DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

GENERATION EXPANSION PLANNING CONSIDERING ELECTRICITY MARKET

by
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October, 2022
IZMIR

GENERATION EXPANSION PLANNING CONSIDERING ELECTRICITY MARKET

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

by
Egemen UYAR

October, 2022
IZMIR

M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled "**GENERATION EXPANSION PLANNING CONSIDERING ELECTRICITY MARKET**" completed by **EGEMEN UYAR** 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 Master of Science.

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my supervisor, Prof. Dr. Engin KARATEPE for all his support, encouragement, invaluable guidance, devotion of his valuable time and all the facility he provided during the development of my thesis. I am grateful to him for his valuable advices that greatly contributed to my academic development.

I would like to extend my sincere thanks to doctoral student Güneş Becerik for always being there for me throughout my study.

Finally, I wish to extend my appreciation to my family and my friends for their endless support and understanding. None of these works would have been possible without their support and patience.

Egemen UYAR

GENERATION EXPANSION PLANNING CONSIDERING ELECTRICITY MARKET

ABSTRACT

The upward trend in electricity demand requires new power plant investments regularly. In this context, generation expansion planning (GEP) is needed for reliable supply of electricity demand considering economic and technical constraints and uncertainty conditions. The GEP studies carried out in this thesis are presented under three main viewpoints. First, a static mixed integer linear programming formulation is presented for the single-bus GEP problem which takes into account the uncertainties in load and wind power generation. A two-level programming technique is used to solve this problem. While the supply-demand balance is achieved by taking into account the uncertainties with Monte-Carlo Simulation method at the lower level, the main objective function and constraints are formulated with the investment decision variables at the upper level. Second, the effect of transmission line constraints on investment decisions is examined with the multi-bus GEP problem. While the aim is to minimize the expected production and curtailment costs by using the DC-Optimal Power Flow method in the presence of load and wind uncertainties at the lower level of the two-level model, minimization of the overall costs is provided at the upper level. Finally, the network-constrained stochastic GEP model is presented in the market environment. In the presented two-level model, the profit maximization of the investor is aimed at the upper level, while the market clearing problem at the lower level is performed under different load and wind power generation conditions. The effects of line limits and uncertainty representations on investment decisions, market clearing price and profit are examined in case studies.

Keywords: Generation expansion planning, wind energy, stochastic programming, uncertainty, electricity market.

ELEKTRİK PİYASASI DÜŞÜNÜLEREK ÜRETİM GENİŞLETME PLANLAMASI

ÖZ

Elektrik talebindeki artış eğilimi, düzenli olarak yeni santral yatırımlarını gerektirmektedir. Bu bağlamda, ekonomik ve teknik kısıtlar ile belirsizlik koşulları dikkate alınarak, elektrik talebinin güvenilir bir şekilde tedariği için üretim genişletme planlamasına (ÜGP) ihtiyaç duyulmaktadır. Bu tezde yürütülen ÜGP çalışmaları üç ana bakış açısı altında sunulmaktadır. İlk olarak, yük ve rüzgar enerjisi üretimindeki belirsizlikleri hesaba katan tek baralı ÜGP problemi için statik bir karma tamsayılı doğrusal programlama formülasyonu sunulmuştur. Bu problemi çözmek için iki seviyeli bir programlama tekniği kullanılmıştır. Arz-talep dengesi Monte-Carlo Simülasyon yöntemi ile belirsizlikler dikkate alınarak alt seviyede sağlanırken, üst seviyede yatırım karar değişkenleri ile temel amaç fonksiyonu ve kısıtlar formüle edilmiştir. İkinci olarak, iletim hattı kısıtlarının yatırım kararları üzerindeki etkisi, çok baralı ÜGP problemi ile incelenmektedir. İki seviyeli modelin alt seviyesinde yük ve rüzgar belirsizliklerinin varlığında DC-Optimal Güç Akışı yöntemi kullanılarak beklenen üretim ve kısıntı maliyetlerinin minimize edilmesi amaçlanırken, üst seviyede toplam maliyetlerin minimize edilmesi sağlanmaktadır. Son olarak, şebeke kısıtlı stokastik ÜGP modeli piyasa ortamında sunulmaktadır. Sunulan iki seviyeli modelde, üst seviyede yatırımcının kâr maksimizasyonu hedeflenirken, alt seviyede piyasa takas problemi farklı yük ve rüzgar enerjisi üretim koşulları altında gerçekleştirilmektedir. Hat limitlerinin ve belirsizlik koşullarının yatırım kararları, piyasa takas fiyatı ve elde edilecek kazanç üzerindeki etkileri incelenmiştir.

Anahtar kelimeler: Üretim genişletme planlaması, rüzgâr enerjisi, stokastik programlama, belirsizlik, elektrik piyasaları.

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ABBREVIATIONS

GEP	: Generation Expansion Planning
ÜGP	: Üretim Genişletme Planlaması
TEIAS	: Turkish Electricity Transmission Company Head Office
SEP	: Substation Expansion Planning
TEP	: Transmission Expansion Planning
ACLF	: A Load Flow
RPP	: Reactive Power Planning
RES	: Renewable Energy Source
IEA	: International Energy Agency
GENCO	: Generation Company
LP	: Linear Programming
MILP	: Mixed-integer Linear Programming
DP	: Dynamic Programming
MIP	: Mixed-integer Programming
MINLP	: Mixed-integer Nonlinear Programming
GA	: Genetic Algorithm
PSO	: Particle Swarm Optimization
LOLP	: Loss of Load Probability
LOLE	: Loss of Load Expectation
EENS	: Expected Energy Not Served
PDF	: Probability Distribution Function
MCS	Monte-carlo Simulation
ISO	Independent System Operator
DGEP	: Distributed Generation Expansion Planning

HTPEM	: Hong's Two Point Estimate Method
MPEC	: Mathematical Programming with Equilibrium Constraints
GSA	: Gravitational Search Algorithm
DE	: Differential Evolution
CCP	: Chance-constrained Programming
OPF	: Optimal Power Flow
IEEE	: Institute of Electrical and Electronics Engineers
LMP	: Local Marginal Prices
TRANSCO	: Transmission Company
DISCO	: Distribution Company
KKT	: Karush–Kuhn–Tucker
WTG	Wind Turbine Generator
p.u.	Per Unit

LIST OF SYMBOLS

μ	: Mean value
σ	: Standard deviation
k and c	: Shape and scale parameters
o	: Operation condition
w	: Scenario
n	: Bus
Vci, Vr, Vco	: Cut-in, rated and cut-out wind speeds (m/s)
Pr, Pout	: Rated power, output power (MW)
c, r, e, d, w	: Sub-indexes for candidate conventional power plant, the candidate wind power plant, the existing power plants in the system, the load and the scenario
E, C, R, D, cap, o&m	: The upper indexes for existing, candidate, wind farms set, total load, capacity of power plants and operation and maintenance costs
ρ	: Weight of operation condition (h)
X_c, X_r	: Upper-level decision variables for conventional candidate plants and wind farms
X_c^{max}, X_r^{max}	: Maximum number of candidate and wind power plants
P_{cw}^{C}, P_{ew}^{E}. P_{rw}^{R}	: Power production values for each scenario (MW)
P_c^{cap}, P_r^{cap}, P_e^{cap}	: Capacity for candidate, wind and existing power plants (MW)
P_{lw}^{L}	: Power flow on Transmission line l for each scenario w
B_l	: Susceptance of line l
θ_{nw}	: Voltage angle at bus n for scenario w
$C_c^{investment\ (annual)}$ $C_r^{investment\ (annual)}$	: Investment cost for candiate conventional and wind power plants ($/MW year)
$C_e^{production}$ $C_c^{production}$	: Production cost for existing and candidate conventional power plants($/MWh)
$C_c^{o\&m}$, $C_r^{o\&m}$, $C_e^{o\&m}$	: O&M cost for candidate, wind and existing power plants($/MW)
Ω_n^C	: Candidate power plants at bus n.
Ω_n^E	: Existing power plants at bus n.

Ω_n^D	: Loads at bus n.
$C_f^{curtailment}$	: Cost of curtailment ($/MWh)
$C_l^{overload}$	: Overload cost of each line l($/MW)
$r(l)$ and $s(l)$	: Receiving-end and sending-end of line l
P_{fw}^D	: Curtailment values for the load in each scenario
P_{dw}^D	: Load in each scenario
$\gamma_l^{overload}$	: Overload probability of each line l
K_n^C, K_n^S	: Annual investment cost for candidate and stochastic power plants at bus n
φ_w	: Weight of each scenario w
λ_{now}	: LMP at bus n for operation condition of each scenario
$P_{now}^C, P_{now}^E, P_{now}^S, P_{now}^R$	: Power production values of candidate, existing , stochastic and rival plants at bus n for operating condition o of each scenario ω (MW)
u_{nh}^C	: Binary decision variable which is equal to 1 if the investment option h is selected for bus n
X_{nh}^C	: Maximum capacity for candidate investment option h for bus n (MW)
x_n^S	: Investment capacity of stochastic power plant at bus n
X_n^S	: Maximum capacity of stochastic power plant at bus n
x_n^C	: Investment capacity of candidate power plant at bus n
$\alpha_{now}^C, \alpha_{now}^E$	: Supply offer from candidate and existing power plants at bus n for operating condition o of each scenario ω ($/MWh)
C_{no}^R	: Production cost of rival power plant at bus n for operating condition o ($/MWh)
U_{no}^D	: Demand bids at bus n for operating condition o ($/MWh)
F_{nm}^{max}	: Maximum capacity for the line between bus n and m
λ_{now}	: LMP at bus n for operating condition o of each scenario ω ($/MWh)
$\mu_{now}^{C,S,E,R,D,\theta^{min,max}}, \mu_{ow}^{\theta^{ref}},$	: Dual variables for each equation

CHAPTER ONE
INTRODUCTION

1.1 Background and Motivation

The energy demand in the world tends to increase due to the key parameters such as population growth, electrification and development in industries and economies. This increase can be seen in the example of Turkey, which is a developing country with a rapid population growth. In Figure 1.1, it is observed that the energy consumption and peak loads in Turkey for the 10-year period are in an increasing trend. In the study included in the report (TEIAS, 2021), an average of 3.3% and 4.1% increase in electricity demand is predicted in 2031 for low and high scenarios, respectively.

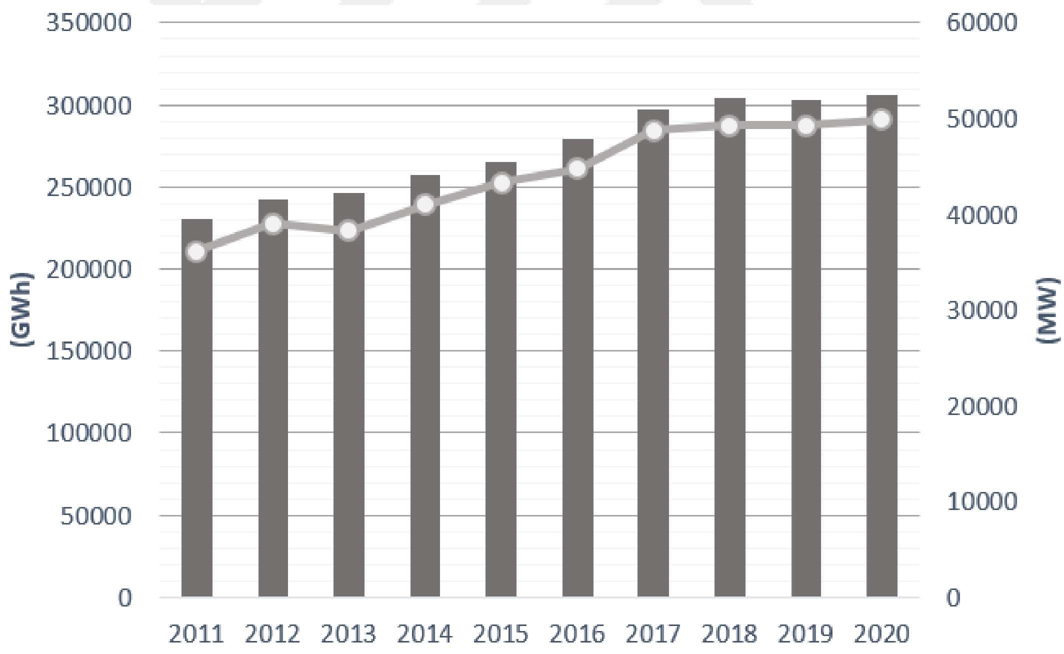

Figure 1.1 Peak power and energy consumption in Turkish electricity system between 2011 and 2020

In this context, it is necessary to determine the system requirements in efficient and reliable way to meet this increase in demand adequately. The decision makers should decide where, when, and in which type and capacity of system elements will be selected. System elements can be considered as generators, substations, transmission lines, reactive power sources (Seifi & Sepasian, 2011). The main study, called power system planning, includes some sub-studies to decide each system element. The first essential step is the estimation of peak load conditions for a given planning period which is called as load forecasting. After this step, the adequacy of the power plants is analyzed and if necessary, investment decisions of new power plants are made by taking into account some technical and economical constraints. This step is known as GEP. Afterwards, SEP study is done to make decisions of substation requirements by knowing load estimation and GEP decisions. As a next step, transmission system adequacy is checked in the scope of TEP study. If necessary, new transmission lines are installed for system. As a final step, ACLF can cause undesirable voltage levels for the bus after all the investment decisions made so far. To cope with this problem, it is necessary to decide on the reactive power sources. This study is called as RPP. Each sub-study of power systems planning which are clarified above can be seen in Figure 1.2.

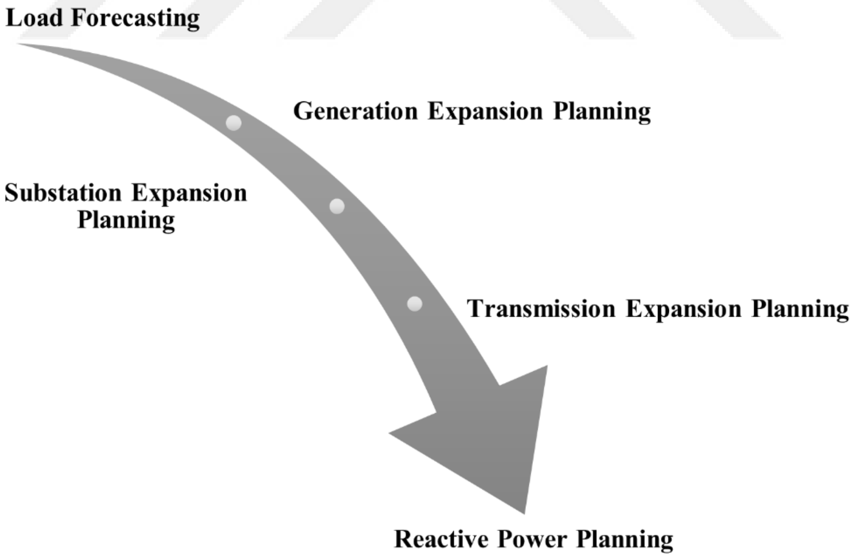

Figure 1.2 Power system planning sub-studies

The main aim of this thesis is to propose the models in assessing adequacy of existing power plants in the foreseen future and deciding the new power plants subject to technical and economical constraints considering electricity markets.

1.2 Generation Expansion Planning

In today's world, direct or indirect dependency of life to the electricity makes an adequate and reliable supply a crucial issue. One of the most important problems for the planning of electrical power systems is to ensure generation-demand balance even in the worst scenarios. Besides, penetration level of intermittent RESs has been increasing gradually for the last decades due to the environmental policies, carbon emission targets and market incentives and so on. As an example, expected investment to renewable energy sources in 2019 was more than the demand growth expectation for the same year as it can be seen from Figure 1.3 (World Energy Investment 2020 – Analysis - IEA). In this regard, integration of more renewable energy sources with uncontrollable power output to the power system makes ensuring adequate supply more difficult and complex (Oree et al., 2017).

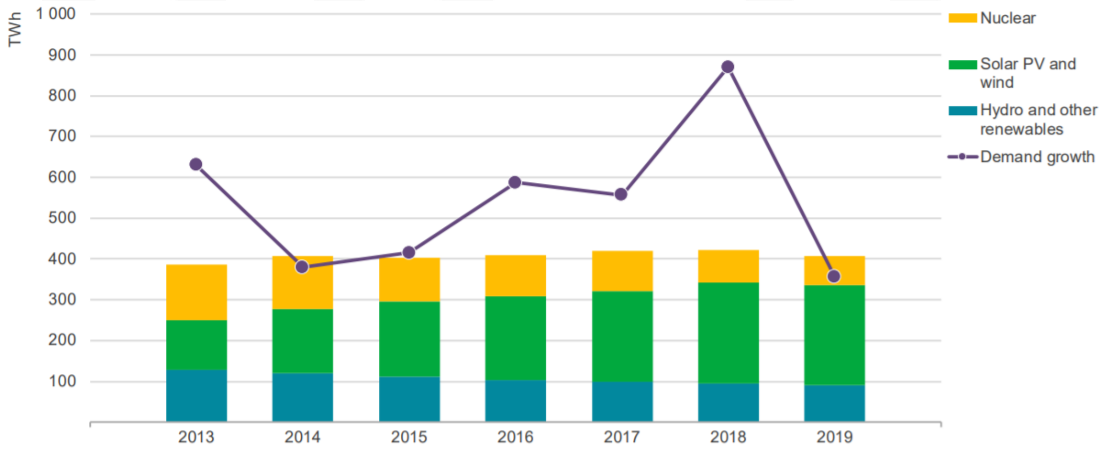

Figure 1.3 Expected investment to renewable energy sources and demand growth in 2019

For this reason, planning a reliable and economically viable power system requires an elaborate consideration of demand and the intermittent characteristic of RES output. In power system planning, load is forecasted for a specified horizon in the initial step. Then, GEP study determines capacity, location, technology type and time for new generation facilities considering future demand conditions subject to wide range of constraints (Gil et al., 2015). These constraints include technical, operational, social, economic, or environmental aspects of power system. In general, objective function of GEP problem highly depend on considered approach. There are two different approaches to address GEP problem: centralized approach and market-based approach (Conejo et al., 2016). The main aim of GEP problem is to minimize total cost or maximizing social welfare in centralized approach while maximizing investor profits in market-based approach. Generally, the results of centralized process can be considered in encouraging the investor with different type of incentives to invest for the benefit of the overall system or to inform investor in efficient participation to the market (Zhou et al., 2011).

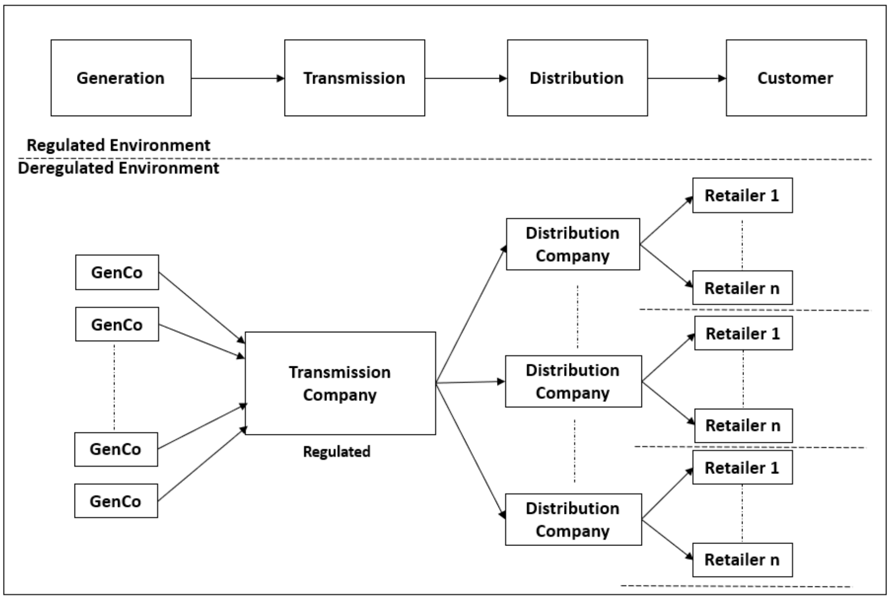

Figure 1.4 Liberalization of the electricity market

As seen in Figure 1.4, the liberalization of electricity industry from vertically integrated to deregulated structure has been illustrated. Historically, GEP is a centralized process which enables the system to meet the future load. The resulting plan covers the constraints of generation, transmission and distribution components and supported by appropriate market decisions. Currently, deregulated models are adopted by the planners which requires a vast number of decisions for generation companies. Each GENCOs are responsible to prepare their expansion plan by aiming their own profit maximization. Transition from centralized to decentralized structure leads to operational and planning challenges due to additional uncertainties such as market price and behavior of rivals. Consequently, representation of uncertainties come from decentralized structure is a substantial issue.

GEP models can be categorized in terms of time horizon, handling of uncertainties, network modelling (Conejo et al., 2016). Each study can be divided into sub-studies and these studies will be addressed from different perspectives such as static or dynamic model, deterministic or stochastic approach, mathematical or metaheuristic solution techniques. In terms of network modelling, single-bus model and network-constrained models are used in GEP problem. Optimal sizing and type of generation units can be determined by using single-bus approach whereas the location of new generation unit can be also obtained additionally by the network constrained approach. Since the single-bus approach is simpler and easier to model, it is more suitable for transmission networks which is not congested. However, as the integration of renewable energy sources into the grid can cause congestion, it becomes important to add network constraints such as transmission line limits and power balances at each bus to the GEP model, although it causes a more complex problem (Kaymaz et al., 2007). In terms of modelling time horizon, static and dynamic model. Static model determines type and size of the generator units to be installed when the planning horizon is represented by a single point of time. The optimal timing of when new units will be built does not determined in static model. In dynamic model, planning horizon is divided into stages, and decisions are made at the beginning of each stage. In terms of uncertainty representation, GEP problem can be described as deterministic or stochastic approach. Deterministic appproach assumes known information for inputs parameters. However, there is usually no perfect information about problem inputs. Thus, decisions are made within uncertain environment. There are some uncertainties in GEP problem such as renewables power outputs, demand, electricity price, investment and fuel cost of units so on (Hemmati et al., 2013a). However, consideration of each details mentioned above may result in a challenging model. Thus, a reasonable balance between accuracy and computational effort should be taken into consideration. The formulations of GEP models are explained in the following chapters.

1.3 Literature Review

The GEP problem is the one of the popular topics in literature and has critical importance for decision makers in the energy sector due to requirement for uninterrupted access to electricity. Thus, it has been widely addressed more than few decades. Due to the inherent complexity and nonlinearity of problem, numerous models and solution techniques have been developed to obtain investment decisions in literature. GEP, starting from the work (Massé et al., 1957) in the 1950s, was a problem in which LP models were applied for objective function and limitations of linear functions. However, the size and complexity of the problem increased with the reliability, the transition from monopoly to competition, integration of renewable generation, environmental considerations and so on. Thus, LP models could not handle challenging GEP problem sufficiently. For this reason, some methods have been developed and systematically applied to GEP problems. In (Borison & Morris, 1984), dynamic programming model is developed for GEP with optimal production mix. There is another study based on the nonlinear programming framework on the development of a static optimal mix (Levin & Zahavi, 1984; Ramos et al., 1999). Bender decomposition technique is proposed for large scale multi-bus GEP problem (L. Chen et al., 1993). DP is used to solve subproblems. The main contribution paper is to include network constraints to the GEP problem and show its importance. Mathematical techniques that have been mostly applied to GEP problems are as follows: LP (Delgado et al., 2011; Q. Chen et al., 2010) et al., 2010), MILP (Koltsaklis et al., 2014; Bakirtzis et al., 2012), DP (Moghaddas Tafreshi et al., 2012a), MIP (You et al., 2016), Benders decomposition (Kazempour & Conejo, 2012; Baringo & Conejo, 2012). GEP problems are often formulated as a MINLP problem. However, MINLP models are generally converted to the its equivalent mixed-integer linear formulation using linearization methods (Valinejad & Barforoushi, 2015). Mathematical based methods may not be sufficient to handle some complex GEP problems. For this reason, many metaheuristic techniques have been developed to remove the barrier on solving GEP problems. In literature, metaheuristic optimization techniques have been widely investigated (Zhu & Chow, 1997; Nara, 2000; Hemmati et al., 2013a). In mathematical methods, computation time is reasonable and ensures global optimum while it generally fails in complex problems. On the contrary, metaheuristic methods mostly gives local optimum but it is easy and useful for implementing on complex problem (Sadeghi et al., 2017). The most frequently used methods in GEP problem are GA (Murugan et al., 2009;Yildirim et al., 2006; Pereira & Saraiva, 2013) and PSO (Saboori & Hemmati, 2016; Hemmati et al., 2016). Other metaheuristic methods have been also investigated and compared each other in terms of their performances in literature (Kannan et al., 2007).

A power system is considered adequate when it has sufficient levels of resources for generation and transmission capacity to always meet the expected electricity demand. Reliability assessment of power system can be handled a system adequacy and security (Billinton & Allan, 1996). Adequacy is associated with having sufficent generation units to meet load requirements while security is the ability of how the power system respond when the disturbance occur. For this reason, reliability of GEP study focuses evaluation of generation adequacy due to the not consideration of dynamic conditions on planning studies. The most widely used reliability indices are LOLP (Rashidaee et al., 2018; Aghaei et al., 2014), LOLE and EENS (Aghaei et al., 2013; Sun et al., 2021). In study (Khodaei et al., 2012), LOLE is integrated into GEP model as a reliability constraint with iterative approach to obtain investment decisions. The increasing integration of RESs into the power system also significantly affects system reliability. In (Rouhani et al., 2014), LOLP has been used as a constraint to limit unserved hours of load in study in presence of RESs. Required reliability level can also be attained by including terms in objective function instead of constraint (Sadegh Javadi et al., 2013;Aghaei et al., 2012).

One of the most important problems in long-term planning is to make a decision in an uncertain environment. The degree of uncertainty in power system has been increasing significantly which may complicate the planning problem and jeopardy the adequacy of the power system. In power system studies, there are some sources of uncertainties such as load, renewable based power generation, electricity prices and so on. In terms of mathematical modelling of optimization problems under uncertainties, some frameworks are stochastic programming (Dantzig, 1955;Conejo et al., 2010), chance constrained programming (Charnes & Cooper, 1959; Manickavasagam et al., 2015) and robust optimization (Soyster, 1973; Abdalla et al., 2020) in literature. These frameworks differ from each other in terms of risk aversion and characterization of uncertainties. Details can be found in (Li & Grossmann, 2021). Modelling of uncertainties is essential so as to have informed investment decisions. One of the most widely used approaches for handling uncertainties in power systems is the probabilistic approach (Jordehi, 2018). In this approach, uncertainties are modelled via PDFs. The most common methods to include uncertainty into planning problems are MCS and scenario-based approach (Soroudi & Amraee, 2013). In MCS, the PDF of the objective function of the problem is obtained by using the PDF of the uncertain input parameters with the fixed value of the decision variables. In the scenario-based approach, the PDF of the uncertain parameter is divided into several segments. Within each segment that corresponds to the scenario the probability is calculated for the uncertain variable (Conejo et al., 2010). Historical data can be used to represent different operating condition in the system. However, these data usually include quite number of values and it is not applicable to work on such a large amount of information. Consequently, there are several techniques to reduce large amount historical wind and load data. In (Baringo & Conejo, 2013b), load duration curve and K-means clustering methods are compared for representation of load and wind power production and their correlation in investment decision. Both methods are also enabled to represent uncertainties of load and wind production. In (Baringo & Conejo, 2013a), stochastic behaviour of wind power plants is addressed in GEP problem by representing wind generation and load via scenarios without strategic behavior of the investor. K-means clustering method is used to obtain lower number of operating conditions by reducing data sets of load and wind power production. In addition to the previous study, strategic behavior of investor is considered, and the market price is also represented via scenarios in the generation investment problem (Baringo & Conejo, 2014).

Liberalization of electricity, i.e., from vertically integrated structure to deregulated structure, accompanies some changes in models, objectives, solution approaches and even participants for GEP problem (Kagiannas et al., 2004). In vertically integrated structure, determination of optimal plans is addressed for generation units with aim of maximizing social welfare or minimizing overall cost. In this structure, the central planner undertakes to ensure a reliable supply and meet the anticipated load. Moreover, power system planning problems such as transmission expansion, natural gas systems expansion and unit commitment can be combined with GEP problem (Sadeghi et al., 2017). In (You et al., 2016), MIP formulation is proposed for cooptimization GEP&TEP problem under load and wind uncertainty. The objective function considers minimizing total cost of generation units and transmission lines. In (Seddighi & Ahmadi-Javid, 2015), multistage stochastic programming model is presented for GEP&TEP and different uncertainties are represented via scenarios. The objective function includes minimization of generation, transmission, socio-environmental and load shedding costs. In (Tekiner et al., 2010), MILP formulation is proposed for stochastic multi-objective GEP problem. Uncertainties about demand and availabilities of components are handled via monte-carlo simulation. The aim of problem is to minimize overall costs and air emissions. Unit commitment constraints can be included in long-term planning studies in order to obtain more optimal solutions (Koltsaklis & Georgiadis, 2015; Pereira et al., 2017). In (Flores-Quiroz et al., 2016), proposed framework is modelled as MILP and solved Dantzig–Wolfe decomposition and a column generation approach for resulting generally in computational tractability. Real power system is considered to show the importance of unit commitment constraints. The aim proposed model is to minimize model is to minimize the investment and operational costs. Along with the liberalization of electricity industry, GENCOs became privatized and named as agents who aim to sell their production in electricity market. The objective function of GEP problem has been evolved from minimization of overall costs to maximization of profit (Ramos et al., 1999). In deregulated environment, GENCOs send their investment plans and price offers to the ISO. After market is cleared by the ISO, market clearing prices are obtained and output signals are delivered to the each individual GENCO. Now, the agent's decision does not only affect its own profits but also affects the decisions of other participants. It is called as “strategic decisions” in literature (Kagiannas et al., 2004). Consequently, modeling of the GEP problem become more challenging since it is required to model competition between GENCOs as well as representation of power system in technical manner. In the study (Hogan, 1997), each agent's profit maximization problem is addressed by considering network constraints. In the literature, game theory and Cornout model are commonly investigated to model the GEP problem under deregulated environment (Sadeghi et al., 2017). In (Sarjiya et al., 2019), competition between agents is represented with game theory for multi-objective GEP problem. In the two-level optimization, both economic and reliability objectives are considered. It is observed that less expensive results are obtained game theory in contrast to imporeved genetic algorithm. Yet, in terms of computation time, game theory takes longer time to solve the optimization problem. In (Barati et al., 2019), a novel approach is proposed for DGEP. This model includes both economic and technical constraint of private investor. HTPEM is used to handle DG’s uncertainties and overcome computational burden. In (Hemmati et al., 2013b), the impact of wind power uncertainties in electricity market is investigated for profit maximization problem of GENCOs. MCS is utilized to handle uncertainty in the problem. LOLE and reserve margin constraints are incorporated into problem. The problem is organized as master and slave sectors. The profit maximization problem of each GENCOs is in slave sector while technical constraints are checked by ISO in master sector. Cournot model is utilized to obtain market prices.

The general overview of GEP studies is summarized in Table 1.1 in the view of reliability, optimization method, time horizon, network model, uncertainty, renewable energy and market structure.

Table 1.1 The general overview of GEP studies

	Reliability	Optimization Method	Time horizon	Network Model	Uncertainty	Renewable Energy	Market Structure
Valinejad & Barforoushi, 2015	Yes	Mathematical (MPEC, MILP)	Dynamic	Network-constrained	Offering and investment decisions of rivals	No	Decentralized
Delgado et al., 2011	Yes	Mathematical (LP)	Dynamic	Single-bus	fossil fuel prices, CO2 emission allowance prices	Yes	Centralized
Chen et al., 2010	Yes	Mathematical (LP)	Dynamic	Single-bus	low carbon factors	Yes	Centralized
Koltsaklis et al., 2014	Yes	Mathematical (MILP)	Dynamic	Network-constrained	generation and carbon emission trading prices, and operating costs	Yes	Centralized
Bakirtzis et al., 2012	Yes	Mathematical (MILP)	Dynamic	Single-bus	Demand, budget, CO2 price, RES target, fuel price	Yes	Centralized
Moghaddas Tafreshi et al., 2012)	Yes	Mathematical (DP)	Dynamic	Network-constrained	Deterministic	No	Decentralized
Sadeghi et al., 2017	Yes	Metaheuristic (GSA)	Dynamic	Single-bus	Deterministic	Yes	Decentralized

Table 1.1 Continues

	Reliability	**Optimization Method**	**Time horizon**	**Network Model**	**Uncertainty**	**Renewable Energy**	**Market Structure**
You et al., 2016	Yes	Mathematical (MIP)	Dynamic	Network-constrained	Wind and Load	Yes	Centralized
Kazempour & Conejo, 2012	No	Mathematical (Benders Decomposition)	Static	Network-constrained	rival producer investment, rival producer offering and demand	No	Decentralized
Baringo & Conejo, 2012	No	Mathematical (Benders Decomposition)	Static	Network-constrained	Demand level, wind intensities	Yes	Decentralized
A. J. C. Pereira & Saraiva, 2013	Yes	Metaheuristic (GA)	Dynamic	Network-constrained	Load	Yes	Decentralized
Saboori & Hemmati, 2016	Yes	Metaheuristic (PSO)	Dynamic	Single-bus	Deterministic	Yes	Centralized
Rashidaee et al., 2018	Yes	Mathematical (MIP)	Dynamic	Single-bus	Deterministic	No	Centralized
Barati et al., 2019)	No	Metaheuristic (GA)	Static	Network-constrained	Wind speed, Solar radiation	Yes	Centralized

Table 1.1 Continues

	Reliability	Optimization Method	Time horizon	Network Model	Uncertainty	Renewable Energy	Market Structure
Hemmati et al., 2013b	Yes	Metaheuristic (PSO)	Dynamic	Single-bus	output power of wind farms	Yes	Decentralized
Koltsaklis & Georgiadis, 2015	Yes	Mathematical (MILP)	Dynamic	Network-constrained	CO_2 emission pricing and cap, Renewables penetration target	Yes	Centralized
Barati et al., 2015	Yes	Metaheuristic (GA)	Dynamic	Network-constrained	Deterministic	No	Centralized
Kamalinia & Shahidehpour, 2010	Yes	Mathematical (MILP)	Dynamic	Network-constrained	Wind generation	Yes	Decentralized
Rajesh et al., 2016	Yes	Metaheuristic (DE algorithm)	Dynamic	Single-bus	Deterministic	Yes	Centralized
Pozo et al., 2013	No	Mathematical (MILP)	Dynamic	Network-constrained	Demand	Yes	Decentralized
Tohidi et al., 2013	Yes	Mathematical (MIP)	Dynamic	Network-constrained	Outages of generatin, gunits and transmission lines	No	Centralized

Table 1.1 Continues

	Reliability	Optimization Method	Time horizon	Network Model	Uncertainty	Renewable Energy	Market Structure
S. Pereira et al., 2017	Yes	Mathematical (MINLP)	Dynamic	Single-bus	RES variability	Yes	Centralized
Ağralı et al., 2017	No	Mathematical (MILP)	Dynamic	Network-constrained	carbon price	Yes	Decentralized

As seen in Table 1.1, different viewpoints have been used in GEP problems. In terms of the reliability, renewable energy sources can negatively affect system reliability due to their variable power output. For this reason, basic reliability indices such as LOLE, LOLP and EENS has been widely taken into account in literature. On the other hand, GEP is a highly complex problem involving many interrelated objectives. In this context, metaheuristic methods have been widely used due to simplicity of its implementation. In terms of network modelling, DC network representation is mostly used. In addition, deterministic and stochastic models are adopted for the representation of the uncertainties. Even though there is a reasonable balance between modeling accuracy and computational effort, most studies in the literature have addressed uncertainties with many different approaches in order to make a well-informed decisions. The GEP problem has been comprehensively studied in many researches from centralized environment to decentralized environment. Addressing the GEP and TEP problem under market environment and impact of market-compatible policies on investment decisions may be investigated for further studies as research interests.

1.4 Organization of the Thesis

The studies within the scope of this thesis are presented in five chapters as follows;

In Chapter 1, the motivation of this thesis is presented. Then, the general overview of power system planning studies and the importance of GEP in planning studies are explained briefly. Finally, the literature review of GEP studies is given.

Chapter 2 presents single-bus static GEP which is formulated as a MILP problem by considering the uncertainties in load and wind power generation. In the proposed probabilistic GEP problem, it is aimed to minimize the investment and operational costs.

In Chapter 3, stochastic GEP model is presented by taking into account network constraints and uncertainties in load and wind power generation. Monte Carlo approach is used to deal with uncertainties and check probabilistic constraints. Two-level programming method is proposed to model problem. The impacts of overloading and line limits on GEP are investigated through investment plans and total costs.

In Chapter 4, stochastic GEP model is presented by considering network constraints within market environment. Stochastic two-level model is proposed where upper problem represents the investment decisions with the aim of maximizing profit and its lower problem represents the market clearing under different load and wind power uncertainties. This two-level mathematical framework is reformulated as MPEC. The impact of the system line limits, stochastic wind power option and rival’s investment uncertainty on the problem outputs is investigated via case studies.

In Chapter 5, the discussion of this thesis study is presented.

In Chapter 6, the general overview of this thesis study and some concluding remarks are presented.

CHAPTER TWO
GENERATION EXPANSION PLANNING UNDER WIND POWER GENERATION AND LOAD UNCERTAINTIES

Investments in renewable energy sector is increased rapidly in global scale. Planning studies subject to economic and technical constraints should be carried out with the increasing investments in order to ensure reliable supply of electricity demand. Variable load demand and the uncertain nature of renewable energy sources make the impact of uncertainty on investment decisions an important issue in long-term power system planning studies. In the planning problem, uncertainty should be addressed carefully to identify risks and opportunities in investments. In this study, a static MILP formulation is presented for the single-bus generation expansion planning problem considering the uncertainties in load and wind power generation. A stochastic programming approach is used to deal with the load and wind generation uncertainties represented by a set of scenarios in optimization problem. The aim of the proposed method is to minimize the total costs of the system subject to technical constraints. The impacts of modeling uncertainties on investment decisions are compared by using deterministic and stochastic approaches and results are presented with the investigation of investment decisions from technical and economic aspects.

Ensuring the generation-demand balance under different operation conditions in a reliable and economical way emerges as an important and current problem in planning studies with the increase in the share of renewables in electrical power systems. GEP is an optimization problem that determines the capacity, location, technology type and time of new power plants in order to meet future load conditions (Diaz et al., 2020). GEP can be formulated as a mixed integer linear optimization problem in terms of mathematical modelling. The aim of the problem is to ensure economic operation by minimizing the total cost under various constraints. Due to the increasing integration of RESs, the change in environmental policies and market incentives, it has become very important to consider RESs within the GEP problem in recent years. The main reason for this is that RESs can compete with fossil fuel-fired plants due to their cheaper costs and meet the need for reaching the targets of environmental policies. However, the stochastic behavior of RESs and their dependence on environmental conditions makes the decision-making process more challenging. Therefore, the impact of uncertainties on production costs for GEP models has been an important research topic.

In the last decades, many studies have been carried out on the inclusion of uncertainties in the GEP problem. Modeling of uncertainties has high importance in order to solve the operational problem in stochastic GEP models. Estimated load, availability or cost of fuel, outages of generation units, environmental targets, regulatory policies and power output of RESs are the most common uncertainties considered in GEP studies(Oree et al., 2017). Many approaches have been developed dealing with uncertainties in planning studies (Jordehi, 2018). One of the most common methods used to deal with uncertainties in GEP problem is scenario-based approach which describes the uncertainties with scenarios to represent the different operating conditions of the system in the long term. These scenarios can be represented by weight values depending on the problem (Baringo & Conejo, 2011; Davoodi et al., 2022; Pourahmadi et al., 2020; Tohidi et al., 2013) or Monte Carlo Simulation (Hemmati et al., 2013b; Manickavasagam et al., 2015). Apart from this, robust optimization models can also be used in probabilistic GEP optimization (Abdalla et al., 2020; Abdin et al., 2022). In terms of modeling, the GEP problem is handled as a single-bus or network constrained model in power systems. Optimum capacity and type of generation units can be determined in the single-bus approach while capacity, type and location information can be obtained in the network-constrained approach. In the literature, single-bus, probabilistic GEP studies have been investigated in many aspects. In proposed study (Y. Sun et al., 2012), the static, single-bus GEP problem address probabilistic power production from renewables with particle swarm optimization using chance constrained programming. In study(Rajesh et al., 2016), a single-bus GEP model is applied to a real system to examine the share of power plants under increasing wind energy penetration and the capacities of wind farms are determined using a scenario-based model with emission policy alternatives and reserve margin levels. In the study of (Abdalla et al., 2020), the single-bus GEP model, which takes into account both long-term and short-term uncertainties, is solved with the robust optimization method. In the study (Hemmati et al., 2013b), a single-bus GEP optimization is proposed to maximize the expected profit of generation companies considering various constraints in the electricity market. In the study (Pourmoosavi & Amraee, 2021), a single-bus multi-period GEP model is proposed to identify new power plants within the scope of low carbon policy. In the study (Rashidaee et al., 2018), a single-bus, dynamic, mixed integer linear GEP problem is proposed considering the reserve margin and loss of load probability constraints.

In this study, single-bus static GEP is formulated as a MILP problem by taking into account the uncertainties in load and wind power generation. In the proposed probabilistic GEP problem, it is aimed to minimize the investment and operational costs. Uncertainties in the GEP problem are dealt with Monte Carlo Simulation and two-level programming method is proposed to model problem. The impacts of load and wind speed uncertainty on GEP plans are investigated through investment plans and costs.

2.1 Modelling of Load and Wind Uncertainties

In this study, the GEP problem is addressed for both deterministic and probabilistic approaches and the results are compared. In the deterministic approach, the wind and load are represented by a single scenario, while in the probabilistic approach, the load and wind uncertainties are modeled with scenarios. The estimated load is modeled with the normal distribution while wind speed is modeled independently with the Weibull distribution. The distribution functions of both uncertainties are given in (2.1) and (2.2), respectively.

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

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

$$Pout = \begin{cases} 0 & 0 \le V \le V_{ci} \\ \dfrac{P_r(V - V_{ci})}{V_r - V_{ci}} & V_{ci} \le V \le V_r \\ P_{rated} & V_r \le V \le V_{co} \\ 0 & V_{co} \le V \end{cases} \tag{2.3}$$

In a normal distribution, μ is the mean value and σ is the standard deviation. In this study, the μ and σ/μ ratio is taken as 1800 MW and 0.10, respectively. In the Weibull distribution, the shape (k) and scale (c) parameters determine the characteristic of the wind speed. The characteristic of the wind turbine is calculated according to the speeds given in (2.3). In the scenarios considered, the wind speed characteristics are k=5.4, c=2.7; wind cut-in, rated and cut-out speeds are used as Vci = 4 m/s, Vr = 12 m/s and Vco = 22 m/s, respectively (Hemmati et al., 2016). The probability distribution of load at different load characteristics and distribution of WTG output power are given in Figure 2.1 and Figure 2.2.

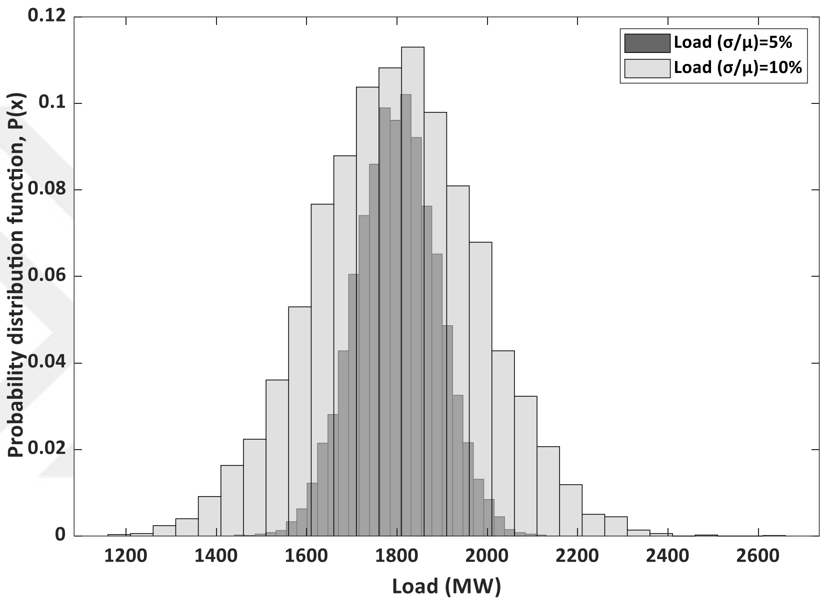

Figure 2.1 Distribution of load at different load characteristics

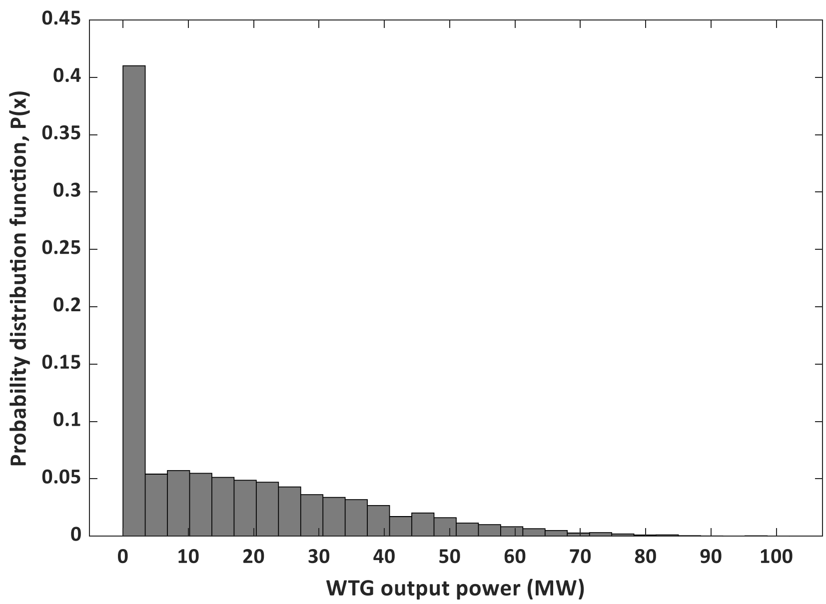

Figure 2.2 Distribution of WTG output power

2.2 Mathematical Formulation of Single-bus Stochastic GEP Problem

In the single-bus approach, the aim is to find the type and capacity of generation plants without considering the network constraints of the system. In this study, the GEP problem is dealt with a static and single-bus approach. The upper-level problem of two-level model aims the best investment decisions by minimizing production costs, the expected production cost is calculated by considering the optimum production cost under the MCS in the lower-level problem. The operation of the two-level model used is summarized in Figure 2.3.

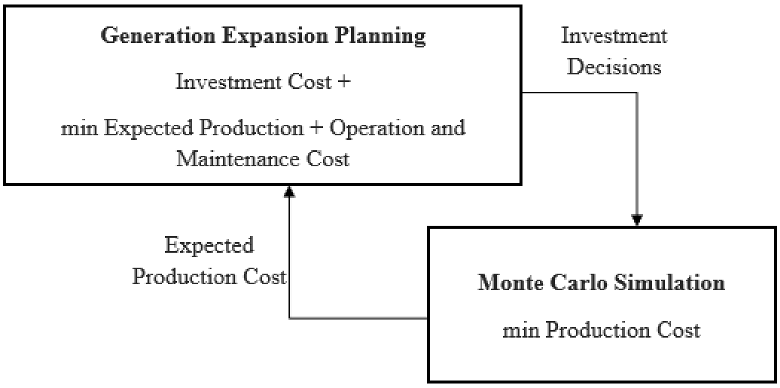

Figure 2.3 Proposed flowchart for GEP

The formulation is given based on the proposed method as follows:

$$\begin{aligned} \min \sum_{c} C_c^{investment\ (annual)} P_c^{cap} X_c + \sum_{r} C_r^{investment\ (annual)} P_r^{cap} X_r \\ + \rho \left[\sum_{e} C_e^{production} P_{ew}^{E} + \sum_{c} C_c^{production} P_{cw}^{C} \right] \\ + \left[\sum_{e} C_e^{o\&m} P_e^{cap} \right. \\ \left. + \sum_{c} C_c^{o\&m} P_c^{cap} X_c + \sum_{c} C_r^{o\&m} P_r^{cap} X_r \right] \end{aligned} \quad (2.4)$$

s.t.

$$X = (X_c^1, \dots, X_c^n, X_r^1, \dots, X_r^n), \forall c, \forall r \quad (2.5)$$

$$0 \leq X_c \leq X_c^{max}, \forall c \quad (2.6)$$

$$0 \leq X_r \leq X_r^{max}, \forall r \quad (2.7)$$

$(P_{ew}^{E}, P_{cw}^{C}, P_{dw}^{D})$ = {

$$\min \sum_{e} C_{e}^{production} P_{ew}^{E} + \sum_{c} C_{c}^{production} P_{cw}^{C} \tag{2.8}$$

s.t.

$$\sum_{e} P_{ew}^{E} + \sum_{c} P_{cw}^{C} + \sum_{r} P_{rw}^{R} = \sum_{d} P_{dw}^{D} \tag{2.9}$$

$$0 \leq P_{cw}^{C} \leq P_{c}^{cap} X_{c} \ , \forall c \tag{2.10}$$

$$0 \leq P_{ew}^{E} \leq P_{e}^{cap}, \forall e \tag{2.11}$$

} , $\forall$ w

The sub-indexes c, r, e, d, w used in the equations represent the candidate conventional power plant, the candidate wind power plant, the existing power generation plants in the system, the load and the scenario, respectively. The upper indexes used in the equations are E, C, R, D, cap, o&m, refer to existing, candidate, and wind farms set, total load, unit capacity of power plants and operation and maintenance costs, respectively. The objective function given in (2.4) minimizes the total investment, expected electricity production costs and operation&maintenance costs. The ρ value of 8760 for the annual production costs and the annual investment costs of the candidate power plants are used for the costs in the reference year. The upper-level decision variables are the number of generating plants (X_c, X_r); constraints are the maximum allowable number of candidate generation units given in (2.6) and (2.7). In the lower-level problem, the objective function is given in (2.8) and its variables are the production values of power plants for the operating conditions in each scenario (P_{cw}^{C}, P_{ew}^{E}). P_{rw}^{R} values represent the wind power outputs from sample scenario in the MCS. In lower level, the constraints are given in (2.9)-(2.11). (2.9) is the equality constraint for generation-demand balance. (2.9) – (2.11) represent the power generation limits of candidate conventional and existing power plants, respectively.

2.3 Case Studies on Single Bus Stochastic GEP

The two-level mixed-integer linear optimization model presented for probabilistic GEP is solved in MATLAB. The existing power plant is assumed to be a coal-fired power plant with 500 MW nominal capacity. In the optimization, candidate power plants are considered as coal, natural gas combined cycle, hydroelectric and wind power plants, respectively. The capacity of each generation unit is 300, 400, 200 and 100 MW, respectively. The maximum number of generation units is five for coal, natural gas and hydroelectric power plants while this is fifteen for wind power plant. Fuel, operation and maintenance costs are taken into account (Abdalla et al., 2020; Careri et al., 2011) while calculating the costs. In the first stage of the study, which will be referred to as Case-1, electricity generation plans are obtained by considering deterministic and probabilistic scenarios. In Table 2.1 investment plans and costs obtained under deterministic and probabilistic scenarios are given.

Table 2.1 Case-1 deterministic/ probabilistic GEP plans

Scenario	Investment Plan	Total Cost (M$/year)
Deterministic	S2(x3), S3(x4), S4(6)	859, 740
Probabilistic	S1(x1), S2(x4), S3(x1), S4(5)	713, 760

As seen in Table 2.1, investment plans and total costs obtained by deterministic and probabilistic modeling are different. In deterministic approach, mean values of uncertain parameters are considered. It is observed that the deterministic scenario has higher total cost than probabilistic one as expected when the results are compared. In probabilistic approach, uncertainties are described through distribution functions for load and wind, and the optimization process is carried out by obtaining expected production costs considering multiple scenario combinations under Monte Carlo Simulation. After the investment decisions are determined, it is observed that the generation-demand balance is guaranteed for the deterministic and probabilistic scenarios under all conditions when the obtained production plans are tested with 8760 different probabilistic load and wind scenarios. In the obtained plan for the deterministic approach, it is seen that the planner has a conservative point of view, therefore investment more than necessary will be required. As a result, it is observed that more acceptable investment decisions in terms of cost can be obtained with the investment plan of probabilistic model. In the second phase of this paper, referred to as Case-2, the effect of different load variations on investment plans has been examined. The worst-case scenario changes due to the change of the extreme points of the probability distribution function although the average value of the load does not change with the change of the σ/μ ratio of the load. In this case, the wind characteristic is assumed to be the same as the characteristic discussed in Case-1. Table 2.2 shows the effect of load characteristics on GEP plans and total cost.

Table 2.2 The effects of load characteristics on GEP plans

Case	Load Characteristic (σ/μ)	Investment Plan	Total Cost (M$/year)
2.1	5 %	S2(x4), S3(x1),	649,160
2.2	7 %	S2(x5), S4(x1)	667,840
2.3	10 %	S1(x1), S2(x4), S3(x1), S4(x5)	713,760

As the standard deviation of the load increases, probabilistic GEP decisions change and it is observed that the total cost also increases. This is mainly due to the worst-case scenarios in the tails of the probability distribution functions correspond to a greater load in the high standard deviation scenario. It is also observed that the number of investments made in the wind farm has increased due to the probabilistic change in the load characteristics.

2.4 Conclusions

In this study, two-level optimization model is used for static and single-bus GEP problem and uncertainties are dealt with scenario-based approach. The impacts of uncertainties with deterministic and probabilistic scenario approaches on investment decisions have been compared in terms of total costs. As a result of the case studies, it has been observed that the investment decisions obtained in the probabilistic GEP model, in which the uncertainties are included with the Monte Carlo Simulation, can have more economic results. The inclusion of uncertainties to the planning studies plays an important role in making more reliable as well as more economical investment decisions considering that the renewable energy integration in power grid is increasing day by day. Therefore, the development of planning models by representing different uncertainties is becoming increasingly important as a current research topic.

CHAPTER THREE
NETWORK CONSTRAINED GENERATION EXPANSION PLANNING CONSIDERING WIND AND LOAD UNCERTAINTIES

The share of intermittent RE sources in power system, especially wind, is increasing year by year. As renewable energy sources have no fuel cost and no emission, they have been the triggers of the energy transition. According to the outlook of the IEA (World Energy Investment 2020 – Analysis - IEA), the worldwide share of renewable energy technologies will increase from 15% in 2019 to than 60% in 2070. However, fast growth of these intermittent sources makes some problems more challenging such as supply adequacy and generation-demand balance. On the one hand, congestion is experienced more mainly due to the inclusion of renewable energy sources in GEP problem. In this sense, network constraints need to be included in the GEP model to observe their impact on investment plans (Barati et al., 2019). This enables more realistic representation of system and makes possible to obtain location of new power plants on the system. On the other hand, sources of uncertainty such as the wind energy and load demand have an impact on decision making of investments. This makes modelling with uncertainties significant in order to obtain informed decisions and enables to arise new approaches in terms of generation expansion (Aien et al., 2016). In centralized approach, the main aim of the planner is to make investment decisions by minimizing overall total costs. The one of the frameworks for handling uncertainties in optimization problem is stochastic programming (Li & Grossmann, 2021). There are many studies in the literature in which uncertainties are included in GEP problem. In study (Anders, 1981), CCP is firstly used to solve a stochastic generation planning model with reliability constraints. Power flow in transmission lines and LOLP are considered as probabilistic reliability criteria and solution procedure is compared for both continuous and discrete random generation and load cases. In study (Álvarez López et al., 2007), two-level stochastic programming is used to solve joint transmission and generation expansion problem in which risk factor is incorporated into objective function by using mean-variance Markowitz theory. The models from deterministic model to stochastic model with risk and probabilistic constraints are investigated. In (You et al., 2016), MIP formulation is proposed for co-optimization of GEP&TEP problem under load and wind variability. The objective function of problem consists of minimization investment and operational costs of generation units and transmission lines. In study (Mazadi et al., 2009), obtain probabilities using CCP are discussed for GEP problem under load uncertainty. Modified iterative algorithm solves the deterministic equivalent of the CCP formulation using an iterative procedure, which enable to obtain solutions with less iteration. OPF on the IEEE 30-bus system is utilized to present results. In study (Sun et al., 2012), chance-constrained optimization model is used for incorporating probabilistic power production from renewables into GEP problem for China. The model is solved by using PSO algorithm. In study (Manickavasagam et al., 2015), CCP is used to model GEP problem under load uncertainty. Joint CCP is obtained by using deterministic approximations and solved via sensitivity integrated iterative algorithms. The required level of reliability is obtained at lower cost by comparing the proposed method with previous methods on IEEE 30 and 118-bus systems. In study (Hemmati et al., 2016), two-level model is proposed for TEP-GEP problem in deregulated environment. The main aim of slave level is to maximize profit while ISO checks adequacy and reliability constraints of the system. The proposed model is solved by using PSO algorithm and MCS is utilized to integrate wind farm uncertainty to the problem.

In this study, stochastic programming-based method is proposed for generation expansion planning that considers the uncertainties in load and wind power generation. Uncertainties are represented via two random variables that are integrated into GEP model using probabilistic constraints. The main aim of the proposed method is minimizing overall costs that includes investment, fuel, curtailment, operation and maintenance and overload costs of the system. The effect of overloading and different transmission line limits on investment decisions is investigated under different case studies. The results showed that proposed method can be used to obtain informed investment plan under different uncertainties and network representations in GEP problems.

3.1 Modeling of the Load and Wind Uncertainty Scenarios

In this study, the GEP problem is addressed through probabilistic approach that load and wind uncertainties are modeled via scenarios. The estimated load and wind speed are modeled with the normal distribution and weibull distribution, respectively. The probability distribution of load at each bus and WTG output power is given in Figure 3.1 and Figure 3.2. The distribution functions of both uncertainties were given in equation (2.1), (2.2) and (2.3), respectively.

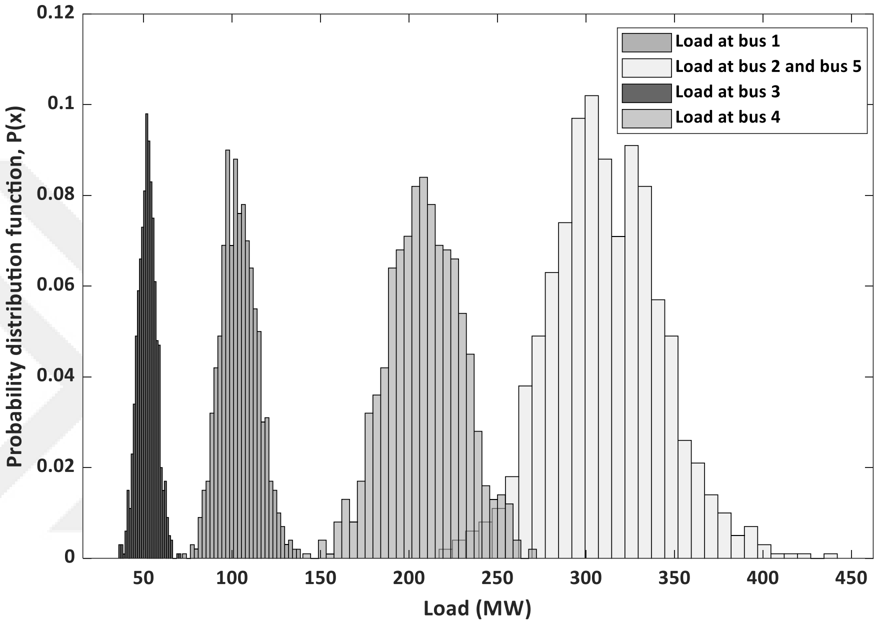

Figure 3.1 Probability distribution of load at each bus of network

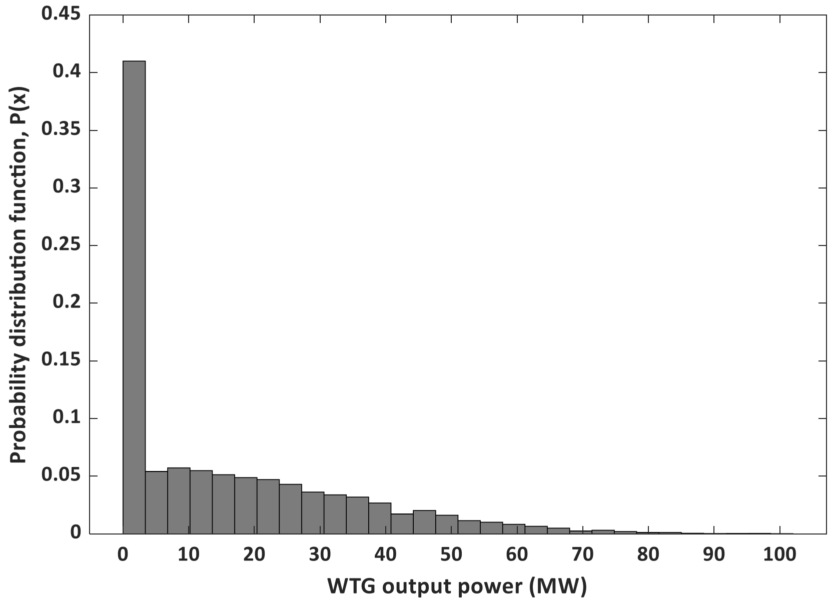

Figure 3.2 Distribution of WTG output power

3.2 Mathematical Formulation of Two-level, Stochastic and Network Constrained GEP Problem

In the network constrained approach, the aim is to find the type, capacity and location of power plants. Based on this, a dc model that neglects losses is used for the representation of transmission network. Two-level programming is a useful technique for combining two separate optimization problems. In this study, GEP problem and DC-OPF are solved jointly which are two separate optimization problems. The GEP problem which aims the best investment decisions by minimizing total cost is solved at the upper level. In the lower level, DC-OPF is performed and expected production and load curtailment costs are calculated under the Monte Carlo Simulation.The operation of the two-level model is summarized in Figure 3.3.

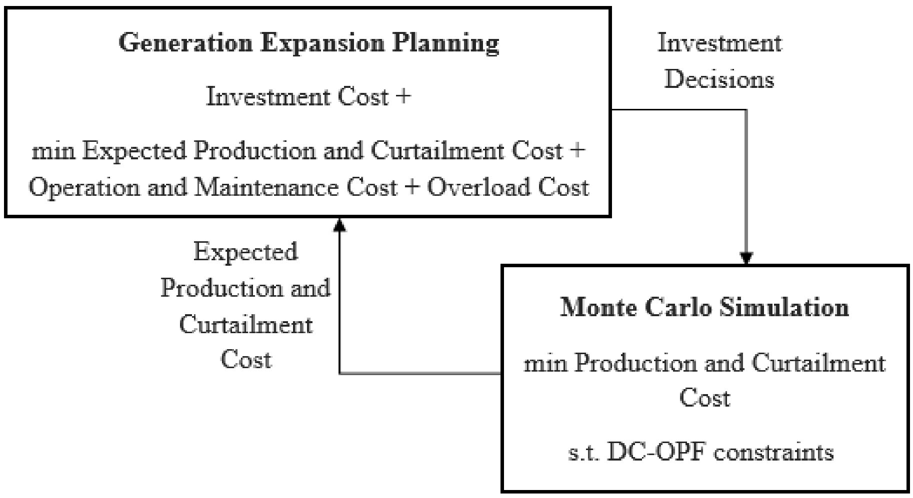

Figure 3.3 Proposed flowchart for GEP

As it can be seen in Figure 3.3, while the overall cost is minimized at the upper level, the expected production and load curtailment costs are calculated by obtaining optimum power output of the plants, curtailment level of loads and angles of buses for each scenario in the lower-level problem. In the optimization process, the decision variables of the upper-level problem determine the upper limits of the decision variables for power output of the plants in the lower-level optimization. The expected production and curtailment costs are calculated with Monte Carlo Simulation for different load-wind scenarios in the lower level. After the Monte Carlo Simulation, PDF of the power flows obtained for each scenario are extracted so that overall probability of exceeding the limit is obtained for each line. Then, total overload cost is calculated accordingly. In this regard, the best investment decision is determined by considering the expected costs, investment cost, O&M cost and overload cost jointly. The mathematical formulation of the probabilistic network constrained GEP problem is given as follows:

$$\begin{aligned}\min \sum_{c} C_c^{investment\ (annual)} P_c^{cap} X_c + \sum_{r} C_r^{investment\ (annual)} P_r^{cap} X_r \\ + \rho \left[\sum_{e \in \Omega_n^E} C_e^{production} P_{ew}^E \right. \\ \left. + \sum_{c \in \Omega_n^C} C_c^{production} P_{cw}^C + \sum_{f \in \Omega_n^D} C_f^{curtailment} P_{fw}^D \right] \\ + \left[\sum_{e} C_e^{o\&m} P_e^{cap} + \sum_{c} C_c^{o\&m} P_c^{cap} X_c + \sum_{r} C_r^{o\&m} P_r^{cap} X_r \right] \\ + \sum_{l} C_l^{overload}\ \gamma_l^{overload}\end{aligned} \tag{3.1}$$

s.t.

$$X = (X_c^1, \dots, X_c^n, X_r^1, \dots, X_r^n)\ , \forall c, \forall r \tag{3.2}$$

$$0 \leq X_c \leq X_c^{max}\ , \forall c \tag{3.3}$$

$$0 \leq X_r \leq X_r^{max}, \forall r \tag{3.4}$$

$$\begin{aligned}(P_{ew}^E, P_{cw}^C, P_{dw}^D, P_{fw}^D) = \Bigg\{ \\ \min \sum_{e \in \Omega_n^E} C_e^{production} P_{ew}^E + \sum_{c \in \Omega_n^C} C_c^{production} P_{cw}^C \\ + \sum_{f \in \Omega_n^D} C_f^{curtailment} P_{fw}^D\end{aligned} \tag{3.5}$$

s.t.

$$\begin{aligned}\sum_{e \in \Omega_n^E} P_{ew}^E + \sum_{c \in \Omega_n^C} P_{cw}^C + \sum_{r \in \Omega_n^R} P_{rw}^R + \sum_{f \in \Omega_n^D} P_{fw}^D - \sum_{l|s(l)=n} P_{lw}^L + \sum_{l|r(l)=n} P_{lw}^L \\ = \sum_{f \in \Omega_n^D} P_{dw}^D\end{aligned} \tag{3.6}$$

$$0 \leq P_{cw}^C \leq P_c^{cap} X_c\ , \forall c \tag{3.7}$$

$$0 \leq P_{ew}^{E} \leq P_{e}^{cap}, \forall e \tag{3.8}$$

$$0 \leq P_{fw}^{D} \leq P_{dw}^{D}, \forall f, \forall d \tag{3.9}$$

$$P_{lw}^{L} = B_l \left(\theta_{s(l)w} - \theta_{r(l)w}\right), \forall l \tag{3.10}$$

$$-\pi \leq \theta_{nw} \leq \pi, \forall n \tag{3.11}$$

$$\theta_{nw} = 0 : n = ref.\ node \tag{3.12}$$

$$\}, \forall w$$

The sub-indexes c, r, e, d, f, w and l used in the equations represent the candidate conventional power plant, the candidate wind power plant, the existing power generation plants in the system, load, curtailment, scenario and transmission line, respectively. The upper indexes used in the equations are E, C, R, D, cap, o&m, refer to existing, candidate, and wind farms set, total load, unit capacity of power plants and operation and maintenance costs, respectively. The objective function given in (3.1) minimizes the total investment, expected production and curtailment costs, operation&maintenance cost and overload cost. $\gamma_l^{overload}$ refers to total sum of the overload probabilities of line l for all scenarios. The ρ value of 8760 for the annual production costs and the annual investment costs of the candidate power plants are used for the costs in the reference year. The upper-level decision variables are the number of power plants (X_c, X_r); constraints are the maximum allowable number of candidate generation units given in (3.3) and (3.4) In the lower-level problem, the objective function is given in (3.5) and its variables are the production values of power plants (P_{cw}^{C}, P_{ew}^{E}) and curtailment values for each load (P_{fw}^{D})in each scenario. P_{rw}^{R} values represent the wind power outputs from each scenario in the Monte Carlo Simulation. In lower level, the constraints are given in equations (3.6) – (3.12). (3.6) is the equality constraint for generation-demand balance in each bus. Equation (3.7) and (3.8) represent the power production limits of candidate conventional and existing power plants, respectively. Equation (3.9) defines the load curtailment limits for each load. Power flows through transmission lines are integrated to the model via equation (3.10). (3.11) is the bound of voltage angles while the (3.12) represents the voltage angle at the reference bus.

3.3 Case Studies on Two Stage, Stochastic and Network constrained GEP

Network constrained and probabilistic GEP model is presented via two-level MILP optimization model and solved via MATLAB. Garver's 6-bus system is utilized to assess the proposed GEP model considering uncertainties of wind and load. In the optimization, candidate power plants are considered as combined cycle, hydroelectric and wind power plants, respectively. The capacity of each power plants is 100 MW. The maximum number of generation units is three for CCGT and hydroelectric power plants while it is ten for wind power plant. Fuel, operation and maintenance costs are taken into account (Abdalla et al., 2020; Careri et al., 2011) while calculating the costs. The load curtailment cost is considered as 90 $/MWh. Uncertainties are described through distribution functions for load and wind, and the optimization process is carried out by obtaining expected production and curtailment costs considering multiple scenario combinations under Monte Carlo Simulation. After the investment decisions are determined, it is observed that the generation-demand balance is guaranteed for the overloading and no overloading scenarios under all conditions when the obtained production plans are tested with 8760 different probabilistic load and wind scenarios.

3.3.1 Case 1: Effect of the Line Overloading

In the first stage of the study, which will be referred to as Case-1, investment plans are obtained by considering overloading and no overloading scenarios for transmission lines. Results are given in Table 3.1.

Table 3.1 Case-1 GEP plans with and without overloading

Scenario	Investment Plan	Total Cost (M$/year)
Overloading	S1(bus 5, x3), S3(bus 2, x3)	326, 650
No overloading	S1(bus 5, x3), S3(bus 2, x4)	307, 650

As seen in the above table, investment plans and total costs obtained for with and without overloading scenarios are different. In the overloading case, it is observed that total cost is higher than no overloading scenario. The main reason for this is that the latter does not include any additional cost due to overloading.

3.3.2 Case 2: Effect of the Line Limits

In the second phase of this study, referred to as Case-2, the effect of transmission line limits on investment plans and total cost has been investigated. Results for this scenario are provided in Table 3.2.

Table 3.2 Case-2 The effects of transmission line limits on GEP plans

Case	Transmission line limits	Investment Plan	Total Cost (M$/year)
2.1	50 %	S1(bus 4, x3), S3(bus 2, x3)	369, 220
2.2	75 %	S1(bus 5, x3), S3(bus 2, x3)	338, 870
2.3	100 %	S1(bus 5, x3), S3(bus 2, x3)	326, 650

As the transmission line limits decrease, probabilistic GEP decisions change and it is observed that the total cost also increases gradually. The decrease in the line limits both increases the total overload cost and causes the investment plan to change as in the transition from Case 2.1 to Case 2.2.

3.4 Conclusions

In this study, two-level optimization model is used for static and network constrained GEP problem and uncertainties are dealt with scenario-based approach. The impacts of overloading and transmission line limits on investment decisions and total cost have been investigated through case studies. As a result of the case studies, it has been observed that consideration of overloading and network constraints has a direct impact on investment decisions and total cost. As a consequence of this, the development of planning models that represent different uncertainties and include network constraints remains a current research topic. Apart from this, transmission line congestions results LMPs at system buses within market environment and it effects profit of private investors directly. This will be our next research topic.

CHAPTER FOUR
GENERATION EXPANSION PLANNING: DECENTRALIZED APPROACH

With liberalization of electricity industry that emerged in the mid-1980s, generation, transmission, and distribution operations are separated and owned by independent companies, such as GENCOs that compete with each other by selling power for maximum profit, TRANSCO to deliver power via high voltage system with respect to monopoly, and DISCO who are independent and provide power to the end user. Power system also includes ISO who is responsible for market operations while ensuring the reliability of a power system (Shahidehpour et al., 2002). In deregulated environment, GENCOs send their investment plans and price offers to the ISO. After market is cleared by the ISO, market clearing prices are obtained and output price signals are delivered to the each individual GENCO.

From GENCO's point of view, it has become vital to be able to analyze and model the behavior of the market in order to get informed investment decisions. GEP problem is the one that has been dealt with comprehensively. The objective function of GEP problem has changed from minimization of total costs to the profit maximization with the liberalization of electricity industry (Ramos et al., 1999). In that manner, GEP problem can be modelled centralized approach which aims to maximize social welfare. On the other hand, the market-based model aims to maximize GENCO's profit in a competitive electricity pool. Now, the GENCO's decision does not only affect its own profits but also affects the decisions of other participants. It is called as "strategic decisions" in literature (Kagiannas et al., 2004). Consequently, modeling of the GEP problem become more challenging since it is required to model competition between GENCO's as well as representation of power system in technical manner. In literature, the different models have been developed for GEP problems under deregulated environment.

In the study (Hogan, 1997), each GENCO's profit maximization problem is addressed by considering network constraints. Game theory and Cornout model are commonly investigated to model the GEP problem under deregulated environment (Sadeghi et al., 2017). In (Sarjiya et al., 2019), competition between agents is represented with game theory for multi-objective GEP problem. The two-level optimization method is used to handle the economic and reliability objective functions. The optimization results show that levelized total cost using game theory is lower than the improved genetic algorithm while computation time is pretty much higher. In (Barati et al., 2019), new model for DGEP is proposed based on private investor's perspective. However, it does not only include the economic objectives and constraints of the private investors but also, the technical constraints of the power network are included. HTPEM is used to include DG’s uncertainties and overcome computational burden due to these uncertainties. In (Hemmati et al., 2013b), the impact of wind power uncertainties in electricity market is investigated for profit maximization problem of GENCOs. Monte-Carlo simulation is utilized to include uncertainty to the problem. Security and reliability constraints such as LOLE and reserve margin are incorporated into problem. The problem is organized as master and slave sectors. The profit maximization problem of each GENCOs is in slave sector while technical constraints are checked by ISO in master sector. Cournot model is utilized to obtain market prices. In (Baringo & Conejo, 2013a), stochastic behaviour of wind power plants was addressed in GEP problem by representing wind generation and load via scenarios without strategic behavior of the investor. K-means clustering method was used to obtain lower number of operating conditions by reducing data sets of load and wind power production. In addition to the previous study, strategic behavior of investor is considered in (Baringo & Conejo, 2011), and the market price is also represented via scenarios for generation investment problem in (Baringo & Conejo, 2014).

In this chapter, stochastic GEP model is presented by taking into account network constraints and uncertainties in load and wind power generation within market environment. Stochastic two-level model is proposed where upper-level problem represents the investment decisions with the aim of maximizing profit and its lower-level problem represents the market clearing under different load and wind power production conditions. The proposed model is demonstrated using case studies.

4.1 GEP Problem in Market Environment

In terms of uncertainties, the GEP problem can be handled with a deterministic and stochastic approach. In this section, stochastic programming (Conejo et al.,

2010) is used and uncertainties in the wind power production and load are represented via scenarios (Birge & Louveaux, 2011) Load and wind duration curve method (Baringo & Conejo, 2011) is used in order to handle the uncertainty of and correlation between wind power production and load. In this section, a static, network constrained approach is considered with two-bus and six-bus test systems. In this model, the upper part aims to maximize profit of GENCO while in the lower part market clearing problem is solved. This model is generally called as two-level model in literature (Conejo et al., 2016). Subsequently, two-level model turns into single level problem, which is called as MPEC (Luo et al., 1996). MILP formulation is attained after using some linearization methods. Proposed two-level model can be shown in Figure 4.1.

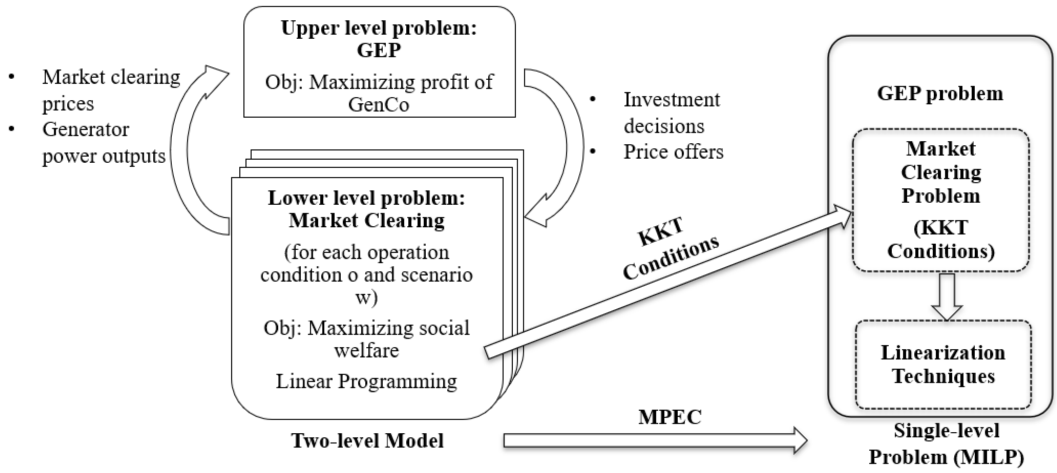

Figure 4.1 Two-level model for proposed GEP problem

4.2 Mathematical Formulation of GEP Problem in Market Enviroment

4.2.1 Two-level Formulation

The mathematical formulation of GEP problem under decentralized environment is given based on a two-level model. It includes an upper-level problem with equations (4.1)–(4.9) and a lower-level problem with equations (4.10)–(4.19) for each operating condition o and scenario w. The mathematical formulation is given as follows:

$$\min \quad \sum_{n}(K_n^C x_n^C + K_n^S x_n^S) \tag{4.1}$$

$$- \sum_{w} \varphi_w \sum_{o} p_o \sum_{n} \big[\lambda_{now}(P_{now}^C + P_{now}^E + P_{now}^S)$$

$$- P_{now}^C C_n^{production} - P_{now}^E C_n^{production}\big]$$

subject to

$$x_n^C = \sum_{h} u_{nh}^C X_{nh}^C \; \forall n \tag{4.2}$$

$$\sum_{h} u_{nh}^C = 1, \forall n \tag{4.3}$$

$$u_{nh}^C \; \in \; \{0, 1\} \; \forall n, \forall h \tag{4.4}$$

$$0 \leq \; x_n^S \leq X_n^S \; \forall n \tag{4.5}$$

$$\sum_{n}(K_n^C x_n^C + K_n^S x_n^S) \leq K^{max} \tag{4.6}$$

$$\alpha_{now}^C \geq 0 \; \forall o, \forall n, \forall w \tag{4.7}$$

$$\alpha_{now}^E \geq 0 \; \forall o, \forall n, \forall w \tag{4.8}$$

Lower-level problems (4.10)‒(4.19) $\forall o$, $\forall \omega$ (4.9)

$$\min \quad \sum_{n}[\alpha_{now}^C P_{now}^C + \alpha_{now}^E P_{now}^E + C_{no}^R P_{now}^R - U_{no}^D P_{now}^D] \tag{4.10}$$

subject to

$$P_{now}^D + \sum_{m \in \Omega_n} B_{nm}(\theta_{now} - \theta_{mow}) - P_{now}^C - P_{now}^S - P_{now}^E - P_{now}^R \tag{4.11}$$

$$= 0 \quad : \lambda_{now} \quad \forall \text{n}$$

$$0 \leq P_{now}^C \leq x_n^C \quad : \mu_{now}^{C^{min}}, \mu_{now}^{C^{max}} \quad \forall \text{n} \tag{4.12}$$

$$0 \leq P_{now}^S \leq Q_{no}^S x_n^S \quad : \mu_{now}^{S^{min}}, \mu_{now}^{S^{max}} \quad \forall \text{n} \tag{4.13}$$

$$0 \leq P_{now}^E \leq P_n^{E^{max}} : \mu_{now}^{E^{min}}, \mu_{now}^{E^{max}} \quad \forall \text{n} \tag{4.14}$$

$$0 \leq P_{now}^R \leq P_{nw}^{R^{max}} : \mu_{now}^{R^{min}}, \mu_{now}^{R^{max}} \quad \forall \text{n} \tag{4.15}$$

$$0 \leq P_{now}^D \leq Q_{no}^D P_n^{D^{max}} : \mu_{now}^{D^{min}}, \mu_{now}^{D^{max}} \quad \forall \text{n} \tag{4.16}$$

$$B_{nm}(\theta_{now} - \theta_{mow}) \leq F_{nm}^{max} : \mu_{now}^F \; \forall \text{n} \tag{4.17}$$

$$-\pi \le \theta_{now} \le \pi: \ \mu_{now}^{\theta^{min}}, \mu_{now}^{\theta^{max}} \ \forall \text{n} \tag{4.18}$$

$$\theta_{now} = 0 \ \ : \mu_{ow}^{\theta^{ref}} \ \ \ n = ref. \tag{4.19}$$

In (4.1), the proposed objective function of upper-level problem is given which includes expected revue, investment cost and production cost. $\lambda_{now}(P_{now}^{C} + P_{now}^{E} + P_{now}^{S})$ is the revenue of GENCO while λ_{now} is the market clearing price at bus n for operation condition o and scenario w. Annualized investment cost $\sum_n (K_n^C x_n^C + K_n^S x_n^S)$ is considered since static approach is adopted. Production costs for candidates C_n^C and existing power plants C_n^E are multiplied by their power outputs P_{now}^C and P_{now}^E, their corresponding weights for each operation condition p_o and weight of scenario φ_w. This makes production costs comparable to annualized investment cost. Investment is only available in discrete blocks, which is modeled via constraint (4.2) - (4.4). Constraint (4.5) means that power outputs of stochastic power plants are continuous for the sake of simplicity. Equation (4.6) is constraint for the inclusion of the upper limit of the investor's maximum annual financial resources. Constraints (4.7) - (4.8) represent the nonnegativity of supply price offers for conventional candidate and existing power plants, respectively. It is assumed that price offer of stochastic power plant is zero for the sake of simplicity. The optimization problem of market clearing is detailed in next section.

In the lower level (4.10) - (4.19), market clearing is performed where objective function (4.10) is maximizing social welfare. There is no term from stochastic unit due to our zero-price offer assumption. Constraints (4.11) means the power balance equations for each operation condition at each bus and dual variable for this constraint is market clearing price λ_{now}. Constraints (4.12) and (4.15) are the generator output power limits for candidate, stochastic, existing and rival power plants. The constant Q_{no}^S is added to limit power output of stochastic power plant with corresponding intensity level. It is important to note that installed capacity is used as an upper bounds for the power output of the candidate plants. Constraint (4.16) enforces the consumed power by each end user. Q_{no}^D represents the demand factor for each operation condition at each bus. Constraint (4.17) limits the power flow from bus n to bus m with the transmission line capacity. Constraint (4.18) bounds voltage angle while Constraint (4.19) assigns reference bus that its voltage angle is zero.

$\lambda_{now}, \mu_{now}^{C^{min}}, \mu_{now}^{C^{max}}, \mu_{now}^{S^{min}}, \mu_{now}^{S^{max}}, \mu_{now}^{E^{min}}, \mu_{now}^{E^{max}}, \mu_{now}^{R^{min}}, \mu_{now}^{R^{max}}, \mu_{now}^{D^{min}}, \mu_{now}^{D^{max}}, \mu_{now}^{F},$ $\mu_{now}^{\theta^{min}}, \mu_{now}^{\theta^{max}}$ and $\mu_{ow}^{\theta^{ref}}$ are the dual variables of lower-level problem.

4.2.2 Mathematical Programming with Equilibrium Constraints Formulation

Each lower-level problem (4.10) - (4.19) is linear and continuous. They can be replaced by using the KKT conditions (Kuhn & Tucker, 1951). That is, the proposed two-level model can be formulated as a stochastic MPEC (Conejo et al.,2012). Instead of lower-level problem (4.10) - (4.19), the following MPEC is obtained with the help of KKT conditions.

$$\min \quad (4.1) \tag{4.20}$$

$$\text{subject to}$$

$$(4.2)-(4.8),\ (4.11) \text{ and } (4.19) \tag{4.21}$$

$$\frac{\partial L_{ow}}{\partial P_{now}^{C}} = \propto_{now}^{C} - \lambda_{no\omega} - \mu_{now}^{C^{max}} - \mu_{now}^{C^{min}} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.22}$$

$$\frac{\partial L_{ow}}{\partial P_{now}^{S}} = -\lambda_{no\omega} - \mu_{now}^{S^{max}} - \mu_{now}^{S^{min}} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.23}$$

$$\frac{\partial L_{ow}}{\partial P_{now}^{E}} = \propto_{now}^{E} - \lambda_{no\omega} - \mu_{now}^{E^{max}} - \mu_{now}^{E^{min}} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.24}$$

$$\frac{\partial L_{ow}}{\partial P_{now}^{R}} = C_{no}^{R} - \lambda_{no\omega} - \mu_{now}^{R^{max}} - \mu_{now}^{R^{min}} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.25}$$

$$\frac{\partial L_{ow}}{\partial P_{now}^{D}} = -U_{no}^{D} + \lambda_{no\omega} + \mu_{now}^{D^{max}} - \mu_{now}^{D^{min}} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.26}$$

$$\frac{\partial L_{ow}}{\partial \theta_{now}} = \sum_{m \in \Omega_n} B_{nm}(\lambda_{no\omega} - \lambda_{mo\omega}) + \sum_{m \in \Omega_n} B_{nm}(\mu_{nmo\omega}^{F} - \mu_{mno\omega}^{F}) + \mu_{now}^{\theta^{max}} - \mu_{now}^{\theta^{min}} + \left(\mu_{ow}^{\theta^{ref}}\right)_{n=ref} = 0 \quad \forall n, \quad \forall o, \quad \forall w \tag{4.27}$$

$$0 \le P_{now}^{C} \perp \mu_{now}^{C_{min}} \ge 0 \ \forall n, \quad \forall o, \quad \forall w \tag{4.28}$$

$$0 \leq (x_n^C - P_{now}^C) \perp \mu_{now}^{C_{max}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.29}$$

$$0 \leq P_{now}^S \perp \mu_{now}^{S_{min}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.30}$$

$$0 \leq (Q_{no}^S x_n^S - P_{now}^S) \perp \mu_{now}^{S_{max}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.31}$$

$$0 \leq P_{now}^E \perp \mu_{now}^{E_{min}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.32}$$

$$0 \leq \left(P_n^{E^{max}} - P_{now}^E\right) \perp \mu_{now}^{E_{max}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.33}$$

$$0 \leq P_{now}^R \perp \mu_{now}^{R_{min}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.34}$$

$$0 \leq \left(P_{nw}^{R^{max}} - P_{now}^R\right) \perp \mu_{now}^{R_{max}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.35}$$

$$0 \leq P_{now}^D \perp \mu_{now}^{D_{min}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.36}$$

$$0 \leq \left(Q_{no}^D P_n^{D^{max}} - P_{now}^D\right) \perp \mu_{now}^{D_{max}} \geq 0 \; \forall n, \quad \forall o, \quad \forall w \tag{4.37}$$

$$0 \leq \left(F_{nw}^{max} - B_{nm}(\theta_{now} - \theta_{mow})\right) \perp \mu_{nmow}^{F_{max}} \geq 0 \; \forall n, \; \forall o, \forall m \in \Omega_n, \forall w \tag{4.38}$$

$$0 \leq (\pi + \theta_{now}) \perp \mu_{now}^{\theta^{min}} \geq 0 \;\; \forall n, \forall o, \forall w \tag{4.39}$$

$$0 \leq (\pi - \theta_{now}) \perp \mu_{now}^{\theta^{max}} \geq 0 \;\; \forall n, \forall o, \forall w \tag{4.40}$$

After some linearization methods (Ruiz & Conejo, 2009), this MPEC can be reformulated as MILP problem which can be solved using currently available branch-and-cut solvers.

4.3 Case Studies On GEP Problem with Market Environment

In this section, proposed model is illustrated with the case studies that details are as below.

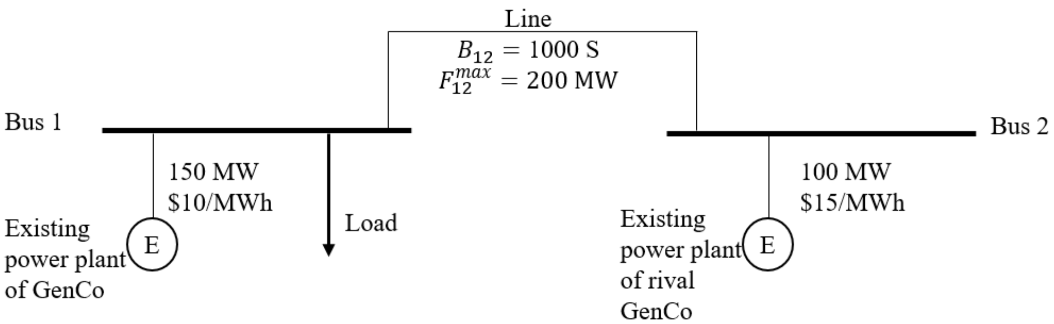

Figure 4.2 Two-bus system for Case-1 and Case-2

In proposed two-bus system, which can be seen in Figure 4.2, there is a line between bus 1 and bus 2 that has 200 MW capacity and susceptance of 1000 S. The impact of change in transmission line limit on results will be investigated in Case-1. It is assumed that there are two GENCOs competing with each other and having existing power plants at different buses. In the first case, while one of these GENCOs intends to invest a new power plant, but its rival is not. Production costs and capacities of existing plants are 150 MW and $10/MWh for GENCO and 100 MW and $15/MWh for rival GENCO. It is assumed that rival GENCO supply its production cost as an offer. For candidate power plant, it has $55, 000/MW as an investment cost and $12/MWh as a production cost. The maximum load is considered as 300 MW and there is only one operation condition. Demand bid is equal to $35/MWh. Supply offer for candidate stochastic power plant is considered as 0 $/MWh. Investment cost cap is determined to be $10 million. In case-1, stochastic power plant is not considered while it is considered as a candidate option in Case-2. It has 200 MW capacity, and its investment cost is $66,000/MW. Apart from this, two operation conditions and two scenarios are considered in addition to the case-1 in case-2. The first scenario has 0.6 probability and correspond to no new investment for rival GENCO. The other scenario has 0.4 probability for the investment of 40 MW conventional power plant of rival GENCO to the bus 1. It is considered that production cost for this plant is $13/MWh. Details can be found in Table 4.1.

Table 4.1 Data for defining Case-1 and Case-2

	Case-1	Case-2			
Scenario	1	1 (0.6 prob.)		2 (0.4 prob.)	
Operation condition	1	1	2	1	2
Demand factor (p.u.)	1	1	0.8	1	0.8
Wind power capacity factor (p.u.)	-	0.35	0.70	0.35	0.70
Supply offer for candidate stochastic power plant of GENCO ($/MWh)	-	0	0	0	0
Consumer bids ($/MWh)	35	35	32	35	32
Rival GENCO investment	-	-	-	Yes	Yes
Rival GENCO offer for new investment ($/MWh)	-	-	-	13	13

4.3.1 Case 1: Effect of Line Limits for Determistic Case

In the first case, there is no congestion on the line. Thus, local marginal prices for each bus are the same and equal to \$35/MWh. The impact of line limit on the result can be shown in Table 4.2.

Table 4.2 Results for Case-1

Scenario	Investment Plan	LMP (\$/MWh)	Annual Profit (M\$/year)
Case-1 (Line limit 200 MW)	S1(100 MW)	Bus1:35 Bus2:35	38.74
Case-1 (Line limit 80 MW)	S1(100 MW)	Bus1:35 Bus2:15	41.45
Case-1 (Line limit 50 MW)	S1(100 MW)	Bus1:35 Bus2:15	47.50

As a result of first case, investment plan is to install 100 MW new capacity to the bus 1. Supply offer for portfolio of GENCO is equal to demand bid since it is a strategic producer. That is, it makes such an offer to create a higher market price. The change in line limit affects the LMP and total annual profit. Through the decrease in the line limit, a part of the load dispatch more cheaply from rival GENCO decreases, and GENCO's increases, it results increase in annual profit.

4.3.2 Case 2: Integrating Candidate Wind Power Plant and Investment Uncertainty of Rival

In Case-2, stochastic wind power option and rival's investment uncertainty are included. The investment decision of the rival power plant is considered as the source of uncertainty. Based on this, it is expected to decrease in total profit with respect to deterministic scenario which is a no investment option for rival. The decrease amount of profit is 3.25 M\$. The installation of strategic GENCO will be the wind power plant at Bus 2 and its capacity is determined as 142.86 MW. In the first scenario of Case-2, LMPs are equal to the supply offers of GENCO since its existing power plant is dispatched. Supply offer is equal to the demand bids due to the strategy of GENCO. In the second scenario of Case-2, GENCO's power output drops with the amount of new installed capacity of rival which is 40 MW in both operation condition compared to the first scenario. LMPs depend on line limits as well as how much of the power plants are dispatched. In the second operation condition of second scenario of Case-2, all power plants are fully dispatched except for the existing power plant of GENCO. However, LMP is still equal to the offer of this plant since the next MW's to be provided at bus 1 will be delivered by this plant.

4.4 Conclusions

In this section, we have investigated the GEP problem in under market environment, where a single GENCO aims to maximize its profits. The problem is modeled with stochastic two-level model. While the generation expansion problem is handled at the upper level, there is the market clearing problem at the lower level. This two-level mathematical framework is formed as MPEC with the help of KKT conditions and reformulated as MILP with some linearization methods. In the first of the case studies, the effect of the system line limit on the problem outputs is examined, while in the second, the investment option of a stochastic wind farm and the rival GENCO's investment uncertainty are incorporated into model. In addition to line limits, it has been observed that the rival's investment decision uncertainty reduces GENCO's profit and can affect LMP. In future studies, GEP study will be conducted for larger systems under different uncertainty sources such as load, stochastic power plant output and market price in a decentralized environment.

CHAPTER FIVE
DISCUSSION

GEP is a highly complex problem involving many interrelated power system analysis studies. It is usually modeled as two-level model and lower level of the problem is mainly to balance the load while meeting the operational constraints. Integration of renewable energy sources into the grid led to make power plant investment decisions in more uncertain and risky environment. From a market perspective, private investors with different objectives are often involved in making investment decisions. Uncertainties of other investors and market price complicate this problem more. In this context, the problem, which is complex and uncertain by its nature, must be handled carefully in order to make informed investment decisions. The most widely used method of incorporating uncertainty into planning problems are MCS and scenario-based approach (Soroudi & Amraee, 2013). In MCS, the fixed value of the decision variables and the PDF of the uncertain input parameters are used to obtain the PDF of the objective function of the problem. In the scenario-based approach, the PDF of the uncertain parameter is split into several blocks. In each block, the probability of the uncertain variable corresponding to the scenario is calculated (Conejo et al., 2010). In the scope of this thesis, the integration of load and wind uncertainties with MCS into the two-level GEP problem are discussed for single-bus and network constrained models in Chapter 2 and Chapter 3, respectively. The scenario-based approach, on the other hand, is discussed in Chapter 4 integrating a rival investor's uncertain investment decision into the problem.

The development of market mechanisms in the energy industries has changed traditional GEP models and solution approaches. The objective function of GEP problem has been evolved from minimization of overall costs to maximization of profit (Ramos et al., 1998). However, the market mechanism includes the following uncertain parameters in addition to a regulated market; investment decisions of other players, bid strategies and electricity price of the market and so on. This makes modeling of the GEP problem more challenging since it is required to include competition between GENCO’s as well as additional uncertainty. Chapter 2 and Chapter 3 deal with a GEP problem under a regulated electricity market whose objective function is minimization of total costs while Chapter 4 examine a market-based investment problem that single GENCO competes in an electricity pool market with the aim of maximizing its profit.

For GEP problems, it is generally sufficient to determine only the candidate power plant type and size if the transmission lines are not congested. However, the increase in the share of renewable energy plants generally causes congestion in transmission lines (Bird et al., 2014). Therefore, the inclusion of network constraints to the GEP model has become even more important and will also facilitate the selection of the best locations where new generation capacities can be built. For the sake of simplicity, GEP problem with a single-bus approach where network constraints are not included, is considered in Chapter 2. Then, network constrained GEP model are discussed for six-bus and two-bus system in Chapter 3 and Chapter 4, respectively. The effects of overloading and transmission line limits on investment decisions and total cost are investigated with case studies in Chapter 3.

GEP is a considerably complex problem due to mixed-integer and nonlinear structure. In that manner, many researchers have developed different type of modeling approaches and optimization methods. A great number of solution methods have been investigated to solve this problem. These methods can be classified into mathematical and metaheuristic optimisation techniques (Hemmati et al., 2013a). Even if mathematical optimisation techniques ensure the global solution in a reasonable amount of time, they are not capable of dealing with the complex optimization problems. On the contrary, metaheuristic optimisation techniques may give local solutions as a results while they can make sure achieving feasible results with reasonable computational effort. In Chapters 2 and 3, a metaheuristic optimization method is used to solve the proposed stochastic two-level optimization problems while MPEC that let to represent both the investment decisions and the electricity market has been considered in Chapter 4.

CHAPTER SIX
CONCLUSION

In this thesis, GEP is studied in the view of different aspects. The general overview of this study and some concluding remarks are presented in this chapter as follows.

In Chapter 2, the effects of uncertainties with deterministic and probabilistic scenario approaches on investment decisions have been investigated in terms of total costs. Two-level optimization is used to model both economic dispatch and GEP problem together where the GEP problem is solved at the upper level and the economic dispatch is solved at the lower level. Uncertainties are dealt with scenario-based approach while the problem is solved by using the metaheuristic optimization technique. The main aim is to present the importance of including uncertainties in planning studies. In this sense, two different cases are considered. One is for comparison between deterministic and probabilistic scenarios while the other one is for the effect of different load variations on investment plans. It is worth mentioning that the investment decisions obtained in the probabilistic GEP model, in which the uncertainties are included with the Monte Carlo Simulation, can have more economic results. From the load variation point of view, an increase in the standard deviation of the load results in different investment decisions and increase in total cost. The results show that it is essential to include uncertainties in the GEP problem to make more economical and informed investment decisions.

The previous chapter describes the GEP problem from the perspective of a single-bus approach that determines only the plant type and its capacity. Unlike the problem in the previous chapter, Chapter 3 addresses a generation investment problem, in which the transmission network constraints are included in the problem. The representation of the network is DC model and power losses are not taken into account for simplicity. Garver’s 6-bus system is used for proposed GEP model. As in Chapter 2, uncertainties in the GEP problem are dealt with Monte Carlo Simulation and two-level programming method is proposed to model problem. The effects of transmission line limits and overloading on investment decisions and overall cost have been investigated via case studies. The results show that consideration of overloading and network constraints has a direct impact on investment decisions by changing GEP plans. It is important to consider not only network constraints but also the cost of exceeding line limits in optimization process to make a meaningful investment decision.

In the previous two chapters, GEP problem is illustrated from the central planner's point of view which determines the investment plan which has the least cost. On the contrary, Chapter 4 deals with a market-based investment problem. This study considers a single GENCO that is competing in an electricity market to maximize its profit. First, the impact of the transmission line limit on the results is examined. It is observed that LMP and total annual profit have changed with respect to transmission line limit. Along with the decline in the line limit, a part of the load dispatch from rival GENCO decreases. Consequently, strategic GENCO's share in this dispatch increases and it results increase in annual profit accordingly. Apart from this, GENCO makes offer to create a higher market price. Secondly, stochastic wind power option and rival's investment uncertainty are included. The investment decision of the rival power plant is considered as the source of uncertainty. It is observed that rival's investment decision uncertainty have an impact on GENCO's profit and may affect LMP with respect to no investment scenario of rival.

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APPENDICES

APPENDIX A: GARVER 6 BUS TEST SYSTEM

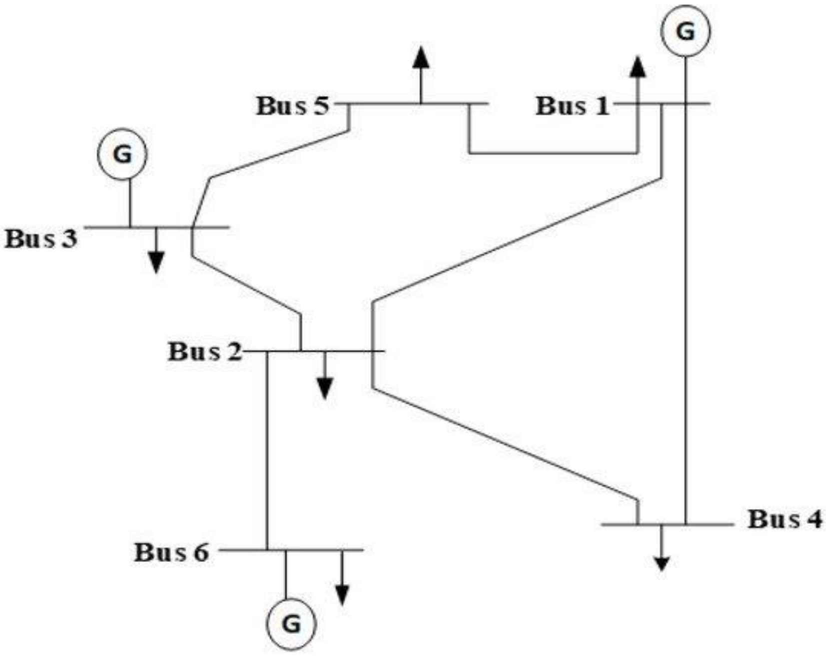

Figure A.1 Garver 6-bus test system

Table A.1 Bus data of the Garver system

Bus	Type	P_D, MW	Q_D, MVAr	P^{max}, MW	P^{min}, MW	Q^{max}, MVAr	Q^{min}, MVAr
1	Vu	80	16	160	0	48	210
2	PQ	240	48	–	–	–	–
3	PV	40	8	370	0	101	210
4	PQ	160	32	–	–	–	–
5	PQ	240	48	–	–	–	–
6	PV	0	0	610	0	183	210

Table A.2 Line data of the Garver system

Bus F	Bus T	r_{ij}, pu	x_{ij}, pu	b^{sh}, pu	S^{max}, MVA	C_{ij},$
1	2	0.040	0.400	0.00	120	40
1	3	0.038	0.380	0.00	120	38
1	4	0.060	0.600	0.00	100	60
1	5	0.020	0.200	0.00	120	20
1	6	0.068	0.680	0.00	90	68
2	3	0.020	0.200	0.00	120	20
2	4	0.040	0.400	0.00	120	40
2	5	0.031	0.310	0.00	120	31
2	6	0.030	0.300	0.00	120	30
3	4	0.059	0.590	0.00	120	59
3	5	0.020	0.200	0.00	120	20
3	6	0.048	0.480	0.00	120	48
4	5	0.063	0.630	0.00	95	63
4	6	0.030	0.300	0.00	120	30
5	6	0.061	0.610	0.00	98	61