achieved with significant investments on transmission network. Flexible AC Transmission System (FACTS) devices, on the other hand, can be used to improve the transfer capacity and increase flexibility while minimizing the side effects of variability to meet the objectives of planning problem. Nowadays, FACTS devices can be incorporated with electric power systems thanks to advancements achieved in power electronic components, particularly in terms of cost reduction. Investment on these devices considerably increases the strategic flexibility due to modular, scalable structure with short construction times. For example, installing series FACTS devices on selected lines to control the power flow or shunt devices to specific buses to control voltage magnitudes is applicable and economically preferable choice to increase resilience of the power system under uncertainty condition (Chatzivasileiadis et al.,2011).

Existing planning models are inadequate to deal with the uncertainty because they lack strategies to deal with the risk posed by the nature of the problem. In the light of these background, this dissertation aims to develop a stochastic transmission expansion planning model that can assist power system planners to coordinate transmission expansion planning with various uncertainties. In the following sections the research topic is briefly introduced, the scope of the study is explained, and the key goals of this dissertation are outlined.

1.2 Transmission Expansion Planning

Power system planning is a procedure whose objective is to invest or enhance the current system components to sufficiently satisfy the loads for a predicted future. It can be categorized from various viewpoints. However, a time-horizon perspective is necessary to define the boundaries between different power system studies (Seifi & Sepasian, 2011). Figure 1.3 shows power system studies based on time horizon perspective.

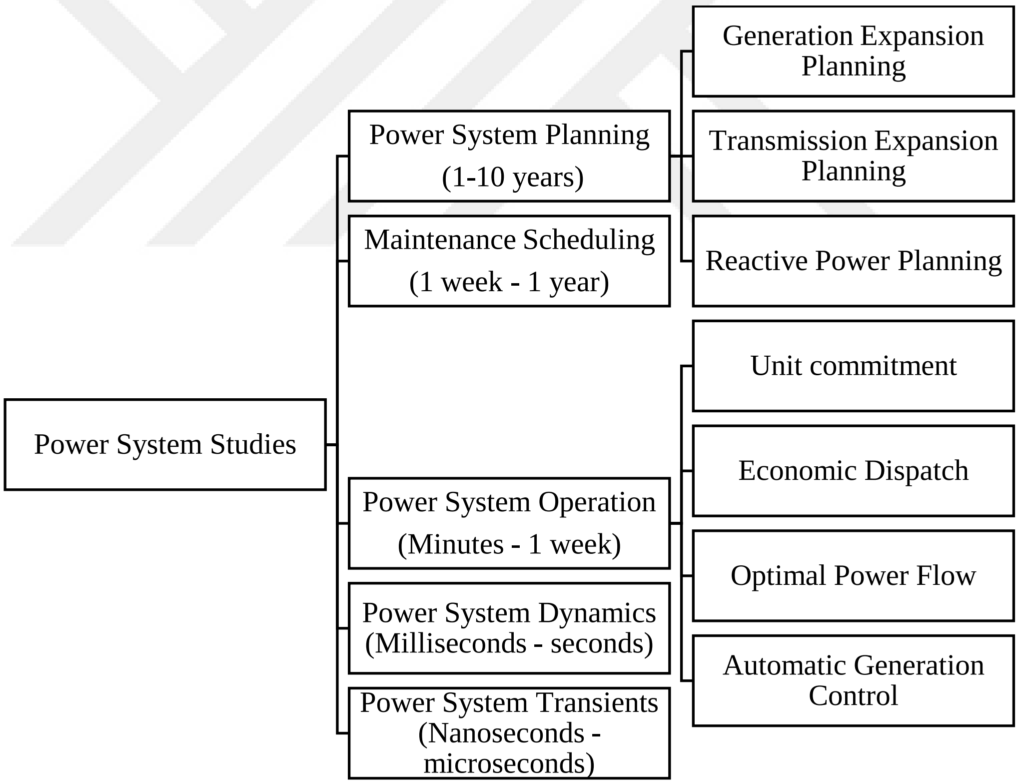

Figure 1.3 Power System Studies Based on Time Horizon Perspective

Traditionally, studies that last from one year to ten years are called as power system planning. It is mainly categorized by generation expansion planning, transmission expansion planning and reactive power planning, respectively. Load forecasting for the anticipated study period is the most crucial phase in any planning problem to establish the necessary generation requirement. In this context, generation expansion planning is developed that seeks to find location, type and capacity of generation units that meets the forecasted load. Once the load is forecasted and the generation requirements are known, transmission expansion planning study is conducted. Transmission expansion planning decides the optimum routes to transmit power efficiently and reliable to the load centers where the investment and operational costs are minimized under various constraints. Lastly, the reactive power planning is implemented after transmission expansion planning to find necessary reinforcements on reactive power. The obtained transmission investment may not always perform satisfactorily under AC network conditions due to voltage magnitudes. To solve such infeasibilities, reactive power planning is conducted to find location, sizing, and type of reactive power sources.

By its own nature, TEP problem is a large-scale, nonlinear, nonconvex, mixed-integer structure (Da Silva et al., 2000). It has been receiving extensive attention in recent years and a large amount of research work has conducted with the purpose of simplifying the problem, alleviating computational burden and highlighting the growing concerns on uncertainty. This may be explained by the integration of RES and deregulation of the power industry, which has increased the level of risk due to uncertainty and the complexity of the problem. The traditional structure of a TEP problem with either deterministic or stochastic input is given in Figure 1.4. The comprehensive formulation of a general TEP problem is formulated as an economic dispatch problem with network constraints. Although the objective functions varied from different perspectives, it is expected that the final investment decisions will meet the adequacy and security criteria for all conditions. From modelling perspective AC or DC network models are used. In that manner, many researchers either linearize the AC power flow equations or use the DC network models for the tractability and computational concerns.

Depending on the network representation the formulation of the overall TEP problem build as a mixed integer linear programming (MILP) or mixed integer non-linear programming (MINLP) optimization. In MILP formulation, duality of the lower-level problem integrated as constraints of the upper-level problem. This means optimization turns into a single level problem. Within the classical approaches, MILP approach arguably the most popular approach which is capable of handling DC network model. If stochastic inputs are used, the problem is generally solved with decomposition methods, bender's decomposition, Lagrange relaxations.

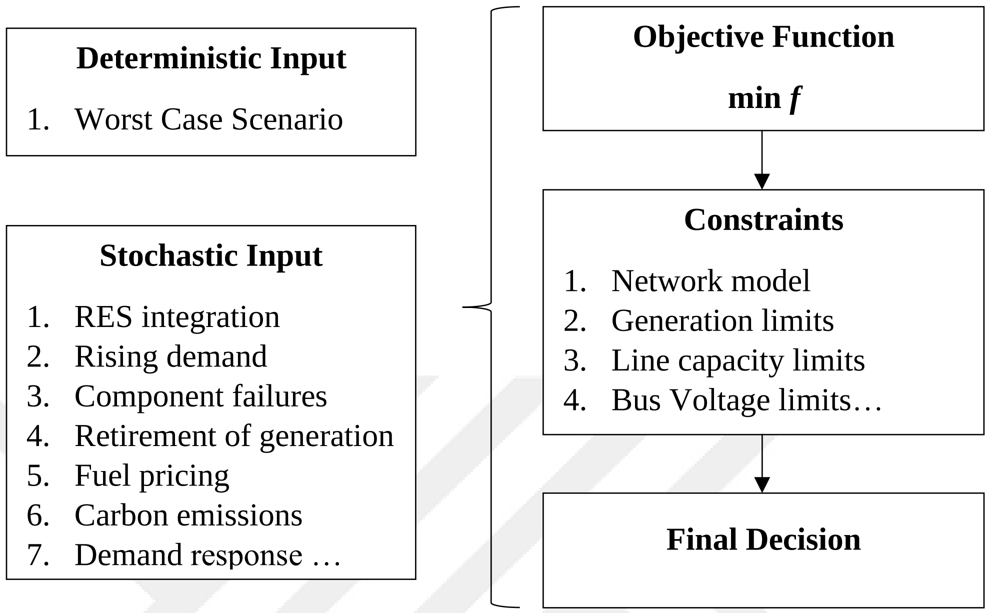

Figure 1.4 Traditional structure of a TEP problem

A similar formulation is also pursuit with the MINLP methods to reduce the bilevel problem into a single level. In general, Karush-Kuhn Tucker (KKT) conditions of the lower-level problem integrated as constraints of the upper-level problem. MINLP techniques are widely used due the nonlinear and nonconvex characteristics of AC power flow equations. However, meta-heuristic approaches like genetic algorithm, swarm intelligence, differential evaluation is also attracting attention due to the simple implementation on large scale networks. Particularly, meta-heuristic methods offer relatively good solutions with a reasonable amount of computation time.

1.3 Research Motivation and Problem Definition

As highlighted in the background, the share of RES in overall energy consumption will continue to rise dramatically. For this reason, the power grid is becoming increasingly stressed with the integration of large-scale renewable sources. This brings with its risk and randomness which is inherently existing in power network. The current grid is not capable of accommodate with the large amount of uncertainty due to rely on utilizing intermittent sources like wind energy in vast and remote regions which is far from demand centers and existing transmission networks. Therefore, it is crucial to develop reliable and economically viable transmission investment. TEP is a complex problem that involves numerous levels of power system studies. These studies include the operational behavior of system which changes stochastically with the integration of large-scale renewable sources. Therefore, the uncertainty and the operation under unprecedented uncertainty conditions poses a significant challenge for planning problem. This is the primary driving force behind the present work. This dissertation, which is framed in this context, tries to respond to following research problems that are raised from the technical, economical and flexibility viewpoints of such situation:

- How should the TEP model be formulated by handling uncertainty simply and accurately?
- How should the TEP model be evaluated considering various uncertainties at different confidence levels ?
- How should the TEP model be approached when an AC network model is considered?
- What level of risk should be included in TEP model to maintain a proper balance between economic, technical and flexibility standpoints?
- How should the TEP model be handled when considering FACTS devices under uncertainty?

In this framework, the main goal of this dissertation is to develop a stochastic optimization model that considers uncertainty and the overload risk of operational decision to support the investment decision for transmission network with high levels of renewable integration. To achieve the main research objective, this dissertation proposes a two-level model to analyze long term transmission expansion under load, wind power and N-1 contingency uncertainties. The representation of the proposed framework is given in Figure 1.5.

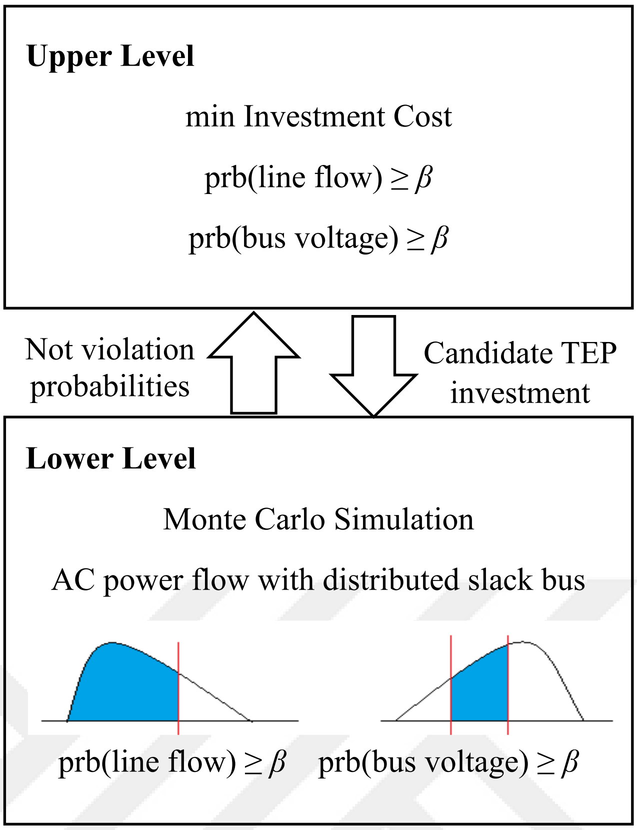

Figure 1.5 Representation of the proposed framework

The goal of this research is to enhance the existing transmission infrastructure by expanding or include the controllability of the transmission parts into the operational problem in a sense of economic dispatch while taking the load and/or generation uncertainty into account. In this context, a stochastic AC transmission expansion planning is proposed to solve the investment problem that considers chance constrained distributed slack bus approach. The generation adequacy and network constraints are evaluated using a probabilistic participation factor power flow in a sense of economic dispatch. It is worthy of note that the significant effect of slack bus is usually ignored to obtain a feasible result in the operational part of the optimization. When considered with RES, slack bus absorbs the uncertainty in power network. For this reason, the mismatch power from uncertainties and transmission losses is managed using generation participation factors combined with AC power flow equations. A scenario set with the combination of load, wind, and N-1 contingency uncertainties are handled using Monte Carlo Simulation (MCS) and the loading limits for the transmission lines and bus voltages are enforced as probabilistic constraints using chance constraint programming.

The following research targets are evaluated in this thesis:

- To formulate probability distribution functions of line flow and bus voltages which are obtained from the analysis that considers combinations of load wind and N-1 contingency uncertainties under nonlinear AC power flow equations.
- To propose a probabilistic participation factor power flow in a sense of economic dispatch under TEP problem for handling the uncertainty. Distributed slack bus concept is adapted under the stochastic TEP by combining participation factors with nonlinear AC power flow equations through a modified Jacobian matrix under Monte Carlo Simulations.
- To formulate a chance constraint programming approach through directly probability distribution functions of both bus voltage and line flow to obtain a risk aware TEP investment.
- To propose a flexible solution strategy for a chance constrained stochastic TEP coordinated with wind power and FACTS devices.
- To test the proposed model on medium and large size test network under a new set of uncertainty scenarios.

The proposed optimization model is implemented in MATLAB programming environment. The overall objective is to provide an expansion decision that can effectively cope with different uncertainties and risk levels to assist the power system planner in the decision-making process. Under uncertain operating conditions, the proposed model could adequately simulate the complex decision-making process that planners would encounter in medium and large-scale power systems.

1.4 Literature Review on Stochastic Transmission Expansion

Transmission expansion planning is always one of the top concerns in power systems studies, which must be addressed continuously to meet the adequacy while maintaining the reliability of the system. There has been a sharp rise in the number of publications on stochastic TEP, notably in the last ten years, which highlights the growing issues on uncertainty. The earlier works on TEP problem date back to 1970. In (Fischl and Puntel, 1972; Villasana et al., 1985), the system integrity has been described with adjoint or transportation models that investigates the shortest paths between the load and the generators. In (Romero & Monticelli, 1994), authors propose a hierarchical Benders' decomposition method to solve a two level TEP problem. These works mainly solved with linearized versions of the network representation with MILP approach due to high accuracy of linear solvers. On the other hand, different heuristic search algorithms based on physical and natural phenomena have been studied as an alternative to conventional optimization techniques. In (Gallego et al, 1998), authors propose a general framework using an extended genetic algorithm for solving the TEP problem. (Alguacil et al., 2003), the authors present a MILP approach to the TEP problem by modeling the transmission losses using linear expressions and considering the quadratic approximation of the power flow equations to eliminate the dependency of the Benders partitioning procedure. In (Rider et al., 2007), authors developed the very first approach for AC TEP model as a MINLP to solve TEP problem with constructive heuristic algorithm. The above-mentioned studies have guided the studies in the literature from different perspectives. Some review articles that look at the studies from a wider perspective are also given respectively. A detailed literature review on TEP problem from different aspects is given in (Latorre et al., 2003; Hemmati et al., 2013). In (Lumbreras et al., 2016), authors examine the new challenges and vast array of projects and development plans of nations in European context. In (Gomes and Saravia, 2019a), review, authors specifically outline the gaps and approaches that can contribute renewable and distributed electricity markets. Lastly, a complementary review with recent publications is also given in (Mahdavi et al., 2018). From the context of stochastic TEP following subjects are defined in this literature review:

- Network representation
- Solution methods in terms of treatment of uncertainty
- Managing risk of operation
- Coordination of TEP with FACTS devices

1.4.1 Network Representation

From network representation perspective, TEP problem is either modeled by DC or AC network models. TEP problem mainly handles DC or linearized AC network representation due to MILP solvers which has high accuracy. However, the current physical network has a nonlinear nonconvex structure. Therefore, an AC based model gives more accurate representation of the network behavior.

In stochastic TEP models, DC model formulation generally used to represent the network and the electrical quantities. In DC models, bus voltages considered flat and reactive power, power losses are ignored. Therefore, the final investment from DC models should be analyzed with AC studies. In the stochastic TEP literature, the DC model has been frequently preferred in terms of ease of application and reducing the computational burden. In (Freitas et al., 2019), the transmission network is represented by the DC model and TEP is solved considering multiple generation scenarios. In (Mortaz and Valenzuala, 2019), the impact of wind and solar generation on TEP is evaluated with comparison of DC and AC optimal power flows models. In (Moraes et al., 2020), a four-stage model using DC and AC power flow models is presented examining the effects of wind generation on the TEP model. In (Jadidoleslam et al., 2017), a bi-level DCTEP model is presented, which prioritizes minimizing investment costs and maximizing system reliability while considering maximum use of wind energy. Traditionally, the nonlinearity of AC power flow equations in power system planning is not considered frequently due to its mathematical complexity. However, the AC power flow model has been attracted researchers to reformulate the nonlinear equations for a more accurate representation of power system operation. In (Zhang et al., 2013), a TEP model with linearization on reactive power, voltage magnitudes, and network losses is proposed. In (Roald & Andersson, 2017), an analytical model based on linearization of the AC power flow equations is presented to maintain network constraints within their bounds with a pre-specified probability. In (Zhou et al., 2020), a stochastic co-optimization of generation and transmission expansion model is presented by using a linearized power flow model. In another promising study (Rahmani et al., 2010), to reduce the computational effort of TEP when using AC model, a meta-heuristic concurrent approach for network and reactive power planning is presented in which DC and AC model are used sequentially. In a similar context, a mixed AC and DC power flow model is proposed for TEP in the presence of wind farms and a meta-heuristic method is used to cope with complex models due to uncertainties of power networks and nonlinearities of AC power flow (Moradi et al., 2016). In another study, a strictly pure AC power flow model based on penalty functions is used to solve TEP problem by using a meta-heuristic technique without considering uncertainty and generation cost (Alhamrouni et al., 2014). In (Das et al., 2019), AC based TEP model is transformed into a MILP problem and the mathematical computation burden with dimensionality concerns are pointed out particularly when the size of the power system gets larger. For this reason, a two-stage optimization strategy is presented in which the DC model is used in the first stage to provide an initial estimation for the AC model to reduce the computational effort when N-1 safety constraints are included into AC model based TEP problem. In another TEP study, the exact AC power flow equations are used to include the impact of reactive power and system losses on the planning model (Farrag et al., 2019). In the context of planning, DC power flow is accurate enough to produce decisions for long term planning problem, although the planning results with AC power flow must then be evaluated (De Silva et al., 2006). In (Hooshmand et al., 2012), an ACTEP model associated with reactive power planning is proposed by considering reliability through expected energy not supplied index. In (Asadamongkol & Eua-arporn, 2013), a three-stage procedure is presented to solve TEP with AC model based on generalized Bender’s decomposition. In another study, a robust TEP with AC load flow is presented considering intermittent RES and loads (Chatthaworn & Chaitusaney, 2015). In (Abbasi & Abdi, 2017), a pareto based optimization model is used to analyze the effect of network models with wind generation on TEP solutions. In (Alaee et al., 2016), investment and reliability costs are considered in the objective function of TEP problem with AC power flow under different uncertain load conditions.

1.4.2 Solution methods based on treatment of uncertainty

Based on treatment of uncertainty, there are several approaches to solve stochastic TEP problem in the literature. The key distinction between these models is in how uncertainty is described and how optimization with uncertainty is approached. The traditional approach for stochastic TEP requires solving a set of equations that represent network change under uncertainty. Motivated by the two-level structure of TEP problem, many researchers partition TEP problem into investment and operation sub-problems. The investment part is an optimization that minimizes the total investment cost, while the operation part handles the uncertainty to find the decision for operational sub-problem for various uncertainty realization.

In the context of the stochastic TEP model, the treatment of uncertainty can be categorized as probabilistic, stochastic, and parametric models. In probabilistic models, uncertainty scenarios can be developed based on a specific probability distribution of the uncertain data. These models require a known probability distribution function (PDF) of uncertain variables to be sampled one at a time to estimate the statistical parameters of output variables. To address different operational uncertainty sources, Monte Carlo Simulation (MCS), point estimation method (PEM) or analytical techniques has received broad use in a TEP optimization framework. Particularly MCS is widely used to utilize various uncertainties as a sample input in which a deterministic optimization can use them to calculate the output variables repetitively. For example, in (Akbari et al., 2011), a multi-stage stochastic model for TEP is developed with benders decomposition that considers available transfer capability of transmission lines. MCS is applied to generate uncertainty scenarios and the objective of the overall optimization is to minimize the sum of investment and expected operation cost of the system. In (Hooshmand et al., 2012), authors developed a multi objective planning problem to minimize investment cost and maximize social benefit. Additionally, Expected Energy Not Supplied (EENS) is included in the system constraints to improve the reliability of the system. In (Akbari et al., 2012), authors proposed a stochastic multi-objective optimization for TEP with voltage security consideration using AC-OPF. A scenario reduction technique is applied MCS to minimize scenarios handled in the optimization and the objectives are to minimize the sum of investment, expected operation and load curtailment cost with maximize the expected loading factor. In (Park et al., 2015), a two-stage stochastic programming model is proposed for TEP problem that considers joint distribution of load and wind uncertainties using copula functions. MCS is used to handle uncertainties and expected generation, wind curtailment and load curtailment cost is minimized for different uncertainty scenarios in the lower part of the TEP optimization. In (Abbasi et al., 2017), authors propose a stochastic TEP model that handles uncertainty using PEM and the objective function considers investment and expected values of congestion and load curtailment costs. In (Qiu et al., 2017), authors propose a stochastic decomposition-based approach for TEP framework to assess the impact of wind power and demand response using MCS. Load curtailment is incorporated as a risk constraint and its impact on TEP decision is investigated. In (Gomes et al., 2019b) authors propose a novel multi stage planning framework to ensure worst case conditions, operational constraints, and N-1 contingency criterion with AC OPF model. In (Yuan et al., 2020) authors developed a two-stage Benders decomposition model that considers wind power and demand uncertainty. In the proposed model, invested lines and distributed series reactors are determined in the first stage whereas the OPF is performed for different uncertainty scenarios in the second stage.

In stochastic models, clustering techniques are also applied in many studies with a limited number of scenarios which are given with certain probabilities. Large number of scenario consideration is a challenging problem for stochastic models. Therefore, many researchers try to reduce the number of scenarios handled in the TEP optimization using various clustering techniques (Xu & Wunsch, 2005). In addition, scenario tree and special scenario generation methods are also applied in the context of TEP optimization. In (Carriónet al., 2007), a MILP approach for vulnerability constrained TEP model is proposed by using the expected value of load curtailment to assess the impact of credible deliberate attack scenarios under TEP problem. In (Bagheri,2016) a data driven, two-stage stochastic TEP is proposed to minimize the total expansion and expected operational costs under the worst-case distribution. In (Jadidolesam et al., 2017) authors propose a stochastic TEP model with the private investment absorption for development of the wind power in a bilevel optimization. In the lower-level, load and wind uncertainties are modelled by K-means clustering and the expected values of market clearing and reliability measures to guide investment problem. In (Moeini-Aghtaie et al., 2012a, 2012b), a Non-Dominated Sorting Genetic Algorithm II model is proposed to solve multi-objective TEP problem that investigates the effect of demand and wind power uncertainties using MCS and PEM on investment, congestion, and EENS cost. In (Saberi et al., 2017), authors present a probabilistic comparison between MCS and PEM model to determine the TEP decision under demand, wind power and energy price uncertainties. Bender's decomposition is used to solve overall TEP problem which master level minimizes investment cost, and slave level includes the expected cost of energy not served, congestion cost and congestion rent.

In parametric models, gap theory, robust optimization and fuzzy decision methods have been widely attractive for the treatment of uncertainty in decision-making. Unlike stochastic programming, which requires a precise knowledge of the load and RES distribution, these methods require the range of variation of the uncertain parameters. Particularly robust optimization method is widely used to solve TEP problem which covers all possible realization of an uncertainty set. In (Yu et al., 2011) authors propose a robust TEP model with Taguchi's orthogonal array testing method that generates generation dispatch, load and wind uncertainties. In (Jabr et al., 2013), authors developed a two-stage robust TEP model that minimizes expansion and curtailment cost of load and renewable generation using Bender decomposition. Unlike stochastic approaches this model does not require the PDF of net injections of load and RES uncertainty. In (Chen et al., 2014), authors develop a robust TEP model where the maximum cost and regret of the expansion plan are minimized. The uncertainties are modelled as polyhedral uncertainty set and the trilevel problem is solved in two levels using (KKT conditions. In (Ruiz et al., 2015) the authors propose an adaptive robust optimization model to find investment decisions that minimizes total cost and worst-case realization of demand growth, availability of generation unit uncertainties using the uncertainty sets. In (Denghan et al., 2017), unlike the previous adaptive robust models (Jabr et al., 2013; Chen et al., 2014;Ruiz et al., 2015) linear decision rules-based model is utilized to alleviate tractability issues seen in decomposition-based models. Using linear decision rules converts the adaptive robust model into a single tractable MILP problem. In (Chatthaworn, & Chaitusaney, 2015), authors propose a robust TEP model that minimizes total cost using a meta-heuristic adaptive tabu search method. In (Han et al., 2017), authors propose a robust optimization approach that considers load and wind uncertainties as parameter sets which converts the TEP problem into a deterministic optimization that optimal investment is derived iteratively using genetic algorithm. In (Wu et al.,2018), authors develop a robust TEP model that considers N-k contingency and the uncertainty of load demand and renewable energy source (RES) generation mixed integer linear programming problem.

Consequently, from the problem formulation perspective, the objectives of stochastic network expansion solution can be categorized by the total cost of investment and operation, the loss of load probability, load curtailment or congestion cost and unserved energy. However, these objectives are reevaluated with the deregulation of power system given how rapidly the environment for the network is changing. In a deregulated environment, TEP problem should consider minimizing investment cost with the aim to increase reliability, social welfare, and flexibility in operation and minimize the risk, congestion, and environmental impacts. Additionally, the objectives of this problem show that the modern TEP must be solved by combining network driven and cost-effective perspectives. Since uncertainties are handled in the operational problem weighted sum of the overall cost under various operating conditions is optimized through expected cost of operation or probabilistic guarantees in network constraints. The effectiveness of both methods depends on how rigorously operating conditions are handled and how to choose scenarios to find the representative network behavior. Therefore, treatment of uncertainty is significant to find a TEP solution. However, the challenges with large numbers of operating conditions must be handled to reduce tractability and computational burden.

1.4.3 Managing risk of operation

Operational risk is the key parameter for finding the conservativeness of TEP model. Due to the uncertainty of the RES and load, the power flow and voltages also become uncertain and the risk of exceeding the operational limits are anticipated. Generally, chance constrained or conditional value at risk (CVaR) models are applied to TEP optimization to limit the risk in operational problem. Chance constrained programming is beneficial when probabilistic risk is utilized in stochastic TEP optimization. The risk of overlimit can be obtained from the PDF of state vectors and it can be included either in the objective function or the constraints of the planning optimization. In this way, an acceptable level of violation probability is considered, which intuitively relaxes the hard constraints imposed on TEP optimization. In recent literature, chance constraint formulation is widely applied in stochastic TEP optimization. In (Yu et al., 2009), a scenario-based approach for load and wind uncertainty is analyzed using probabilistic power flow in MCS, and chance constraints on line loading constraints are handled in TEP optimization. In (Orfanos et al., 2012), load, wind, and N-1 contingency uncertainties are analyzed through scenarios with an acceptable probability of load curtailment. In (Yu et al., 2009; Orfanos et al., 2012), both authors consider a scenario-based approach for handling uncertainty, and the resulting optimization is solved by probabilistic power flow without considering operational cost. However, in (Jabr, 2013) the probability of having load curtailment is obtained through generation adequacy problems instead of the line overload probability found in probabilistic power flow. In (Yang & Wen, 2005), generation expansion and load uncertainty are handled using MCS, and the line capacity violations having an acceptable probability are modeled through chance constrained TEP optimization. In (Zheng et al., 2014), a three-line overload risk index is considered under TEP optimization with load, wind, and N- contingency uncertainties, and the proposed formulation gives a comprehensive risk control model. In (Hojjatt et al., 2016), an equivalent linear model for stochastic congestion management is proposed using chance constraints on transmission lines. In (Qiu et al., 2016) the authors quantified the probabilistic load curtailment degree by a capped load curtailment probability, which is incorporated into the multi-stage TEP model. In (Qiu et al., 2017), the authors propose a stochastic TEP framework to assess the impacts of wind power and demand response which incorporates load curtailment as a risk constraint. In (Zhang Y. et al.,2017) the authors propose a chance constrained TEP model that utilizes wind power generation with a high probability.

When uncertainty is modeled as stochastic process, the profit or cost is a random variable which can be described by a probability distribution. The uncertainty of the operational problem can be handled using the expected value of this random variables. However, to assess these expected values properly with their magnitudes conditional value at risk models (CVaR) are used. A model with chance constraints only restricts the likelihood of probabilistic constraints being violated. However, a CVaR constrained model, limits both the probability and the magnitude of violations, which can be of interest to the expansion planner. (Conejo et al.,2010). In TEP literature, the degree of conservatism in an expansion choice result in a reduced cost while maintaining the required level of system reliability. In (Molina et al., 2014), risk of not reaching an expected return and tolerance to risk is measured by CVaR approach. In (Jiang et al. 2019), stochastic TEP model considering risk is proposed where CVaR is considered as a measure of overload risk. In (Da Costa et al, 2020), authors showed that CVaR criterion allows to control the load curtailment.

1.4.4 Coordination of TEP and FACTS devices

FACTS devices allow to control the power system operation, by offering flexibility on power flows and voltages in the network (Hingorani & Gyugyi, 2000). The fundamental objective of these devices is to improve system resilience that ensures loading of transmission lines up to their loading capacities, utilize available generation and control outages before they spread (Song & Johns, 1999). The capability of transmission system may be reduced by several limitations like angular, transient, and dynamic stability, voltage magnitude and thermal limits. Limitations on power flow can always be handled by the expansion on transmission lines; but alternatively, FACTS devices can be used as an option to satisfy the objectives of the system. These controllers reduce the total system cost, improve the system security, flexibility, and reliability.

FACTS devices have a wide range of applications in power studies. Power flow studies relied on conventional power flow is generally dealt with generator control and voltage regulation, usually achieved by tap-changing and phase-shifting transformers and reactive compensation. Power flow control can be handled using phase shifting transformers as well as series reactors (Hingorani & Gyugyi, 2000). Transmission expansion planning with the coordination of FACTS devices is still an ongoing research problem in the literature. Technological progress on FACTS controllers has made available several different investment possibilities on existing transmission lines to the installation of FACTS. It is not an exact alternative for expanding transmission network but the use in the occasions for reducing congestions, relieving overloads especially for security conditions is beneficial. To study FACTS devices from an economic and security viewpoint, several approaches are proposed. The most highlighted papers for the TEP studies that consist of FACTS controllers from economic or security viewpoints are given as follows.

In (Chatzivasileiadis et al., 2011), authors compare investment alternatives considering the installation of FACTS devices with security constrained optimal power flow. The power flow constraints, total generation costs and the generation dispatch are evaluated under uncertatinty to assess whether to invest in a FACTS device or a transmission line. In (Li et al., 2017), authors propose a robust planning model considering transmission lines, generators, and FACTS devices to solve severe ramping events due to uncertainty of wind power. In (Zhang X. et al., 2017), authors incorporate a continuously variable series reactor (CVSR) into a multi stage, security constrained TEP problem. A decomposition approach is applied for the nonlinear part of the power flow equations to reduce the computational burden. In (Urganlı & Karatepe, 2017), authors propose a TEP model that considers reactive power planning, and the allocation of TCSC devices to minimize investment of lines, reactive power sources and operational costs. Uncertainties are modelled with clusters and resulting TEP problem is formulated as MINLP problem. In (Ersavas & Karatepe, 2017); authors present a MILP approach that is solved by genetic algorithm for allocation of FACTS devices by considering load uncertainty. In (Zhang X. et al., 2018), authors propose an approach for the allocation of FACTS devices in the transmission network considering multiple operating states and contingencies. Base and contingency conditions are handled with three different load patterns and resulting optimization formulated as MINLP problem. In (Esmaili et al., 2020) authors propose a TEP model that integrates TCSC to enhance line capacity, and superconducting fault current limiters to control short-circuit levels. A multi-stage planning model formulated as MINLP problem, and the authors propose linearization technique within a Benders' decomposition scheme. The coordination of TEP and FACTS devices results in economically attractive optimal expansion plans. In (Franken et al. 2020), authors propose a TEP approach for the simultaneous allocation of high voltage direct current, phase shifting transformers and TCSC. The proposed approach is formulated as a MILP problem and the operating points for FACTS devices are determined by minimizing expansion costs. As the recent studies from the literature show that the inclusion of FACTS devices provide flexibility and increase the system security/reliability of the investment decision.

1.5 Organization of the Thesis

The structure of this thesis is organized as follows:

In Chapter 1, the main motivation behind this dissertation is presented along with the problem definition and research targets. The definitions related TEP problem and solution approaches are discussed in a general perspective. A detailed literature review of stochastic TEP problem based on network representation, solution methods, risk management and coordinated TEP with FACTS studies are discussed.

Chapter 2 begins with reviewing the complementary solutions for stochastic TEP models based on the problem formulation and from the network representation. The implementation of the stochastic DC power flow and DC optimal power flow model is presented with the load and wind uncertainty. The expected cost of load curtailment and generating costs will be examined under various uncertainty scenarios. The operational constraints of the optimal power flow model are converted probabilistic constraints using a chance constraint formulation and utilized in a TEP optimization with budget constraints. The numerical studies on Garver’s test system are handled with a sample TEP study to analyze investment results under different uncertainties.

In Chapter 3, treatment of slack bus generator is analyzed in terms of different probabilistic power flow methodologies using AC network formulation. Single slack bus and distributed slack bus approaches are implemented to obtain overlimit probabilities for uncertain operating conditions. Two methods of dealing with AC network constraints are also explored in accordance with the application in the TEP problem.

In Chapter 4, a stochastic AC transmission expansion planning with a chance constrained distributed slack bus approach are presented. The problem formulation, case studies and the testing procedure is described in detail and the results are demonstrated on IEEE Reliability test system (RTS) and IEEE 118 bus test networks. A detailed discussion based on models, case studies and test results are also presented.

In Chapter 5, a study that presents coordinated TEP and FACTS devices is handled with unified and separate approaches. The impact of series and shunt FACTS devices on network operation is analyzed under different confidence levels. Numerical studies are carried out on IEEE RTS test network and the operational flexibility is investigated with respect to overlimit assessment.

In Chapter 6, the key conclusions, limitations, and future work are presented with concluding remarks.

CHAPTER TWO
MODELLING STOCHASTIC TRANSMISSION EXPANSION PLANNING

As the power network grows gradually with new uncertain inputs, new approaches have arisen in terms of expansion and operation of the transmission network. In that manner, stochastic programming is a widely used approach when incorporating uncertainties like RES, load, or availability of components into TEP problem. Generally, in stochastic models, scenario modelling is adopted, and a two/multi-stage optimization is developed for solving the investment optimization for different operating conditions. The main strategy is to partition the problem into investment and operation sub-problems. The investment decision in the upper part minimizes the total investment cost, whereas uncertain scenarios are handled in the operational lower part. Within this frame the problem formulation for the operational part of TEP can be classified as:

Load curtailment minimization: This approach monitors how much of the forecasted load is curtailed so that the network can serve load without violating the line capacity constraints. Load curtailment is measured by optimal power flow (OPF) and the system is expanded to minimize it.

Overload minimization: This approach is based on overloaded network which satisfies forecasted load for all circumstance. Overload is quantified for each operating condition by power flow and the system is expanded until total overload is eliminated.

At the core of the problem, both approaches try to satisfy the future forecasted load under uncertain operating conditions. Yet, from modelling perspective load curtailment minimization requires an optimal power flow and overload minimization method requires a power flow analysis. Using optimal power flow seems to be more suitable to consider both technical and economic aspects of planning problem. However due to the complexity and computational burden of nonlinear equations; it becomes extremely difficult solve especially for large scale AC networks. In the next section modelling of uncertainties and the mathematical formulation for the operational subproblems of probabilistic load curtailment and overload minimization approaches are implemented. A case study for load curtailment minimization model is presented on Garver test network and the results are presented considering different investment budget.

2.1 Modelling Uncertainties

TEP is usually performed for a long-term planning horizon. When transmission system operator decides the investment plans to be carried out, future generation, demand growth and availability of units. should be considered. In such an uncertain environment, these uncertainties must be properly represented. Traditionally, the characteristics of wind and load uncertainty are handled with its appropriate probability distributions. In the literature, the variation in load is generated using Normal distribution function N(μ,σ^2) as in (2.1).

$$y = f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{2.1}$$

where μ is the mean value and σ^2 is the variance. Traditionally, the load in the original network data is taken as mean values, the standard deviation σ is changed to create different loading scenarios. Therefore, σ/μ ratio of the load uncertainty determines different loading conditions. Wind speed is modelled through Weibull distribution. The shape (k) and scale (c) parameters are determined to model long-term wind speed as in (2.2).

$$y = f(x|c,k) = \frac{k}{c}\left(\frac{x}{c}\right)^{k-1} e^{-\left(\frac{x}{c}\right)^k} \tag{2.2}$$

The characteristics of the wind turbine are determined according to the wind cutting speeds. Since the wind turbine has a non-linear characteristic, the probability distribution of the wind power output is obtained using (2.3), by using the cutting speeds and wind speed distribution.

$$P_w = \left\{\begin{matrix} 0 & 0 \le V \le V_{ci} \\ \frac{P_r(V - V_{ci})}{V_r - V_{ci}} & V_{ci} \le V \le V_r \\ P_r & V_r \le V \le V_{co} \\ 0 & V_{co} \le V \end{matrix}\right\} \tag{2.3}$$

Lastly, transmission availability is generated by using uniform distribution function. Random forced outage rate (FOR) values are generated to model the availability of transmission line. If the random variable is smaller than the FOR, then it is called as outage. For simplicity, all uncertainties are considered independently. MCS is used to incorporate uncertainties based on their probability distribution functions under TEP optimization.

2.2 Probabilistic Power Flow Under Uncertainties

Power flow is an answer to many fundamental questions in power network and it is also an important preliminary analysis tool for the real-time operating conditions in power systems. It helps not only monitoring the system but also supports the decision making in planning studies. Increased intermittent RES power, load growth, and unexpected contingency events in transmission systems inevitably leads to increased degrees of uncertainty in the operating conditions. Therefore, it is essential to adopt a probabilistic framework to provide more realistic outcomes. Unlike deterministic power flow, probabilistic power flow requires inputs with their distributions to obtain system states and power flows in terms of probability distribution functions.

Probabilistic methods for power flow analysis can be categorized as numerical and analytical approaches. MCS is the most common numerical technique since its flexible nature allows non-linear power flow equations, different operating conditions, and spatial/time correlations of the uncertainties (Yu et al., 2009a; Xu et al., 2013; Bin et al.,2018; Hagh et al., 2018; Da Silva and Castro, 2019). In the analytical approaches, the inputs considered as mathematical expressions that represents the uncertainty. Analytical approaches calculate the PDF of output variables by using arithmetic properties of linearization (Taylor series, moments) and approximation (point estimation) introduced by the power balance equation (Tuineme et al., 2020).

2.2.1 *Problem Formulation of the Probabilistic Power Flow*

Power flow control is crucial to maintain line loading, manage power system congestion, reduce line overload, and make the most efficient use of the available transmission lines. Therefore, in this study, a probabilistic DC power flow formulation is implemented to find the probabilistic power flows in transmission lines. DC power flow is a linearized form of AC power flow. So, the following assumptions are applied to general formulations. Active power losses are negligible since R is much smaller than X. Voltage angle differences are assumed to be small. Magnitudes of bus voltages have a flat voltage profile. Based on these assumptions, bus voltage angle is considered as decision variable and active power injections are known parameters of the DC power flow. For each bus i, injected power P_i is calculated by the difference between bus generation and load values as in (2.5). B_{ij} in (2.4) is the reciprocal of the reactance between bus i and bus j. DC power flow equations can be written as follows:

$$P_i = \sum_{j=1}^{N} B_{ij}(\theta_i - \theta_j) \tag{2.4}$$

$$P_i = P_{Gi} - P_{Di} \tag{2.5}$$

$$\theta = B^{-1} P_i \tag{2.6}$$

2.2.2 *Case Studies for the Probabilistic Power Flow*

The presented DC power flow model has been applied to the modified Garver test system given in Figure 2.1. This system has three conventional generators, five loads and six buses. Original bus and line data values in per unit can be found at Appendices. Modification on the test system is given as follows: Lines 2-6 and 4-6 are connected to original test system. Upper bounds of the generators located at buses 1,3 and 6 is determined as 3.5, 3.6 and 6.1 pu. In the probabilistic power flow analysis, load and wind uncertainty is considered. While the load in the original data is taken as mean values, the standard deviation is assumed to be 0.10. The generator at the 3rd bus is replaced with a wind turbine. Rated power of wind turbine (P_{rate}) is considered as 3.6 pu. The shape (k) and scale (c) parameters of wind speed is 5.4 and 2.7 m/s, and wind turbine characteristics V_{ci}, V_r, ve V_{co} are 4,10 and 22 m/s, respectively. The uncertainty data for load with its distribution is given in Figure 2.2(a) and the wind speed distribution is given in Figure 2.2(b).

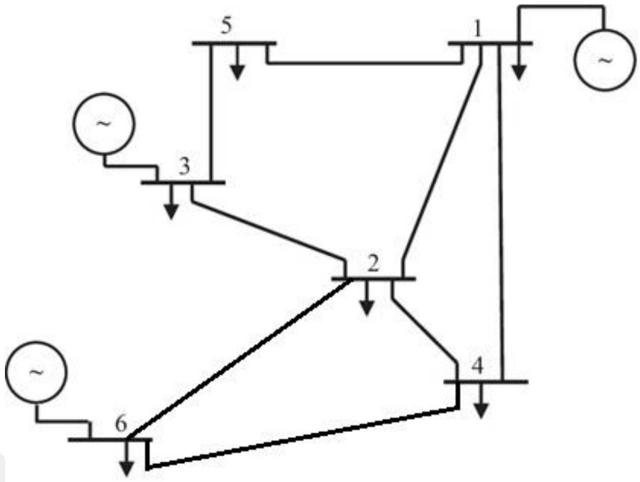

Figure 2.1 Modified Garver test system

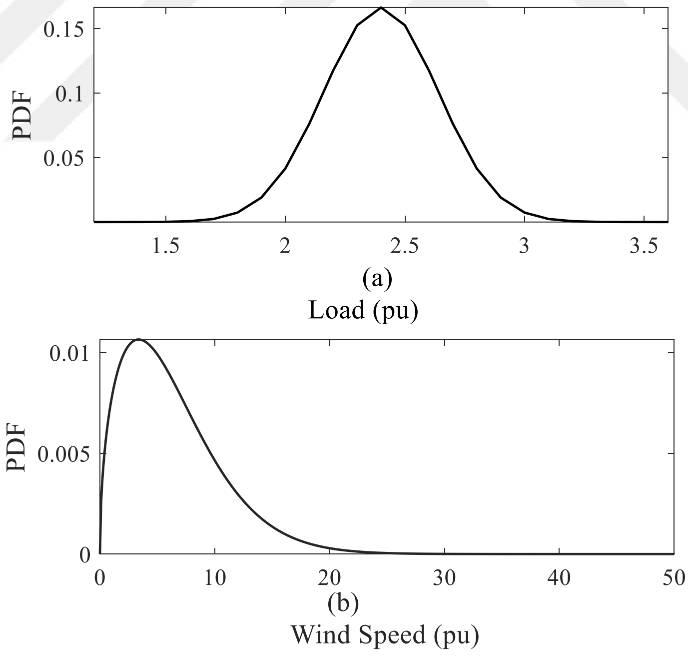

Figure 2.2 (a) Load distribution (b) Wind speed distribution

The output of the probabilistic power flow solution process consists of PDFs active power flows of transmission lines as shown in Figure 2.3. The approach used for MCS is an iterative process in which the deterministic DC power flow represented in (2.1) to (2.3) is solved by considering a set of input variables from randomly generated scenarios. After MCS, a statistical analysis can be performed on power flow PDFs to find the overload probabilities. Suppose that the branch limit for all transmission lines is considered 1.5 per unit, the overload probability for the lines 1-5, 3-5, 2-6 and 4-6 are calculated as 0.30, 0.26, 1.00 and 1.00 respectively.

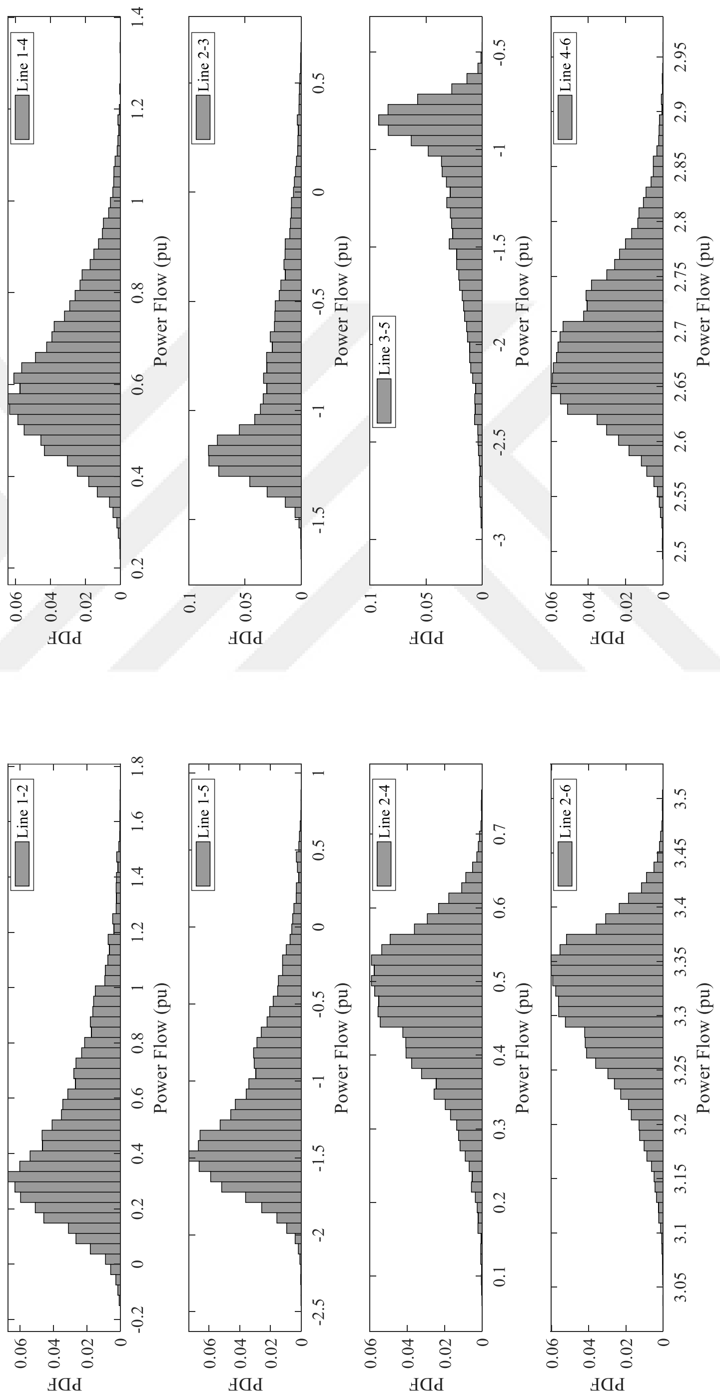

Figure 2.3 Active power PDFs of transmission lines in Garver test system

2.3 Probabilistic Optimal Power Flow Under Uncertainties

The operation of a power system involves systematic coordination of generating units that supply the demand in all conditions. This coordination requires the technical and economic aspects of generators and the constraints of the power network. In fact, by looking at only these features, we can achieve the operational decision with a simple load flow. Yet, the load flow solution does not involve economic management for generators. The problem of both considering network constraints and the economics for generators is economic dispatch (ED). The goal of the ED is to find the output power of each generator for a single period so that it meets all demands at minimum cost concerning the technical constraints of the generation units. In a network where the generation units are close to each other, network constraints can be ignored. In such a situation, the solution of the ED gives the generator output power from cheapest to most expensive; however cheaper generating units may not always be near the load nodes. Therefore, network constraints need to be addressed along with the ED problem, which is called the optimal power flow (OPF). OPF aims to find power dispatch to supply all demands while satisfying the network constraints. OPF solution is the most comprehensive among other analysis, but it requires a complex optimization structure, especially with nonlinear network constraints. In this study a probabilistic optimal power flow problem is implemented with a DC network model under load and wind uncertainties. The impact of uncertainties on generation and load curtailment costs were investigated using MCS.

2.3.1 Problem Formulation of the Probabilistic Optimal Power Flow

In this study, the effect of load and wind power plant output uncertainties on optimal power flow problem is investigated. The expected values of generation and load curtailment costs are determined using MCS under different scenarios and results are presented. Generally, in OPF, a planner determines the change of output of power plants and the future load to reflect appropriately in the optimization problem (Capitenascu et al., 2011). These uncertainties are modelled through the help of long-term observation and mathematical methods. In this study, load and wind uncertainty data is considered in the analysis is the same as in section 2.1. The network model is chosen to be as DC model. DC load flow method neglects the network losses, assume voltage amplitude on each bus as 1 per unit (pu) and considers the voltage angle difference between neighboring bus are small. In this way, the non-linear AC power flow equations are linearized, and linear optimization techniques can be used to solve OPF problem. Load and wind speed uncertainty is considered as independent random variables ξ_1 and ξ_2 and the OPF is modelled as follows:

$$\min \sigma \left(\sum_{g \in \Omega^G} C_{gen} P_g + \sum_{w \in \Omega^W} C_{wind} P_w + \sum_{LC \in \Omega^d} C_{curt} P_{LC} \right) \tag{2.7}$$

subject to

$$\sum_{g \in \Omega^G} P_g + \sum_{w \in \Omega^W} P_w - \sum_{l|s(l)=n} P_l + \sum_{l|r(l)=n} P_l + \sum_{LC \in \Omega^d} P_{LC} - \sum_{d \in \Omega^d} P_d = 0 \quad \forall n \tag{2.8}$$

$$P_l = B_l\big(\theta_{s(l)} - \theta_{(r(l))}\big) \quad \forall l \in \Omega^{L+} \tag{2.9}$$

$$-f_{max} \leq P_l \leq f_{max} \quad \forall l \in \Omega^{L+} \tag{2.10}$$

$$0 \leq P_g \leq P_g^{max} \quad \forall g \in \Omega^G \tag{2.11}$$

$$0 \leq P_{LC} \leq P_d^{max}\,(\xi_1) \quad \forall LC \in \Omega^d \tag{2.12}$$

$$0 \leq P_w \leq P_w^{max}\,(\xi_2) \quad \forall w \in \Omega^W \tag{2.13}$$

$$-\pi \leq \theta_n \leq \pi \quad where\ \theta_1 = 0\ (reference) \tag{2.14}$$

where Cg, Cw, Cls is the cost of conventional generator, wind and load curtailment, respectively. Annualized costs are considered in the objective function in (2.7) where σ is assumed as 8760. The symbols g, w, d, LC is the set of conventional generator, wind, load and load curtailment and L is the set of candidate lines. (2.8) represents the power balance equation. (2.9) is used to find power flows. Equations (2.10) to (2.14) are the constraints of the OPF problem. Unlike the deterministic analysis, the upper bounds of load and wind uncertainty are updated according to its distributions. MCS is used to determine the expected costs under uncertainty scenarios. In the first step, the randomly selected sample cases are evaluated until the MCS convergence criterion is met; in this case it is a pre-determined large sample number; and at last, the expected long-term values of generation and load curtailment costs can be found. The presented probabilistic optimal power flow is applied on Garver's test system in Figure 2.1. Modification on the test system is assumed to be the same as section 2.1. Additional cost parameters for generators are given as follows: Generation costs are considered as 15 $/MWh and load curtailment cost is considered 60 $/MWh. The capacity of lines is 1.5 pu. The optimization problem is solved by linear programming using MATLAB.

2.3.2 Case Studies for the Probabilistic Optimal Power Flow

In the first study, expected generation and load curtailment cost under different levels of load uncertainty are investigated with stochastic OPF formulation. As it can be seen in Figure 2.4(a) and Figure 2.4(b), the generation cost of the scenario with high σ/μ ratio is low while the cost of load curtailment is high. Bottlenecks in the transmission line have increased the load curtailment costs of the system. Wind power is utilized more when the uncertainty is considered as low to the extent permitted by the line limits. In that manner, the cost of generation was lower than in the case of a high σ/μ ratio. It is inferred that the line constraints significantly restrict system performance. Therefore, the change in generation and load curtailment costs obtained by increasing the transmission line capacity is given in Figure 2.5. Considering that the new line investments have been made here which means line limits have been increased from 1.5 pu to 2.5 pu and the power transfer corridor for wind power plants has been improved. Figure 2.5(b) shows a significant reduction in load curtailment cost when the line limits are increased. Especially in the scenario where the σ/μ ratio is small, the cost of load curtailment decreased dramatically. In that manner, it is observed the impact of transmission has a significant effect on load curtailment cost while maintaining generation-consumption balance.

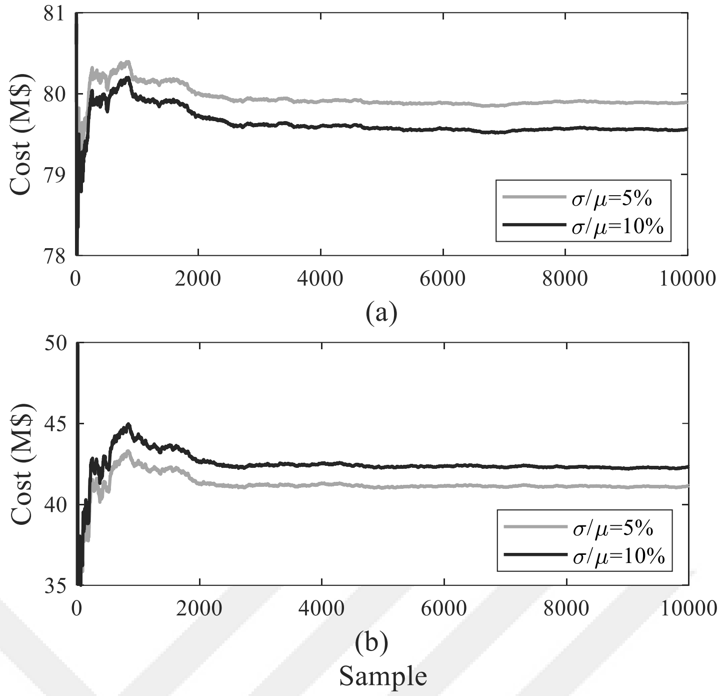

Figure 2.4 (a) Generation cost (b) Load curtailment cost for different load uncertainty scenarios

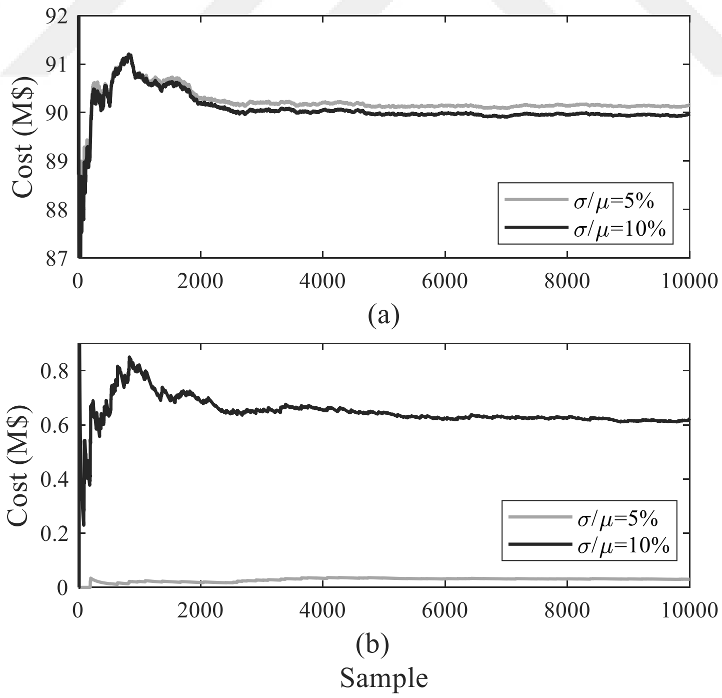

Figure 2.5 (a) Generation cost (b) Load curtailment cost for different load uncertainty scenarios when transmission capacity is increased

In the second study, expected generation and load curtailment costs are investigated under wind uncertainty scenarios using stochastic OPF formulation. The effect of wind uncertainty is examined under three different scenarios given in Table 2.1 for different wind speed and wind turbine conditions.

Table 2.1 Wind uncertainty scenarios

Scenario	**Weibull**	**Turbine Characteristics**
S1	*k*=5.4 m/s, *c*=2.7 m/s	V_{ci}=4 m/s, V_{rate}=10 m/s, V_{co}=22 m/s
S2	*k*=5.4 m/s, *c*=2.7 m/s	V_{ci}=3 m/s, V_{rate}=5 m/s, V_{co}=15 m/s
S3	*k*=7 m/s, *c*=2.5 m/s	V_{ci}=4 m/s, V_{rate}=10 m/s, V_{co}=22 m/s

For different wind power conditions, generation costs and load curtailment costs are set to different expected cost values for each scenario, as shown in Figure 2.6. In scenario 3, generation and load curtailment costs were lowest, as the wind power is high. In scenario 2, the output power of the wind is less because the cutting speeds are lower than scenario 1. Therefore, the cost of generation was higher in Figure 2.6(a).

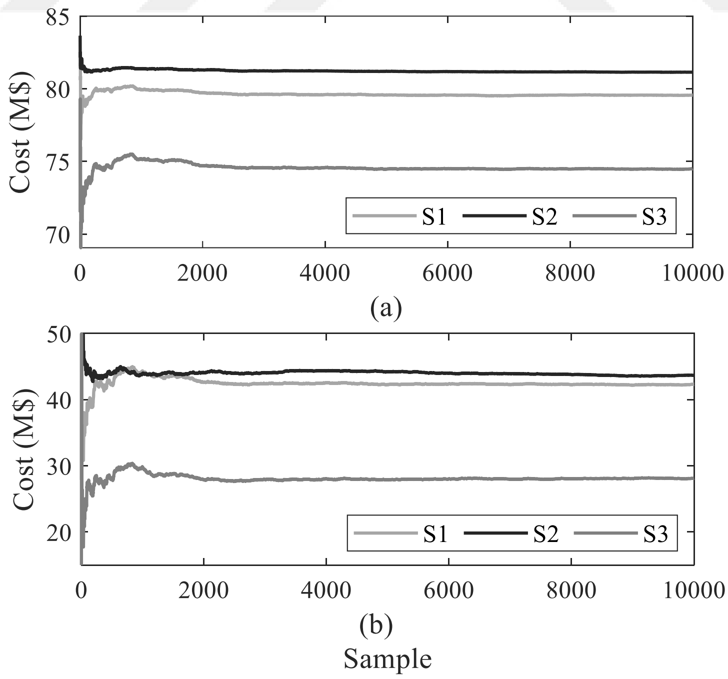

Figure 2.6 (a) Generation cost (b) Load curtailment cost for different wind power scenarios

To examine the effect of transmission line capacity under different uncertainty conditions, line capacities have been increased to 2.5 pu and the obtained generation and load curtailment costs are given in Figure 2.7. In all three scenarios, a significant decrease was observed in load curtailment costs as seen in Figure 2.7(b). As a result, it is seen that transmission line investments have an important role in reducing load curtailment costs.

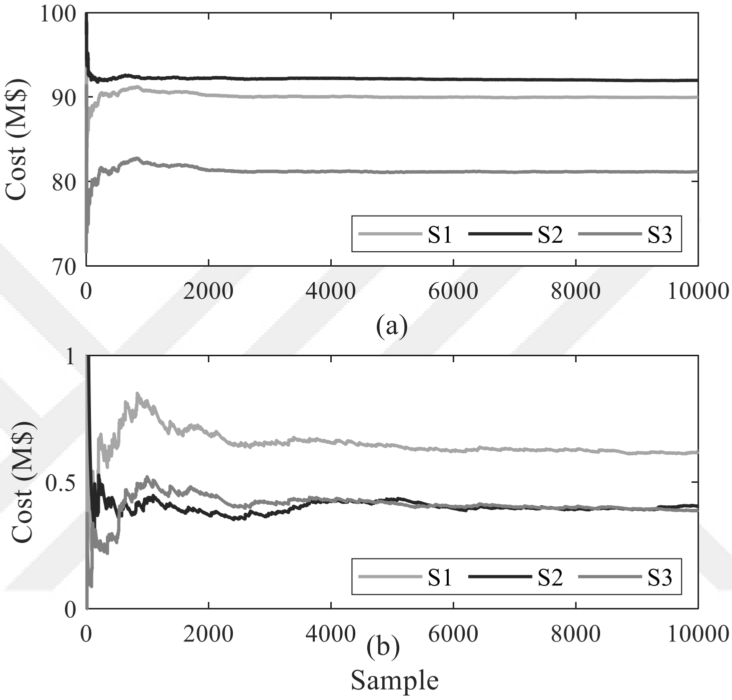

Figure 2.7 (a) Generation cost (b) Load curtailment cost for different wind uncertainty scenarios when transmission capacity is increased

Consequently, it was observed that the uncertainties of load and the wind are effective on both generation and load curtailment costs. Congestion in transmission lines, reduce the cost of load curtailment as the load uncertainty increases. Transmission congestion increases the cost of load curtailment costs as the load uncertainty increases. Considering the long-term operational costs as well as network investments play a major role in planning, it is seen that load and wind uncertainties should be included in the modeling in determining the expected cost values.

2.4 Integration of Subproblems into Stochastic TEP problem

The deterministic DC TEP model based on a load curtailment minimization approach is given as follows:

$$\min \sum_{(i,k)\epsilon\Omega} c_{ik}n_{ik} + p_f \sum_{j\epsilon\Gamma} r_j \tag{2.15}$$

subject to

$$S^T f + P_g + P_r = P_d \tag{2.16}$$

$$f_{ik} - \gamma_{ik}(n_{ik}^0 + n_{ik})(\theta_i - \theta_k) = 0 \tag{2.17}$$

$$|f_{ik}| \leq (n_{ik}^0 + n_{ik})\bar{f}_{ik} \tag{2.18}$$

$$0 \leq g \leq \bar{g} \tag{2.19}$$

$$0 \leq r \leq d \tag{2.20}$$

$$0 \leq n_{ik} \leq \bar{n}_{ik} \tag{2.21}$$

The above mathematical formulation is a two-level framework that finds the economical transmission investment trying to minimize load curtailment and satisfy the adequacy of the system (Romero & Monticelli, 1994; Orfanos et al., 2012). The objective function minimizes the total investment and load curtailment cost, given in (2.15) and the constraints of nodal power balance in (2.16), DC power flow and the operational limits are given in (2.17) to (2.21). The penalty term assigned in the objective function assist the optimization process to minimize the load curtailment. When this problem is solved with heuristic methods, optimization continues until the penalty term becomes zero. In the stochastic version of this model, the uncertainty scenarios are handled in the lower level (operation) of the problem. Traditionally, MCS handles uncertain operating conditions, and these scenarios are repeatedly analyzed by the OPF formulation until the MCS stopping criterion is met. As a result, the expected value of load curtailment is added to objective function to guide the investment decision. Furthermore, the risk of violation in the operational constraints of the lower-level problem can be addressed in the constraints of investment optimization or the objective function. If it is handled in the constraints, chance constraint programming is used to convert deterministic operational constraints into probabilistic ones. On the other hand, if it is considered in the objective function, the expected load curtailment amount is obtained in the lower problem, and it is used in the objective function with a specified penalty value.

In the solution of DC TEP optimization, many candidate TEP plans are evaluated with a linear optimization to find the overall load curtailment. This requires time consuming network evaluation especially for larger size systems. Therefore, an alternative version to find the load curtailment is to calculate the sum of the overload percentages of the lines to reflect the overload of the system (Yu et al.,2009). The problem formulation of overload minimization-based model is given followingly:

$$\min \sum_{(i,k)\epsilon\Omega} c_{ik} n_{ik} + p_f \sum_{(i,k)\epsilon\Omega} e_{ik} \tag{2.22}$$

subject to

$$S^T f + P_g = P_d \tag{2.23}$$

$$0 \leq g \leq \bar{g} \tag{2.24}$$

$$0 \leq n_{ik} \leq \bar{n}_{ik} \tag{2.25}$$

where

$$f_{ik} = \gamma_{ik}(n_{ik}^0 + n_{ik})(\theta_i - \theta_k) \tag{2.26}$$

$$e_{ik} = \left\{ \begin{array}{cc} 0 & |f_{ik}| \leq (n_{ik}^0 + n_{ik})\bar{f}_{ik} \\ \dfrac{|f_{ik}| - (n_{ik}^0 + n_{ik})\bar{f}_{ik}}{(n_{ik}^0 + n_{ik})\bar{f}_{ik}} & |f_{ik}| > (n_{ik}^0 + n_{ik})\bar{f}_{ik} \end{array} \right\} \tag{2.27}$$

The penalized term in the objective function is converted to sum of overload percentages in (2.22). The nodal balance equations in (2.23) and the operational constraints in (2.24) and (2.25) are organized to avoid load curtailment parameter. The power flow solution in (2.26) can readily acquire the total of the overload percentages of the lines which is given in (2.27). From the computational time perspective, first approach requires an OPF to find the load curtailment for investment optimization. However, in the latter method, load flow study is enough to find overload of the system. Therefore, the computation time is very short. In terms of accuracy, both models use penalty schemes that can achieve the same optimal solution. Because heuristics minimize the objective function until the penalized variables are zero. In the stochastic version of this approach, a probabilistic power flow method is used to check the overload in the system. Unlike the deterministic model, the system operation constraints can be expressed with distribution functions, since they deal with large number of scenarios instead of a single scenario. Depending on the mathematical formulation the overload percentages of the lines can be handled in the constraints of the TEP optimization. If the planner chooses to allow overload risk, a chance constraint programming approach can be used in the optimization constraints as in (2.28) to convert deterministic constraints into in the probabilistic ones.

$$e_{ik} = \begin{cases} 0 & Pr\left\{\left|f_{ij}\right| \leq \overline{f}_{ij}\right\} \geq \beta \\ \beta - Pr\left\{\left|f_{ij}\right| \leq \overline{f}_{ij}\right\} & Pr\left\{\left|f_{ij}\right| \leq \overline{f}_{ij}\right\} < \beta \end{cases} \tag{2.28}$$

In the next section, stochastic transmission expansion planning is implemented with a load curtailment minimization approach. The investment decisions are investigated under different investment budgets and confidence levels using chance constraint programming.

2.5 Stochastic TEP with Different Investment Budgets

In this study, a chance constrained TEP framework which has two random variables are used to explore the possibility of transmission decisions under different investment budgets. The following section 2.5.1 describes the procedure of chance constrained programming approach. In Section 2.5.2, the mathematical formulation of chance constrained TEP problem is given. In Section 2.5.3, case studies are illustrated, and results are given.

2.5.1 Chance Constrained Programming

Charnes and Cooper develop chance constrained programming (CCP), which is a useful stochastic approach in optimization problems with random variables (Charnes & Cooper, 1959). This approach relies on the basis when the decision maker handles the random variables using probabilistic constraints. The objective of a stochastic models with chance constraints is to make the best choice before the realization of random data while allowing the constraints to be violated with a given probability. Therefore, the chance constraints need to be satisfied with at least α_i times, where α_i is the probability specified by the decision makers for finding the optimal solution (Liu ,2009). A general CCP problem is formed as:

$$\min f(x) \tag{2.29}$$

subject to

$$prb\{h_i(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0, i = 1,2, \dots, m\} \geq \alpha_i \tag{2.30}$$

where $x \in R^n$ is the vector of decision variables, (2.29) is the objective function, (2.30) is stochastic constraint function, ξ is a stochastic vector with a given probability distribution function $\phi(\boldsymbol{\xi})$, α_i refers confidence level (Liu ,2009). Traditionally stochastic models are mathematical programs with uncertain input which is approximated with probability distributions. In this context, a solution to a stochastic optimization with CCP is a linear optimization that requires the conversion of the chance constraints to their equivalent deterministic formulations. Assume that the ith constraint function $h_i(\boldsymbol{x}, \boldsymbol{\xi})$ has the form in (2.31)

$$\sum_{j=1}^{n} a_{ij} x_j - b_i \leq 0 \tag{2.31}$$

where a_{ij} and b_i are assumed to be independently normally distributed random variables. If then $prb\{h_i(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \alpha_i$ if and only if

$$\sum_{j=1}^{n} E\left[a_{ij}\right] x_j + \phi^{-1}(\alpha_i) \sqrt{\sum_{j=1}^{n} V\left[a_{ij}\right] x_j^2 + V[b_i]} \leq E[b_i] \quad i = 1,2, \dots, m \tag{2.32}$$

where E is expected value and V is variance of the random variable in (2.32).

2.5.2 *Mathematical Formulation of a Stochastic Chance Constrained TEP*

In this section, a chance constrained TEP formulation is illustrated. Load and wind uncertainties are defined as two independent random variable ξ1 and ξ2. The objective function to be minimized is given as in (2.33)

$$\min \sum_{l \in \Omega^{L+}} C_{line} x_l + \sigma \left(\sum_{g \in \Omega^G} C_{gen} P_g + \sum_{w \in \Omega^W} C_{wind} P_w + \sum_{LC \in \Omega^d} C_{curt} P_{LC} \right) \quad (2.33)$$

subject to

$$\sum_{l \in \Omega^{L+}} C_{line} x_l \leq C_b \quad (2.34)$$

$$x_l = \{0,1\} \quad \forall l \in \Omega^{L+} \quad (2.35)$$

$$\sum_{g \in \Omega^G} P_g + \sum_{w \in \Omega^W} P_w - \sum_{l|s(l)=n} P_l + \sum_{l|r(l)=n} P_l + \sum_{LC \in \Omega^d} P_{LC} - \sum_{d \in \Omega^d} P_d = 0 \quad \forall n \quad (2.36)$$

$$P_l = B_l\big(\theta_{s(l)} - \theta_{(r(l))}\big) \quad \forall l \setminus l \in \Omega^{L+} \quad (2.37)$$

$$P_l = x_l B_l\big(\theta_{s(l)} - \theta_{(r(l))}\big) \quad \forall l \in \Omega^{L+} \quad (2.38)$$

$$-f_{max} \leq P_l \leq f_{max} \quad \forall l \setminus l \in \Omega^{L+} \quad (2.39)$$

$$-x_l f_{max} \leq P_l \leq x_l f_{max} \quad \forall l \setminus l \in \Omega^{L+} \quad (2.40)$$

$$0 \leq P_g \leq P_g^{max} \quad \forall g \in \Omega^G \quad (2.41)$$

$$0 \leq P_{LC} \leq P_d^{max}\,(\xi_1) \quad \forall LC \in \Omega^d \quad (2.42)$$

$$0 \leq P_w \leq P_w^{max}\,(\xi_2) \quad \forall w \in \Omega^W \quad (2.43)$$

$$-\pi \leq \theta_n \leq \pi \quad where\ \theta_1 = 0\ (reference) \quad (2.44)$$

where Cline, Cgen, Cwind, Ccurt are cost of line, conventional generators, wind generator, and load curtailment, respectively. σ is chosen as 8760 to make annualized generation and load curtailment costs. For the symbols g, w, d, LC and L+ refer conventional generators, wind generator, load demand, load curtailment, and candidate lines. x is the binary decision variable. Cb is line investment budget. (2.36) presents power balance equation. (2.37) and (2.38) are DC power flow equations for existing and candidate lines. (2.39) and (2.40) are the capacity limits of existing and candidate lines. In (2.40), lines that are not selected to be built are enforced to have zero capacities. (2.41), (2.42), (2.43), and (2.44) represent the upper and lower bounds of variables in this problem. Upper bounds of wind and load in (2.42) and (2.43) are updated with respect to different confidence levels using chance constraint formulation in (2.32).

2.5.3 Case Studies on Garver's Test System

Garver's six-bus test system is used to evaluate the proposed chance constrained TEP model considering uncertainties of wind and load. It is studied in different confidence levels and investment budgets. The test network has three conventional generators, five loads and six lines (Rider et al.,2007). We consider 15 candidate lines and allow one candidate line for each possible corridor. Input data used in the simulations can be found in Appendices. Upper bounds of conventional generators are modified as 2.25 pu, 5.40 pu and 6 pu for the generators located at bus 1, 3, and 6. Generation costs are assumed as 10 $/MWh, 25 $/MWh and 15 $/MWh, respectively. Load curtailment cost is 120 $/MWh for all loads. The mathematical formulation of TEP is a mixed-integer non-linear problem and it is solved using the BONMIN (Basic Open-source Nonlinear Mixed Integer programming) solver via MATLAB (Bonami and Lee,2007). We establish the following three different cases:

Case 1: considering only load uncertainty

Case 2: considering only wind uncertainty

Case 3: considering both load and wind uncertainty

where the confidence levels are chosen as 99%, %90 and %80. Budget is also changed in each confidence level to explore the impact when considering these uncertainties in TEP decisions.

Case 1: Hourly load profile is randomly generated. To capture it's volatility, we assume that the load is normally distributed with $N(\mu,\sigma^2)$ (Orfanos et al., 2013; Makarov et al., 2009). μ is the expected value and σ^2 is the variance. For each load bus in sequence, expected value is 0.4922 pu, 1.4765 pu, 0.2461 pu, 0.9843 pu, 1.4765 pu and variance is 0.0122 pu,0.1098 pu, 0.0031 pu, 0.0488 pu, 0.1098 pu, respectively. Figure 2.8 and Figure 2.9 are the annualized total and generation costs of expansion decisions for different budgets and confidence levels. As the budget increases, the total and generation costs are decreasing. In lower budget levels, the required lines supplied the loads cannot be installed. Therefore, the load curtailment is high. Figure 2.10 indicates that when the budget increases it is possible to build some of the candidate lines and the load curtailment can be eliminated. For 99% confidence level, the load curtailment cannot be eliminated until $400,000 due to the budget constraint. The reason behind this result is that the optimization process prefers load curtailment instead of making a transmission investment.

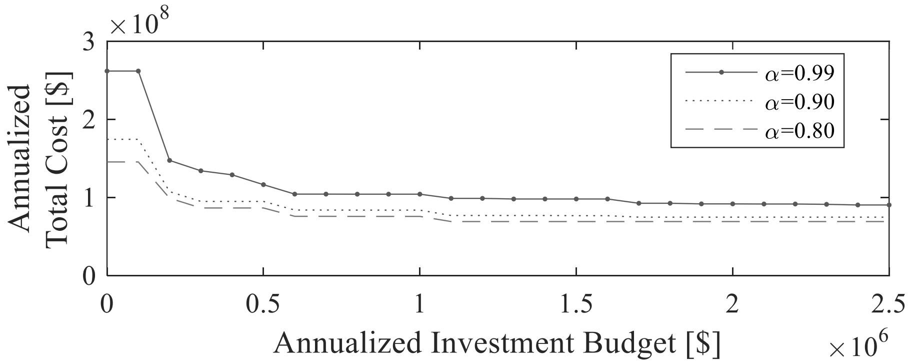

Figure 2.8 Investment budget vs. total cost for Case-1

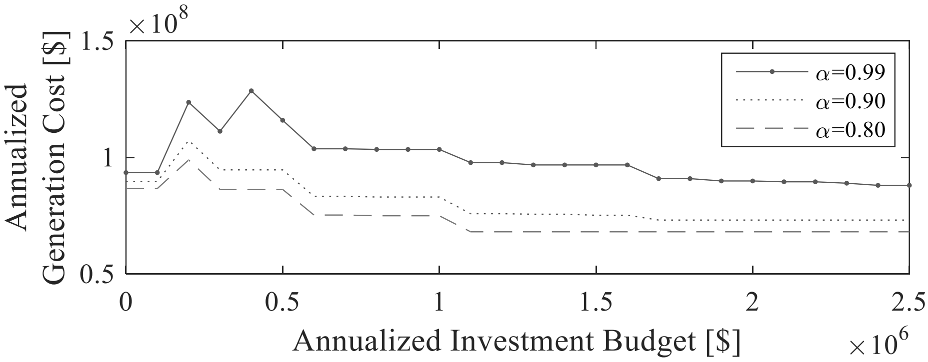

Figure 2.9 Investment budget vs. generation cost for Case-1

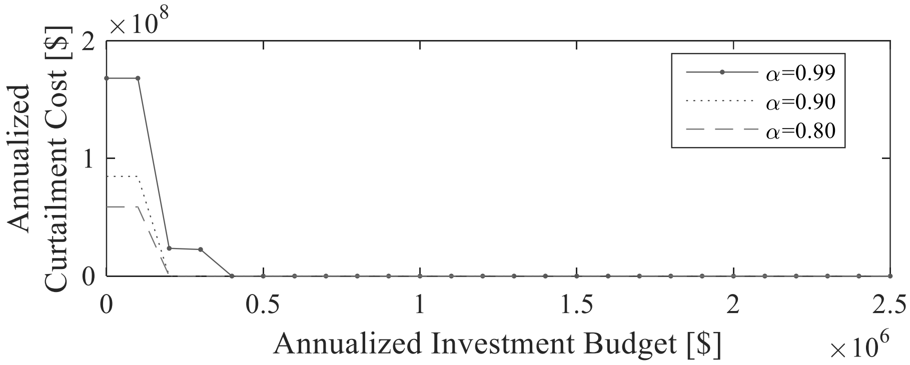

Figure 2.10 Investment budget vs. load curtailment cost for Case-1

Table 2.2. shows the examples of investment decisions with different budgets and confidence levels. The optimization process tends to build lines to reduce load curtailment and generation cost if the investment budget is sufficient. Transmission expansion decisions are also changing with confidence levels. This allows transmission planner to decide which lines to be built for different confidence levels.

Table 2.2 Investment Decisions for Case-1

Annualized Investment Budget [M$]	**Confidence Level (α)**		
	α = 0.99	**α = 0.90**	**α = 0.80**
0.2	l_4	l_4	l_4
0.3	l_{10}	l_{14}	l_{14}
0.4	l_4, l_6	l_{14}	l_{10}
0.5	l_4, l_{14}	l_{10}	l_{10}
1	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}
1.5	l_4, l_{10}, l_{12}, l_{14}	l_1, l_{10}, l_{12}, l_{14}	l_{10},l_{12},l_{14}
2.0	l_4, l_{10}, l_{12}, l_{14}, l_{15}	l_{10}, l_{12}, l_{14}, l_{15}	l_{10},l_{12},l_{14}
2.1	l_1, l_{10}, l_{12}, l_{14}, l_{15}	l_{10}, l_{12}, l_{14}, l_{15}	l_{10},l_{12},l_{14}
2.3	l_1, l_4, l_{10}, l_{12}, l_{14}, l_{15}	l_{10}, l_{12}, l_{14}, l_{15}	l_{10},l_{12},l_{14}
2.5	l_8, l_{10}, l_{12} ,l_{14},l_{15}	l_{10},l_{12},l_{14}, l_{15}	l_{10},l_{12},l_{14}

Case 2**:** In this case, we assume that the generator at bus 6 is retired and replaced with wind generator that has rated capacity of 3.542 pu. The total rated capacity of conventional generators is sufficient for supplying total demand even in the worst realization of the demand. Penetration level of wind power is 48% and wind scenarios are considered with normal distribution as in (Wang et al., 2008; Makarov et al., 2009). To capture its volatility, we consider that the wind is normally distributed with $\mu = 2$ and $\sigma^2 = 0.36$. In Figure 2.11, as the budget increases, annualized total cost is decreasing. High confidence level means high wind availability. Figure 2.12 depicts that highest confidence level leads to lower generation cost especially in higher investment budgets. However, generation cost swings due to the load curtailment since it cannot be eliminated at lower investment budgets as shown in Figure 2.13.

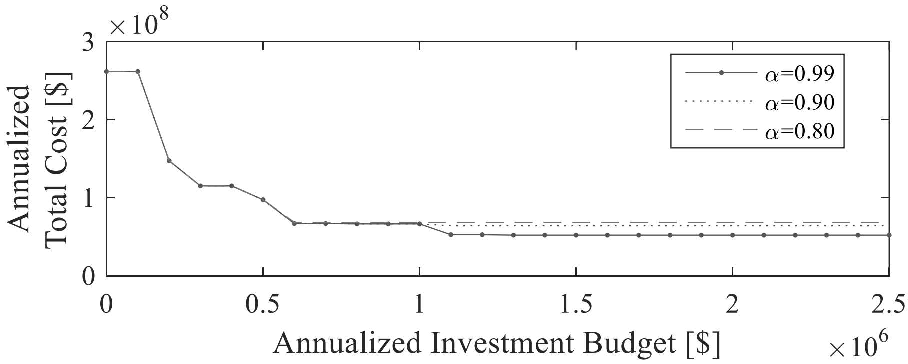

Figure 2.11 Investment budget vs. total cost for Case-2

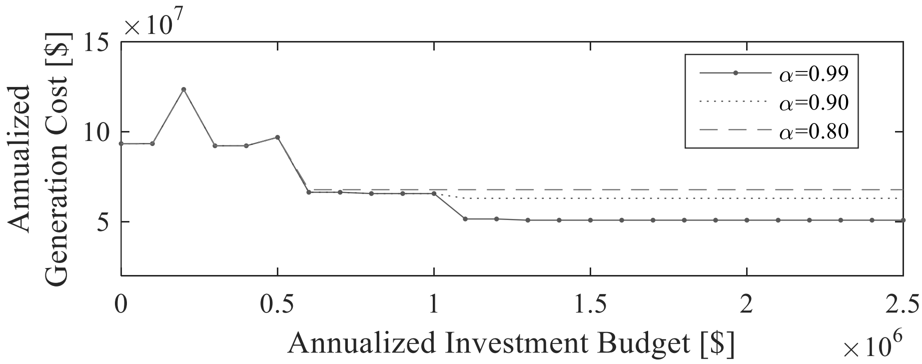

Figure 2.12 Investment budget vs. generation cost for Case-2

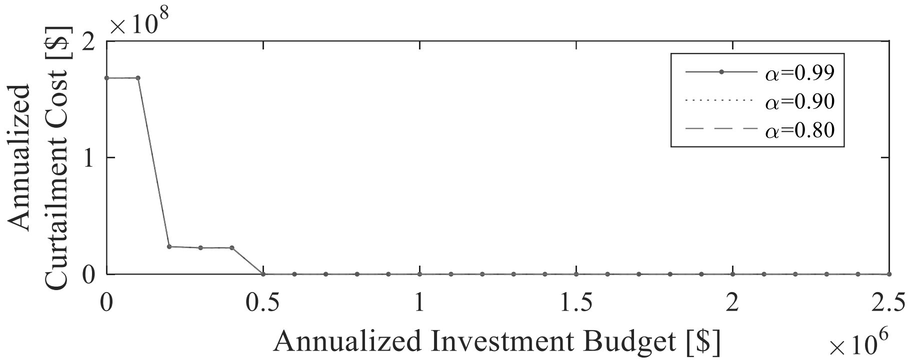

Figure 2.13 Investment budget vs. load curtailment cost for Case-2

Table 2.3 shows the investment decisions that are built for different budgets and confidence levels. Optimization process tends to build more lines through bus 6 because generation cost is decisive in total cost. This is understandable because the investment to utilize wind power is more economically attractive than the investment in lines through conventional generators.

Table 2.3 Investment Decisions for Case-2

Annualized Investment Budget [M$]	**Confidence Level (α)**		
	α = 0.99	**α = 0.90**	**α = 0.80**
0.2	l_4	l_4	l_4
0.3	l_{10}	l_{10}	l_{10}
0.5	l_4, l_{14}	l_4, l_{14}	l_6, l_{10}
1	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_{10}, l_{14}
1.2	l_{10}, l_{12},l_{14}	l_{10}, l_{12},l_{14}	l_{10}, l_{14}
2.0	l_{10}, l_{14}, l_{15}	l_{10}, l_{12},l_{14}	l_{10}, l_{14}
2.5	l_{10}, l_{14}, l_{15}	l_{10}, l_{12},l_{14}	l_{10}, l_{14}

Case 3: In this case, both wind and load uncertainties are considered. Each scenario is represented with different confidence levels, where W and L stand for wind and load. As seen in Figure 2.14, at the lowest wind and highest load confidence levels, total cost results in the highest value for each investment budget. On the other hand, at the highest wind and lowest load confidence levels, total cost results in the lowest value. For each scenario, optimization process leads to a solution utilizing maximum amount

of wind in the system. Figure 2.15 depicts that the load curtailment cannot be eliminated during the low budget constraints for each pair of confidence levels. There is no significant change in TEP plans where the investment budget is higher than \$1.5e6 for each confidence level as shown in Table 2.4.

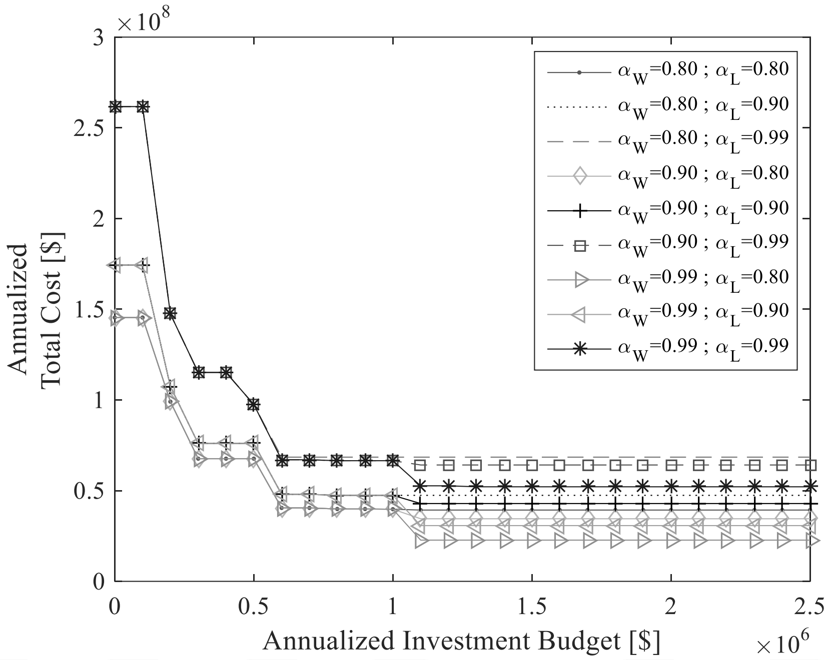

Figure 2.14 Investment budget vs. total cost for Case-3

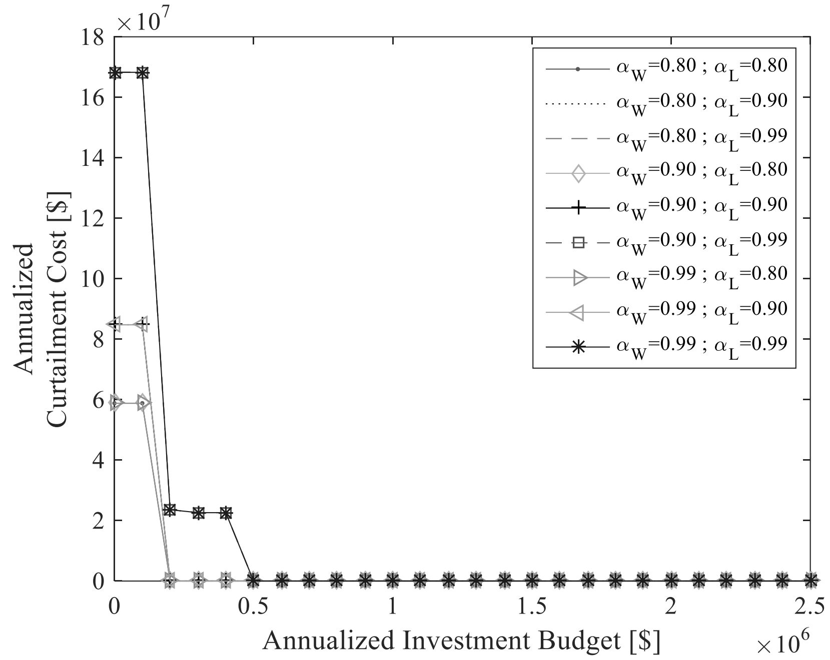

Figure 2.15 Investment budget vs. load curtailment cost for Case-3

Table 2.4 Investment Decisions for Case-3

Confidence Level (α)	Annualized Investment Budget [M$]						
	0.2	**0.3**	**0.4**	**0.5**	**0.9**	**1**	**1.5**
$\alpha_W = 0.99$ $\alpha_L = 0.99$	l_4	l_{10}	l_{10}	l_4, l_{14}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_{10}, l_{14}, l_{15}
$\alpha_W = 0.99$ $\alpha_L = 0.90$	l_4	l_{14}	l_{14}	l_{10}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}
$\alpha_W = 0.99$ $\alpha_L = 0.80$	l_4	l_{14}	l_{10}	l_{10}	l_3, l_{10}, l_{14}	l_5, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}
$\alpha_W = 0.90$ $\alpha_L = 0.99$	l_4	l_{10}	l_{10}	l_4, l_{14}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}
$\alpha_W = 0.90$ $\alpha_L = 0.90$	l_4	l_{14}	l_{10}	l_{10}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}
$\alpha_W = 0.90$ $\alpha_L = 0.80$	l_4	l_{14}	l_{10}	l_{10}	l_3, l_{10}, l_{14}	l_5, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}
$\alpha_W = 0.80$ $\alpha_L = 0.99$	l_4	l_{10}	l_{10}	l_4, l_{14}	l_{10}, l_{14}	l_{10}, l_{14}	l_{10}, l_{14}
$\alpha_W = 0.80$ $\alpha_L = 0.90$	l_4	l_{14}	l_{14}	l_{14}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}	l_3, l_{10}, l_{14}
$\alpha_W = 0.80$ $\alpha_L = 0.80$	l_4	l_{14}	l_{10}	l_{14}	l_3, l_{10}, l_{14}	l_5, l_{10}, l_{14}	l_{10}, l_{12}, l_{14}

Consequently, a deterministic formulation for chance constrained programming is applied on TEP considering load and wind uncertainties under different investment budgets. It is shown that, the model proposed could well accommodate uncertain factors with different risk levels. This framework gives transmission planner an opportunity to compromise between the investment budget and uncertainties. It is observed that there is a trade-off between investment budget and load curtailment. If a planner desires to eliminate load curtailment and utilize more wind power, a sufficient budget is necessary. The results also show that as the budget increases the generation cost becomes decisive in total cost. Compared with confidence levels and investment budgets demonstrate that investment budget predominantly determines transmission expansion plans. More flexibility is required in making expansion decisions when uncertainties are included in planning studies.

CHAPTER THREE
MODELLING PROBABILISTIC POWER FLOW FOR STOCHASTIC AC-TEP PROBLEM

Due to the variable nature, a power system with high-RES will need a well-developed network infrastructure capable of transmitting the renewable energy output from remote locations to any other area with low renewable output. The system's power flow patterns are anticipated to change significantly over time, depending on the availability of RES power. Therefore, many uncertainty scenarios are examined using OPF to adequately handle the operational states of the network investments. However, due to the network's size and ability to handle a variability of scenarios along with OPF's nonlinear nature, a more complicated combinatorial problem is produced that may eventually become intractable. The operating conditions that may stress various areas of the network can be significantly different. So that the conventional practice of evaluating the OPF for the peak demand scenario is no longer appropriate for the TEP problem. OPF should be computationally efficient in TEP optimization to ensure tractability and produce results with an acceptable level of accuracy (Fitiwi et al., 2016). Transmission expansion planning is primarily begun with selecting the network representation. What levels of specifics can be incorporated in TEP model depends on the representation of power network. In long term planning, it is important to determine network representation to formulate the operational problem. In the planning studies, power flow is the main study to control or obtain system behavior which is adopted under AC, DC, or linearized AC formulations. Since the main purpose of this dissertation is to build an AC-TEP model, the mathematical formulations of AC power flow and participation factor AC power flow are derived in the next sections.

3.1 AC Network Model with Conventional Power Flow Equations

Using AC power flow analysis gives a complementary solution for system operation which finds bus voltage amplitude and angles, active and reactive power flows of lines and line losses under the steady state conditions. Despite being the most realistic model and implicitly modeling network losses, the AC network model's application in TEP problems is highly limited due to its mathematical complexity, nonlinearity, and nonconvex nature. The equations used in AC power flow analysis can be solved by different power flow methodologies such as Gauss Seidel, Newton-Raphson (NR) or Fast Decoupled methods. Typically, the core of the most popular solutions of systems of nonlinear equations is a Newton-Raphson algorithm due to the quadratic rate of convergence characteristic. A detailed description of AC power flow equations (Saadat, 1999) is given as follows:

$$P_i = \sum_{k=1}^{n} |V_i||V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \tag{3.1}$$

$$Q_i = -\sum_{k=1}^{n} |V_i||V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \tag{3.2}$$

$$P_i^{sp} = P_{Gi} - P_{Di} \tag{3.3}$$

$$Q_i^{sp} = Q_{Gi} - Q_{Di} \tag{3.4}$$

$$\begin{bmatrix} \Delta P_2 \\ \vdots \\ \Delta P_n \\ \Delta Q_2 \\ \vdots \\ \Delta Q_n \end{bmatrix}^{(v)} = \begin{bmatrix} \frac{\partial P_2}{\partial \delta_2} & \cdots & \frac{\partial P_2}{\partial \delta_n} & \frac{\partial P_2}{\partial |V_2|} & \cdots & \frac{\partial P_2}{\partial |V_n|} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial P_n}{\partial \delta_2} & \cdots & \frac{\partial P_n}{\partial \delta_n} & \frac{\partial P_n}{\partial |V_2|} & \cdots & \frac{\partial P_n}{\partial |V_n|} \\ \frac{\partial Q_2}{\partial \delta_2} & \cdots & \frac{\partial Q_2}{\partial \delta_n} & \frac{\partial Q_2}{\partial |V_2|} & \cdots & \frac{\partial Q_2}{\partial |V_n|} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Q_n}{\partial \delta_2} & \cdots & \frac{\partial Q_n}{\partial \delta_n} & \frac{\partial Q_n}{\partial |V_2|} & \cdots & \frac{\partial Q_n}{\partial |V_n|} \end{bmatrix}^{(v)} \begin{bmatrix} \Delta \delta_2 \\ \vdots \\ \Delta \delta_n \\ \Delta |V_2| \\ \vdots \\ \Delta |V_n| \end{bmatrix}^{(v)} \tag{3.5}$$

$$J1_{ii} = \frac{\partial P_i}{\partial \delta_i} = \sum_{k \neq i} |V_i||V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i \tag{3.5a}$$

$$J1_{ik} = \frac{\partial P_i}{\partial \delta_k} = -|V_i||V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.5b}$$

$$J2_{ii} = \frac{\partial P_i}{\partial |V_i|} = 2|V_i||Y_{ii}| \cos(\theta_{ii}) + \sum_{k \neq i} |V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \, , \forall i \tag{3.5c}$$

$$J2_{ik} = \frac{\partial P_i}{\partial |V_k|} = |V_i||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.5d}$$

$$J3_{ii} = \frac{\partial Q_i}{\partial \delta_i} = \sum_{k \neq i} |V_i||V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i \tag{3.5e}$$

$$J3_{ik} = \frac{\partial Q_i}{\partial \delta_j} = -|V_i||V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.5f}$$

$$J4_{ii} = \frac{\partial Q_i}{\partial |V_i|} = -2|V_i||Y_{ii}| \sin(\theta_{ii}) - \sum_{k \neq i} |V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i \tag{3.5g}$$

$$J4_{ik} = \frac{\partial Q_i}{\partial |V_k|} = -|V_i||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.5h}$$

$$\begin{bmatrix} \Delta\delta^{(v)} \\ \Delta V^{(v)} \end{bmatrix} = \begin{bmatrix} J1^{(v)} & J2^{(v)} \\ J3^{(v)} & J4^{(v)} \end{bmatrix}^{-1} \begin{bmatrix} \Delta P^{(v)} \\ \Delta Q^{(v)} \end{bmatrix} \tag{3.6}$$

where complex injected powers and the specified complex injected powers are calculated for each bus using (3.1) to (3.4). P_{Gi}, Q_{Gi}, P_{Di} and Q_{Di} indicates the active and reactive power of the generator and load at bus i, g_{ik} and b_{ik} are the real and imaginary parts of network admittance matrix, V and δ are the bus voltage amplitude and the voltage angle, respectively. δ_{ik} is the difference of voltage angles between buses i and k. The difference between the specified and calculated injected powers is used to calculate bus power injection increments for both injected reactive and active powers for nodes. The Newton-Raphson method iteratively updates these unknowns until a prespecified convergence criteria is reached. The relationship between the complex power increments and the state vectors can be written in a matrix notation as in (3.5). The set of nonlinear equations expressed in (3.5b) to (3.5h) forms the Jacobian matrix to be used in the iterative solution. There are $(n-1)$ real power, $(n-1-m)$ reactive power constraints. The size of the Jacobian matrix is $(2n-2-m) \times (2n-2-m)$. The left part of the (3.5) consist of $(n-1) \times 1$ and $(n-1-m) \times 1$ size vector for the incremental active and reactive power injections. The right side of the Jacobian matrix is the increments of state vectors which consist of $(n-1) \times 1$ and $(n-1-m) \times 1$ variables for voltage angle and magnitude, respectively. To find the incremental change on bus voltage and angles (3.6) must be solved iteratively. The flowchart of the NR method for AC power flow is given in Figure 3.1.

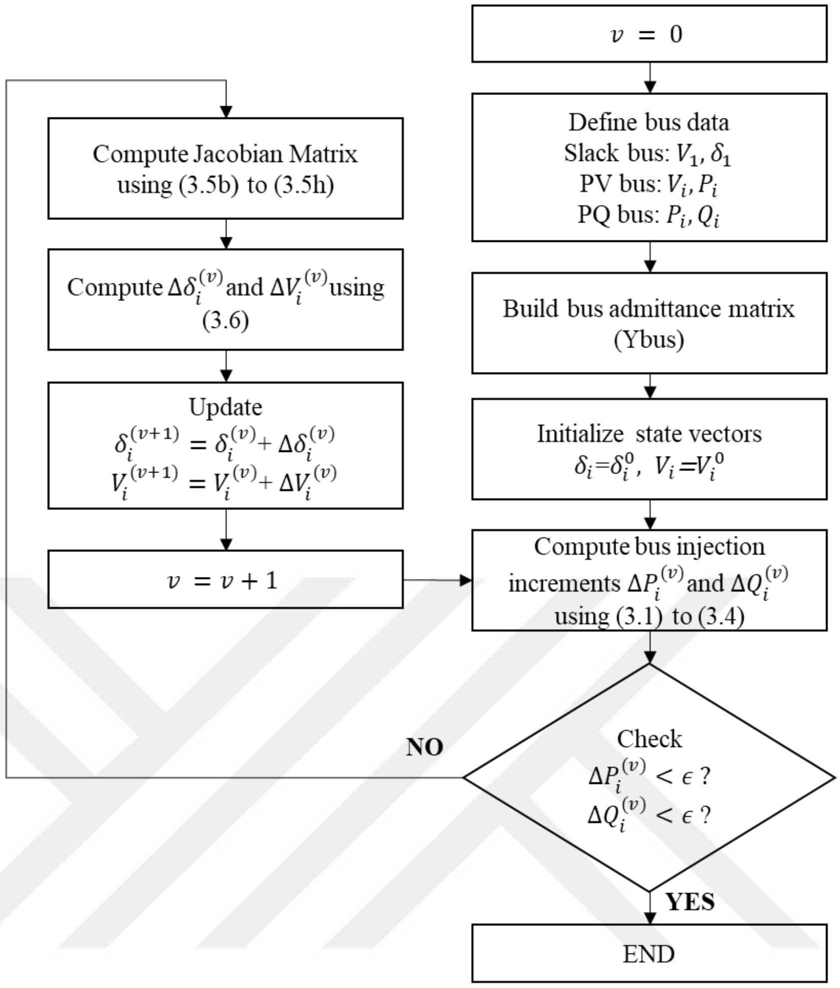

Figure 3.1 Flowchart for the Newton Raphson Algorithm

3.2 AC Network Model with Participation Factor Power Flow Equations

As renewable energy becomes more integrated, the ability to adjust to variability becomes more important (Chandler, 2011; Orfanos et al.,2013; Jabr, 2013; Mortaz &Valenzuela, 2019; Salkuti, 2019). One way to respond to this variability is to change generator outputs depending on the imbalance power. No matter which method is used, slack bus in power flow is a matter that should be paid attention considering the uncertainty conditions. Originally, slack bus is a mathematical necessity for power flow solutions. It is responsible for compensating losses and balancing power mismatches in the network. However, the behavior of slack bus in probabilistic power flow is different from the conventional load power models. Especially in the case of uncertainty, the slack bus absorbs all the uncertainties (Dimitrovski & Tomsovic, 2005a; 2005b; Huynh et al., 2018). For example, replacing conventional generators with renewables that have lower voltage support has resulted in a larger risk of voltage instability as well as huge overloading levels in transmission lines. For this reason, treatment of slack bus is crucial in planning context. Since we cannot remove the slack bus from the load flow analysis which ensures the feasibility of the system, two methods have been proposed in the literature to solve this problem (Dimitrovski & Tomsovic, 2005a; 2005b). The first method is to convert the slack bus into PV bus that is inspired from the PV to PQ bus conversion in AC load flow analysis. If the slack bus extends its real power generation limit, it is output is fixed with a threshold and the some of the selected PV buses are relaxed in order to solve the load flow problem. The alternative way to model the behavior of slack bus is the distributed slack bus model. In this way, if the slack bus limits are violated, the excess load is distributed to the other conventional generators according to its capacities. If these two methods are compared in terms of modelling, it is much easier to apply distributed slack bus model, since there is no bus type conversion. When it is adopted, the mismatch power and the transmission losses are assigned among conventional generators using participation factors (Le et al., 2013).

Several studies in the literature have combined the participation factors with power flow studies to find an economical dispatch of generators. The pioneer work is presented in (Guoyu et al., 1985), in which the treatment of slack bus is introduced under decoupled economic dispatch using participation factor power flow. In (Zobian & Ilic, 1997), the generator contributions are derived by reformulating the power flow problem in terms of distributed slack bus concept. The net power mismatch resulting from each flow is a function of all flows present in the system where the power mismatch can be compensated for by allocating the power imbalance according to the generation participation factors. In (Tong & Miu,2005), the participation factors are incorporated into the three-phase power flow equations of Newton Raphson formulation, and this distributed slack bus concept is applied to generator domains of unbalanced distribution systems to anticipate the growth of distributed generators. In (Jang et al.,2005), authors proposed a modified power flow approach in a sense of economic dispatch to remove the burden on the slack bus. In (Careri et al., 2011), a distributed slack bus formulation with an N-1 contingency is adopted in the probabilistic power flow to distribute the active power mismatch across all the thermal units in the system. In (Tang et al., 2015), a fast adjustment methodology is proposed for real-time economic dispatch problems considering distributed slack bus approaches with load, RES, and power loss considerations. Recently, in (Dhople et al., 2020), authors re-examine the concept of distributed slack bus definition and compare the power flow solutions with a single slack bus model. It is evident that the distributed slack bus concept with the participation factor power flow is a promising tool for the evaluation of different operating conditions of the power system and it is also compatible with economic dispatch studies.

The concept of slack bus is a necessity for finding a feasible solution in power flow analysis. It is required since transmission losses are not known as priori. Therefore, a generator is selected to operate as a reference to cover the losses to obtain a feasible solution. This is called as single slack bus model. In the economic dispatch, the difference between generation and demand refers to system power imbalance and the distributed slack bus concept is adopted with participation factors (Guoyu et al., 1985; Zobian and Ilic, 1997; Dimitrovski & Tomsovic, 2005(a); Careri et al., 2011; Dhople et al.,2020) In this way, the imbalance power distributed among the conventional generators based on specified participation factor. In the uncertain operating conditions, the treatment of slack bus behavior is crucial. The uncertain characteristic of load and intermittent RES power deviates active and reactive power injections of buses, which directly changes the power flow patterns and bus voltages throughout the system. In that manner, the conventional load-flow equations are modified with generation participation factors to distribute the real power mismatch. Consequently, the next section provides the information to find optimal operating points for generators and the participation factors.

Traditional economic dispatch problem (Guoyu et al., 1985; Meisel, 1993; Jang et al.,2005; Tang et al.,2015; Reddy, 2017) finds the real power generation for each plant providing the minimum generation cost that satisfies the power balance equation for the network. Lagrange multiplier method is typically used to solve such problem and the equal incremental cost is denoted as λ which is also the lagrange multiplier of the Lagrange function is given in (3.7) (Wood et al., 1999; Saadat, 1999)

$$L = \sum_{i=1}^{NG} C_i(P_{Gi}) + \lambda \left(\sum_{i=1}^{N} P_{Di} + \sum P_{IMB} - \sum_{i=1}^{NG} P_{Gi} \right) \quad (3.7)$$

where $C_i(P_{Gi})$ is the total generation cost and C_i is the generation cost equation of each plant which is a quadratic function of generator active power $C_i = c_i + b_i P_{Gi} + a_i P_{Gi}^2$. In the traditional formulation total system generation is equal to total load and loss of the system. However, in our study, transmission losses and mismatched power from uncertainties are represented as P_{IMB}. The derivatives which are given in (3.8) and (3.9) with respect to equal incremental cost and generator output are solved together to find the coordination equation for all generators.

$$\frac{\partial L}{\partial \lambda} = \sum_{i=1}^{NG} P_{Gi} - \sum_{i=1}^{N} P_{Di} - \sum P_{IMB} = 0 \quad (3.8)$$

$$\frac{\partial L}{\partial P_{Gi}} = 2a_i P_{Gi} + b_i + \lambda = 0 \quad (3.9)$$

It is inferred from the solution given in (5) that generator output is a function of λ. The analytical solution can be obtained for λ by substituting the (3.10) into (3.9). Consequently, the equal incremental cost λ found in (3.11) is the optimal scheduling of the generation.

$$P_{Gi} = \frac{\lambda - b_i}{2a_i} \quad (3.10)$$

$$\lambda = \frac{-b_i + \dfrac{\sum_{i=1}^{N} P_{Di} + \sum_{i=1}^{NG} \frac{b_i}{2a_i}}{\sum_{i=1}^{NG} \frac{1}{2a_i}}}{2a_i} + \frac{\sum P_{IMB}}{2a_i \sum_{i=1}^{NG} \frac{1}{2a_i}} \quad (3.11)$$

The first part of the (3.11) is the scheduled generator powers when mismatch does not consider in the formulation. In the second part, a portion of mismatch power is added to the first part to satisfy the power balance in the system. In the proposed model, the generator output which is used in power flow analysis is determined using (3.12), where the $P_{Gi_{upd}}$ is equal to the optimal scheduling of generation λ. The division of the mismatch power is calculated through the participation factors which is determined by using the generator cost function as in (3.13).

$$P_{Gi_{upd}} = P_{Gi_{sch}} + Pf_i \sum P_{IMB} \quad (3.12)$$

$$Pf_i = 2a_i \sum_{i=1}^{NG} \frac{1}{2a_i} \quad (3.13)$$

The participation factors calculated in (3.13) are all positive, which means that all participating generators will increase its scheduled power when the net power imbalance is positive. Additionally, the sum of participation factors for all generators must be added to one. In our study, the participation factors and nonlinear AC power flow equations are handled together with a modified Jacobian matrix. Therefore, to find the state vectors **V** and θ, the injected power equations for each bus are written as in equations (3.14) and (3.15).

$$P_i(V,\theta) = \sum_{i=1}^{N}\sum_{k=1}^{N} |V_i||V_k|[G_{ik}\cos(\theta_i - \theta_k) + B_{ik}sin(\theta_i - \theta_k)] \quad (3.14)$$

$$Q_i(V,\theta) = \sum_{i=1}^{N}\sum_{k=1}^{N} |V_i||V_k|[G_{ik}\sin(\theta_i - \theta_k) - B_{ik}cos(\theta_i - \theta_k)] \quad (3.15)$$

The specified (known) parameters for each bus are calculated in (3.16) and (3.17). The updated generator output and participation factors are determined by (3.12) and (3.13) which can be used in the modified power flow solution. Subsequently, the mismatch power for each bus is determined by the (3.18) and (3.19) as follows:

$$\mathrm{P}_{sp,i} = P_{Gi_{upd}} - P_{Di} \quad (3.16)$$

$$Q_{sp,i} = Q_{Gi} - Q_{Di} \quad (3.17)$$

$$\Delta\mathrm{P} = \mathrm{P}_{sp,i} - P_i \quad (3.18)$$

$$\Delta\mathrm{Q} = Q_{sp,i} - Q_i \quad (3.19)$$

The modified Jacobian matrix consist of derivate vectors with participation factors are given in (3.20) and the incremental values for voltage magnitude, angle and mismatch power can be calculated using (3.21)

$$\begin{bmatrix} \Delta P_1 \\ \vdots \\ \Delta P_n \\ \Delta Q_1 \\ \vdots \\ \Delta Q_{n-m} \end{bmatrix}^{(v)} = \begin{bmatrix} \frac{\partial P_1}{\partial \delta_1} & \cdots & \frac{\partial P_1}{\partial \delta_n} & \frac{\partial P_1}{\partial |V_1|} & \cdots & \frac{\partial P_1}{\partial |V_{n-m}|} & Pf_i \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \frac{\partial P_n}{\partial \delta_1} & \cdots & \frac{\partial P_n}{\partial \delta_n} & \frac{\partial P_n}{\partial |V_1|} & \cdots & \frac{\partial P_n}{\partial |V_{n-m}|} & Pf_m \\ \frac{\partial Q_1}{\partial \delta_1} & \cdots & \frac{\partial Q_1}{\partial \delta_n} & \frac{\partial Q_1}{\partial |V_1|} & \cdots & \frac{\partial Q_1}{\partial |V_{n-m}|} & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \frac{\partial Q_{n-m}}{\partial \delta_1} & \cdots & \frac{\partial Q_{n-m}}{\partial \delta_n} & \frac{\partial Q_{n-m}}{\partial |V_1|} & \cdots & \frac{\partial Q_{n-m}}{\partial |V_{n-m}|} & 0 \end{bmatrix}^{(v)} \begin{bmatrix} \Delta \delta_1 \\ \vdots \\ \Delta \delta_n \\ \Delta |V_1| \\ \vdots \\ \Delta |V_{n-m}| \\ \Delta P_{IMB} \end{bmatrix}^{(v)} \tag{3.20}$$

$$J1_{ii} = \frac{\partial P_i}{\partial \delta_i} = \sum_{k \neq i} |V_i||V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i \tag{3.20a}$$

$$J1_{ik} = \frac{\partial P_i}{\partial \delta_k} = -|V_i||V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.20b}$$

$$J2_{ii} = \frac{\partial P_i}{\partial |V_i|} = 2|V_i||Y_{ii}| \cos(\theta_{ii}) + \sum_{k \neq i} |V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \ , \forall i \tag{3.20c}$$

$$J2_{ik} = \frac{\partial P_i}{\partial |V_k|} = |V_i||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.20d}$$

$$J3_{ii} = \frac{\partial Q_i}{\partial \delta_i} = \sum_{k \neq i} |V_i||V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i \tag{3.20e}$$

$$J3_{ik} = \frac{\partial Q_i}{\partial \delta_j} = -|V_i||V_k||Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.20f}$$

$$J4_{ii} = \frac{\partial Q_i}{\partial |V_i|} = -2|V_i||Y_{ii}| \sin(\theta_{ii}) - \sum_{k \neq i} |V_k||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \ , \forall i \tag{3.20g}$$

$$J4_{ik} = \frac{\partial Q_i}{\partial |V_k|} = -|V_i||Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) \quad , \forall i, \forall k \neq i \tag{3.20h}$$

$$J5_i = \frac{\partial P_i}{\partial P_{IMB}} = Pf_i \quad , for\ generator\ buses \tag{3.20i}$$

$$J5_i = \frac{\partial P_i}{\partial P_{IMB}} = 0 \quad , for\ load\ buses \tag{3.20j}$$

$$J6_i = \frac{\partial Q_i}{\partial P_{IMB}} = 0 \quad , \forall i \tag{3.20k}$$

$$\begin{bmatrix} \Delta \delta^{(v)} \\ \Delta V^{(v)} \\ \Delta P_{IMB}^{(v)} \end{bmatrix} = \begin{bmatrix} J1^{(v)} & J2^{(v)} & Pf \\ J3^{(v)} & J4^{(v)} & 0 \end{bmatrix}^{-1} \begin{bmatrix} \Delta P^{(v)} \\ \Delta Q^{(v)} \end{bmatrix} \tag{3.21}$$

The size of the Jacobian matrix is (nxn), where the n is the total number of buses in a power system. An artificial variable P_{IMB} is introduced in the mismatch vector. Proposed modified power flow solution continues until the convergence tolerance is achieved for the iterative solution. The final calculated state vectors V and θ are used to determine power flows which is required in the TEP optimization. The generators are also bounded by their limits and the bounds are checked after power flow solution. If the generator exceeds its limit, the output power of the generator is fixed at its limit, and then participation factor power flow is re-applied to the case with that fixed generator outputs.

The relationship between the complex power increments and the state vectors can be written in a matrix notation as in (3.20). The nonlinear equations expressed in (3.20a) to (3.20k) forms the Jacobian matrix is modified with a column vector that considers participation factors are used in the iterative solution. The derivatives of active power with respect to imbalance power gives the participation factors for generator buses. There are different methods to calculate the participation factors which leads different types of power flow solutions (Meisel, 1993). Since the main aim of this dissertation is to operate generation unit in an economical manner, cost functions of the generators are used in terms of calculating the economic operating condition. In order to find the state variables of the power flow solutions equation (3.21) must be solved iteratively to find the incremental change on bus voltage magnitude, voltage angles and imbalance power. The flowchart of the participation factor power flow method is given in Figure 3.2. For the sake of clarity, the above following steps are handled in the iterative process:

Step 0: Initialize iteration counter and define the known and unknown parameters for different type of buses (PV, PQ, slack) to be used in power flow solutions.

Step 1: Build the bus admittance matrix using network line data.

Step 2: Initialize voltage magnitude, voltage angle and imbalance power for the iterative process.

Step 3: Compute bus complex power injection increments using (3.16) to (3.19) for the iterative process.

Step 4: Check incremental complex power injections to be less than prespecified tolerance. If so, iterative process converged. If not, compute the elements of Jacobian matrix using (3.20a) to (3.20k).

Step 5: Compute the incremental voltage magnitudes, angles and imbalance power using (3.21). Update voltage magnitude and angles using incremental and initial values.

Step 6: Update the iteration counter and continue at Step 3.

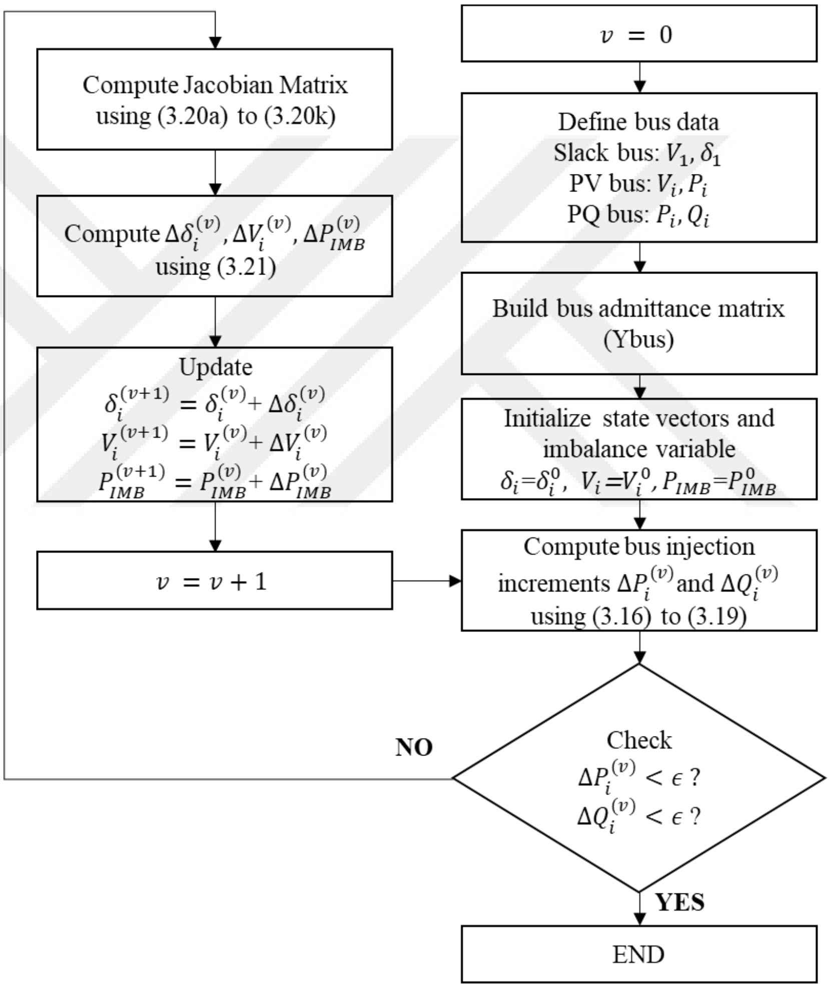

Figure 3.2 Flowchart for the participation factor power flow algorithm

3.3 Probabilistic Comparison of Conventional and Proposed Participation Factor Power Flow

This study is conducted to show the overload probability and cumulative distribution function (CDF) comparison between conventional AC power flow (ACPF) and the proposed participation factor power flow (PF-ACPF) on the IEEE RTS 24 bus network as shown in Figure 3.3. Input data used in the simulations can be found in Appendices. In the ACPF, the scheduled generator power for generators is determined using in (3.12) to make a fair comparison between two models. The uncertainty data for the test network is given as follows. The mean value of the load is increased 25% from its original value. σ/μ ratio of load is considered 20%. Weibull characteristic of wind speed is a=7, b=2.5 m/s and the turbine characteristic are as follows Vci=4, Vr=10, Vco=22 m/s. Wind turbine is located at buses 3, 4, 5 and 6 which is given in Fig. 3 and its rated capacity is 50 MW for each turbine. L4-9 is considered as the N-1 contingency of the system. MCS is used to obtain the PDF of line loading and voltage magnitudes and the violation probabilities for each line (L) and voltage magnitude (V) is given in Table 3.1.

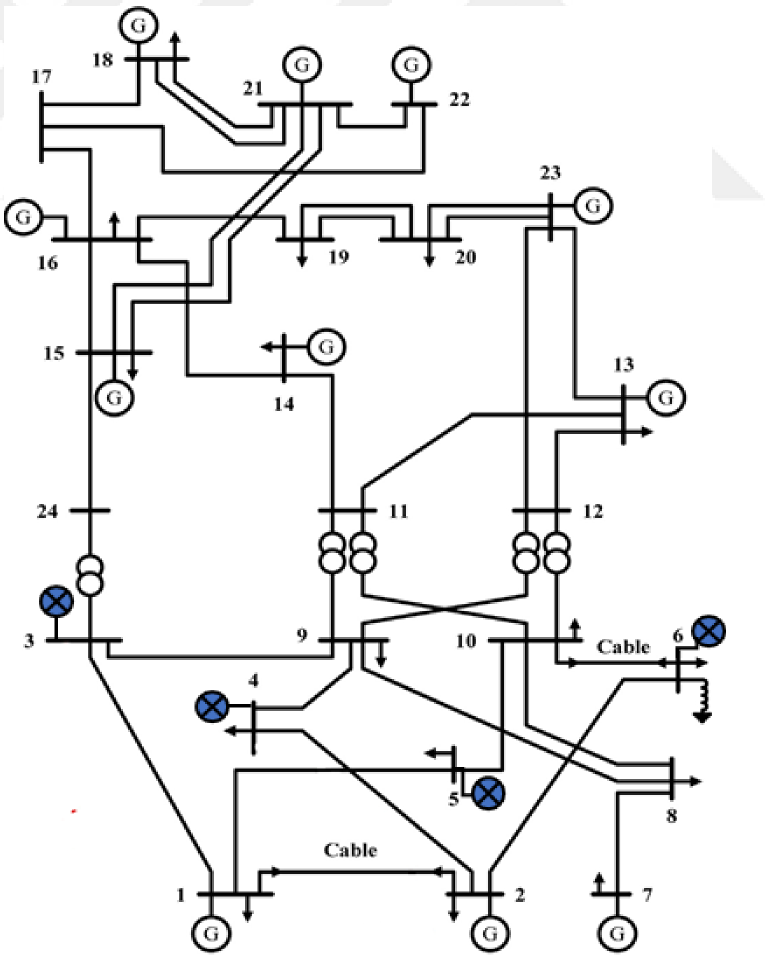

Figure 3.3 Modified IEEE RTS test network

Table 3.1 Comparison of overload probabilities between ACPF and PFACPF

Line/Voltage	**w/o N-1 Contingency**		**w/ N-1 Contingency**	
	PF-ACPF	**ACPF**	**PF-ACPF**	**ACPF**
L1-2	0.03	0.22	-	-
L1-3	-	0.09	0.20	0.57
L1-5	0.93	0.99	0.99	0.99
L2-4	0.07	0.39	-	-
L2-6	0.05	0.24	0.34	0.66
L5-10	0.02	0.04	0.09	0.33
L7-8	0.04	0.04	0.05	0.06
L8-10	-	-	0.01	0.02
L12-13	0.16	0.09	0.18	0.14
L12-23	0.41	0.19	0.46	0.22
V3	0.84	0.75	0.93	0.91
V4	0.43	0.27	0.10	0.02
V5	0.11	0.22	0.34	0.63
V6	1.00	1.00	1.00	1.00
V8	0.57	0.54	0.61	0.63
V9	0.31	0.19	0.36	0.31
V10	0.93	0.94	0.98	0.98
V11	0.15	-	0.26	0.02
V12	0.02	-	0.03	-
V14	0.05	-	0.08	-
V24	0.03	-	0.05	-

It is observed that lines connected to slack bus generators are significantly overloaded in the ACPF model. This is due to the difference in generation dispatch for each model. In ACPF, the slack bus generator (G1) is responsible for the mismatched power in the network. However, in PF-ACPF, all active power mismatch is distributed in the conventional generators using participation factors. In this way, distributing imbalance among generators reduce the violation on the lines connected through slack bus generator. The results shows that the biggest differences between two power flows occur when the system has stressful uncertain operating condition. In particularly, the violation probabilities of lines 2-4, 2-6 and voltage magnitudes at bus 3, 4, 5 and 6 differs due wind turbine connections. It is also observed that the system is heavily loaded from the buses 6 to 15 so that in the most stressful scenarios the ACPF supplies the load by slack bus generator. When the system has an outage condition, the overload information is important for dispatch procedure. It is observed in Table 3.1, the overload probabilities of lines are increased for both models. However, the overload probability of the lines connected to slack bus is less in PF-ACPF model due to distribution of mismatch power. As an example, the CDF of power flow on line 1-3 and voltage magnitude at bus 4 for without N-1 contingency are given in Figure 3.4.

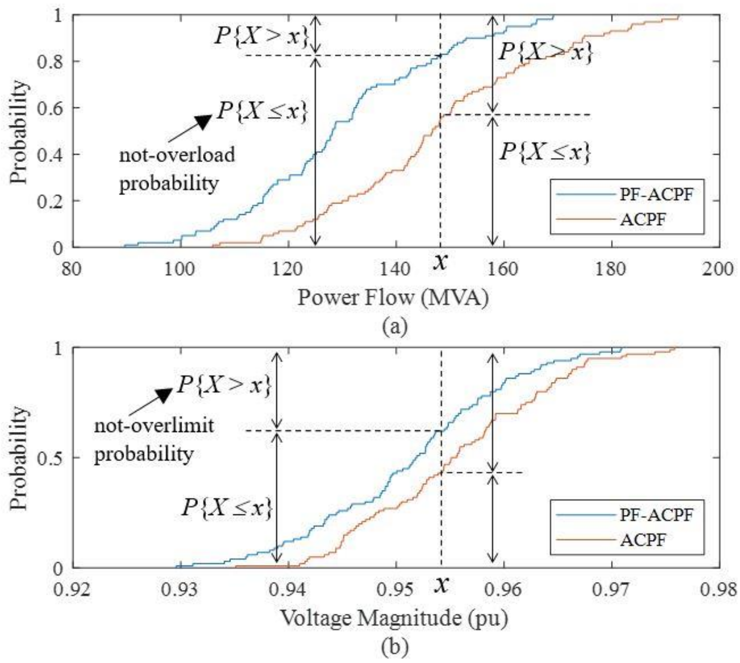

Figure 3.4 CDF of (a) power flow of line 1-3, (b) voltage magnitude at bus 4 without N-1 contingency

In Figure 3.4(a), the capacity of this line is 175 MVA and it is observed that the violation probability of the ACPF higher than the PF-ACPF due to single slack bus consideration. On the other hand, in Figure 3.4(b), the violation probability of voltage magnitude at bus 4 has extended to different margins. Line 1-3 and voltage magnitude at bus 4 for with N-1 contingency is given in Figure 3.5. The loading margin line 1-3 is different for both models. The result showed that using the single slack bus method to derive violation probability values directly in the chance-constraint optimization does not accurately reflect the probability of violation in a realistic way. For this reason, in our study, the simple computational capability of power flow is adapted to the TEP with uncertain operating conditions. It is crucial to assess this behavior in a planning context since it may lead to different investment decisions.

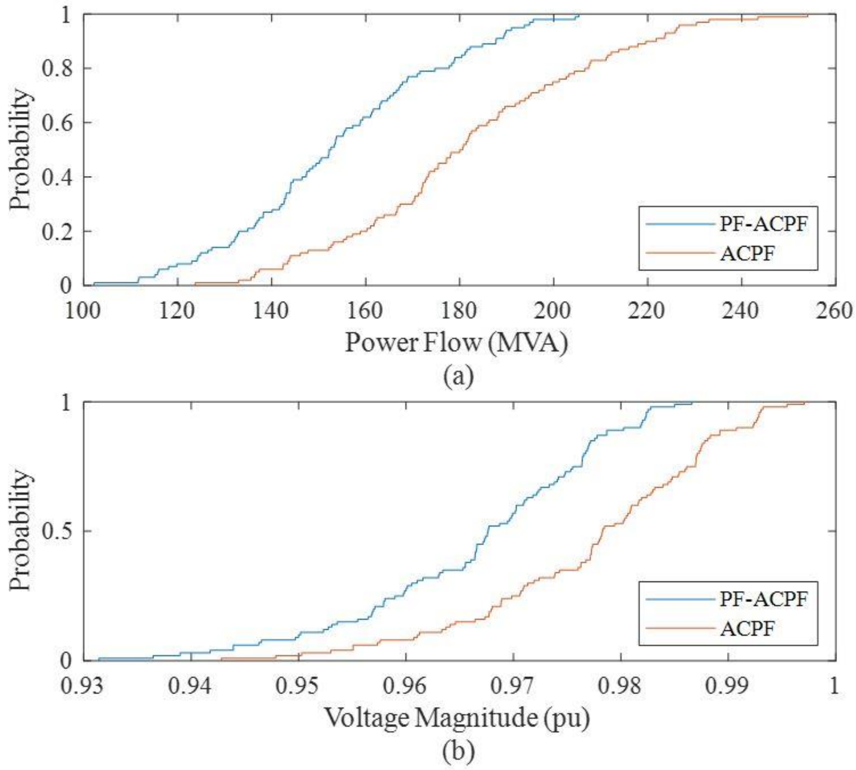

Figure 3.5 CDF of (a) power flow of line 1-3, (b) voltage magnitude at bus 4 with N-1 contingency

CHAPTER FOUR

STOCHASTIC AC TRANSMISSION EXPANSION PLANNING: A CHANCE CONSTRAINED DISTRIBUTED SLACK BUS APPROACH WITH WIND UNCERTAINTY

In this section, the mathematical formulation of the stochastic AC TEP model with probabilistic participation factor power flow is given. The operational sub-problem given in the previous section is applied to each candidate network infrastructure to simply obtain the probabilistic constraints in both base and contingency operating conditions. The mathematical formulation of ACTEP is a mixed-integer non-linear problem, and it is solved using the genetic algorithm (GA) solver. As a metaheuristic optimization technique, genetic algorithm is a great interest for solving the TEP and many other problems (Da Silva et al., 2000; Escobar et al., 2004; De Silva et al. 2006; Yu et al.,2009; Rahmani et al. 2010; Swain et al. 2021). In this study, the main problem for GA is the investment optimization that minimizes the total investment cost subject to probabilistic line loading and voltage constraints and the number of invested lines. In the constraints of GA, the participation factor power flow is adapted under MCS to find the output power of conventional generators in each of the sample scenarios. The distributed slack bus concept is utilized in the AC power flow equations with generator participation factors. Subsequently, chance constraint programming is applied to the PDF of the state vectors to find the overload probabilities of network constraints. The resulting probabilistic constraints trigger the TEP investment decision according to pre-specified risk levels instead of satisfying the hard constraint. The proposed stochastic TEP framework is implemented in the MATLAB environment and tested on IEEE Reliability Test System and IEEE 118 Bus test system. Input data used in the simulations and the nomenclature can be found in Appendices. TEP investment results are obtained under different uncertainty conditions for wind, load, and N-1. The final stage involves testing the investment plans obtained under a new set of uncertainty conditions, examining the investment plans with respect to various confidence levels.

4.1 Flowchart of the proposed AC-TEP problem

The flowchart of the proposed TEP framework is summarized in Figure 4.1, and the solution process is described as follows:

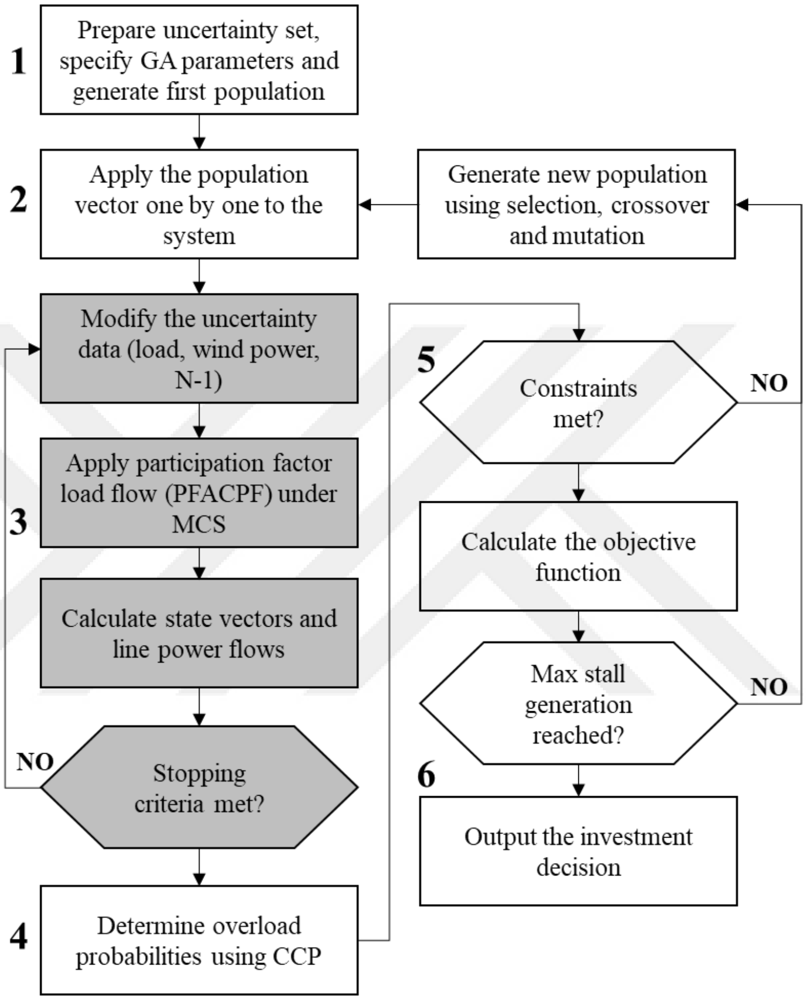

Figure 4.1 Flowchart of the stochastic TEP with PFACPF

- *Block 1*: At this stage, load, wind power, and N-1 contingency data are prepared using the distributions given in Section-A. The acceptable level of non-overload probability is predefined for the network constraints. The parameters for GA, such as population size, generation, crossover, mutation, and elite count are specified, and lastly, the initial population for the evaluation is created.
- *Block 2:* The population vector, which consists of various TEP infrastructures, is applied to the system one at a time. Line impedance and the bounds of transmission lines are updated according to the candidate TEP infrastructure.

- *Block 3:* MCS begins by sampling various operation scenarios to apply the uncertainty data to the system. Subsequently, scheduling of the generators is calculated, and the participation factor power flow is applied to the candidate infrastructure to find the state vectors Pg, Qg, |V|, θ and line power flows. The formulation for this block is given in Section-B. This part is evaluated for both base and contingency case conditions. Convergence of the MCS is checked based on a pre-specified sampling number.
- *Block 4:* Using the chance constraint formulation, the PDF of the state vectors is constructed, and the overload probability of each line and bus voltage is determined. This part is also evaluated for both base and contingency case conditions.
- *Block 5:* Transmission line loading and voltage magnitude constraints are checked, and the objective function is calculated. If the constraints are not satisfied, a new infrastructure is generated by selection, crossover, and mutation operations and by re-applying the procedure from block (2) to (5).
- *Block 6:* The optimization is terminated if the maximum stall generation limit is checked, resulting in the final investment decision. The selection, crossover, and mutation operations generate a new infrastructure if the termination does not satisfy. The best population with the least fitness value must be reached to find an optimal investment decision.

4.2 Mathematical Formulation of the Proposed AC-TEP Model

The mathematical formulation for the chance constrained AC TEP optimization is given as follows:

$$\min \sum_{(i,k)} Cost_{ik} n_{ik} \tag{4.1}$$

s.t.

$$prb\left\{(n_{ik} + n_{ik}^{0}) S_{ik}^{from} \le (n_{ik} + n_{ik}^{0}) \overline{S}_{ik}\right\} \ge \beta \tag{4.2}$$

$$prb\left\{(n_{ik} + n_{ik}^{0}) S_{ik}^{to} \le (n_{ik} + n_{ik}^{0}) \overline{S}_{ik}\right\} \ge \beta \tag{4.3}$$

$$prb\left\{\underline{|V|} \le |V| \le \overline{|V|}\right\} \tag{4.4}$$

$$prb\left\{(n_{ik} + n_{ik}^{0} - 1) S_{ik}^{c,from} \le (n_{ik} + n_{ik}^{0} - 1) \overline{S}_{ik}\right\} \ge \beta, \;\; c = (i,k), c \in \Omega^{c} \tag{4.5}$$

$$prb\{(n_{ik}+n_{ik}^0-1)S_{ik}^{c,to} \le (n_{ik}+n_{ik}^0-1)\overline{S}_{ik}\} \ge \beta, \qquad c=(i,k), c \in \Omega^c \tag{4.6}$$

$$prb\left\{\underline{|V^c|} \le |V^c| \le \overline{|V^c|}\right\} \tag{4.7}$$

$$0 \le n_{ik} \le \overline{n_{ik}} \tag{4.8}$$

where

$$S_{ik}^{from} = \sqrt{(P_{ik}^{from})^2 + (Q_{ik}^{from})^2} \tag{4.9}$$

$$P_{ik}^{from} = V_i^2 g_{ik} - V_i V_k (g_{ik} cos\theta_{ik} + b_{ik} sin\theta_{ik}) \tag{4.9a}$$

$$Q_{ik}^{from} = -V_i^2 \left(b_{ik}^{sh} + b_{ik}\right) - V_i V_k (g_{ik} sin\theta_{ik} - b_{ik} cos\theta_{ik}) \tag{4.9b}$$

$$S_{ik}^{to} = \sqrt{(P_{ik}^{to})^2 + (Q_{ik}^{to})^2} \tag{4.10}$$

$$P_{ik}^{to} = V_i^2 g_{ik} - V_i V_k (g_{ik} cos\theta_{ik} - b_{ik} sin\theta_{ik}) \tag{4.10a}$$

$$Q_{ik}^{to} = -V_k^2 \left(b_{ik}^{sh} + b_{ik}\right) + V_i V_k (g_{ik} sin\theta_{ik} + b_{ik} cos\theta_{ik}) \tag{4.10b}$$

$$S_{ik}^{c,from} = \sqrt{(P_{ik}^{c,from})^2 + (Q_{ik}^{c,from})^2} \tag{4.11}$$

$$P_{ik}^{c,from} = (V_i^c)^2 {g_{ik}}^c - V_i^c V_k^c ({g_{ik}}^c cos{\theta_{ik}}^c + {b_{ik}}^c sin{\theta_{ik}}^c) \tag{4.11a}$$

$$Q_{ik}^{c,from} = -(V_i^c)^2 \left(b_{ik}^{c,sh} + {b_{ik}}^c\right) - V_i^c V_k^c ({g_{ik}}^c sin{\theta_{ik}}^c - {b_{ik}}^c cos{\theta_{ik}}^c) \tag{4.11b}$$

$$S_{ik}^{c,to} = \sqrt{(P_{ik}^{c,to})^2 + (Q_{ik}^{c,to})^2} \tag{4.12}$$

$$P_{ik}^{c,to} = (V_i^c)^2 {g_{ik}}^c - V_i^c V_k^c ({g_{ik}}^c cos{\theta_{ik}}^c - {b_{ik}}^c sin{\theta_{ik}}^c) \tag{4.12a}$$

$$Q_{ik}^{c,from} = -(V_i^c)^2 \left(b_{ik}^{c,sh} + {b_{ik}}^c\right) + V_i^c V_k^c ({g_{ik}}^c sin{\theta_{ik}}^c + {b_{ik}}^c cos{\theta_{ik}}^c) \tag{4.12b}$$

The above TEP optimization finds the minimum investment decision that satisfies the given operational constraints on line flow and voltage. The objective function in (4.1) is a cost function that minimizes the investment cost for transmission lines that satisfies the probabilistic over limits for base and N-1 contingency conditions for each network decision. The equation set from (4.2) to (4.4) gives the base case whereas (4.5) to (4.7) give the contingency conditions. The parameters with superscript *c* show the modified variables when a transmission line (i,k) is outage. Lastly, bounds of the network expansion variables is given in (4.8).

In the TEP optimization, the uncertainty scenarios are evaluated with participation factor power flow under MCS, and the PDFs of line flows and voltage magnitudes are determined to be used in chance constraint framework. The chance constrained method is one of the promising approaches for solving optimization problems under various uncertainties. A probabilistic or chance constraint is expressed as an inequality in generic way in the optimization process whose to find the best solution which maintain feasible with probability at least $1-\varepsilon$ (β), for a given violation probability of ε. In this study, the probabilities are calculated based on the calculation of not violation probability which is required to be more than a pre-specified confidence level. The not violation probabilities are calculated using probability distribution functions and these probabilities guide the planning optimization by constraint checking mechanism. Consequently, PDF of the complex power flows are constructed after the MCS with the given formulation in (4.9) to (4.12).

4.3 Case Studies on IEEE RTS 24 Bus Test Network

In this section, the proposed model is applied to the IEEE RTS 24 bus network with respect to different not-overload probability consideration. The uncertainty data for the test network is given as follows. The mean value of the load is increased 25% from its original value. σ/μ ratio of load is considered 20%. Weibull characteristic of wind speed is a=7, b=2.5 m/s and the turbine characteristic are as follows Vci=4, Vr=10, Vco=22 m/s. Wind turbine is located at buses 3, 4, 5 and 6 which is given in its rated capacity is 50 MW for each turbine. Transmission availability is determined by the forced outage rate (FOR), which is sampled from a standard uniform distribution to determine the failure of transmission lines. The outage rate for transmission lines is assigned as 1%. The selection of the contingency set is based on the lines that connect either the wind turbines or the weaker parts of the network. For simplicity, all uncertainties are considered independently. In the operational sub-problem of the optimization, 100 scenarios are evaluated according to probability distributions. Lines L3-9, L4-9, L5-10, L6-10, L8-9, L11-13, L12-13, L15-21, L16-19, and L18-21 are selected as N-1 contingency candidates and FOR of each line is assigned from a standard uniform PDF to define its unavailability. In the upper level of the optimization, there are thirteen variables for IEEE 24 bus test system. The GA parameters for the IEEE 24 bus test network is assumed as population size is 200, total number of generations is 100 and the crossover fraction is 0.8. We consider four candidate lines for each possible corridor and three case studies are established as follows:

- Case-1: Considering only load and wind uncertainty
- Case-2: Considering only load and N-1 contingency uncertainty
- Case-3: Considering load, wind, and N-1 contingency uncertainty

where the confidence levels are chosen between 85 to 100%. The resulting TEP investments for case studies are given in Table 4.1. It has been observed that the proposed model provides alternative TEP decisions to the planner by choosing a pre-specified risk level. As the non-overload probability β decreases less expensive TEP decisions are obtained for all case studies.

The comparison between case-1 and case-3 shows that, the inclusion of N-1 contingency increases the investment cost significantly. However, as the risk decreases, the difference between the investment cost of the expansion plan decreases. It is observed that adequate configurations can be obtained with using PF-ACPF with and without considering N-1 contingency. The security consideration increases the cost and the number of lines invested through conventional generators. Particularly, lines 1-2, 10-11 and 20-23 are the most invested lines in each risk level. Besides it also observed that, the cost of difference between two risk levels both in cases 1 and 3 decreases as the planner chooses to take risk in planning decision. Additionally, the comparison between case-2 and case-3 show that the integration of wind turbines increases the investment cost in each risk level. Network is heavily loaded in the lower part and with the inclusion of wind turbine connection both line loading and voltage magnitude violations are observed. For example, when β=85% TEP plan of case-1 is investigated with a new set of uncertainty data, lines 2-4, 5-10 and 12-23 takes risk up to 11% however the major violation is observed on voltage magnitudes at bus6 and 8 especially in N-1 contingency constrained network consideration. As the non-overload probability β increases both line loading and voltage violation probability is reduced with additional investments. It is also concluded that with a small additional investment in the system, the probability of line loading and voltage magnitude could be kept at a satisfactory level considering wind power uncertainty.

Another interesting observation can be seen on the TEP plans where β=90%. In case-2, lines 12-23 and 1-2 takes risk up to 10% and the voltage at bus 8 has a violation probability of 5% and 9% for both base and contingency network consideration. When the wind uncertainty is considered in case-3, lines 1-2 and 20-23 are significantly affected both line loading and voltage violations. With the addition of 7 transmission lines in case 3, the network can accommodate the increased planning risk due to wind uncertainty to meet the same standard of system adequacy and security with minimal budget. The expected generation cost for each plan is also calculated for each case study. It varies between 15015 $/h -15083 $/h, 30804 $/h – 31033 $/h and 29939 $/h -30091 $/h for different β in Case-1, Case-2, and Case-3, respectively. Expected generation cost for each plan increases as the beta decreases. Yet, the most crucial point in the proposed model is to rationally model PDFs of voltages and line flows in response to uncertain operating conditions with distributed slack bus. Distributed slack bus concept is mainly used to ensure the distribution of mismatch power under uncertainty operating conditions in an economical manner. In other words, the probabilistic constraints guide the line investment optimization with a sense of economic dispatch.

Table 4.1 TEP decisions for IEEE 24-bus test network

Case Studies	**Case-1**				**Case-2**				**Case-3**			
TEP- β	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 1.00**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 1.00**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 1.00**
L1-2	-	-	-	-	-	-	-	1	1	5	1	6
L1-3	-	-	-	1	-	-	-	-	-	-	-	2
L1-5	1	1	1	1	1	1	2	4	1	1	1	1
L2-6	-	-	1	1	-	1	1	5	1	1	2	5
L3-24	3	3	1	-	2	3	3	5	1	3	4	5
L6-10	1	-	-	-	2	1	-	4	-	-	-	4
L9-12	-	-	2	2	1	1	4	3	2	1	5	3
L10-11	2	3	1	2	5	5	5	5	4	4	5	5
L10-12	2	3	1	2	-	1	-	4	-	1	2	1
L11-13	-	2	1	1	4	4	5	4	3	4	5	4
L12-23	1	2	1	1	-	-	1	1	-	-	-	1
L15-21	-	-	-	-	-	-	1	5	-	-	-	4
L20-23	-	-	-	1	1	1	1	2	3	5	3	4
Total (M$)	6,42	7,95	10,15	16,12	9,52	13,56	17,29	50,69	11,69	14,36	19,95	55,61

4.4 Assessment of IEEE RTS Network TEP Decisions Under Different Uncertainty Scenarios

In this section, the obtained three TEP plans in Case-3 are evaluated under different wind speed conditions to find the probabilities of line overloading and voltage violation. Load and N-1 contingency is sampled from the same uncertainty set that was used in the optimization procedure whereas wind speed scenarios are sampled from four different Weibull characteristic. The shape (k) and scale (c) parameters of different Weibull characteristics of wind speeds are given, and the wind power PDF of each wind cases are given in Figure 4.2 as low, medium, extremely high, and high wind speeds were assigned to cases ranging from 1 to 4. Table 4.2 shows the probability of line loading and voltage magnitude violations under various wind speed conditions when Case-3 TEP decisions are implemented in the network.

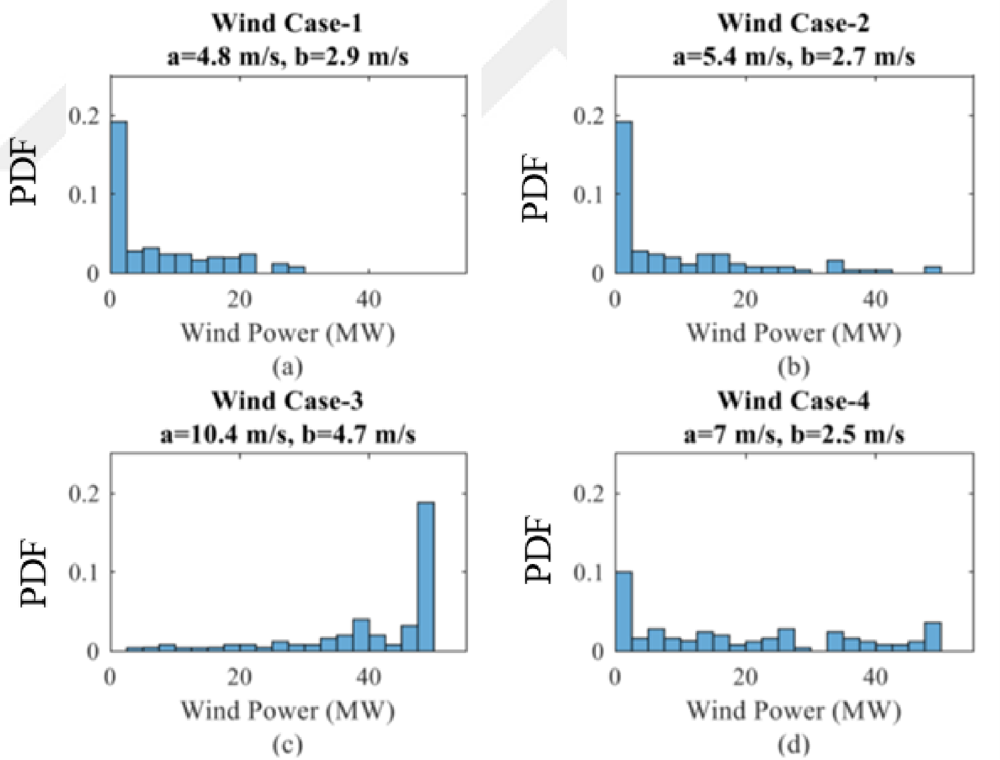

Figure 4.2 Histogram of wind power of different wind speed Weibull distributions.

Table 4.2 Overload probabilities (%) for different wind speed cases without capacitor addition

	Wind Cases	Wind-1			Wind-2			Wind-3			Wind-4		
Network	**Line/ Voltage**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**
w/o Cont.	L12-23	8	-	-	6	2	5	-	-	-	2	2	4
	L12-13	-	-	2	-	-	-	-	-	-	-	-	-
	L5-10	-	-	-	-	-	-	2	1	1	3	1	-
	V3	-	-	-	1	1	-	-	-	-	-	-	-
	V6	2	1	-	3	3	-	1	1	-	1	1	-
	V8	3	3	-	3	-	-	5	5	1	5	5	-
w/ Cont.	L5-10	-	-	-	-	-	-	2	2	1	3	2	-
	L12-13	11	-	1	9	-	-	1	-	-	5	-	-
	V3	1	-	-	7	1	-	6	-	-	5	1	-
	V4	-	2	-	1	2	-	-	-	-	-	-	-
	V6	16	9	-	17	11	6	11	8	-	15	9	-
	V8	10	10	5	10	1	-	10	11	8	10	1	5
	V12	2	-	-	2	2	-	2	-	-	2	-	-
	V24	-	2	-	-	-	-	-	1	-	-	2	-

Table 4.3 Overload probabilities (%) for different wind speed cases without capacitor addition

	Wind Cases	Wind-1			Wind-2			Wind-3			Wind-4		
Network	**Line/ Voltage**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**	**TEP 0.85**	**TEP 0.90**	**TEP 0.95**
w/o Cont.	L12-23	8	2	1	6	2	5	-	-	1	2	2	4
	L5-10	-	-	-	-	-	-	2	2	1	3	2	-
	V3	-	-	-	1	-	-	-	-	-	-	-	-
	V6	1	1	-	1	1	-	1	-	-	1	1	-
	V8	1	1	-	1	1	-	1	1	-	1	1	-
w/ Cont.	L5-10	-	-	-	-	-	-	2	2	1	3	2	-
	L12-13	11	-	-	10	-	-	1	-	-	5	-	-
	V3	10	-	-	7	1	-	6	-	-	4	1	-
	V4	1	2	-	1	2	-	-	1	-	-	-	-
	V6	9	5	-	1	5	-	5	3	-	6	5	-
	V8	8	8	2	8	8	2	9	9	3	9	9	4
	V12	2	-	-	1	-	-	2	-	-	1	-	-
	V24	-	2	-	-	2	-	-	-	-	-	2	-

The analysis of different wind speeds clearly shows that the probability of voltage violation increases, particularly for lower risk and wind speed conditions. Especially in wind case-1 contingency constrained test results, the voltage at bus 6 has a 16% probability of overload, and the voltage at bus 8 has a 10% and 5% probability of overload at higher risk levels. The bus 8 has reached its overload limit. Additionally, for each risk level in wind case-2, voltage at bus 6 is violated beyond its risk level in contingency constrained network. To address voltage security issues, two capacitors with capacities of 5 and 6 MVAR are added to buses 6 and 8, respectively. After that, the same testing procedure is applied to the TEP plans and the resulting violation probabilities are given in Table 4.3. It is observed that the voltage magnitude violations at buses 6 and 8 have fallen under acceptable levels.

Based on the test results, we can determine which lines will be overloaded for a given uncertainty scenario with different wind speed considerations. However, this test can be done repeatedly to examine the range of overload for each line and to investigate the impact of both load and wind speed characteristics on system power flow. In this way, the probabilistic behavior of uncertainties will be better reflected in the overload assessment. Therefore, 50 MCSs were computed using the uncertainty characteristics of wind speed, load, and N-1 as in the optimization. In this way, the overload probabilities are given as an interval for each line, and the uncertainty assessment can be handled comprehensively. As an example, the violation probability margins of line voltage magnitude at bus 6 for contingency constrained network is given in Figure 4.3. It is observed that voltage magnitude at bus 6 has different probability margins due to the combination of a new set of uncertainties. Particularly in varying wind speed conditions, voltage magnitude at bus 6 is prone to have risk of violation; so that the overload margin information becomes critical for guiding planners' decision. In Figure 4.3a, the outliers of the overload probability increase by up to 11-12% at lower wind speeds (wind-1 and wind-2). However, the mean overload probability for each TEP decision is almost below its pre-specified not overload probability. The overload probability margin observed in wind case-3 is lower than in other wind cases for each TEP decision since it has the highest wind speed characteristic

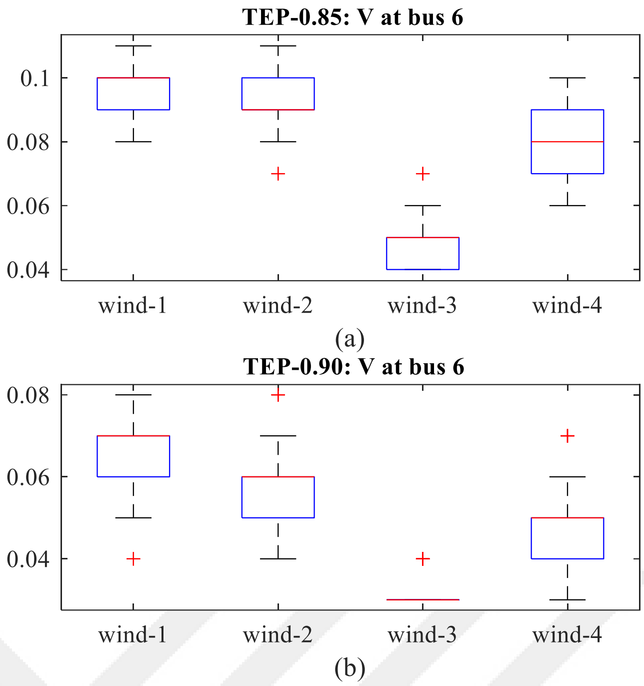

Figure 4.3 Violation probability of voltage magnitude at bus 6 of (a) TEP-0.85; (b) TEP-0.90.

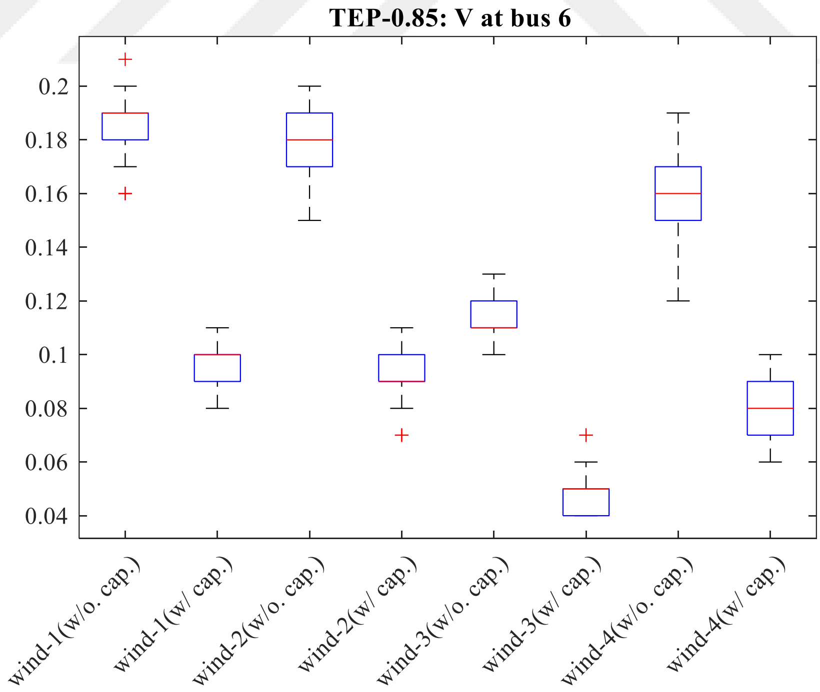

Figure 4.4 Probability of voltage magnitude violation at bus 6 of TEP-0.85 decisions with and without capacitor addition

There is not any violation on TEP-0.95 decision; so, it is not given. The violation probability margins of voltage magnitude at bus 6 are shown in Figure 4.4 with and without capacitor addition. Without the addition of a capacitor, the outliers for overload probability increase to 18% for the higher wind speed condition in Case 4, and to 20% for the lower wind speed condition. After the capacitor is added, the overload probability margins for each wind case are determined to be less than the accepted confidence level. Consequently, based on the test results it is observed that the overload probability margin provides a detailed information for assessing the overload and violation for each TEP decision, which would be valuable when considering various risk levels in TEP optimization.

4.5 Case Studies on IEEE 118 Bus Test Network

In this section, the proposed model is applied to the IEEE 118 bus network with respect to different not-overload probability consideration. The uncertainty data for the test network is given as follows:

- The mean value of the load is increased 20% from its original value. σ/μ ratio of load is considered 5%.

- Weibull characteristic of wind speed is a=7, b=2.5 m/s and the turbine characteristic are as follows Vci=4, Vr=10, Vco=22 m/s.

- Wind turbine is located at buses 43, 44, 45, 47, 48, 50, 51, 52 and 53 its rated capacity is 10 MW for each turbine.

- Lines L43-44, L44-45, L45-46, L46-47, L47-49, L48-49, L49-50, L51-52, L52-53, L53-54, L50-57, and L51-58 are selected as N-1 contingency candidates and FOR of each line is assigned from a standard uniform PDF to define its unavailability.

In the upper level of the optimization, there are thirteen variables for IEEE 118 bus test system. The GA parameters for the test network is assumed as followingly: Population size is 100, total number of generations is 200 and the crossover fraction is

0.8. We consider three candidate lines for each possible corridor and only the case study-3 which considers all uncertainties are established. The confidence levels are chosen as 80, 90 and 100%. The resulting TEP investments for case this study is given in Table 4.4. It has been observed that the proposed model provides alternative TEP decisions for a large power system by choosing a pre-specified risk level. As the non-overload probability β decreases less expensive TEP decisions are obtained for all risk levels. The main reason for investment is the overloading in transmission lines.

A similar test procedure is also applied to the IEEE 118 bus test system. Weibull characteristic of different wind speed cases for testing procedure is given followingly:

- Wind Case-1: k=6 m/s, c=3 m/s
- Wind Case-2: k=7 m/s, c=2.5 m/s
- Wind Case-3: k=10.4 m/s, c=5.4 m/s

Table 4.4 TEP decisions for IEEE 118-bus test network

TEP- β	**TEP 0.80**	**TEP 0.90**	**TEP 1.00**
L11-12	1	1	2
L2-12	1	1	1
L7-12	1	1	1
L45-46	1	1	1
L46-47	-	-	1
L70-71	-	1	1
L71-72	-	1	1
L70-75	-	1	1
L90-91	-	-	1
L100-104	-	-	1
Total (M$)	4,19	9,65	16,56

The wind power considered for the three wind cases is low, medium, and high wind speed conditions, respectively. The violation probability margins of lines for the TEP plans 0.80 and 0.90 risk levels are given in Figure 4.5 and Figure 4.6. It is observed that the overloaded lines have different probability margins due to the combination of new set of uncertainties. The outliers of the overload probability increase up to 20%

and 14% for the TEP-0.80 and TEP-0.90 decisions, respectively. However, the mean overload probability for each TEP decision is almost below its pre-specified not overload probability for each wind case study. The overload probability margin observed in wind case-3 is very low than in other wind cases for TEP decision since it has the highest wind speed characteristic. There is not any violation on voltage magnitude so, it is not given. Since there is more investment in TEP-0.90 plan line 70-71, 71-72 and 70-75 has no violation probability. The expected generation cost of TEP plans is also calculated as 14838 $/h for the TEP-0.80 and TEP.0.90 plans and 14822 $/h for the TEP-1.00 plan, respectively. The results show a similar trend with previous studies that the expected generation cost is higher in risk taking TEP plans.

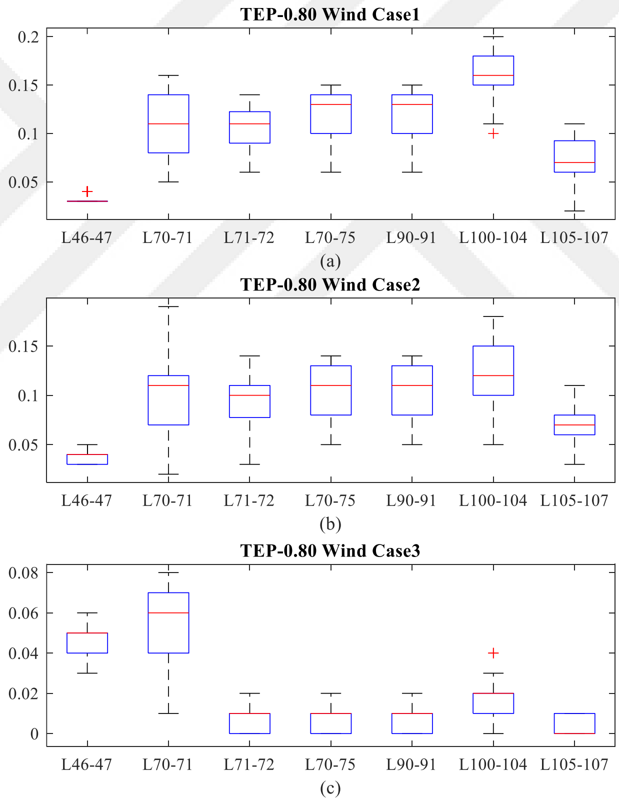

Figure 4.5 Probability of line overloads for TEP-0.80 decisions

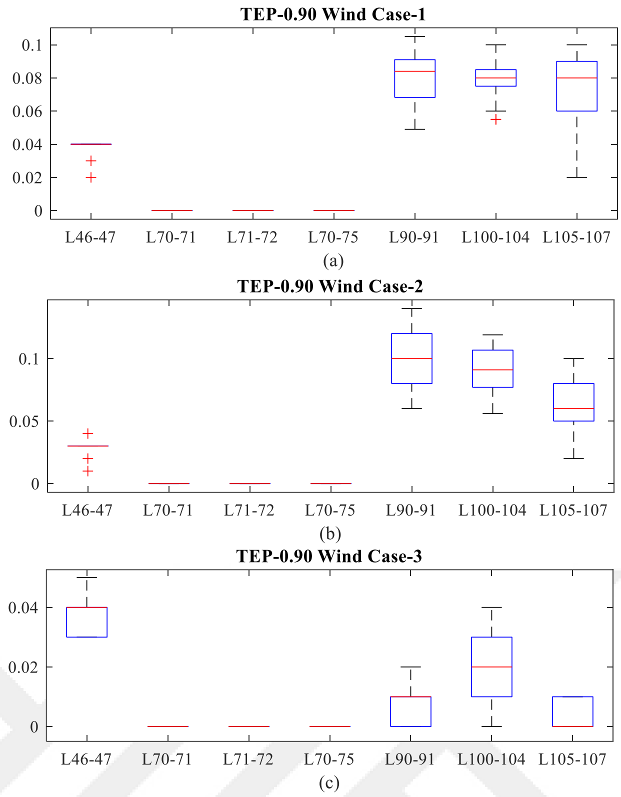

Figure 4.6 Probability of line overloads for TEP-0.90 decisions

4.6 Discussion

TEP is a complex problem that involves numerous levels of power system analysis studies. These studies include the operational behavior of system which changes stochastically with the integration of large-scale renewable sources. The problem is mainly provided by the generators to balance the load at minimal cost while meeting the operational limits. Generally, the economic dispatch is applied for a specified time steps. Renewable energy forecasts, such as wind farms, does not have a sufficient precision unless they are within a very short time span (Tang et al., 2015). In that manner, the uncertainty in the system should be handled carefully to find the operational behavior of the system. A grid with renewable sources can result in power flows that exceed line capacity and voltage limits. When a line's capacity is exceeded, the probability of line tripping will also increase (Exposito et al.,2004) Therefore, the amount of overload level is a key to identify risk in planning studies under uncertainties. From the solution point of view, two main approaches are used to solve this problem under TEP. These are based on line overload probability (Yang & Wen, 2005; Yu et al., 2009; Zheng et al., 2014) and load curtailment probability (Orfanos et al., 2013; Akbari et al., 2012; Qiu et al., 2017). At the core of the problem, both approaches try to satisfy the future forecasted load under uncertain operating conditions. Yet, from modelling perspective first one requires a power flow analysis; the second one requires an optimization procedure called optimal power flow. Using optimal power flow seems to be more suitable to consider both technical and economic aspects of planning problem. However due to the complexity and computational burden of nonlinear equations; it becomes very difficult problem especially for large scale networks. Therefore, in this dissertation, the modified power flow analysis promises to find a secure and economical investment decision as well as offering the possibility to directly use the probability distribution functions of line flows and bus voltages instead of indirect means.

A probabilistic power flow approach is convenient when the uncertainty is handled in the operational problem. Generally, the steady-state power flow studies use the full AC power flow formulation to assess the losses and the reactive compensation requirements, both for the base and N-1 contingency conditions. However, the nonlinearity of AC power flow equations in power system planning is not considered frequently due to its mathematical complexity. The AC power flow model has been attracted researchers to reformulate the nonlinear equations for a more accurate representation of power system operation (De Silva et al., 2006; Rahmani et al., 2010; Hooshmand et al.,2012; Zhang et al., 2013; Asadamongkol & Eua-arporn, 2013; Alhamrouni et al., 2014; Moradi et al., 2016; Roald & Andersson, 2018; Das et al., 2019; Farrag et al., 2019; Zhou et al., 2020). As far as the concerns on power loss, voltage and reactive power issues which require AC network modeling have been the subject of research together with the TEP problem. However, it is a complex problem which involves single/multiple objectives, integer, and discrete variables. When the operational problem is nonlinear, the solution space is likely to have more than one minimum. For this reason, it is even more difficult to achieve a feasible result within the specified time frame. Another important issue is that the probabilistic power flow suffers from the very existence of slack bus. The slack bus generator is a mathematical necessity for finding a feasible solution but with the stochastic operating conditions it absorbs uncertainty. This situation contradicts the studies of uncertainty. The output of slack bus generator is generally beyond its limits unless constraints are imposed on slack bus generator (Dimitrovski & Tomsovic, 2005). In that point, the imbalance power can be distributed among the dispatchable generators using participation factors. This methodology can be easily adopted in the existing power flow formulation with an artificially introduced parameter. This concept is called a distributed slack bus approach. In probabilistic power flow studies distributed slack concept is efficient, simple to implement and does not require an optimization to find the state vectors V and θ for different operating conditions. In this paper, the generator cost coefficients are used to find the optimal generator outputs based on equal incremental cost criterion under uncertain conditions. In that manner, the economic management of generators are obtained in a sense of economic dispatch. Proposed probabilistic model cannot be extended to an optimal power flow by simply introducing an artificial variable for imbalance power. However, the proposed method has the potential to be a suitable alternative for traditional single slack bus power flow analysis in associated with economic dispatch studies. Treatment of slack bus with modified power flow approaches proposed promising results for operational problem with the minor modifications on existing power flow studies (Dimitrovski & Tomsovic, 2005(a); 2005(b); Jang et al., 2005; Expósito et al., 2004).

In this study, uncertainties of wind, load and N-1 contingency are considered simultaneously to obtain the probability distribution function under nonlinear AC power flow with distributed slack bus concept. A method is proposed to combine over limit risk constrained stochastic TEP problem with participation factor power flow. The risk is defined as the non-over limit probability of each investment decision such that high risk level means risk-averse approach. It is observed from the results that when the risk level is increased, the number of candidate lines selected in the planning scheme and the total investment cost will also increase. Such an outcome is certainly within the expectation. However, maintaining line flows and bus voltages within their prescribed limits is the foremost operational criterion. Therefore, a risk-taking strategy is effective for reducing both number of invested lines and cost of investment. Another important observation is that when the system is heavily loaded and renewable integration is higher in weaker part of the network, there may also be a risk of voltage variations as well as line overloads. The location and size of voltage support must be carefully handled to maintain voltage profile within the specified limits. Thanks to AC network modeling, more realistic solutions can be achieved by adding voltages constraints to the investment optimization. To the best of author's knowledge, no prior work has utilized AC power flow analysis with distributed slack bus concept in chance constrained TEP problem. Therefore, it goes without saying that although power flow analysis is a powerful tool, it is a subject that is open to development when used in planning studies.

Testing of TEP plans is another issue that has been overlooked in the literature. In this study, the final stage of the study involves testing the investment plans obtained under a new set of uncertainty conditions, examining the investment plans with respect to various confidence levels allows, and presenting the benefits and drawbacks of the proposed method. As a result, the main differences between other existing studies and the method proposed in this paper are that exact probability distribution functions are obtained under nonlinear AC power flow with distributed slack bus concept to be used in chance constrained TEP problem by using a simple formulation and algorithm approach.

The potential limitation of the proposed method is that this model with nonlinear AC power flow needs a meta-heuristic method to perform the optimization process through probability distribution functions that used in the chance constrained optimization. As a metaheuristic optimization technique, genetic algorithms are of great interest for solving the TEP problem (Yu et al., 2009; Rahmani et al., 2010; Da Silva et al., 2000; De Silva et al.,2006; Escobar et al., 2004). The proposed method utilizes the advantages of distributed slack bus-based AC power flow, meta-heuristic technique, and Monte Carlo Simulation, instead of using AC optimal power flow formulations integrated with TEP problem that may result in convergence problem. On the other hand, although the convergence of the methods to the global optimum solution cannot be guaranteed in nonlinear programming problems, heuristic optimization algorithms can produce promising results for the solution of difficult optimization problems such as AC-TEP (Rider et al., 2007; Rahmani et al., 2010; Hooshmand et al., 2012; Alaee et al.,2016; Moradi et al., 2016; Alhamrouni et al., 2014).

Table 4.5 Required time for obtaining each TEP plan

Test Network	TEP- β	Required Time
IEEE 24 RTS	TEP-0.85	3.20 h
	TEP-0.90	2.18 h
	TEP-0.95	5.68 h
	TEP-1.00	4.20 h
IEEE 118 Bus	TEP-0.80	21.87 h
	TEP-0.90	32.01 h
	TEP-1.00	21.01 h

Although it is difficult to say that these algorithms are superior to each other, depending on the setup of the problems, it is difficult to say that metaheuristic methods do not have a chance of finding better solutions than those obtained with mathematical approaches based on decomposition techniques (Da Silva et al.,2000; De Silva et al.,2006).The main drawback of using a genetic algorithm to solve TEP optimization is that the time required give a decision scale exponentially with the increasing number of decision variables, population, and generation considerations. In our model, both systems are executed in MATLAB R2018a. The average CPU time for obtaining one TEP decision for the two test networks are recorded, for the simulations on IEEE 24 bus and IEEE 118 bus test system. Table 4.5 shows the average execution time for a single TEP decision that considers load, wind, and N-1 contingency uncertainties. It is observed that, as the system grows, the time required to solve the optimization problem also increases.

CHAPTER FIVE
STOCHASTIC TRANSMISSION EXPANSION PLANNING WITH FACTS DEVICES IN TERMS OF FLEXIBLITY ASPECT

The electric power network is highly complex interconnected system which is necessary to deliver electricity from generation units to loads. Apart from the delivery of power, transmission interconnections enable to reduce the cost of electricity and improve the reliability of the power system. In fact, more generators would be required to provide the load with the same reliability if a power system relied solely on local generators rather than a main grid, and the cost of electricity would be significantly higher. Therefore, transmission network acts as an alternative for new generation resources (Hingorani & Gyugyi, 2000).

In the recent years, the investments on new renewable generation facilities have been increased dramatically due to issues related to energy, environment, and the deregulation of power companies. In that manner, it has become essential to increase transfer capability with new technologies like FACTS-devices to better utilize the current power system capacities. The extensive utilization of renewable sources with the rising demand has increased congestion in power grid. One option to relieve congestion is transmission expansion planning. However, the challenges for high expenses and long construction times makes transmission expansion planning unfavorable in some cases. Alternatively, FACTS-devices can quickly and effectively adjust the network parameters to improve system performance. For example, a thyristor-based device allows to control shunt or series compensation and phase shifting which will make possible to control power flow and voltage control in power system studies.

A growing area of application for FACTS devices can be seen in renewable energy sector. In particularly, wind farms with variable output have to provide reactive power and keep the voltage within its limits. Besides, the lack of sufficient transfer capability leads to the ineffective use of the power obtained from the renewable sources. Although investing in FACTS devices is an alternative unit to enhance power system performance, it is not a definitive solution for the problems that may be encountered in power system. Therefore, it’s reasonable to investigate a coordination between expansion decision and utilization of these devices to obtain a flexible decision for power system operation.

In the light of these concerns, a coordinated transmission expansion planning with wind power generation and FACTS devices is presented. In the previous chapter, a participation factor load flow in a sense of economic dispatch is used to handle the operation level of TEP optimization. The resulting investment decision is tested with different uncertainty conditions and corrective measures are taken by planners’ experience to ensure the operational limits of the system. In the modernized power system, flexibility is a key attribute for dealing with the uncertainty of the system. Coordination of TEP with FACTS devices may enable to control the adequacy of the operation which assist the planners to make system work efficiently under various uncertain operating conditions. Therefore, in this part of the dissertation, two modelling schemes for TEP problem with FACTS devices are proposed and the operational flexibility is discussed with coordination of TEP with FACTS devices.

5.1 Modelling FACTS Devices in TEP Problem

The configuration of FACTS devices can be categorized as shunt and series. In this dissertation, Thyristor-Controlled Series Capacitor (TCSC) device is used for power flow control and Static Var Compensator (SVC) device is used to control reactive power and voltage profile. Power flow control has traditionally been relied on generator outputs and voltage regulation. In traditional network studies, phase-shifting and tap-changing transformers, reactive power compensation regulates the power flow by changing the voltage magnitude and phase angles. Series reactors and capacitors may alter the power flow via changing the electrical parameters of transmission lines. In addition, it is advantageous to use series capacitive compensation in the maximum loading conditions to increase the power transfer without overloading (Acha et al., 2004). From an operational perspective, the focus of TCSC devices is to manage power flows throughout the network in an adaptable manner by using series capacitor banks. On the other hand, SVC acts as a shunt connected variable reactance that adjusts reactive power to regulate the magnitude of voltage. In AC networks, SVC is used extensively for fast reactive power support and voltage regulation.

The steady-state models of FACTS devices can be modelled either variable reactance or power injection. The mathematical model for a TCSC devices is given in (5.1) to (5.4) as follows:

$$x_{TCSC} = k_{TCSC} x_{ik} \tag{5.1}$$

$$x_{ik} = x_{ik} + x_{TCSC} \tag{5.2}$$

$$g_{ik,new} = \frac{r_{ik}}{\sqrt{r_{ik}^2 + (x_{ik} + x_{TCSC})^2}} \tag{5.3}$$

$$b_{ik,new} = -\frac{x_{ik} + x_{TCSC}}{\sqrt{r_{ik}^2 + (x_{ik} + x_{TCSC})^2}} \tag{5.4}$$

TCSC is included in the transmission model by simply changing the reactance by adding a variable reactance parameter x_{TCSC}. x_{ik} represents the equivalent reactance of transmission line and k_{TCSC} is the compensation level. In this study, the operational range of TCSC is assumed to be -0.7x_{ik} to 0.2x_{ik} to avoid overcompensation. The mathematical model for SVC is given in (5.5).

$$Q_{svc} = \Delta Q_{inj} \tag{5.5}$$

Where the injected reactive power from SVC is assumed to be between -20 to 20 MVAR. Since the operational problem is solved by the participation factor power flow, the variable reactance from TCSC is introduced as an adjustment in admittance matrix. The injected reactive power from SVC is included in the power balance equations.

5.2 Methodology and Mathematical Formulation for Coordinated TEP with FACTS Devices

In the case studies two solution approaches are implemented on a coordinated TEP problem with FACTS devices. In the separate approach FACTS allocation is handled after TEP optimization. Unlike the previous study of overload assessment in Chapter

4, this approach finds the allocation of FACTS devices based on a chance constrained FACTS allocation problem. After the assessment of overloads, the allocation of FACTS devices is solved by a chance constrained optimization with different uncertain operating conditions for finding the location and size of FACTS devices in the network. In this way, the planner seeks to find a better utilization of transmission investment with the coordination of FACTS devices in a pre-specified risk level. The representation of the model is presented in Figure 5.1 and the mathematical formulation for the FACTS allocation problem is given as follows:

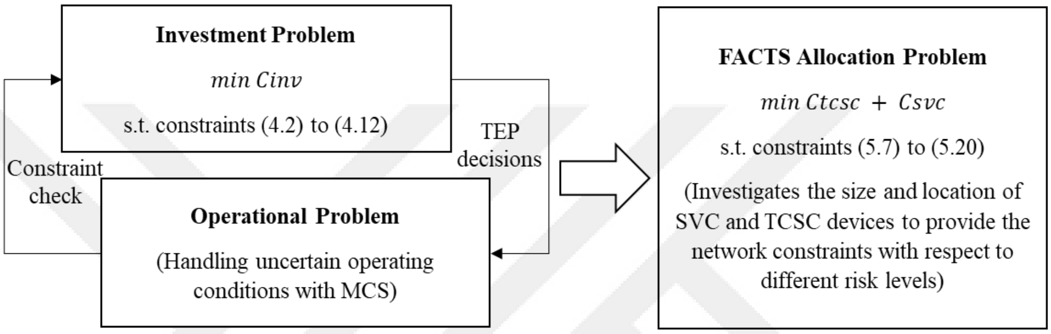

Figure 5.1 Representation of the separate approach

$$min \sum_{(TCSC)} Cost_{TCSC} n_{TCSC} S_{TCSC} + \sum_{(SVC)} Cost_{SVC} n_{TCSC} Q_{SVC} \tag{5.6}$$

$$prb\{S_{ik}^{from} \leq \overline{S}_{ik}\} \geq \beta \tag{5.7}$$

$$prb\{S_{ik}^{to} \leq \overline{S}_{ik}\} \geq \beta \tag{5.8}$$

$$prb\left\{\underline{|V|} \leq |V| \leq \overline{|V|}\right\} \tag{5.9}$$

$$prb\{S_{ik}^{c,from} \leq \overline{S}_{ik}\} \geq \beta, \quad c = (i,k), c \in \Omega^c \tag{5.10}$$

$$prb\{S_{ik}^{c,to} \leq \overline{S}_{ik}\} \geq \beta, \quad c = (i,k), c \in \Omega^c \tag{5.11}$$

$$prb\left\{\underline{|V^c|} \leq |V^c| \leq \overline{|V^c|}\right\} \tag{5.12}$$

$$0 \leq n_{TCSC} \leq \overline{n_{TSCS}} \tag{5.13}$$

$$\underline{k_{TCSC}} \leq k_{TCSC} \leq \overline{k_{TCSC}} \tag{5.14}$$

$$0 \leq n_{SVC} \leq \overline{n_{SVC}} \tag{5.15}$$

$$\underline{Q_{SVC}} \leq Q_{SVC} \leq \overline{Q_{SVC}} \tag{5.16}$$

where

$$S_{ik}^{from} = \sqrt{(P_{ik}^{from})^2 + (Q_{ik}^{from})^2} \tag{5.17}$$

$$P_{ik}^{from} = V_i^2 g_{ik,new} - V_i V_k \big(g_{ik,new} cos\theta_{ik} + b_{ik,new} sin\theta_{ik}\big) \tag{5.17a}$$

$$Q_{ik}^{from} = -V_i^2 \big(b_{ik}^{sh} + b_{ik,new}\big) - V_i V_k \big(g_{ik,new} sin\theta_{ik} - b_{ik,new} cos\theta_{ik}\big) \tag{5.17b}$$

$$S_{ik}^{to} = \sqrt{(P_{ik}^{to})^2 + (Q_{ik}^{to})^2} \tag{5.18}$$

$$P_{ik}^{to} = V_i^2 g_{ik,new} - V_i V_k \big(g_{ik,new} cos\theta_{ik} - b_{ik,new} sin\theta_{ik}\big) \tag{5.18a}$$

$$Q_{ik}^{to} = -V_k^2 \big(b_{ik}^{sh} + b_{ik,new}\big) + V_i V_k \big(g_{ik,new} sin\theta_{ik} + b_{ik,new} cos\theta_{ik}\big) \tag{5.18b}$$

$$S_{ik}^{c,from} = \sqrt{(P_{ik}^{c,from})^2 + (Q_{ik}^{c,from})^2} \tag{5.19}$$

$$P_{ik}^{c,from} = (V_i^c)^2 g_{ik,new}{}^c - V_i^c V_k^c \big(g_{ik,new}{}^c cos\theta_{ik}{}^c + b_{ik,new}{}^c sin\theta_{ik}{}^c\big) \tag{5.19a}$$

$$\begin{aligned} Q_{ik}^{c,from} &= -(V_i^c)^2 \big(b_{ik}^{c,sh} + b_{ik,new}{}^c\big) \\ &- V_i^c V_k^c \big(g_{ik,new}{}^c sin\theta_{ik}{}^c - b_{ik,new}{}^c cos\theta_{ik}{}^c\big) \end{aligned} \tag{5.19b}$$

$$S_{ik}^{c,to} = \sqrt{(P_{ik}^{c,to})^2 + (Q_{ik}^{c,to})^2} \tag{5.20}$$

$$P_{ik}^{c,to} = (V_i^c)^2 g_{ik,new}{}^c - V_i^c V_k^c \big(g_{ik,new}{}^c cos\theta_{ik}{}^c - b_{ik,new}{}^c sin\theta_{ik}{}^c\big) \tag{5.20a}$$

$$\begin{aligned} Q_{ik}^{c,from} &= -(V_i^c)^2 \big(b_{ik}^{c,sh} + b_{ik,new}{}^c\big) \\ &+ V_i^c V_k^c \big(g_{ik,new}{}^c sin\theta_{ik}{}^c + b_{ik,new}{}^c cos\theta_{ik}{}^c\big) \end{aligned} \tag{5.20b}$$

where the objective function in (5.6) consists of total investment cost of TCSC and SVC devices. The investment cost of SVC and TCSC are equal to \$40/kvar respectively. The constraints from proposed stochastic AC TEP model in Chapter 4 is implemented in (5.7) to (5.12) are implemented with the inclusion of TCSC and SVC device parameters in (5.1) to (5.5). The power flow equations with the updated parameters are given in (5.17) to (5.20). The decision variables that represent location and size of the FACTS devices are bounded in (5.13) and (5.14) for TCSC and (5.15) and (5.16) for SVC. In the solution process the pre-specified TEP investment is implemented in the constraints and the allocation of FACTS devices are found under uncertain operating conditions with respect to different risk levels represented by the chance constraints.

Alternatively, in the unified approach the coordinated TEP with FACTS devices problem is considered jointly in the optimization problem. The decision variables are determined as location and size of the FACTS devices with the candidate line investment. This problem is solved by a two-level stochastic problem with the inclusion of decision variables and constraints related to FACTS allocation into the stochastic AC-TEP problem. The representation of the model is presented in Figure 5.2.

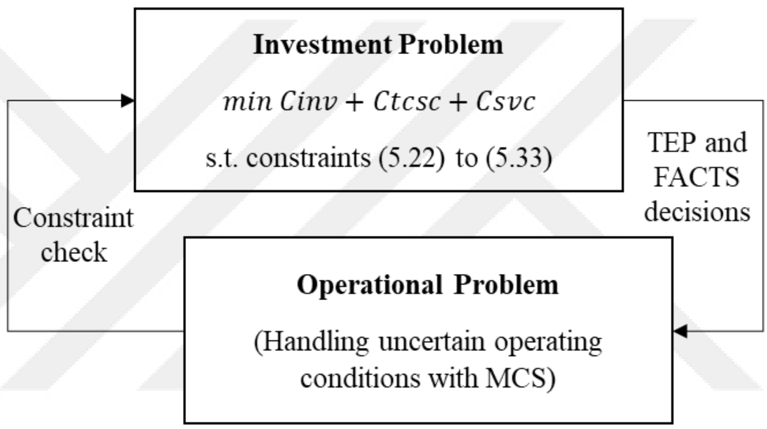

Figure 5.2 Representation of the unified approach

The mathematical formulation of the unified approach is given as follows:

$$\min \sum_{(i,k)} Cost_{ik} n_{ik} + \sum_{(TCSC)} Cost_{TCSC} n_{TCSC} S_{TCSC} + \sum_{(SVC)} Cost_{SVC} n_{TCSC} Q_{SVC} \tag{5.21}$$

subject to

$$prb\left\{(n_{ik} + n_{ik}^{0}) S_{ik}^{from} \leq (n_{ik} + n_{ik}^{0}) \overline{S}_{ik}\right\} \geq \beta \tag{5.22}$$

$$prb\left\{(n_{ik} + n_{ik}^{0}) S_{ik}^{to} \leq (n_{ik} + n_{ik}^{0}) \overline{S}_{ik}\right\} \geq \beta \tag{5.23}$$

$$prb\left\{\underline{|V|} \leq |V| \leq \overline{|V|}\right\} \tag{5.24}$$

$$prb\left\{(n_{ik} + n_{ik}^{0} - 1) S_{ik}^{c,from} \leq (n_{ik} + n_{ik}^{0} - 1) \overline{S}_{ik}\right\} \geq \beta, \quad c = (i,k), c \in \Omega^{c} \tag{5.25}$$

$$prb\left\{(n_{ik} + n_{ik}^{0} - 1) S_{ik}^{c,to} \leq (n_{ik} + n_{ik}^{0} - 1) \overline{S}_{ik}\right\} \geq \beta, \qquad c = (i,k), c \in \Omega^{c} \tag{5.26}$$

$$prb\left\{\underline{|V^c|} \le |V^c| \le \overline{|V^c|}\right\} \tag{5.27}$$

$$0 \le n_{ik} \le \overline{n_{ik}} \tag{5.28}$$

$$0 \le n_{TCSC} \le \overline{n_{TSCS}} \tag{5.29}$$

$$0 \le n_{SVC} \le \overline{n_{SVC}} \tag{5.30}$$

$$\underline{k_{TCSC}} \le k_{TCSC} \le \overline{k_{TCSC}} \tag{5.31}$$

$$\underline{Q_{SVC}} \le Q_{SVC} \le \overline{Q_{SVC}} \tag{5.32}$$

where (5.33)

$$Equation\ (5.17)\ to\ (5.20)$$

where the objective function in (5.21) minimizes the total investment cost of lines. The bounds of probabilistic line capacity and bus voltage constraints are given in (5.22) to (5.27) and the bounds related decision variables are given in (5.28) to (5.32). The power flow equations used in probabilistic constraints with modified variables are also given in (5.33).

5.3 Case Studies on IEEE 24 Bus Test System

In this section, the proposed coordinated TEP with FACTS model is applied to the IEEE RTS 24 bus network with respect to different not-overload probability consideration. In the upper level of the optimization, there are thirteen variables for IEEE 24 bus test system. The uncertainty and the candidate lines assumed to be the same as in the previous studies given in Chapter 4. TCSC devices are allowed to be connected to all 5 candidate lines (1-2, 11-13, 11-14, 12-13, 13-23). These lines are selected based on their overload levels under different uncertainty considerations. SVC devices are allowed to be connected all the load buses (total 14 buses). The GA parameters for the IEEE 24 bus test network is assumed as population size is 200, total number of generations is 100 and the crossover fraction is 0.8. We consider five candidate lines, one TCSC and one SVC devices in the optimization. The allocation of more than one SVC and TCSC into the same bus/line is not allowed.

The case studies are implemented based on considering load, wind, and N-1 contingency uncertainty. The main objective behind this study is to show the operational flexibility that FACTS devices bring into network expansion problem under separate and unified FACTS consideration with TEP optimization. In the first case study, a coordinated TEP study is implemented with a single and multiple FACTS devices in a unified approach. The overlimit risk level for the probabilistic chance constraints is assumed to be 15%. The network investment decision for different number of FACTS consideration is given in Table 5.1. Case studies 1, 2, and 3 describes no FACTS, one SVC and one TCSC, and one SVC consideration, respectively. It has been observed that by selecting a predetermined risk level the proposed approach offers different TEP decisions. Considering the number of line investments made, TEP decision with only one SVC produces more economic investment decision.

Table 5.1 FACTS investment decisions obtained from unified approach

Case Studies	**Investment Decision**	**FACTS Decision**	**Total Cost (M$)**
No FACTS	1-2(1), 1-5(1), 2-6(1), 3-24(1), 9-12(2), 10-11(4), 11-13(3), 20-23(3)	-	11,69
SVC(1) and TCSC(1)	1-5(1), 2-6(1), 3-24(3), 10-11(3), 11-13(2), 20-23(1)	Bus 10 (4 MVAR), Line 13-23 (-0.20)	10,76
SVC (1)	1-5(1), 2-6(1), 3-24(2), 9-12(1), 10-11(3), 11-13(2)	Bus 6 (8 MVAR)	10,07

The overload assessment of each investment plan is investigated with an uncertainty set similar to input characteristic. The computational results and overload probability levels are given in Table 5.2.

Table 5.2 Overload probabilities (%) of the investment decisions obtained from unified approach

Case Studies		1	2	3
w. out contingency	L1-2	-	5	5
	L5-10	3	3	3
	L11-14	-	-	3
	L12-23	2	-	7
	V4	-	1	-
	V6	1	-	1
	V8	5	9	7
	V24	-	-	-
with contingency	L1-2	-	6	5
	L5-10	3	3	3
	L12-13	5	-	15
	V3	5	2	3
	V4	-	5	2
	V6	15	15	11
	V8	10	15	14
	V9	-	4	-
	V12	2	-	4
	V24	-	6	2

It is observed that particularly, bus 6 and bus 8 voltage profiles are the most affected by the wind uncertainty. Therefore, strategic placement of SVC on the lower part of the network where wind turbine generators are abundant improves the voltage profile to a prespecified risk level. On the other hand, TCSC placement is mainly provide the adequacy of the network when the wind uncertainty is not enough to satisfy the variable loading conditions. The generators at bus 13 and bus 23 are the largest capacity generators in the network. Therefore, the lines 12-13 and 12-23 are generally congested. After the placement of TCSC in line 13-23, the power flow in the overloaded lines like (12-13) has been reduced, and that results in an increased loadability of the power system. In TEP optimization, the best strategy to address network constraints, particularly those brought on by the lack of control over grid flows, may not always involve expanding the transmission network in the typical upgrading manner [Blanco et al.,2009]. Therefore, introducing renewables in a highly meshed network necessitate to utilization of FACTS devices to increase power transfer capability and controllability of the network. In that manner, it is also inferred that in Table 5.2 considering a unified approach for TEP and FACTS allocation provides investment plans at similar overlimit levels with less line investment.

In the second case study, a separate approach is adopted where investment and FACTS allocation is considered consecutively. First, the obtained TEP investment for 15% risk level is applied to the network data. Then the FACTS allocation based on minimizing the investment cost of FACTS devices are handled to satisfy the network constraints under different uncertain operating conditions. In the previous overload assessment analysis given in Chapter 4, it is observed that there are more overloads in the low and medium wind speed conditions; therefore, FACTS allocation decisions are assessed under three wind case studies which considers low (k=4.8, c=2.9), medium (k=7, c=2.5), and high (k=10.4, c=5.4) wind speed conditions. Since this analysis is done after the investment optimization; new line investment is not allowed. However, the effect of FACTS allocation according to different confidence levels is explored by a chance constrained FACTS allocation optimization. The risk level for the probabilistic chance constraints is assumed to be 15 and 10%. The FACTS allocation decision for different case studies is given in Table 5.3.

Table 5.3 FACTS investment decisions obtained from separate approach

Wind Case Studies	$\boldsymbol{\beta}$ **= 85%**	$\boldsymbol{\beta}$ **= 90%**
Low	Bus 11 (4 MVAR)	Bus 6 (8 MVAR) Line 12-13 (0.10Xline)
Medium	Line 13-13 (-0.10Xline)	Bus 6 (4 MVAR) Line 13-13 (0.20Xline)
High	Line 13-13 (0.20Xline)	Line 13-13 (-0.10Xline)

The result for different wind speed case studies in Table 5.3 show that separate approach produces different investment decisions for FACTS allocation at different risk levels. In lower confidence level only one FACTS device utilization is sufficient to satisfy the network constraints. As the confidence level increases more investments are made particularly for low and medium wind speed conditions. However, it should be noted that FACTS investment is not an alternative to line investment. The main purpose here is to invest with a corrective manner based on a pre-determined transmission investment. Therefore, the FACTS investment to be made can provide the network constraints for a certain level of confidence. It is inevitable to make line investments to be able to operate at higher confidence levels. Another important observation from Table 5.3 is that, as the wind speed increases the number of FACTS investment is also decreasing. This can be also confirmed with the overload assessment of β = 85% investment decision which can be seen on Table 5.4.

Table 5.4 Overload probabilities (%) of the investment decisions obtained from separate approach for different wind speed conditions

Case Studies		**Low**	**Medium**	**High**
w. out contingency	L5-10	-	1	2
	L12-23	8	1	3
	V3	-	-	-
	V6	2	2	1
	V8	3	3	5
with contingency	L5-10	-	1	2
	L12-13	11	6	1
	V3	11	5	6
	V4	1	1	1
	V6	15	15	11
	V8	10	10	11
	V12	2	2	2

It is observed that, low wind speed condition has the highest overload levels on both bus voltage and line power flows. This is mainly due to the adequacy of the power system since the wind turbines are connected to the lower network. When these conditions occurred, the system load is satisfied with the high-capacity conventional generators in the upper network. Due to the congestion on lines 11-14, 12-13, and 12-23, both bus voltages and power flow through buses 11, 12, 13, and 23 are affected by the uncertainty. Besides, strategic placement of SVC or TCSC also reduces the overload levels on bus voltages both base and contingency conditions.

In the last case study, computational results of both unified and separate approaches are compared in terms of cost and overload levels. In that manner, transmission investments are obtained for different wind speed conditions and the results of unified and separate approaches are compared with respect to economic and technical standpoints. The investment decision results of both approaches are given in Table 5.5. In this table, the abbreviation ‘U’ and ‘S’ stands for unified and separate approach. As expected, it is observed that the obtained decision of unified approach provides less expensive investment decisions. Furthermore, the allocation of FACTS device is also changed for each plan which provides alternative decisions for the planner. The overload assessment of investment plans is given in Table 5.6. Power systems operate in a complicated operational environment; hence it is essential to take many sorts of uncertainty into account while planning. Consequently, based on these results using separate approach allows planner to diversify the uncertainty and investigate the impact on network operation at a pre-specified confidence level. In that manner, with a small investment, a planner can easily adapt the network according to different uncertainty conditions.

Additionally, utilizing proper FACTS devices into the network allows to increase the confidence level of an operation of a transmission investment with higher risk levels with no additional line investment. Yet in separate approach, the line investment is handled initially so more transmission lines are invested in comparison to unified approach. This may consider to be economically unfavorable however line investment using separate approach ensures a more robust model with less amount of overloads on power flows and bus voltages. On the other hand, using unified approaches gives a complementary solution for both TEP and FACT allocation decision. Therefore, less expensive TEP investment decisions can be achieved. Especially in some scenarios, installing FACTS devices instead of line investments made to ensure network constraints reveals a planning decision that can provide both economic and technical constraints at desired confidence levels.

Table 5.5 Investment decisions of TEP and FACTS devices based on different wind speed conditions considering unified or separate approach

Case Studies	Investment Decision	FACTS Decision	Total Cost (M$)
1- **Low (U)**	1-5(1), 3-24(2), 6-10(2), 9-12(1), 10-11(4), 11-13(5)	Line 13-23 (-0.10Xline)	10,13
2- **Low (S)**	1-2(1), 1-5(1), 2-6(1), 3-24(1), 9-12(2), 10-11(4), 11-13(3), 20-23(3)	Bus 11 (4 MVAR)	12,31
3- **Medium (U)**	1-5(1), 2-6(1), 3-24(3), 10-11(3), 11-13(2), 20-23(1)	Bus 10 (4 MVAR), Line 13-23 (-0.20Xline)	10,76
4- **Medium (S)**	1-2(1), 1-5(1), 2-6(1), 3-24(1), 9-12(2), 10-11(4), 11-13(3), 20-23(3)	Line 13-13 (-0.10Xline)	12,20
5- **High (U)**	1-2(1), 2-6(1), 3-24(2), 10-11(5), 11-13(3)	Bus 8 (4 MVAR) Line 13-23 (-0.30 Xline)	9,49
6- **High (S)**	1-2(1), 1-5(1), 2-6(1), 3-24(1), 9- 11(4), 11-13(3), 20-23(3)	Line 13-13 (0.20Xline)	12,07

Table 5.6 Overload probabilities (%) of the investment decisions obtained from both unified and separate approach for different wind speed conditions

Case Studies		**1**	**2**	**3**	**4**	**5**	**6**
w. out contingency	L1-2	-	-	5	-	-	-
	L1-5	-	-	-	-	9	-
	L2-4	3	-	-	-	-	-
	L5-10	10	-	1	1	-	2
	L11-14	-	-	1	-	2	-
	L12-23	7	8	-	1	-	3
	V3	1	-	-	-	3	-
	V4	1	-	1	-	1	-
	V6	3	2	2	2	2	1
	V8	9	3	8	3	9	5
with contingency	L1-2	-	-	8	-	-	-
	L2-4	8	-	1	-	-	
	L5-10	10	-	1	1	-	2
	L12-13	-	11	-	6	-	1
	V3	8	11	3	5	12	6
	V4	9	1	7	1	12	1
	V6	12	15	15	15	15	11
	V8	14	10	15	10	14	11
	V9	-	-	5	-	-	-
	V12	1	2	-	2	-	2
	V24	5	-	5	-	3	-

In Table 5.6, the number of overloads on both power flows and bus voltages may observed to be more than separate approach. However, all these overloads are below its pre-specified risk level. The main challenge behind the unified approach is to determine uncertainty scenarios that evaluated under operation level. The scenario set significantly affects both TEP and FACTS investment decision. However, the resulting investment decision is flexible alternative with a less expensive decision. Therefore, if the planner tries to find a coordinated decision with TEP and FACTS allocation at a specified confidence level, a unified approach is convenient. As a result, it can take many years to design and build new generators and transmission lines; so that ensuring flexibility to meet variable renewable generation growth is essential to meet the adequacy of the power system.

5.4 Conclusions

The restructuring of a system with an increasing uncertainty rate brings along many problems. This study investigates the impact of FACTS devices in operational flexibility is investigated by a unified and separate approaches. FACTS devices are used in voltage and power flow control, which are the backbone of expansion planning, offering alternatives to the planner instead of investing in lines. It is inferred that FACTS devices can be used to increase transfer capability of the power network. FACTS devices can be installed quickly compared to new line investments, which can take years to construct. In that manner, FACTS installation offers flexibility for future reinforcements and enables better utilization of the network. A coordination between line and FACTS investment could generate a flexible decision; however, the superiority of the unified or separate approach is not clear. From the uncertainty perspective a separate approach produces many alternative decisions according to different uncertainty sets. However, if the uncertainties are modelled comprehensively a reliable system design can be achieved with a unified approach that results less expensive decisions.

CHAPTER SIX
CONCLUSIONS AND FUTURE WORK

There is an increasing interest to invest in transmission network, not only to replace aging equipment with renewable energy sources, but also to expand grid capacity to facilitate electricity trade. However, long-term TEP for large scale networks is fraught with highly penetrated renewable energy sources with unexpected levels of uncertainty. A transmission plan must meet the technical and economical constraints and operational flexibility is also anticipated to achieve a reliable investment. The candidate investments plans should be evaluated systematically for different perspectives, demonstrating the risk of violation from the operational viewpoint. Therefore, the primary research goal of this dissertation, is to provide a TEP model that considers uncertainty, risk assessment and flexibility. To that purpose, a chance constrained AC TEP model has been built, with the key characteristics listed below:

- A two level MINLP optimization model, based on "AC network" which handles the operational part using a modified power flow problem.
- Participation factor power flow which handles uncertain operating conditions in a sense of economic dispatch is modelled without using an optimization framework for operational decision.
- Treatment of slack bus is handled with distributed slack bus approach which coherently captures variability of different uncertainties in network operation.
- Risk of violation is handled in the constraints of the investment optimization that allows to find feasible plans with a pre-specified threshold.
- To propose a flexible solution strategy with a chance constrained stochastic TEP coordinated with wind power and FACTS devices.

In Chapter 2, the modelling aspects of TEP sub-problems are investigated. Probabilistic power flow and optimal power flow methods are implemented in DC network representation and a case study with load curtailment minimization approach is handled with TEP optimization under different budget and uncertainty considerations. The operational problem is mainly provided by the generators to balance the load at minimal cost while meeting the operational limits. Both load curtailment and overload minimization approach can satisfy the network constraints for the uncertain operating conditions. However, to ensure tractability and deliver solutions with an acceptable level of accuracy, OPF should be computationally efficient in TEP optimization. Due to the network's size and ability to handle uncertainty along with nonlinear AC-OPF is a challenge in TEP optimization. In the case studies, it is observed that the proposed TEP model with chance constrained DC-OPF formulation could well accommodate uncertain factors. This framework gives transmission planner an opportunity to compromise between the investment budget and uncertainties. There is a trade-off between investment budget and load curtailment. If the planner desires to eliminate load curtailment and utilize more wind power, a sufficient budget is necessary. The results also show that as the budget increases the generation cost becomes decisive in total cost. Comparison between the confidence levels and investment budgets demonstrate that investment budget predominantly determines transmission expansion plans. More flexibility is required in making expansion decisions when uncertainties are included in planning studies. Transmission planners can consider of their priorities in TEP decisions under uncertainties by using the proposed framework.

In Chapter 3, slack bus treatment in probabilistic AC power flow is investigated. Slack bus has a major role in power flow studies and its location and behavior significantly affect the overall investment decision. Even a moderate amount uncertainty is allowed in the system, the resulting power flow distributions can contain values beyond generating margins of the slack generator. In the case of TEP, optimal power flow generally used to determine system operational behavior. Particularly, generation dispatch is a sub-problem for TEP analysis which is directly affected line capacity, voltage magnitude violations of both base and contingency conditions. A fast and easily implemented algorithm is preferable for the time and convergence criterions for TEP optimization. Therefore, the use of a modified power flow for finding the adequacy of the operation gives promising results to obtain both technical and economic aspects of the generator outputs. In that manner, the comparison of conventional slack bus and distributed slack bus algorithms are implemented on a test network and the over limit scheme of both models are compared. Participation factor power flow includes an artificially introduced total mismatch variable which, distributes mismatch power using participation factors in a distributed slack bus manner. In this context, slack bus treatment is handled, and the generator outputs are updated according to its cost coefficients. The numerical results show that, the proposed participation factor power flow captures the impact of uncertainty on operation level. Especially, the concentrated burden on slack bus in probabilistic power flow is alleviated with a distributed slack bus approach which is beneficial for investment optimization.

In Chapter 4, a full probabilistic chance constrained ACTEP framework based on participation factor power flow is proposed. The probabilistic participation factor power flow is evaluated load, wind, and N-1 contingency uncertainties under Monte Carlo simulation. A stochastic TEP optimization is implemented using genetic algorithm and the line capacity and bus voltage constraints are converted into probabilistic chance constraints. The final investment plans with different risk levels are evaluated in the various studies and tested under different wind speed considerations. In the case studies it is observed that as the operating conditions get stressful, especially for N-1 contingencies, the mismatch power comes from uncertainties absorbed by the slack bus itself. Therefore, the slack bus behavior should be carefully handled in operational sub-problem. The intermittent characteristic of renewable units and the contingency consideration brings additional stress that needs to be considered. Chance constraints of both base and contingency conditions are applied in the constraints of the TEP optimization to incorporate probabilistic risk for future planning decision. The results of the proposed TEP problem shows that as the risk level increases more transmission investment is needed. A risk-taking strategy is effective for reducing both number of invested lines and cost of investment while maintaining line flows and bus voltages within their prescribed limits. In terms of computational effort, the use of PF-ACPF is promising to obtain the adequacy of the generators as well as considering the treatment of slack bus which affects the overall investment decision in the long-term transmission planning context. Especially, in heavily loaded cases, risk of over limit on both voltage and power flow is increased. Therefore, location and size of voltage support can maintain voltage profile in pre-specified risk limits. Using AC network modelling can enable obtaining realistic results for power system operation.

In Chapter 5, a coordinated TEP problem with FACTS devices in investigated. Unified and separate approaches are coordinated with TEP optimization to investigate the flexibility of FACTS device that brings to the TEP investment. It is evident that a sufficient flexibility to accommodate the growth of uncertainty is required for handling the impact of uncertainty in power system planning. As penetration levels of RES rises, the level of examination in power network becomes more important in planning studies. Therefore, planners should establish flexibility during the early stages of transmission investments to handle uncertain and variable system conditions. In the unified approach, the uncertainty scenarios evaluated in the operational level which is important to find a proper investment decision. The scenario set significantly effects TEP optimization. On the other hand in separate approach, as the confidence level increases more FACTS investments are made to alleviate the network constraints in a pre-specified over limit. The main approach is to invest in a corrective manner which can provide constraints for a certain confidence level. Therefore, planner can determine FACTS investments for various uncertainty considerations but to operate in higher confidence levels line investment is inevitable.

For the future studies, a stochastic chance constrained ACTEP framework can be extended in two different ways with some modifications. First, different uncertainties such as marketing uncertainties will be included in a deregulated environment considering generation and transmission company profits in a chance constraint programming. Additionally, this model can be transformed into dynamic programming with some modifications in nonlinear power flow equations. The potential limitation of the proposed method is that this model needs a metaheuristic method to proceed the optimization through exact probability distribution function to be fed chance constraints at the upper level. Since this model is not as fast as the DC or linearized AC model, studies on dynamic decisions will be made as a future study by making some compromises from the network model. At this point, this issue can be said as a shortcoming of the proposed method. Needless to say, power system planning is still an ongoing research area, and it is obvious that further work is necessary in terms of the decision-making in TEP problem under different uncertainty environment with risk-based approach.

REFERENCES

Abbasi, S., & Abdi, H. (2017). Multiobjective transmission expansion planning problem based on ACOPF considering load and wind power generation uncertainties. *International Transactions on Electrical Energy Systems, 27*(6), e2312.

Acha, E., Fuerte-Esquivel, C. R., Ambriz-Perez, H., & Angeles-Camacho, C. (2004). *FACTS: modelling and simulation in power networks.* John Wiley & Sons.

Akbari, T., Rahimi-Kian, A., & Bina, M. T. (2012). Security-constrained transmission expansion planning: A stochastic multi-objective approach. *International Journal of Electrical Power & Energy Systems, 43*(1), 444-453.

Akbari, T., Rahimikian, A., & Kazemi, A. (2011). A multi-stage stochastic transmission expansion planning method. *Energy conversion and Management, 52*(8-9), 2844-2853.

Alaee, S., Hooshmand, R. A., & Hemmati, R. (2016). Stochastic transmission expansion planning incorporating reliability solved using SFLA meta-heuristic optimization technique. *CSEE Journal of Power and Energy Systems, 2*(2), 79-86.

Alguacil, N., Motto, A. L., & Conejo, A. J. (2003). Transmission expansion planning: A mixed-integer LP approach. *IEEE Transactions on Power Systems*, *18*(3), 1070-1077.

Alhamrouni, I., Khairuddin, A., Ferdavani, A. K., & Salem, M. (2014). Transmission expansion planning using AC-based differential evolution algorithm. *IET Generation, Transmission & Distribution, 8*(10), 1637-1644.

Asadamongkol, S., & Eua-arporn, B. (2013). Transmission expansion planning with AC model based on generalized Bender's decomposition. *International Journal of Electrical Power & Energy Systems, 47*, 402-407.

Bagheri, A., Wang, J., & Zhao, C. (2016). Data-driven stochastic transmission expansion planning. *IEEE Transactions on Power Systems*, *32*(5), 3461-3470.

Bin, L., Shahzad, M., Bing, Q., Shoukat, M. U., Shakeel, M., & Mohammedsaeed, E. K. (2018). Probabilistic computational model for correlated wind farms using copula theory. *IEEE Access*, *6*, 14179-14187.

Blanco, G. A., Olsina, F. G., Ojeda, O. A., & Garcés, F. F. (2009, June). *Transmission expansion planning under uncertainty the role of FACTS in providing strategic flexibility*. [Conference] In 2009 IEEE Bucharest PowerTech, pp. 1-8. IEEE.

Bonami, P., & Lee, J. (2007). BONMIN user’s manual. Numer Math, 4, 1-32.

Capitanescu, F., Ramos, J. M., Panciatici, P., Kirschen, D., Marcolini, A. M., Platbrood, L., & Wehenkel, L. (2011). State-of-the-art, challenges, and future trends in security constrained optimal power flow. *Electric Power Systems Research*, *81*(8), 1731-1741.

Careri, F., Genesi, C., Marannino, P., Montagna, M., Rossi, S., & Siviero, I. (2011, May). *Probabilistic load flow procedure for assessing the distributed generation impact on the high voltage network*. [Conference] In 2011 8th International Conference on the European Energy Market (EEM) (pp. 882-888). IEEE.

Carrión, M., Arroyo, J. M., & Alguacil, N. (2007). Vulnerability-constrained transmission expansion planning: A stochastic programming approach. *IEEE Transactions on Power Systems*, *22*(4), 1436-1445.

Chandler, H. (2011). *Harnessing variable renewables: A guide to the balancing challenge*. Paris, France: International Energy Agency. https://www.oecd.org/publications/harnessing-variable-renewables-9789264111394-en.htm

Chatthaworn, R., & Chaitusaney, S. (2015). Improving method of robust transmission network expansion planning considering intermittent renewable energy generation and loads. *IET Generation, Transmission & Distribution*, *9*(13), 1621-1627.

Chatzivasileiadis, S., Krause, T., & Andersson, G. (2011, July). *Flexible AC Transmission Systems (FACTS) and power system security—A valuation framework.* [Conference] In 2011 IEEE Power and Energy Society General Meeting (pp. 1-8). IEEE.

Chen, B., Wang, J., Wang, L., He, Y., & Wang, Z. (2014). Robust optimization for transmission expansion planning: Minimax cost vs. minimax regret. *IEEE Transactions on Power Systems, 29*(6), 3069-3077.

Conejo, A. J., Baringo, L., Kazempour, S. J., & Siddiqui, A. S. (2016). *Investment In Electricity Generation and Transmission.* Cham Zug, Switzerland: Springer International Publishing, 119.

Conejo, A. J., Carrión, M., & Morales, J. M. (2010). *Decision Making Under Uncertainty in Electricity Markets* (Vol. 1, pp. 376-384). New York: Springer.

Council, G. W. E. (2022). *Global Report 2022.* https://gwec.net/global-wind-report-2022/

Da Costa, L. C., Thomé, F. S., Garcia, J. D., & Pereira, M. V. (2020). Reliability-constrained power system expansion planning: A stochastic risk-averse optimization approach. *IEEE Transactions on Power Systems, 36*(1), 97-106.

Da Silva, A. M. L., & de Castro, A. M. (2018). Risk assessment in probabilistic load flow via Monte Carlo simulation and cross-entropy method. *IEEE Transactions on Power Systems, 34*(2), 1193-1202.

Da Silva, E. L., Gil, H. A., & Areiza, J. M. (2000). Transmission network expansion planning under an improved genetic algorithm. *IEEE Transactions on Power Systems, 15*(3), 1168-1174.

Das, S., Verma, A., & Bijwe, P. R. (2019). Security constrained AC transmission network expansion planning. *Electric Power Systems Research,* 172, 277-289.

De Silva, I. D. J., Rider, M. J., Romero, R., & Murari, C. A. (2006). Transmission network expansion planning considering uncertainty in demand. *IEEE Transactions on Power Systems, 21*(4), 1565-1573.

Dehghan, S., Amjady, N., & Conejo, A. J. (2017). Adaptive robust transmission expansion planning using linear decision rules. *IEEE Transactions on Power Systems, 32*(5), 4024-4034.

Dhople, S. V., Chen, Y. C., Al-Digs, A., & Domínguez-García, A. D. (2020). Reexamining the distributed slack bus. *IEEE Transactions on Power Systems, 35*(6), 4870-4879.

Dimitrovski, A., & Tomsovic, K. (2005). Slack bus treatment in load flow solutions with uncertain nodal powers. *International Journal of Electrical Power & Energy Systems, 27(9-1*0), 614-619.

Dimitrovski, A., & Tomsovic, K. (2005). Uncertainty in load flow modeling: Application of the boundary load flow. *Automation of Electric Power Systems: Special Issue on Developments in Load Flow and Optimal Power Flow Techniques, 29*(16), 6-15.

Ersavas, C., & Karatepe, E. (2017). Optimum allocation of FACTS devices under load uncertainty based on penalty functions with genetic algorithm. *Electrical Engineering*, *99*(1), 73-84.

Escobar, A. H., Gallego, R. A., & Romero, R. (2004). Multistage and coordinated planning of the expansion of transmission systems. *IEEE Transactions on Power Systems, 19*(2), 735-744.

Esmaili, M., Ghamsari-Yazdel, M., Amjady, N., Chung, C. Y., & Conejo, A. J. (2020). Transmission expansion planning including TCSCs and SFCLs: A MINLP approach. *IEEE Transactions on Power Systems, 35*(6), 4396-4407.

Eurostat: *Share of renewable energy in gross final energy consumption*, (n.d.), https://ec.europa.eu/eurostat/web/products-datasets/-/t2020_rd330

Expósito, A. G., Ramos, J. L. M., & Santos, J. R. (2004). Slack bus selection to minimize the system power imbalance in load-flow studies. *IEEE Transactions on Power Systems*, 19(2), 987-995.

Farrag, M. A., Ali, K. M., & Omran, S. (2019). AC load flow-based model for transmission expansion planning. *Electric Power Systems Research*, 171, 26-35.

Fischl, R. and Puntel, W. (1972) Computer-Aided Design of Electric-Power Transmission Networks. *IEEE Transactions on Power Apparatus and Systems.*

Fitiwi, D.Z., (2016), *Strategies, Methods and Tools for Solving Long-Term Transmission Expansion Planning in Large-Scale Power Systems*, [Doctoral Dissertation], Institute for Research in Technology at Universidad Pontificia Comillas, Spain

Franken, M., Barrios, H., Schrief, A. B., & Moser, A. (2020). Transmission expansion planning via power flow controlling technologies. *IET Generation, Transmission & Distribution, 14*(17), 3530-3538.

Freitas, P. F., Macedo, L. H., & Romero, R. (2020). Flexible Solution Approach for Multistage Transmission Network Expansion Planning with Multiple Generation Scenarios. *Journal of Control, Automation and Electrical Systems, 31*(3), 705-717.

Gallego, R. A., Monticelli, A., & Romero, R. (1998). Transmision system expansion planning by an extended genetic algorithm. *IEE Proceedings-Generation, Transmission and Distribution*, *145*(3), 329-335.

Georgilakis, P. S. (2008). Technical challenges associated with the integration of wind power into power systems. *Renewable and Sustainable Energy Reviews, 12(3),* 852-863.

Godron, P., Cebeci, M. E., Tör, O. B., & Saygın, D. (2018). *Increasing the Share of Renewables in Turkey's Power System: Options for Transmission Expansion and Flexibility. Policy Brief.* İstanbul: SHURA: Energy Transition Center, May.

Gomes, P. V., & Saraiva, J. T. (2019a). State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets. *International Journal of Electrical Power & Energy Systems*, *111*, 411-424.

Gomes, P. V., Saraiva, J. T., Carvalho, L., Dias, B., & Oliveira, L. W. (2019b). Impact of decision-making models in transmission expansion planning considering large shares of renewable energy sources. *Electric Power Systems Research*, *174*, 105852.

Guoyu, X., Galiana, F. D., & Low, S. (1985). Decoupled economic dispatch using the participation factors load flow. *IEEE Transactions on Power Apparatus and Systems*, (6), 1377-1384.

Yu, H., Chung, C. Y., Wong, K. P., Lee, H. W., & Zhang, J. H. (2009). Probabilistic Load Flow Evaluation with Hybrid Latin Hypercube Sampling and Cholesky Decomposition. *IEEE Transactions on Power Systems*, *24*(2), 661-667.

Hagh, M. T., Amiyan, P., Galvani, S., & Valizadeh, N. (2018). Probabilistic load flow using the particle swarm optimisation clustering method. *IET Generation, Transmission & Distribution*, *12*(3), 780-789.

Han, X., Zhao, L., Wen, J., Ai, X., Liu, J., & Yang, D. (2017). Transmission network expansion planning considering the generators' contribution to uncertainty accommodation. *CSEE Journal of Power and Energy Systems*, *3*(4), 450-460.

Hemmati, R., Hooshmand, R. A., & Khodabakhshian, A. (2013). State-of-the-art of transmission expansion planning: Comprehensive review. *Renewable and Sustainable Energy Reviews*, *23*, 312-319.

Hojjat, M., Javidi, M. H., & Yazdanpanah, D. (2016). Stochastic congestion management considering power system uncertainties: a chance-constrained programming approach. *Turkish Journal of Electrical Engineering and Computer Sciences*, *24*(1), 61-75.

Hooshmand, R. A., Hemmati, R., & Parastegari, M. (2012). Combination of AC transmission expansion planning and reactive power planning in the restructured power system. *Energy Conversion and Management*, *55*, 26-35.

Huynh, V. K., Ngo, V. D., Le, D. D., & Nguyen, N. T. A. (2018). Probabilistic power flow methodology for large-scale power systems incorporating renewable energy sources. *Energies*, *11*(10), 2624.

IEA (2021), World Energy Outlook 2021, IEA, Paris, (n.d.), https://www.iea.org/reports/world-energy-outlook-2021

Jabr, R. A. (2013). Robust transmission network expansion planning with uncertain renewable generation and loads. *IEEE Transactions on Power Systems, 28*(4), 4558-4567.

Jadidoleslam, M., Ebrahimi, A., & Latify, M. A. (2017). Probabilistic transmission expansion planning to maximize the integration of wind power. *Renewable energy, 114,* 866-878.

Jang, G. S., Hur, D., Park, J. K., & Lee, S. H. (2005). A modified power flow analysis to remove a slack bus with a sense of economic load dispatch. *Electric Power Systems Research, 73*(2), 137-142.

Jiang, H., Du, E., Miao, M., & Zhang, N. (2019, August). *Stochastic Transmission Expansion Planning Considering the Transmission Overload Risk.* [Conference] In 2019 IEEE Power & Energy Society General Meeting (PESGM) (pp. 1-5). IEEE.

Latorre, G., Cruz, R. D., Areiza, J. M., & Villegas, A. (2003). Classification of publications and models on transmission expansion planning. *IEEE Transactions on Power Systems, 18*(2), 938-946.

Le, D. D., Berizzi, A., Bovo, C., Ciapessoni, E., Cirio, D., Pitto, A., & Gross, G. (2013, August). *A probabilistic approach to power system security assessment under uncertainty.* [Conference] In 2013 IREP Symposium Bulk Power System Dynamics and Control-IX Optimization, Security and Control of the Emerging Power Grid (pp. 1-7). IEEE.

Li, J., Li, Z., Liu, F., Ye, H., Zhang, X., Mei, S., & Chang, N. (2017). Robust coordinated transmission and generation expansion planning considering ramping requirements and construction periods. *IEEE Transactions on Power Systems, 33*(1), 268-280.

Liu, B., & Liu, B. (2009). *Theory and practice of uncertain programming* (Vol. 239, pp. 349-363). Berlin: Springer.

Lumbreras, S., & Ramos, A. (2016). The new challenges to transmission expansion planning. Survey of recent practice and literature review. *Electric Power Systems Research, 134*, 19-29.

Mahdavi, M., Antunez, C. S., Ajalli, M., & Romero, R. (2018). Transmission expansion planning: Literature review and classification. *IEEE Systems Journal*, *13*(3), 3129-3140.

Makarov, Y. V., Loutan, C., Ma, J., & De Mello, P. (2009). Operational impacts of wind generation on California power systems. *IEEE Transactions on Power Systems, 24*(2), 1039-1050.

Meisel, J. (1993). System incremental cost calculations using the participation factor load-flow formulation. *IEEE Transactions on Power Systems, 8*(1), 357-363.

Moeini-Aghtaie, M., Abbaspour, A., & Fotuhi-Firuzabad, M. (2012). Incorporating large-scale distant wind farms in probabilistic transmission expansion planning—Part I: Theory and algorithm. *IEEE Transactions on power systems, 27*(3), 1585-1593.

Moeini-Aghtaie, M., Abbaspour, A., & Fotuhi-Firuzabad, M. (2012). Incorporating large-scale distant wind farms in probabilistic transmission expansion planning—Part II: Case Studies. *IEEE Transactions on Power Systems, 27*(3), 1594-1601.

Molina, J. D., Contreras, J., & Rudnick, H. (2014). A risk-constrained project portfolio in centralized transmission expansion planning. *IEEE Systems Journal, 11*(3), 1653-1661.

Moradi, M., Abdi, H., Lumbreras, S., Ramos, A., & Karimi, S. (2016). Transmission Expansion Planning in the presence of wind farms with a mixed AC and DC power flow model using an Imperialist Competitive Algorithm. *Electric Power Systems Research, 140,* 493-506.

Mortaz, E., & Valenzuela, J. (2019). Evaluating the impact of renewable generation on transmission expansion planning. *Electric Power Systems Research, 169,* 35-44.

Narain G., Hingorani, & Gyugyi, L. (2000). *Understanding FACTS: concepts and technology of flexible AC transmission systems.* Wiley-IEEE Press.

Orfanos, G. A., Georgilakis, P. S., & Hatziargyriou, N. D. (2012). Transmission expansion planning of systems with increasing wind power integration. *IEEE Transactions on Power Systems, 28*(2), 1355-1362.

Romero, R., Monticelli, A., Garcia, A., & Haffner, S. (2002). Test systems and mathematical models for transmission network expansion planning. *IEE Proceedings-Generation, Transmission and Distribution, 149*(1), 27-36.

Ruiz, C., & Conejo, A. J. (2015). Robust transmission expansion planning. *European Journal of Operational Research, 242*(2), 390-401.

Saadat, H. (1999). *Power system analysis.*

Saberi, H., Monsef, H., & Amraee, T. (2017). Probabilistic congestion driven network expansion planning using point estimate technique. IET Generation, Transmission & Distribution, 11(17), 4202-4211.

Salkuti, S. R. (2019). Optimal operation management of grid-connected microgrids under uncertainty. *Indonesian Journal of Electrical Engineering and Computer Science, 16*(3), 1163-1170.

Seifi, H., & Sepasian, M. S. (2011). *Electric Power System Planning: Issues, Algorithms and Solutions* (Vol. 49). Berlin: Springer.

Silva, I. D. J., Rider, M. J., Romero, R., Garcia, A. V., & Murari, C. A. (2005). Transmission network expansion planning with security constraints. *IEE Proceedings-Generation, Transmission and Distribution, 152*(6), 828-836.

Skea, J. (2012). Roadmap 2050: A Practical Guide to a Prosperous, Low-Carbon Europe, European Climate Foundation (2010). https://www.roadmap2050.eu/attachments/files/Roadmap2050-AllData-MinimalSize.pdf

Song, Y. H., & Johns, A. (Eds.). (1999). *Flexible AC Transmission Systems (FACTS)* (No. 30). IET, The Institution of Engineering and Technology

Swain, A., Salkuti, S. R., & Swain, K. (2021). An Optimized and Decentralized Energy Provision System for Smart Cities. *Energies, 14*(5), 1451.

Tang, Y., Zhong, J., & Liu, J. (2015). A generation adjustment methodology considering fluctuations of loads and renewable energy sources. *IEEE Transactions on Power Systems, 31*(1), 125-132.

Tong, S., & Miu, K. N. (2005). A network-based distributed slack bus model for DGs in unbalanced power flow studies. *IEEE Transactions on Power Systems, 20*(2), 835-842.

Tuinema, B. W., Torres, J. R., Stefanov, A. I., Gonzalez-Longatt, F. M., & van der Meijden, M. A. (2020). *Probabilistic Reliability Analysis of Power Systems.* Cham, Switzerland: Springer International Publishing.

Ugranli, F., & Karatepe, E. (2017). Coordinated TCSC allocation and network reinforcements planning with wind power. *IEEE Transactions on Sustainable Energy, 8(4),* 1694-1705.

Velásquez, C., Watts, D., Rudnick, H., & Bustos, C. (2016). A framework for transmission expansion planning: A complex problem clouded by uncertainty. *IEEE Power and Energy Magazine, 14(4),* 20-29.

Villasana R. , Garver L.L., Salon S.J. (1985). “Transmission network planning using linear programming”, *IEEE Transactions on Power Apparatus and Systems, Vol. PAS-104,* No. 2, pp. 349 – 356.

Wang, J., Shahidehpour, M., & Li, Z. (2008). Security-constrained unit commitment with volatile wind power generation. *IEEE Transactions on Power Systems, 23*(3), 1319-1327.

Wind energy in Europe: 2021 Statistics and the outlook for 2022-2026, (n.d.), https://windeurope.org/intelligence-platform/product/wind-energy-in-europe-2021-statistics-and-the-outlook-for-2022-2026/

Wood, A. J., Wollenberg, B. F., & Sheblé, G. B. (2013). *Power Generation, Operation, and Control.* John Wiley & Sons.

Wu, Z., Liu, Y., Gu, W., Wang, Y., & Chen, C. (2018). Contingency-constrained robust transmission expansion planning under uncertainty. *International Journal of Electrical Power & Energy Systems, 101*, 331-338.

Xu, R., & Wunsch, D. (2005). Survey of clustering algorithms. *IEEE Transactions on Neural Networks, 16*(3), 645-678.

Xu, Y., Hu, Q., & Li, F. (2013). Probabilistic model of payment cost minimization considering wind power and its uncertainty. *IEEE Transactions on Sustainable Energy, 4*(3), 716-724.

Yang, N., & Wen, F. (2005). A chance constrained programming approach to transmission system expansion planning. *Electric Power Systems Research, 75*(2-3), 171-177.

Yu, H., Chung, C. Y., & Wong, K. P. (2010). Robust transmission network expansion planning method with Taguchi's orthogonal array testing. *IEEE Transactions on Power Systems, 26*(3), 1573-1580.

Yu, H., Chung, C. Y., Wong, K. P., & Zhang, J. H. (2009). A chance constrained transmission network expansion planning method with consideration of load and wind farm uncertainties. *IEEE Transactions on Power Systems, 24*(3), 1568-1576.

Yuan, Z., Wang, W., Wang, H., & Ghadimi, N. (2020). Probabilistic decomposition-based security constrained transmission expansion planning incorporating distributed series reactor. *IET Generation, Transmission & Distribution, 14*(17), 3478-3487.

Zhang, H., Heydt, G. T., Vittal, V., & Quintero, J. (2013). An improved network model for transmission expansion planning considering reactive power and network losses. *IEEE Transactions on Power Systems, 28*(3), 3471-3479.

Zhang, X., Tomsovic, K., & Dimitrovski, A. (2017). Security constrained multi-stage transmission expansion planning considering a continuously variable series reactor. *IEEE Transactions on Power Systems, 32*(6), 4442-4450.

Zhang, X., Tomsovic, K., & Dimitrovski, A. (2018). Optimal allocation of series FACTS devices in large-scale systems. *IET Generation, Transmission & Distribution*, *12*(8), 1889-1896.

Zhang, Y., Wang, J., Li, Y., & Cao, X. (2017). *Chance-constrained transmission expansion planning with guaranteed wind power utilization.* [Conference] In 2017 IEEE Power & Energy Society General Meeting (pp. 1-5). IEEE.

Zheng, J., Wen, F., Ledwich, G., & Huang, J. (2014). Risk control in transmission system expansion planning with wind generators. *International Transactions on Electrical Energy Systems*, *24*(2), 227-245.

Zhou, Z., He, C., Liu, T., Dong, X., Zhang, K., Dang, D., & Chen, B. (2020). Reliability-constrained AC power flow-based co-optimization planning of generation and transmission systems with uncertainties. *IEEE Access*, *8*, 194218-194227.

Zobian, A., & Ilic, M. D. (1997). Unbundling of transmission and ancillary services. I. Technical issues. *IEEE Transactions on Power Systems, 12*(2), 539-548.

APPENDICES

Table A.1 Bus data of Garver Test System

Bus	Type	Pg	Pl	Ql	Pg_max
1	1	0.5	0.8	0.16	3.5
2	0	0	2.4	0.48	0
3	2	1.65	0.4	0.08	3.6
4	0	0	1.6	0.32	0
5	0	0	2.4	0.48	0
6	2	5.45	0	0	6

Table A.2 Network data of Garver Test System

From	To	R	X	Tap	Cost
1	2	0.04	2.5	1	40
1	4	0.06	1.667	1	60
1	5	0.02	5	1	20
2	3	0.02	5	1	20
2	4	0.04	2.5	1	40
3	5	0.02	5	1	20
2	6	0.03	3.333	1	30
4	6	0.03	3.333	1	30
1	3	0.038	2.632	1	38
1	6	0.068	1.471	1	68
2	5	0.031	3.226	1	31
3	4	0.059	1.695	1	59
3	6	0.048	2.083	1	48
4	5	0.063	1.587	1	63
5	6	0.061	1.639	1	61

Table A.3 Bus data of IEEE RTS Test System

Bus No	Bus Type	Vmag	Vang	Pload	Qload	Pgen	Qgen	Qmin	Qmax	Qshunt
1	1	1.03	0	108	22	172	0	0	0	0
2	2	1.03	0	97	20	172	0	-50	80	0
3	0	1	0	180	37	0	0	0	0	0
4	0	1	0	74	15	0	0	0	0	0
5	0	1	0	71	14	0	0	0	0	0
6	0	1	0	136	28	0	0	0	0	0
7	2	1.02	0	125	25	240	0	0	180	0
8	0	1	0	171	35	0	0	0	0	0

Table A.4 Continues

9	0	1	0	175	36	0	0	0	0	0
10	0	1	0	195	40	0	0	0	0	0
11	0	1	0	0	0	0	0	0	0	0
12	0	1	0	0	0	0	0	0	0	0
13	2	1.02	0	265	54	285.	0	0	240	0
14	0	0.98	0	194	39	0	0	-50	200	0
15	2	1.01	0	317	64	215	0	-50	110	0
16	2	1.01	0	100	20	155	0	-50	80	0
17	0	1	0	0	0	0	0	0	0	0
18	2	1.05	0	333	68	400	0	-50	200	0
19	0	1	0	181	37	0	0	0	0	0
20	0	1	0	128	26	0	0	0	0	0
21	2	1.05	0	0	0	400	0	-50	200	0
22	2	1.05	0	0	0	300	0	-60	144	0
23	2	1.05	0	0	0	660	0	-125	310	0
24	0	1	0	0	0	0	0	0	0	0

Table A.5 Network data of IEEE RTS Test System

From	To	R	X	B	Tap	Smax	Cost
1	2	0.0026	0.0139	0.461	1	175	3
1	3	0.0546	0.2112	0.057	1	175	55
1	5	0.0218	0.0845	0.023	1	175	22
2	4	0.0328	0.1267	0.034	1	175	33
2	6	0.0497	0.1920	0.052	1	175	50
3	9	0.0308	0.1190	0.032	1	175	31
3	24	0.0023	0.0839	0	1.015	400	50
4	9	0.0268	0.1037	0.028	1	175	27
5	10	0.0228	0.0883	0.024	1	175	23
6	10	0.0139	0.0605	2.459	1	175	16
7	8	0.0159	0.0614	0.017	1	175	16
8	9	0.0427	0.1651	0.044	1	175	43
8	10	0.0427	0.1651	0.045	1	175	43
9	11	0.0023	0.0839	0	1.030	400	50
9	12	0.0023	0.0839	0	1.030	400	50
10	11	0.0023	0.0839	0	1.015	400	50
10	12	0.0023	0.0839	0	1.015	400	50
11	13	0.0061	0.0476	0.100	1	500	66
11	14	0.0054	0.0418	0.088	1	175	58
12	13	0.0061	0.0476	0.100	1	175	66
12	23	0.0124	0.0966	0.203	1	175	134
13	23	0.0111	0.0865	0.182	1	500	120
14	16	0.0050	0.0389	0.082	1	500	54

Table A.6 Continues

15	16	0.0022	0.0173	0.036	1	500	24
15	21	0.0063	0.0490	0.103	1	500	68
15	24	0.0067	0.0519	0.109	1	500	72
16	17	0.0033	0.0259	0.055	1	500	36
16	19	0.0030	0.0231	0.049	1	500	32
17	18	0.0018	0.0144	0.030	1	500	20
17	22	0.0135	0.1053	0.221	1	500	146
18	21	0.0033	0.0259	0.055	1	500	36
19	20	0.0051	0.0396	0.083	1	500	55
20	23	0.0028	0.0216	0.046	1	500	30
21	22	0.0087	0.0678	0.142	1	500	94

Table A.7 MW Limits of IEEE RTS Test System

Pmin	Pmax
62.4	750
62.4	450
75	400
207	750
120.6	300
54.3	300
100	450
100	450
60	400
248.6	750

Table A.8 Cost coefficients of IEEE RTS Test System

c_i	b_i	a_i
240	7	0.007
220	10.5	0.008
200	11	0.009
240	7	0.007
200	11	0.009
220	11	0.009
220	10.5	0.008
220	10.5	0.008
240	11	0.0075
240	7	0.007

Table A.9 Bus data of IEEE 118 Bus Test System

Bus No	Bus Type	Vmag	Vang	Pload	Qload	Pgen	Qgen	Qmin	Qmax	Qshunt
1	2	0.955	10.67	87	46	5	0	-5	15	0
2	0	1	11.22	34	15	0	0	0	0	0
3	0	1	11.56	67	17	0	0	0	0	0
4	2	0.998	15.28	51	20	5	0	-300	300	0
5	0	1	15.73	0	0	0	0	0	0	-40
6	2	0.99	13	89	38	0	0	-13	50	0
7	0	1	12.56	32	3	0	0	0	0	0
8	2	1.015	20.77	0	0	5	0	-300	300	0

Table A.10 Continues

9	0	1	28.02	0	0	0	0	0	0	0
10	2	1.05	35.61	0	0	330.5	0	-147	200	0
11	0	1	12.72	119	39	0	0	0	0	0
12	2	0.99	12.2	43	17	300	0	-35	120	0
13	0	1	11.35	58	27	0	0	0	0	0
14	0	1	11.5	24	2	0	0	0	0	0
15	2	0.97	11.23	154	51	10	0	-10	30	0
16	0	1	11.91	43	17	0	0	0	0	0
17	0	1	13.74	19	5	0	0	0	0	0
18	2	0.973	11.53	102	58	100	0	-16	50	0
19	2	0.963	11.05	77	43	5	0	-8	24	0
20	0	1	11.93	31	5	0	0	0	0	0
21	0	1	13.52	24	14	0	0	0	0	0
22	0	1	16.08	17	9	0	0	0	0	0
23	0	1	21	12	5	0	0	0	0	0
24	2	0.992	20.89	0	0	5	0	-300	300	0
25	2	1.05	27.93	0	0	288.4	0	-47	140	0
26	2	1.015	29.71	0	0	350	0	-1000	1000	0
27	2	0.968	15.35	106	22	8	0	-300	300	0
28	0	1	13.62	29	12	0	0	0	0	0
29	0	1	12.63	41	7	0	0	0	0	0
30	0	1	18.79	0	0	0	0	0	0	0
31	2	0.967	12.75	73	46	8	0	-300	300	0
32	2	0.964	14.8	101	39	100	0	-14	-42	0
33	0	1	10.63	39	15	0	0	0	0	0
34	2	0.986	11.3	101	44	8	0	-8	24	14
35	0	1	10.87	56	15	0	0	0	0	0
36	2	0.98	10.87	53	29	10	0	-8	24	0
37	0	1	11.77	0	0	0	0	0	0	-25
38	0	1	16.91	0	0	0	0	0	0	0
39	0	1	8.41	46	19	0	0	0	0	0
40	2	0.97	7.35	34	39	8	0	-300	300	0
41	0	1	6.92	63	17	0	0	0	0	0
42	2	0.985	8.53	63	39	8	0	-300	300	0
43	0	1	11.28	31	12	0	0	0	0	0
44	0	1	13.82	27	14	0	0	0	0	10
45	0	1	15.67	90	38	0	0	0	0	10
46	2	1.005	18.49	48	17	93.63	0	-100	100	10
47	0	1	20.73	58	0	0	0	0	0	0
48	0	1	19.93	34	19	0	0	0	0	15

Table A.11 Continues

49	2	1.025	20.94	148	51	250	0	-85	210	0
50	0	1	18.9	29	7	0	0	0	0	0
51	0	1	16.28	29	14	0	0	0	0	0
52	0	1	15.32	31	9	0	0	0	0	0
53	0	1	14.35	39	19	0	0	0	0	0
54	2	0.955	15.26	193	55	250	0	-300	300	0
55	2	0.952	14.97	107	38	94	0	-8	23	0
56	2	0.954	15.16	143	31	94.63	0	-8	15	0
57	0	1	16.36	20	5	0	0	0	0	0
58	0	1	15.51	20	5	0	0	0	0	0
59	2	0.985	19.37	473	193	200	0	-60	180	0
60	0	1	23.15	133	5	0	0	0	0	0
61	2	0.995	24.04	0	0	200	0	-100	300	0
62	2	0.998	23.43	131	24	71.68	0	-20	20	0
63	0	1	22.75	0	0	0	0	0	0	0
64	0	1	24.52	0	0	0	0	0	0	0
65	2	1.005	27.65	0	0	420	0	-67	200	0
66	2	1.05	27.48	67	31	420	0	-67	200	0
67	0	1	24.84	48	12	0	0	0	0	0
68	0	1	27.55	0	0	0	0	0	0	0
69	1	1.035	30	0	0	664.9	0	-300	300	0
70	2	0.984	22.58	113	34	53.1	0	-10	32	0
71	0	1	22.15	0	0	0	0	0	0	0
72	2	0.98	20.98	0	0	10	0	-100	100	0
73	2	0.991	21.94	0	0	5	0	-100	100	0
74	2	0.958	21.64	116	46	5	0	-6	9	12
75	0	1	22.91	80	19	0	0	0	0	0
76	2	0.943	21.77	116	61	100	0	-8	23	0
77	2	1.006	26.72	104	48	75.8	0	-20	70	0
78	0	1	26.42	121	44	0	0	0	0	0
79	0	1	26.72	67	55	0	0	0	0	20
80	2	1.04	28.96	222	44	294.6	0	-165	280	0
81	0	1	28.1	0	0	0	0	0	0	0
82	2	1	27.24	92	46	59.22	0	0	0	20
83	0	1	28.42	34	17	0	0	0	0	10
84	0	1	30.95	19	12	0	0	0	0	0
85	2	0.985	32.51	41	26	10	0	-8	23	0
86	0	1	31.14	36	17	0	0	0	0	0
87	2	1.015	31.4	0	0	229.3	0	-100	1000	0
88	0	1	35.64	82	17	0	0	0	0	0

Table A.12 Continues

89	2	1.005	39.69	0	0	217.6	0	-210	300	0
90	2	0.985	33.29	133	72	8	0	-300	300	0
91	2	0.98	33.31	0	0	20	0	-100	100	0
92	2	0.993	33.8	111	17	226.8	0	-3	9	0
93	0	1	30.79	20	12	0	0	0	0	0
94	0	1	28.64	51	27	0	0	0	0	0
95	0	1	27.67	72	53	0	0	0	0	0
96	0	1	27.51	65	26	0	0	0	0	0
97	0	1	27.88	26	15	0	0	0	0	0
98	0	1	27.4	58	14	0	0	0	0	0
99	2	1	27.04	0	0	217.8	0	-100	100	0
100	2	1.017	28.03	63	31	248.3	0	-50	155	0
101	0	1	29.61	38	26	0	0	0	0	0
102	0	1	32.3	9	5	0	0	0	0	0
103	2	1.001	24.44	39	27	8	0	-15	40	0
104	2	0.971	21.69	65	43	45.05	0	-8	23	0
105	2	0.965	20.57	53	44	50.78	0	-8	23	20
106	0	1	20.32	73	27	0	0	0	0	0
107	2	0.952	17.53	48	20	8	0	-200	200	6
108	0	1	19.38	3	2	0	0	0	0	0
109	0	1	18.93	14	5	0	0	0	0	0
110	2	0.973	18.09	67	51	25	0	-8	23	6
111	2	0.98	19.74	0	0	34.34	0	-100	1000	0
112	2	0.975	14.99	43	22	43.33	0	-100	1000	0
113	2	0.993	13.74	0	0	99.72	0	-100	200	0
114	0	1	14.46	14	5	0	0	0	0	0
115	0	1	14.46	38	12	0	0	0	0	0
116	2	1.005	27.12	0	0	25	0	-1000	1000	0
117	0	1	10.67	34	14	0	0	0	0	0
118	0	1	21.92	56	26	0	0	0	0	0

Table A.13 Network data of IEEE 118 Bus Test System

From	To	R	X	B	Tap	Smax	Cost
1	2	0.0303	0.0999	0.0254	1	115	18
1	3	0.0129	0.0424	0.01082	1	115	7.6
4	5	0.00176	0.00798	0.0021	1	115	1.8
3	5	0.0241	0.108	0.0284	1	115	16.2

Table A.14 Continues

5	6	0.0119	0.054	0.01426	1	115	9.7
6	7	0.00459	0.0208	0.0055	1	115	4.7
8	9	0.00244	0.0305	1.162	1	400	5.5
8	5	0	0.0267	0	0.985	400	6
9	10	0.00258	0.0322	1.23	1	400	5.8
4	11	0.0209	0.0688	0.01748	1	115	12.4
5	11	0.0203	0.0682	0.01738	1	115	12.3
11	12	0.00595	0.0196	0.00502	1	115	4.4
2	12	0.0187	0.0616	0.01572	1	400	11.1
3	12	0.0484	0.16	0.0406	1	115	24
7	12	0.00862	0.034	0.00874	1	115	6.1
11	13	0.02225	0.0731	0.01876	1	115	13.2
12	14	0.0215	0.0707	0.01816	1	115	12.7
13	15	0.0744	0.2444	0.06268	1	115	36.7
14	15	0.0595	0.195	0.0502	1	115	29.3
12	16	0.0212	0.0834	0.0214	1	115	15
15	17	0.0132	0.0437	0.0444	1	400	7.9
16	17	0.0454	0.1801	0.0466	1	115	27
17	18	0.0123	0.0505	0.01298	1	115	9.1
18	19	0.01119	0.0493	0.01142	1	115	8.9
19	20	0.0252	0.117	0.0298	1	115	17.6
15	19	0.012	0.0394	0.0101	1	115	7.1
20	21	0.0183	0.0849	0.0216	1	115	15.3
21	22	0.0209	0.097	0.0246	1	115	17.5
22	23	0.0342	0.159	0.0404	1	115	23.9
23	24	0.0135	0.0492	0.0498	1	115	8.9
23	25	0.0156	0.08	0.0864	1	400	14.4
26	25	0	0.0382	0	0.96	400	6.9
25	27	0.0318	0.163	0.1764	1	400	24.5
27	28	0.01913	0.0855	0.0216	1	115	15.4
28	29	0.0237	0.0943	0.0238	1	115	16
30	17	0	0.0388	0	0.96	400	7
8	30	0.00431	0.0504	0.514	1	115	9.1
26	30	0.00799	0.086	0.908	1	115	15.5
17	31	0.0474	0.1563	0.0399	1	115	23.4
29	31	0.0108	0.0331	0.0083	1	115	6
23	32	0.0317	0.1153	0.1173	1	115	17.3
31	32	0.0298	0.0985	0.0251	1	115	17.7
27	32	0.0229	0.0755	0.01926	1	115	13.6
15	33	0.038	0.1244	0.03194	1	115	18.7

Table A.15 Continues

19	34	0.0752	0.247	0.0632	1	115	37.1
35	36	0.00224	0.0102	0.00268	1	115	2.3
35	37	0.011	0.0497	0.01318	1	115	8.9
33	37	0.0415	0.142	0.0366	1	115	21.3
34	36	0.00871	0.0268	0.00568	1	115	6
34	37	0.00256	0.0094	0.00984	1	400	2.1
38	37	0	0.0375	0	0.935	400	6.8
37	39	0.0321	0.106	0.027	1	115	15.9
37	40	0.0593	0.168	0.042	1	115	25.2
30	38	0.00464	0.054	0.422	1	115	9.7
39	40	0.0184	0.0605	0.01552	1	115	10.9
40	41	0.0145	0.0487	0.01222	1	115	8.8
40	42	0.0555	0.183	0.0466	1	115	27.5
41	42	0.041	0.135	0.0344	1	115	20.3
43	44	0.0608	0.2454	0.06068	1	115	36.8
34	43	0.0413	0.1681	0.04226	1	115	25.2
44	45	0.0224	0.0901	0.0224	1	115	16.2
45	46	0.04	0.1356	0.0332	1	115	20.3
46	47	0.038	0.127	0.0316	1	115	19.1
46	48	0.0601	0.189	0.0472	1	115	28.4
47	49	0.0191	0.0625	0.01604	1	115	11.3
42	49	0.0715	0.323	0.086	1	115	48.5
42	49	0.0715	0.323	0.086	1	115	48.5
45	49	0.0684	0.186	0.0444	1	115	27.9
48	49	0.0179	0.0505	0.01258	1	115	9.1
49	50	0.0267	0.0752	0.01874	1	115	13.5
49	51	0.0486	0.137	0.0342	1	115	20.6
51	52	0.0203	0.0588	0.01396	1	115	10.6
52	53	0.0405	0.1635	0.04058	1	115	24.5
53	54	0.0263	0.122	0.031	1	115	18.3
49	54	0.073	0.289	0.0738	1	115	43.4
49	54	0.0869	0.291	0.073	1	115	43.7
54	55	0.0169	0.0707	0.0202	1	115	12.7
54	56	0.00275	0.00955	0.00732	1	115	2.1
55	56	0.00488	0.0151	0.00374	1	115	3.4
56	57	0.0343	0.0966	0.0242	1	115	17.4
50	57	0.0474	0.134	0.0332	1	115	20.1
56	58	0.0343	0.0966	0.0242	1	115	17.4
51	58	0.0255	0.0719	0.01788	1	115	12.9
54	59	0.0503	0.2293	0.0598	1	115	34.4

Table A.16 Continues

56	59	0.0825	0.251	0.0569	1	115	37.7
56	59	0.0803	0.239	0.0536	1	115	35.9
55	59	0.04739	0.2158	0.05646	1	115	32.4
59	60	0.0317	0.145	0.0376	1	115	21.8
59	61	0.0328	0.15	0.0388	1	115	22.5
60	61	0.00264	0.0135	0.01456	1	400	3
60	62	0.0123	0.0561	0.01468	1	115	10.1
61	62	0.00824	0.0376	0.0098	1	400	6.8
63	59	0	0.0386	0	0.96	400	6.9
63	64	0.00172	0.02	0.216	1	400	4.5
64	61	0	0.0268	0	0.985	400	6
38	65	0.00901	0.0986	1.046	1	400	17.7
64	65	0.00269	0.0302	0.38	1	400	5.4
49	66	0.018	0.0919	0.0248	1	400	16.5
49	66	0.018	0.0919	0.0248	1	400	16.5
62	66	0.0482	0.218	0.0578	1	115	32.7
62	67	0.0258	0.117	0.031	1	115	17.6
65	66	0	0.037	0	0.935	400	6.7
66	67	0.0224	0.1015	0.02682	1	115	15.2
65	68	0.00138	0.016	0.638	1	400	3.6
47	69	0.0844	0.2778	0.07092	1	115	41.7
49	69	0.0985	0.324	0.0828	1	115	48.6
68	69	0	0.037	0	0.935	400	6.7
69	70	0.03	0.127	0.122	1	400	19.7
24	70	0.00221	0.4115	0.10198	1	115	61.7
70	71	0.00882	0.0355	0.00878	1	115	6.4
24	72	0.0488	0.196	0.0488	1	115	29.4
71	72	0.0446	0.18	0.04444	1	115	27
71	73	0.00866	0.0454	0.01178	1	115	8.2
70	74	0.0401	0.1323	0.03368	1	115	19.8
70	75	0.0428	0.141	0.036	1	115	21.2
69	75	0.0405	0.122	0.124	1	400	18.3
74	75	0.0123	0.0406	0.01034	1	115	7.3
76	77	0.0444	0.148	0.0368	1	115	22.2
69	77	0.0309	0.101	0.1038	1	115	15.2
75	77	0.0601	0.1999	0.04978	1	115	30
77	78	0.00376	0.0124	0.01264	1	115	2.8
78	79	0.00546	0.0244	0.00648	1	115	5.5
77	80	0.017	0.0485	0.0472	1	400	8.7
77	80	0.0294	0.105	0.0228	1	400	15.8

Table A.17 Continues

79	80	0.0156	0.0704	0.0187	1	115	12.7
68	81	0.00175	0.0202	0.808	1	400	4.5
81	80	0	0.037	0	0.935	400	6.7
77	82	0.0298	0.0853	0.08174	1	115	15.4
82	83	0.0112	0.03665	0.03796	1	115	6.6
83	84	0.0625	0.132	0.0258	1	115	19.8
83	85	0.043	0.148	0.0348	1	115	22.2
84	85	0.0302	0.0641	0.01234	1	115	11.5
85	86	0.035	0.123	0.0276	1	400	18.5
86	87	0.02828	0.2074	0.0445	1	400	31.1
85	88	0.02	0.102	0.0276	1	115	15.3
85	89	0.0239	0.173	0.047	1	115	26
88	89	0.0139	0.0712	0.01934	1	400	12.8
89	90	0.0518	0.188	0.0528	1	400	28.2
89	90	0.0238	0.0997	0.106	1	400	17.9
90	91	0.0254	0.0836	0.0214	1	115	15
89	92	0.0099	0.0505	0.0548	1	400	9.1
89	92	0.0393	0.1581	0.0414	1	400	23.7
91	92	0.0387	0.1272	0.03268	1	115	19.1
92	93	0.0258	0.0848	0.0218	1	115	15.3
92	94	0.0481	0.158	0.0406	1	115	23.7
93	94	0.0223	0.0732	0.01876	1	115	13.2
94	95	0.0132	0.0434	0.0111	1	115	7.8
80	96	0.0356	0.182	0.0494	1	115	27.3
82	96	0.0162	0.053	0.0544	1	115	9.5
94	96	0.0269	0.0869	0.023	1	115	15.6
80	97	0.0183	0.0934	0.0254	1	115	16.8
80	98	0.0238	0.108	0.0286	1	115	16.2
80	99	0.0454	0.206	0.0546	1	115	30.9
92	100	0.0648	0.295	0.0472	1	115	44.3
94	100	0.0178	0.058	0.0604	1	115	10.4
95	96	0.0171	0.0547	0.01474	1	115	9.8
96	97	0.0173	0.0885	0.024	1	115	15.9
98	100	0.0397	0.179	0.0476	1	115	26.9
99	100	0.018	0.0813	0.0216	1	115	14.6
100	101	0.0277	0.1262	0.0328	1	115	18.9
92	102	0.0123	0.0559	0.01464	1	115	10.1
101	102	0.0246	0.112	0.0294	1	115	16.8
100	103	0.016	0.0525	0.0536	1	400	9.5
100	104	0.0451	0.204	0.0541	1	115	30.6

Table A.18 Continues

103	104	0.0466	0.1584	0.0407	1	115	23.8
103	105	0.0535	0.1625	0.0408	1	115	24.4
100	106	0.0605	0.229	0.062	1	115	34.4
104	105	0.00994	0.0378	0.00986	1	115	6.8
105	106	0.014	0.0547	0.01434	1	115	9.8
105	107	0.053	0.183	0.0472	1	115	27.5
105	108	0.0261	0.0703	0.01844	1	115	12.7
106	107	0.053	0.183	0.0472	1	115	27.5
108	109	0.0105	0.0288	0.0076	1	115	6.5
103	110	0.03906	0.1813	0.0461	1	115	27.2
109	110	0.0278	0.0762	0.0202	1	115	13.7
110	111	0.022	0.0755	0.02	1	115	13.6
110	112	0.0247	0.064	0.062	1	115	11.5
17	113	0.00913	0.0301	0.00768	1	115	5.4
32	113	0.0615	0.203	0.0518	1	400	30.5
32	114	0.0135	0.0612	0.01628	1	115	11
27	115	0.0164	0.0741	0.01972	1	115	13.3
114	115	0.0023	0.0104	0.00276	1	115	2.3
68	116	0.00034	0.00405	0.164	1	400	0.9
12	117	0.0329	0.14	0.0358	1	115	21
75	118	0.0145	0.0481	0.01198	1	115	8.7
76	118	0.0164	0.0544	0.01356	1	115	9.8

Table A.19 MW Limits of IEEE 118 Bus Test System

Pmin	Pmax
5	30
5	30
5	30
5	30
150	500
100	300
10	30
25	100
5	30
5	30
100	300
100	350
8	30
8	30
25	100

Table A.21 Cost Coefficients of IEEE 118 Bus Test System

c_i	b_i	a_i
32	0.26	0.07
32	0.26	0.07
32	0.26	0.07
32	0.26	0.07
7	0.13	0.01
7	0.13	0.01
32	0.26	0.07
10	0.18	0.01
32	0.26	0.07
32	0.26	0.07
7	0.13	0.01
33	0.11	0.01
32	0.26	0.07
32	0.26	0.07
10	0.18	0.01

Table A.20 Continues

8	30
25	100
8	30
8	30
25	100
50	250
50	250
25	100
25	100
50	200
50	200
25	100
100	420
100	420
80	805.1
30	80
10	30
5	30
5	20
25	100
25	100
150	500
25	100
10	30
100	650
50	500
8	20
20	50
100	300
100	300
100	300
8	20
25	100
25	100
8	20
25	50
25	100
25	100
25	100
25	50

Table A.22 Continues

32	0.26	0.07
10	0.18	0.01
32	0.26	0.07
32	0.26	0.07
10	0.18	0.01
28	0.12	0.01
28	0.12	0.01
10	0.18	0.01
10	0.18	0.01
39	0.13	0.01
39	0.13	0.01
10	0.18	0.01
64	0.8	0.01
64	0.8	0.01
7	0.13	0.01
74	0.15	0.05
32	0.26	0.07
32	0.26	0.07
18	0.38	0.03
10	0.18	0.01
10	0.18	0.01
7	0.13	0.01
10	0.18	0.01
32	0.26	0.07
33	0.11	0.01
7	0.13	0.01
18	0.38	0.03
59	0.23	0.01
7	0.13	0.01
7	0.13	0.01
7	0.13	0.01
18	0.38	0.03
10	0.18	0.01
10	0.18	0.01
18	0.38	0.03
59	0.23	0.01
10	0.18	0.01
10	0.18	0.01
10	0.18	0.01
59	0.23	0.01