MATHEMATICAL PROGRAMMING APPROACHES FOR A GENERATION EXPANSION PLANNING PROBLEM IN A CARBON-CONSTRAINED ENVIRONMENT

by

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ABSTRACT

MATHEMATICAL PROGRAMMING APPROACHES FOR A GENERATION EXPANSION PLANNING PROBLEM IN A CARBON-CONSTRAINED ENVIRONMENT

In this thesis, we study a Generation Expansion Planning (GEP) problem in a carbon-constrained environment from the perspective of a private electricity generating company. The company plans to enter the partially regulated electricity generation market, in which carbon emission permits are traded. Hence, the government requires the company to obey a limit for the total carbon emission. The company determines the amount of installed capacity for different types of power plants, which may or may not include carbon capture and storage (CCS) technology over a predetermined planning horizon. The company's aim is to maximize the net present value of the total profit. The market and the company have some restrictions on the investments. The amount of installed capacity is limited by a maximum and a minimum value for each period for all power plant types. The government constrains the market share of the company in order to prevent monopoly. On the other hand, the company aims to reach certain levels of market share at certain time periods. Moreover, the company restricts the percentage of each type of power plant investments in the portfolio by some upper bound to distribute the investment risk. We first formulate the problem as a deterministic mixed integer linear programming model assuming that all data are known in advance and fixed. Then, we use multi-stage stochastic programming approach to include uncertainties in the parameters. We implement these models for a hypothetical company operating in Turkey. We apply sensitivity analysis in our deterministic model to determine the effects of parameters on the optimal decision.Then, in stochastic model, we analyze the problem by creating scenarios for uncertain parameters.

ÖZET

KARBON KISITLI ÇEVREDE KAPASİTE GENİŞLETME PLANLAMASI PROBLEMİ İÇİN MATEMATİKSEL PROGRAMLAMA YAKLAŞIMLARI

Bu tezde, kısmen regüle edilmiş bir elektrik pazarına girmek isteyen farazi özel bir elektrik üreticisi için yatırım planlaması ele alınmıştır. Ele alınan piyasada karbon salım kısıtı ve buna bağlı olarak karbon ticareti mevcuttur. Bu sebeple, şirket, hükümet tarafından belirlenmiş bir karbon emisyon üst sınırına sahiptir. Üretici şirketin yatırım yapabileceği termal ve yenilenebilir enerji santralleri mevcuttur. Ayrıca, termal enerji santrallerine eklenebilecek karbon yakalama ve tutma (CCS) teknolojileri mevcuttur. Şirketin toplam karbon salımı yatırım tipine bağlı olarak değişebilir. Bu bilgiler ışığında, şirket belirli bir planlama ufkunda net karın bugünkü değerini ençoklamayı amaçlamaktadır. Sektörün ve şirketin uyguladığı bazı kısıtlar vardır. Her yatırım tipi ve her periyod için yatırım yapılabilecek en fazla ve en az yatırım miktarı kısıtı mevcuttur. Ek olarak, şirketin belirli bir zaman periyodu içinde hedeflenen en az ve tekelleşmeyi engellemek için hükümet tarafından müsade edilen en çok pazar payı kısıtları vardır. Ayrıca, yatırımlardan kaynaklı olarak oluşan riski dağıtmak için her bir enerji santrali tipinin, toplam yatırım miktarı arasındaki yüzdesi bir üst sınır ile kısıtlanmıştır. İlk olarak, problem, parametre değerlerinin önceden bilindiği varsayımı ile deterministik karışık tamsayılı doğrusal programlama kullanılarak modellenmiştir. Sonrasında, çok aşamalı rassal programlama yaklaşımı önerilmiştir. Model, Türkiye'de faaliyet gösteren farazi bir firma için uygulanmıştır. Deterministik model yaklaşımında, parametrelerin optimal karar üzerine etkilerini ölçmek için duyarlılık analizi uygulanmıştır. Öte yandan, rassal programlama yaklaşımında, belirsizlik olan parametreler için senaryolar oluşturularak problem incelenmiştir.

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A	set of scenario nodes, $a \in A$
AC_{ula}	added capacity of type u power plant with type l CCS technology in scenario node a (MW)
AC_{ult}	added capacity of type u power plant that includes type l CCS technology in period t (MW)
AC_{ua}^{max}	upperbound on the generation capacity of type u power plant that can be added in scenario node a (MW)
AC_{ut}^{max}	upperbound on the generation capacity of type u power plant that can be added in period t (MW)
AC_{ua}^{min}	lowerbound on the generation capacity of type u power plant that can be added in scenario node a (MW)
AC_{ut}^{min}	lowerbound on the generation capacity of type u power plant that can be added in period t if decided to be built (MW)
AC_{u}^{pot}	total potential of the resourse u in the country (MW)
B	set of load blocks, $b \in B$
b_s	total branch number at stage s
C_a	total installed/projected capacity of the country in scenario node a (MW)
C_t	total installed/projected capacity of the country in period t (MW)
$CO_2^{buy,a}$	amount of carbon credits bought from other entities in scenario node a (ton)
$CO_2^{buy,t}$	amount of carbon credits bought from other entities in period t
$CO_2^{cap,a}$	carbon cap value assigned to the company in scenario node a (ton)
$CO_2^{cap,t}$	carbon cap value assigned to the company in period t (ton)
$CO_2^{sell,a}$	amount of carbon credits sold to other entities in scenario node a (ton)
$CO_2^{sell,t}$	amount of carbon credits sold to other entities in period t
CP_k	carbon price at branch k

D_{ab}	duration of load block b in scenario node a (h)
DF_a	discount factor in scenario node a
F	set of fuel types, indexed by $f \in F$
IC_{ul}	unit capital cost of type u power plant with l type CCS technology (\$/MW)
IR	initial ratio value for second stage
IR_k	initial ratio for branches which seperate from branch k
J	carbon price decision points, $j \in J$
K	set of branches, $k \in K$
L	set of CCS technologies, indexed by $l \in L$
LR	last ratio value for second stage
LR_k	last ratio for branches which seperate from branch k
MC_u	unit maintenance cost of type u power plant (\$/MWh)
N	set of node numbers, $n \in N$
OC_{ul}	unit operation and maintenance cost of type l CCS technology installed at type u power plant (\$/ton)
OMC_u	annual maintenance cost of type u power plant (\$/MWh)
P_j	carbon price values for jth decision to determine policies
PC_a	unit carbon price in scenario node a (\$/ton)
PE_{kn}	electricity price at the nth node of branch k
PE_1	initial electricity price value
PE^{bi}_{uab}	price of electricity that is generated at type u power plant in scenario node a in load block b and sold via bilateral contracts (\$/MWh)
PE^{da}_{uab}	price of electricity that is generated at type u power plant in scenario node a in load block b and sold in the day ahead market (\$/MWh)
PE_{ut}	electricity price that is generated at type u power plant in period t (\$/MWh)
PF_{fa}	unit cost of type f fuel in scenario node a (\$/ton or \$/lt)
PF_{ft}	unit cost of type f fuel in period t (\$/ton or \$/lt)
pr_a	probability of scenario node a

$p_t^{CO_2}$	unit carbon price in period t (\$/ton)
$pred(a)$	set of scenario nodes that includes power plants in operation at scenario node a
Q_{ula}	1, if a type l CCS is installed with type u plant in scenario node a; 0, otherwise
Q_{ult}	1, if a type l CCS is installed with type u plant in period t; 0, otherwise
r_t	interest rate for period t
S	stages, $s \in S$
T	set of time periods, indexed by $t \in T$
$\bar{t}_u$	construction period of type u power plant
TC_u	transportation cost of carbon captured at a power plant at type u power plant in year t (\$/ton)
U	set of power plants, indexed by $u \in U$
X_{ula}	amount of carbon captured in scenario node a at type l CCS technology added with type u plant (ton)
X_{ult}	amount of carbon captured in period t at type l CCS technology added with type u plant (ton)
Y_{ulab}^{bi}	amount of electricity generated at type l CCS technology added with type u power plants in scenario node a and sold via bilateral contracts during load block b (MW)
Y_{ulab}^{da}	amount of electricity generated at type l CCS technology added with type u power plants in scenario node a and sold at the day ahead market during load block b (MW)
Z_{ua}	1, if type u power plant is installed in scenario node a; 0, otherwise
Z_{ut}	1, if type u power plant is installed in period t; 0, otherwise
α_u	capacity factor of type u power plant (%)
α_{ua}	capacity factor of type u power plant in scenario node a (%)
β_{uf}	type f fuel amount consumed at type u power plant to produce a unit of electricity (ton/MWh or lt/MWh)

γ_{ua}	upper bound on the percentage of power plant type u in the portfolio of the company in scenario node a (%)
γ_{ut}	percentage of power plant type u in the portfolio of the company in period t
δ_l	efficiency of type l CCS technology
θ_u	carbon multiplier at type u power plant per unit generation (ton/MW)
κ_a^{max}	upperbound on the total installed capacity of the company enforced by the government in scenario node a (%)
κ_t^{max}	upperbound on the total installed capacity of the company enforced by the government in period t(MW)
κ_a^{min}	company's desired minimum market share in scenario node a (%)
κ_t^{min}	company's desired minimum market share in period t (MW)
π_l	inner electricity need of type l CCS technology (MWh/ton)
ϕ_{ab}^{min}	lower bound on the amount of electricity sold by bilateral contracts for each scenario node a during load block b (%)

LIST OF ACRONYMS/ABBREVIATIONS

CCS	Carbon Capture and Storage
CCGT	Combined Cycle Gas Turbine
EEV	Expectation of Expected Value
EPI	Expectation Under Perfect Information
ESS	Expected Result of Stochastic Solution
ETS	Emissions Trading Scheme
EV	Expected Value
EVPI	Expected Value of Perfect Information
GEP	Generation Expansion Planning
GHG	Greenhouse Gases
IGCC	Integrated Gasification Combined Cycle
MCFCPPs	Molten Carbonate Fuel Cell Power Plants
MSSP	Multi-Stage Stochastic Programming
VSS	Value of Stochastic Solution

1. INTRODUCTION

The energy industry is crucial for a country in the industrialized world since the electricity is essential for different sectors, such as manufacturing, agriculture, transportation, information technology, communications and domestic usage. For last decade or more, the energy industry has undergone a great deal of change due to economical and social developments. Initially, centrally managed power plants, which belong to government, were producing electricity in most industrial countries including Turkey. After the deregulation, private companies are allowed to enter the market to produce and sell electricity, so the competition is started between these companies. In this new environment the operation of private generating facilities no longer depends on utility based centralized procedures but on decentralized decisions of these companies. Another change affecting the industry is the legal requirements imposed to countries, and to companies, in order to mitigate the effects of uprising environmental problems that occurred as a result of the emissions of greenhouse gases (GHG). Many developed countries have agreed to legally binding limitations in their emissions of GHG according to Kyoto Protocol, which was signed in 1997 [1].

The main subject of this thesis is a Generation Expansion Planning(GEP) problem of a private generation company under the new regulations. GEP is an investment planning problem that mainly determines the time and amount of new investments or capacity additions to the existing facilities. If new facilities are to be built, then the problem becomes making decision on mix of power generation, where and how much capacity to install, over a predetermined time horizon. The aim of these problems is to meet the estimated energy demand with the least expected cost. This problem has become increasingly more important for the industry due to the increasing energy demand of the world. The energy demand is mostly satisfied using fossil fuel combustion, giving rise to climate change. The need of taking precautions against the predicted future costs of climate change leads to the introduction of new legal legislations about carbon mitigation. In order to obey these legal legislations, the energy investment planning must cover low carbon emissions type of plant, emissions trading mechanisms, low carbon generation technologies, i.e. integrated gasification combined cycle (IGCC), carbon reduction obligations, etc. [2]. In addition to these, the companies also have an option of making more investments on renewable energy resources [3].

In this thesis, we consider a GEP problem of a private electricity generating company that aims to maximize the net present value of its total expected profit while obeying the constraints on the capacity, market share, invesment portfolio and carbon emissions over a predetermined planning horizon. We are interested in determining the types of power plants, time of investment decisions, size and technological properties of the investments. In addition, while investment decisions are made, the company decides on how much to invest on the technology for carbon mitigation for certain investments or what kind of strategies, i.e. CCS installation or carbon trade, to follow in order to obey carbon restrictions. CCS is a technology involves capturing CO_2 produced by power plants or industrial processes, compresing it for transportation, and subsequently storing in non-atmospheric reservoirs (e.g., unmineable coal seams and deep saline formations). The aim of CCS technology usage is to prevent the release of large amount of CO_2 into the atmosphere. Hence, it is an option for companies, or countries, to mitigate carbon emission. For this problem, we develop a mixed integer linear program, and implement the model, initially on GAMS optimization studio, with data obtained for Turkey's energy industry. Then, we determine the parameters that affect the optimal investment decisions. For these parameters, we create scenarios to apply sensitivity analysis that allow us to analyze the effects of parameters on the optimal decisions. Then, we report the results of the sensitivity analysis. In the second part of the thesis, we develop a multi-stage stochastic programming approach for the problem to handle uncertainties in some parameters; namely electricity prices, fuel costs and carbon credit prices. We implement this model on C# and use Cplex 12.3 as the solver. This approach allows us evaluating alternative generation strategies with the ultimate goal of maximizing profit.

The rest of the thesis is organized as follows: Chapter 2 summarizes the related literature that focuses on generation expansion planning in energy industry and stochastic programming approach in modeling. In Section 3.1, we formulate the problem as a mixed integer program with deterministic parameter values. Then, we deal with uncertainty on the parameters by using a multistage stochastic programming approach in Section 3.2. In Chapter 4, we provide the results of model applied for Turkey electricity market. In Chapter 5, we present the concluding remarks and suggest the potential research areas.

2. LITERATURE REVIEW

The literature review is conducted in two sections. In the first section, we investigate the problems that are related to generation expansion planning in energy industry. In the second part, we focus on the methodological aspects of this topic by examining the applications of stochastic programming approaches in the literature.

2.1. The Generation Expansion Planning in Energy Industry

There are wide range of studies related to the energy investment planning in the literature. The investment decisions in all industries include similar aspects, which are the type, size, time and location of the investments. In other words, the decision is selecting the right type, at the right amount, in the right time and at the right location. However, energy industry includes two different features, in terms of investment decisions, that the other industries do not have: (1) *partial or complete irreversibility*: the initial investment costs cannot be recovered; (2)*high risks*: there are uncertainties in economic environment and regulations that may affect the expected income obtained from the investments [4].

The modeling approaches developed for GEP can be investigated mainly in two categories which are macro and micro approaches [2]. In macro approach, most of complex constraints are neglected and the system is made more simple. This approach generally includes linear programming models. On the other hand, in micro approach the system is modeled more realistically throughout the constraints and more complex operations research tools are used. In micro approach modeling for the GEP problem, two classes of problems have been considered which are centralized and decentralized approaches.

2.1.1. Centralized Approach

In centralized approach, GEP is developed for a whole country or a region. In the literature, various methods have been developed to solve the centralized GEP problem. The formulation of the problem objective and constraints differs with respect to modeling approach, including emission cost and other environmental constraints, transportational and financial constraints and reliability measures. Mo *et al.* [5] suggest a model, which is developed by using stochastic dynamic programming, to solve the centralized GEP problem. They deal with uncertainties in energy demand and fuel prices. These uncertain parameters are modeled by Markov chains. In article [6] a non-linear programming approach is provided, with the details of financial and technical constraints arising from existing technologies, capital costs, minimum demand and capacity. Majumdar and Chattopadhyay [7] present an integrated analysis of GEP and financial decisions. They formulate the GEP problem as mixed-integer linear programming by including all financial constraints. They also employ sensitivity analysis by creating scenarios in order to evaluate several financial planning alternatives. In addition to these, Meza *et al.* [8] evaluate a long term multi-objective GEP model that minimizes simultaneously the costs, environmental effect, imported fuel and fuel price risks, and decides on the locations of the planned generation units in a multi period planning horizon. A case study from the Mexican Electric Power System is used to exemplify the proposed framework. On the other hand, Koo *et al.* [9] develop a robust optimization model for the sustainable energy planning that minimizes total costs in planning capacities of power plants and CCS to be added, stripped or retrofitted based on modified energy flow optimization model.

Anderson [10] reviews the models that investigate the worth of investments in electricity supply industry. The demand and the prices of inputs and outputs are assumed to be exogeneous, and the objective is the minimization of the total cost. An optimization model spans several time periods. This problem is analysed via linear and nonlinear programming, dynamic programming and other methods. Pokharel and Ponnambalam [11] develop a general linear optimization model for investment planning that includes the time value of money, transmission and distribution losses, the environmental pollution costs and system costs. The model is then converted to a multistage stochastic model to reflect a real life planning situation. Additionally, application of various optimization techniques, which include fuzzy logic, artificial neural networks, network flow theory, analytic hierarchy process, decomposition algorithms and heuristic methods such as simulated annealing and genetic algorithm in GEP are investigated in [12].

2.1.2. Decentralized Approach

Another aproach in micro approach modelling is decentralized approach. In decentralized approach, a generating company operating in a deregulated market is taken into account. There are competing firms in the market and the market is affected by the strategies of these competing firms and in turn the decision of each company in the industry is affected by them. Therefore, these models are more complex. For the solution of these models, literature includes different approaches. Botterud *et al.* [13] develop a stochastic dynamic programming model to evaluate optimal investment strategies under centralized and decentralized approach. They also determine time of the investments under uncertainty in demand and future prices. Uncertainy in demand is modeled by a discrete Markov chain. Barforoushi *et al.* [14] develop a framework consisting of dynamic programming and game theory. Again, they propose a stochastic dynamic programming approach for the solution of the GEP problem and develop a game theoretical approach to model interaction between investors in the market. Similar to [13], they model the electricity demand and changes in fuel prices by using Markov chains.

Wang *et al.* [15] propose an incomplete information game model for the competition between generating companies. Each generation company is modeled as an agent. Again, the GEP problem in a competitive electricity market is addressed in [16]. They develop a mathematical model with the objective of maximizing the expected revenues of a generation firm while ensuring the safety in the power system operation and incorporating uncertainties in prices, in generation units reliability, in demand pattern and in investment and operation costs. These uncertainties are modeled by probability distribution functions, and Genetic Algorithms are used as the solution approach. Nanduri *et al.* [17] develop a two-tier matrix game model that iteratively constructs multi-player, multi-year generation expansion strategies for the competing firms. For this model, they suggest a different solution algorithm that considers risk because of volatilities in profit via Conditional value-at-risk approach.

In addition to the previously offered methodologies, Koo *et al.* [9] propose a new methodology for sustainable energy planning by incorporating some aspects such as the uncertainties in fossil fuel prices, carbon emissions trading and addition of CCS to the thermal power plants. There are also some studies in the literature that consider GEP in a carbon-constrained environment. Bakirtzis *et al.* [4] develop a mixed-integer linear program to solve centralized GEP. The objective is to minimize cost, which includes the net present value of the total investment, operation and unmet energy demand. Additionally, carbon emissions cost is added to the objective function so as to take environmental constraints into consideration. Lower bounds and penalties over renewable energy sources are also added. While a long-term investment problem is solved, midterm scheduling problems are added to the problem.

For Chineese energy industry, Zhang *et al.* [18] develop a multi-period optimization model, which decides on the types and timings of new power plants, plant construction, retrofit and timing of the shut downs of existing plants. They also analyze the effect of carbon mitigation strategies in their follow up study [19]. Abadie and Chamorro [1] assess the option to install CCS by considering an EU-based power company, which operates a coal-fired power plant. Since the firm operates in a carbon-constrained environment, it should decide on either the purchase of carbon allowances in the Emissions Trading Scheme (ETS) in order to release CO_2 or, alternatively, the installation of a long lived CCS unit. The firm must decide by comparing the value of the allowances with the cost of the CCS unit. This developed model gives opportunity to this comparison.

Literature also includes multicriteria GEP models because of the conflicting objectives nature of GEP. Kim and Ahn [20] criticize the traditional least-cost GEP because it is inadequate to include conflicting multiple objectives, such as environmental conditions and cost. Therefore, they develop a model with the presence-order dynamming programming approach. In order to make mathematical model more realistic by covering distinct evaluation aspects which are environmental issues and costs in objective function, Antunes *et al.* [21] develop a multi objective mathematical model. They aim to grasp the conflicting nature of GEP and the trade-offs among the contrasting objectives. They also consider demand-side management as an option in the planning process, assuming that there is a sufficiently large market.

As summarized above, the studies in the literature have objective to minimize cost and satisfy the estimated demand. In a centralized approach, the electricity is produced at plants which are managed by government, so minimizing cost by satisfying demand is suitable for this approach. However, as the private energy generation companies enter the industry in a deregulated environment, which is in decentralized approach, the objective changes from minimization cost to maximization profit obtained from the investments. In addition, for a private company, the satisfaction of the total demand is not a requirement. On the other hand, dealing with uncertainty is an important concern in GEP problems, so we need a method to handle uncertainties. This leads us to make additional literature research. We found that there exist stochastic programming approaches to deal with uncertainties in modeling of various problems in the literature. In the following section, we give a brief discussion of the stochastic programming approaches in the literature.

2.2. Stochastic Programming Approaches in Modeling

GEP for the electric industry contains uncertainties due to technological, economical and policy-related aspects. Model parameters, which are mostly affected from these aspects, are carbon prices, electricity prices and fuel costs. Therefore, there is a need for additional methods in order to deal with uncertainties in these parameters. So as to find suitable methods for our case, additional literature review is made about the methods. Higle [22] explains when stochastic programming is applied to a linear programming model. They explore the effect of uncertainties in some parameters in order to illustrate the power of stochastic programming. They also explain two stage and multi-stage recourse problems with illustrative examples. In addition, Pousinho *et al.* [23] state that a stochastic programming approach has the advantage of finding a near optimal solution regarding all possible scenarios. The solution of this approach may not be a global optimal solution to the individual scenarios, but it is a robust solution over all possible realizations of the uncertainties. Additionally, Kristoffersen [24] contributes to literature by investigating stochastic programming applications to power systems. They explain why stochastic programming approach is needed, with the change in the power markets and the problems arising from these changes. Many previous procedures have changed because of decentralization of the electricity generation and the deregulation of the power markets. Hence, new planning and operating problems have emerged, then this situation leads to need for advances in optimization models. Furthermore, it has been widely accepted that there is uncertainty in these problems, so this motivates applications of stochastic optimization.

Bistline [25] uses a two-stage stochastic programming approach and the results of their model suggest that the two most critical risks are natural gas prices and the requirements of climate policy in the near-term planning process. However, this study includes only natural gas, fired power plants especially shale gas. In addition, Pousinho *et al.* [23] develop a stochastic optimization model that aims to maximize the profit of a wind power producer, reducing deviations, and taking into account the uncertainty associated with wind energy production and energy market prices. They determine optimal hourly bids for wind energy. Again, this study is only for producers of one type of energy, which is wind energy.

Bornapour and Hooshmand [26] propose a stochastic model for the problem of placement and operation of Molten Carbonate Fuel Cell Power Plants (MCFCPPs) in distribution networks when used for Combined Heat, Power, and Hydrogen simultaneously. Scenario-based method is used to handle uncertainties of electrical and thermal charges forecasting; the pressures of oxygen, hydrogen, and carbon dioxide imported to MCFCPPs; and the nominal temperature of MCFCPPs. In their method, they use Roulette Wheel Mechanism regarding Probability Distribution Functions of input random variables to generate scenarios. Another scenario-based stochastic programming in energy sector is developed by Pandzic *et al.* [27]. They consider a virtual power plant, which is the concept of aggregating different generation technologies as a single-acting unit in an electricity market. The virtual power plant, in this paper, consists of a storage facility, an intermittent source, and a dispatchable power plant. They offer a two-stage stochastic programming model that maximizes expected profit of the virtual power plant, which includes selling and purchasing electricity in both the day-ahead and balancing markets. The uncertain parameters, which are the power output of the intermittent source and the market prices, are modeled via scenarios generated by using historical data.

In addition to two-stage stochastic programming approach applications, the literature widely includes multi-stage stochastic programming approaches on energy investment planning area. Fürsch *et al.* [28] suggest a linear multi-stage stochastic investment and dispatch model for electricity markets with the objective of minimizing total discounted system costs while satisfying hourly demand, and ensuring that available capacities in each node is enough to meet peak demand. In this model, long-term uncertainties about the deployment of renewable energy sources capacities are handled. Reinelt and Keith [29] develop a stochastic dynamic programming model to analyze generation technology choices and determine optimal investment time by minimizing the expected present value of firm investment decisions when future CO_2 and natural gas prices are uncertain. Roques *et al.* [30] evaluate investment decisions for nuclear and combined cycle gas turbine (CCGT) plants under uncertainty in natural gas, carbon and electricity prices by applying a multi-stage stochastic programming tools. Effects of uncertain future CO_2 emission regulations on carbon prices are also taken into consideration by Echeverri *et al.* [31]. They develop a multi-stage stochastic dynamic model with the objective of minimizing the expected total costs. They determine optimal sequential investment strategies with and without uncertainty on CO_2 emission regulations. Additionally, Schröder [32] studies an expansion planning problem under fuel price uncertainty for Germany over a planning horizon. They model this problem from a game theoretical perspective. They develop deterministic and stochastic model with the aim of maximizing the expected profit. They include the uncertainty by using a scenario based approach that includes different policies in different branches of the scenario tree.

There are studies in the literature that stochastic programming approaches are applied to deal with uncertainty in the parameters for energy investment problems. However, these studies are generally for one type of energy power, some of them lack investment decisions and are not for a private company. In this study, we offer an investment plan, covering all power plant types, except nuclear energy, to a private company by dealing with uncertainties on carbon prices, electricity prices and fuel costs by using stochastic programming approach.

Our aim is to maximize profit on the contrary to studies in the literature and there is no requirement on the satisfaction of total demand. In addition, we consider the problem from a private electricity generating company perspective. As we give the details above, there are studies that handle GEP problem from private generating companies perspective; however our study differs from these articles in terms of following ways: (i) the studies that consider private generating companies are mostly on pricing models, and they model the interaction between the companies in the competition environment using game theoretic approach or simulation, but they lack investment decisions; (ii) the GEP studies do not include the investment decisions on new technology and systematic tools that will help to mitigate the environmental impact of carbon emissions; (iii) some of the studies about GEP solve the model at a single time point; (iv) the studies, which are about long term GEP of private generation companies, lack emission mitigation strategies, and they either include carbon cost based on the generation decisions or do not consider carbon cost at all. Hence, we aim to fill in the gap in the literature that considers long term GEP from a private generating companies perspective in a partially regulated environment that includes emission mitigation strategies, company's portfolio restrictions, the country's limit on the market share and the desired market share of the company.

3. PROBLEM FORMULATION

The main player of the problem that we study in this thesis is a private electricity generating company that aims to operate in a partially regulated environment. This company considers to install power plants in a predetermined planning horizon over which they will maximize the expected profit obtained from producing and selling electricity. While maximizing the expected profit, there are certain constraints that need to be satisfied, which arise from nature of the problem. An important property of a partially regulated industry is that the government prevents monopoly by limiting generating companies to reach to total installed capacity levels that may affect the industry. Therefore, there exists a maximum allowable market share constraint for each time period, which is calculated based on the projected capacity levels of the country. On the other hand, the company has a goal of reaching a minimum market share after entering the electricity generation market. We also include restrictions on the maximum and minimum possible amount of investment for every period for every type of investment option (if there will be an investment). Moreover, in order to distribute the investment risks associated with each type of power plant, the percentage of each type of power plant investments are restricted by some upper bounds.

In the first part of this chapter, we focus on the case with deterministic values of electricity prices, fuel cost and carbon prices. First, we develop a deterministic mixed integer linear programming model. We generate scenarios for the parameters, which include uncertainties, to perform sensitivity analysis that helps us to explore and quantify the impact of possible changes in parameter values on predicted model outputs. Then, in the second part of this chapter, to take into account the uncertainty of electricity market prices, fuel costs and carbon prices, we develop a multi-stage stochastic optimization model for the problem.

3.1. Deterministic Model

In this section, we give the deterministic model for the explained problem.

3.1.1. Problem Statement

We consider a private electricity generating company that makes decisions about installing power plants in a predetermined planning horizon, T, over which they want to maximize the net present value of the profit obtained from producing and selling electricity. They have a set of power plant types, U, including fossil-fuelled plants and renewables to be installed. Each power plant, $u \in U$, requires different construction periods, $\bar{t}_u$, operates with different capacity factor, α_u, and produces different amount of carbon per unit capacity added, θ_u. For each period, $t \in T$, there is a lower bound, AC_{ut}^{min}, and, an upper bound, AC_{ut}^{max} on the capacity of the power plant to be installed. Moreover, for certain plant types that use renewable resources, there are limits on the total potential of the resources that cannot be exceeded in the considered region (or country), AC_u^{pot}. Total number of hours in a period t is taken as D_t.

In this part, we assume that the company sells the generated electricity via only bilateral agreements at a predetermined contract price. These agreements guarantee that the company will be able to sell all electricity generated at any given time. Moreover, the electricity produced by using different sources may be sold at different prices (due to incentives provided for renewable energy resources), PE_{ut}. There is a set of fuel types, F. Each fuel type, $f \in F$, has a unit cost in each period, PF_{ft}.Each thermal power plant requires a certain amount of fuel, β_{uf}, to produce a unit of electricity. There is a set of CCS technologies, L, with different efficiency levels, δ_l, for each CCS type $l \in L$, considered to be installed to appropriate power plants if they are feasible. Furthermore, each CCS requires a certain amount of electricity, π_l, to capture a ton of CO_2 when it is operating.

The decisions on the installation of CCS technology and the power plant are made at the same time due to technological restrictions, meaning that if it is decided to install a power plant, then it is also decided whether it will include a CCS or not. Each power plant requires a unit installation cost that depends on the type, l, of CCS, IC_{ul}, and a unit operating and maintenance cost, OMC_u. Without loss of generality, we assume that when $l = 0$, it means there is no CCS technology installed at that power plant; and if a power plant includes a CCS unit, then the installation cost of the power plant includes the installation cost related to the CCS as well. Moreover, there exists a unit transportation cost per every ton of carbon captured and transferred to the storage site, TC_u, and a unit maintenance cost of CCS unit installed, OC_{ul}.

Another assumption is that the company operates in a market where a cap and trade system is in operation. The cap is a limit on GHGs emissions, especially carbon emissions, and the trade constitutes a market for carbon allowances. The companies have an allocated limit to emit and they may only emit as much carbon as they have allowances for. In this system, the company, which has extra allowances, can sell the additional allowances to other companies that have a deficit. Hence, the company can turn its emission reduction into revenue. On the other hand, the option to buy allowances gives the companies, which have trouble reducing emission level or want to make long-term investments instead of immediate changes, flexibilitiy. Therefore, in our problem, the company has a carbon cap value assigned for each year, $CO_2^{cap,t}$. If the emission amount of the company at a given year is under its cap value, then the company entitles to sell the amount of carbon credits that is under the cap at a given price, $p_t^{CO_2}$. On the other hand, if the emission level of the company is above its cap value, then they have to buy the excess value from other companies at the same price.

From strategic point of view, we assume that the company desires to have a balanced investment portfolio so as to distribute the risk associated with each type of plant over the portfolio. Hence, for every type of power plant, there is an upper bound, γ_{ut}, that limits the percentage of the investment among the total investment of the company at certain time points. This value is determined as a company policy. Furthermore, we assume that the company would like to reach a minimum market share value in the region at certain time points, κ_t^{min}. Moreover, in order to prevent monopoly, the government restricts the market share of each company operating in the market to an upper bound, κ_t^{max}, where the total installed/projected capacity of the country at each year, C_t, is known.

3.1.2. Mathematical Formulation

The objective of the problem is to maximize the net present value of the total profit obtained over a planning horizon. We assume that the installation cost of power plants are paid over the construction period in equal payments. We also assume that the plants are operational throughout the planning horizon without any interruption.

The decision variables of the model are given as follows:

Z_{ut} : 1, if type u power plant is installed in period t; 0, otherwise

AC_{ult} : added capacity of type u power plant that includes type l CCS technology in period t (MW)

X_{ult} : amount of carbon captured in period t type l CCS technology added with type u plant (ton)

Q_{ult} : 1, if a type l CCS is installed with type u plant in period t; 0, otherwise

$CO_2^{sell,t}$: amount of carbon credits sold to other entities in period t

$CO_2^{buy,t}$: amount of carbon credits bought from other entities in period t

The objective function of the mixed-integer linear programming model of the problem is given as follows:

$$\begin{aligned}
\text{Max} \quad z_{NPV} = \sum_{t\in T} \frac{1}{(1+r_t)^t} \Bigg[& \sum_{u\in U}\sum_{l\in L}\sum_{t'\leq t-\bar{t}_u} PE_{ut}\Big(8760\alpha_u AC_{ult'} - \pi_l X_{ult}\Big) \\
& - \sum_{u\in U}\sum_{l\in L}\left(\sum_{t'=t}^{t+\bar{t}_u-1} \frac{IC_{ul}AC_{ult}}{\bar{t}_u}\frac{1}{(1+r_{t'})^{t'-t}} - \sum_{t'\leq t-\bar{t}_u} OMC_u 8760\alpha_u AC_{ult'}\right) \\
& - \sum_{f\in F}\sum_{u\in U}\sum_{t'\leq t-\bar{t}_u}\sum_{l\in L} PF_{ft}8760\beta_{uf}AC_{ult'} \\
& - \sum_{u\in U}\sum_{l\in L}\Big(TC_u X_{ult} + OC_{ul}X_{ult}\Big) \\
& + p_t^{CO_2,sell}CO_2^{sell,t} - p_t^{CO_2,buy}CO_2^{buy,t}\Bigg] \qquad (3.1)
\end{aligned}$$

The objective function (3.1) maximizes the net present worth of the profit obtained over the planning horizon comprising (a) the revenue obtained from producing and selling electricity less the cost of electricity required by the CCS unit if installed; (b) the total installation (or capital) cost of power plants and the maintenance cost; (c) the fuel cost; (d) the transportation and operating cost of the carbon captured; and finally (e) the revenue obtained from selling carbon credits, if possible, and the cost of buying carbon credits, if necessary. Note that the company will either sell or buy carbon credits.

The constraints of our mathematical formulation are as follows:

- *CCS investment and carbon capture:* The plant may capture carbon only if a CCS is installed.

$$X_{ult} \leq \alpha_u \sum_{t' \leq t - \bar{t}_u} AC^{max}_{ut'} \theta_u * 8760 * Q_{ult'}, \quad \forall u \in U, l \in L, t \in T \tag{3.2}$$

- *Carbon capture limit:* This constraint ensures that at each period, the amount of carbon captured cannot exceed the total emission of those corresponding plants installed.

$$\sum_{l \in L} X_{ult} \leq \sum_{l \in L} \sum_{t' \leq t - \bar{t}_u} AC_{ult'} \alpha_u \theta_u * 8760 \quad \forall u \in U, t \in T \tag{3.3}$$

- *Lower and upper bounds on the total generation of specific power plant types:* If a type of power plant is decided to be built, then total generation capacity of that type of power plant must be between upper and lower bounds for every time period and each power plant type. Note that some type of power plants with different CCS technologies can be installed at the same time period. However, the total capacity is limited with an upper bound.

$$AC_{ut}^{min} Z_{ut} \leq \sum_{l \in L} AC_{ult} \leq AC_{ut}^{max} Z_{ut} \quad \forall u \in U, t \in T \tag{3.4}$$

- *Lower and upper bounds on the generation capacity:* If a power plant is decided to be built with a specific CCS technology, then the generation capacity of that plant must be between some lower and upper bounds.

$$AC_{ut}^{min} Q_{ult} \leq AC_{ult} \leq AC_{ut}^{max} Q_{ult} \quad \forall u \in U, l \in L, t \in T \tag{3.5}$$

- *Carbon flow constraint:* There is a cap value assigned to the company that is equal to the total emissions that the company is allowed to emit. If the emissions are greater than the cap value, then the company has to buy carbon credits from other entities; or, on the other hand, if the total emissions are less than the cap value, then the company is entitled to sell the surplus carbon credits. Hence, the total emissions generated from electricity production less the amount of carbon captured less the carbon credits bought, if it is bought, plus the carbon credits sold, if it is sold, must be equal to the cap value assigned to the company.

$$\begin{aligned} \sum_{u \in U} \sum_{l \in L} \sum_{t' \leq t - \bar{t}_u} AC_{ult'} \alpha_u \theta_u * 8760 - \sum_{u \in U} \sum_{l \in L} \delta_{ul} X_{ult} \\ - CO_2^{buy,t} + CO_2^{sell,t} = CO_2^{cap,t} \quad \forall t \in T \end{aligned} \tag{3.6}$$

- *Market share constraint:* The total installed capacity must be between some minimum desired market share and maximum allowable market share among the total installed (projected) capacity of the region or the country. The lower bound is enforced by the company in order to reach a certain market share at specific time points. The upper bound, on the other hand, is enforced by the government in order to prevent monopoly. If the company does not have a desired market share, then κ^{min} can be set to zero. If the government does not enforce any limits on the total capacity installed by a single company, then this can be achieved by setting κ^{max} to one.

$$\kappa^{min} C_t \leq \sum_{u \in U} \sum_{l \in L} \sum_{\bar{t} \leq t} AC_{ul\bar{t}} \leq \kappa^{max} C_t, \quad \forall t \in T \tag{3.7}$$

- *Maximum potential constraint:* Some type of power plants, especially specific renewable resources, may have a maximum potential for the region considered that cannot be exceeded. If there is no maximum potential, AC_u^{pot} can be set to a maximum possible investment value.

$$\sum_{l \in L} \sum_{t \in T} AC_{ult} \leq AC_u^{pot}, \quad \forall u \in U \tag{3.8}$$

- *Portfolio balance constraint:* The energy generation companies usually do not want to invest on single (or a few) type of plants because of the risks associated with each type of plants. In order to distribute the risk, they would like to have a balanced portfolio, in which each type of power plant's share is restricted with some percentage. At specific time points, the following constraint ensures that a certain percentage of the total portfolio can be composed of each type of power plant.

$$\sum_{l \in L} \sum_{\bar{t} \leq t} AC_{ult} \leq \gamma_u \sum_{\bar{t} \leq t} \sum_{u \in U} \sum_{l \in L} AC_{ult}, \quad \forall u \in U, t \in T \tag{3.9}$$

- *CCS installation constraint:* Power plants can be installed with multiple CCS units. This constraint ensures that for each type of power plant at most one type of CCS is added if that power plant is installed.

$$\sum_{l \in L} Q_{ult} \leq Z_{ut}, \quad \forall u \in U, t \in T \tag{3.10}$$

- *Nonnegativity and binary constraints:* The following constraint set ensures that the installation capacity of power plants and the amount of carbon captured, if any, are nonnegative; and the decisions on the type of power plant and CCS technology, if added, are binary.

$$AC_{ult} \geq 0, \quad \forall u \in U, l \in L, t \in T \tag{3.11}$$

$$X_{ult} \geq 0, \quad \forall u \in U, l \in L, t \in T \tag{3.12}$$

$$CO_2^{buy,t}, CO_2^{sell,t} \geq 0, \quad \forall t \in T \tag{3.13}$$

$$Q_{ult} \in \{0,1\}, \quad \forall u \in U, l \in L, t \in T \tag{3.14}$$

$$Z_{ut} \in \{0,1\}, \quad \forall u \in U, t \in T \tag{3.15}$$

We implement the above model with data obtained for Turkey's electricity generation market. In the implementation, we make AC_{ult} and X_{ult} equal to 0 when l CCS type cannot be added to u type power plant for each period t by adding equations to the model. We also make X_{ult} equal to 0 for each period t for all power plant types when $l = 0$ since $l = 0$ means there is no CCS technology installed at that power plant. Note that, the number 8760, used in objective function and some constraints, corresponds to total hours in a year that is multiplication 365 (days in year) by 24 (hours in a day). We present the computational experiments in the Results of the Model Application and Analysis section.

3.2. Stochastic Programming Approach

The need for observing investment strategies for different possible occurences of uncertain parameters, which are electricity prices, fuel costs and carbon prices, in near future in the energy industry forces us to develop a stochastic programming approach. In this part of the study, we develop a multi-stage stochastic optimization model. Uncertain parameters are modeled by scenarios.

3.2.1. Problem Statement

We assume that the company currently has no power plants, but they want to enter a partially regulated electricity generation industry with a target of having predetermined percentages of market share in certain time period in near future. In this part of the study, an important property of a partially regulated industry is taken into consideration in the problem. There is no spot market as in deregulated environments where the electricity price is determined momentarily based on the bids given by generating companies. Instead, there is a day ahead market installed where the companies decide on the amount of electricity that they will sell based on the price realized the day before the actual transaction. This operation is realized in the market, which is called day-ahead market. There is no obligation to participate in the day-ahead market. Another property of this partially regulated environment is the regulations over the amount of electricity sold via bilateral contracts. This amount must be between some lower and upper percentages of the total electricity generated by that company. Furthermore, in the electricity market, a day is divided into different load blocks over which the price of electricity differs. Therefore, a company may sell the generated electricity over these load blocks via bilateral contracts at a predetermined price or sell it in the day-ahead market at a price determined as a result of the market interaction realized the day before. Moreover, the government prevents electricity generating companies from reaching total installed capacity levels that may affect the electricity market as in the deterministic case.

3.2.2. Mathematical Formulation

In this section, we present the mathematical formulation of the model that we develop according to a multi-stage stochastic programming approach.

The decision variables belonging to the model are given as follows:

Z_{ua} : 1, if type u power plant is installed in scenario node a; 0, otherwise

AC_{ula} : added capacity of type u power plant with type l CCS technology in scenario node a (MW)

Q_{ula} : 1, if a type l CCS is installed with type u plant in scenario node a; 0, otherwise

Y^{bi}_{ulab} : amount of electricity generated at type l CCS technology added with type u power plants in scenario node a and sold via bilateral contracts during load block b (MW)

Y^{da}_{ulab} : amount of electricity generated at type l CCS technology added with type u power plants in scenario node a and sold at the day ahead market during load block b (MW)

X_{ula} : amount of carbon captured in scenario node a at type l CCS technology added with type u plant (ton)

$CO_2^{sell,a}$: amount of carbon credits sold to other entities in scenario node a (ton)

$CO_2^{buy,a}$: amount of carbon credits bought from other entities in scenario node a (ton)

The objective function of the model is given as follows:

$$
\begin{aligned}
\max z \quad = \quad & \sum_{a\in A} pr_a DF_a \Bigg[\sum_{u\in U} \Bigg(\sum_{b\in B} D_{ab} \Big(PE^{bi}_{uab} Y^{bi}_{ulab} + PE^{da}_{uab} Y^{da}_{ulab} \Big) \\
& - \sum_{l\in L} IC_{ul} AC_{ula} - \sum_{b\in B} MC_u D_{ab} \Big(Y^{bi}_{ulab} + Y^{da}_{ulab} \Big) \\
& - \sum_{f\in F} \sum_{b\in B} PF_{fa} \beta_{uf} D_{ab} \Big(Y^{bi}_{ulab} + Y^{da}_{ulab} \Big) \\
& - \sum_{l\in L} \Big(TC_u X_{ula} + OC_{ul} X_{ula} \Big) \Bigg) \\
& + PC_a CO_2^{sell,a} - PC_a CO_2^{buy,a} \Bigg]
\end{aligned} \tag{3.16}
$$

The objective function (3.16) maximizes the net present worth of the profit obtained over the planning horizon comprising (a) the revenue obtained from producing and selling electricity; (b) the total installation (or capital) cost of power plants and the maintenance cost; (c) the fuel cost; (d) the transportation and operating cost of the carbon captured; and finally (e) the revenue obtained from selling carbon credits, if possible, and the cost of buying carbon credits, if necessary.

The constraints of the model that we develop according to stochastic programming approach are rewritten as follows:

- *Lower and upper bounds on the total installed capacity of specific power plant types:*

$$AC_{ua}^{min} Z_{ua} \leq \sum_{l \in L} AC_{ula} \leq AC_{ua}^{max} Z_{ua} \quad \forall u \in U, a \in A \tag{3.17}$$

- *Lower and upper bounds on the installed capacity:*

$$AC_{ua}^{min} Q_{ula} \leq AC_{ula} \leq AC_{ua}^{max} Q_{ula} \quad \forall u \in U, l \in L, a \in A \tag{3.18}$$

- *Maximum potential constraint:*

$$\sum_{\bar{a} \in pred(a)} \sum_{l \in L} AC_{ul\bar{a}} \leq AC_{u}^{pot} \quad \forall u \in U \tag{3.19}$$

- *Market share constraint:*

$$\kappa^{min} C_a \leq \sum_{\bar{a} \in pred(a)} \sum_{u \in U} \sum_{l \in L} AC_{ul\bar{a}} \leq \kappa^{max} C_a \quad \forall a \in A \tag{3.20}$$

- *Portfolio balance constraint:*

$$\sum_{\bar{a} \in pred(a)} \sum_{l \in L} AC_{ul\bar{a}} \leq \gamma_{ua} \sum_{u \in U} \sum_{\bar{a} \in pred(a)} \sum_{l \in L} AC_{ul\bar{a}} \quad \forall u \in U, a \in A \tag{3.21}$$

- *Relationship between added capacity and generation*: The amount of electricity generated and sold cannot exceed the total installed capacity times the capacity factor.

$$Y^{bi}_{ulab} + Y^{da}_{ulab} + \pi_l X_{ula} \leq \alpha_{ua} \sum_{\bar{a} \in pred(a)} AC_{ul\bar{a}} \quad \forall u \in U, l \in L, b \in B, a \in A \tag{3.22}$$

- *Lower and upper bound on the amount of electricity sold via bilateral contracts*: The amount of electricity sold via bilateral contracts must be between some upper and lower bound based on the total generation of the company. If there are no such restrictions, the bounds can be set to zero and one, respectively.

$$\begin{aligned} \phi^{min}_{ab} \sum_{u \in U} \sum_{l \in L} (Y^{bi}_{ulab} + Y^{da}_{uab}) \leq \sum_{u \in U} \sum_{l \in L} Y^{bi}_{ulab} \\ \leq \phi^{max}_{ab} \sum_{u \in U} \sum_{l \in L} (Y^{bi}_{ulab} + Y^{da}_{ulab}) \quad \forall b \in B, a \in A \end{aligned} \tag{3.23}$$

- *CCS investment and carbon capture:*

$$X_{ula} \leq \alpha_{ua} \times 8760 \sum_{\bar{a} \in pred(a)} AC^{max}_{u\bar{a}} \theta_u Q_{ula} \quad \forall u \in U, l \in L, a \in A \tag{3.24}$$

- *Carbon capture limit:*

$$X_{ula} \leq \sum_{b \in B} \left(Y^{bi}_{ulab} + Y^{da}_{ulab} \right) \theta_u \quad \forall u \in U, l \in L, a \in A \tag{3.25}$$

- *Carbon flow constraint:*

$$\sum_{u\in U}\sum_{l\in L}\sum_{b\in B} D_{ab}\left(Y^{bi}_{ulab} + Y^{da}_{ulab}\right)\theta_u - \sum_{u\in U}\sum_{l\in L}\delta_{ul}X_{ula}$$
$$- CO_2^{buy,a} + CO_2^{sell,a} = CO_2^{cap,a} \quad \forall a \in A \tag{3.26}$$

- *CCS installation constraint:*

$$\sum_{l\in L} Q_{ula} \le Z_{ua} \quad \forall u \in U, a \in A \tag{3.27}$$

- *Nonnegativity and binary constraints:*

$$Y^{bi}_{ulab}, Y^{da}_{ulab} \ge 0 \quad \forall u \in U, l \in L, a \in A, b \in B \tag{3.28}$$
$$AC_{ula}, X_{ula} \ge 0 \quad \forall u \in U, l \in L, a \in A \tag{3.29}$$
$$CO_2^{buy,a}, CO_2^{sell,a} \ge 0 \quad \forall a \in A \tag{3.30}$$
$$Q_{ula} \in \{0,1\} \quad \forall u \in U, l \in L, a \in A \tag{3.31}$$
$$Z_{ua} \in \{0,1\} \quad \forall u \in U, a \in A \tag{3.32}$$
$$\tag{3.33}$$

In the implementation, we make AC_{ula} and X_{ula} equal to 0 when l CCS type cannot be added to u type power plant for each scenario node a by adding equations to the model. We also make X_{ula} equal to 0 for each scenario node a for all power plant types when $l = 0$ since $l = 0$ means there is no CCS technology installed at that power plant. In the following chapter, we provide our analysis with data obtained for Turkey's electricity generation market.

4. ANALYSIS OF THE MODEL RESULTS ON A SAMPLE CASE

In this chapter, we first introduce the data used in the models. Then, we present the results of deterministic model and sensitivity analysis. Finally, we discuss the results of stochastic optimization model and analyze the value of stochastic solution.

4.1. Deterministic Model and Sensitivity Analysis Results

We collect data for Turkey's electricity generation industry. Then, we implement the model, which we develop in the previous section by using these data, and analyze the results. After we give related data for the system, in which the hypothetical company operates, we present the results of base scenario and the sensitivity analysis in the following sections.

4.1.1. Related Data

In our model, there are nine power plant options, which are considered to be installed. The power plant types abbreviations used in data tables and their explanations are given in Table 4.1.

Table 4.1. Power Plant Types.

Abbreviation	**Explanation**
Hc	Hard coal
HcIgcc	Hard coal plant that uses IGCC technology
Lig	Lignite
LigIgcc	Lignite plant that uses IGCC technology
Ngcc	Natural gas plant with combined cycle
Hydro	Hydroelectric
Wind	Wind
Geo	Geothermal
Solar	Solar

As it is seen from Table 4.1, there is no nuclear energy as a power plant type. We do not include nuclear energy option in our study since, the government determines the installation time and location of the nuclear energy power plant and launches tender for it. The companies cannot decide on nuclear power plant installation on their own. In addition, Hard coal and Lignite power plants can also be installed with the IGCC technology. IGCC is a technology that produces electricity from a solid or liquid fuel with the application of gasification. First, it uses high pressure gasifier to convert coal and other carbon based fuels into pressurized gas, which is also called syngas (synthesis gas). Syngas is actually a mixture of primarily hydrogen and carbon monoxide. Then, the electricity is produced by converting the syngas in a combined cycle power block, which consists of a gas turbine and a steam turbine process including a heat recovery steam generator. It is commonly used with coal.

In addition, there are three different CCS technologies available to be installed with thermal power plants. Their abbreviations and explanations are given Table 4.2.

Table 4.2. CCS Technology Types.

Abbreviation	**Explanation**
Pre	precombustion
Post	postcombustion
Oxy	oxy-fuel

We provide the construction periods, $\bar{t}$, maximum, Y_{ut}^{max}, and minimum annual installation capacities for power plants, Y_{ut}^{min}, and potential capacity for renewable energy generation, Y_{u}^{pot}, capacity factor, α_u, fuel usage multiplier, β_{uf}, carbon emission multiplier, θ_u, and the efficiency levels of CCS technologies, δ_{uPre}, δ_{uPost}, δ_{uOxy}, for each type of power plant, u, [33,34] in Table 4.3. Note that we take the planning time horizon as 30 years, starting with year 2015 and end by 2045.

Objective function coefficients, which are the contract electricity price and the fuel price in the initial year of the planning time period, the unit installation costs of power plants (which also depend on the CCS technology used (if any)), maintenance cost of

Table 4.3. Data related to power plants.

$\boldsymbol{u}$	$\bar{t}$	Y_{ut}^{max}	Y_{ut}^{min}	Y_{u}^{pot}	α_u	β_{uf}	θ_u	δ_{uPre}	δ_{uPost}	δ_{uOxy}
Hc	5	600	150	-	0.8	0.66	0.33	0.8	0.9	0.95
HcIgcc	5	600	150	-	0.8	0.66	0.08	0.9	0.8	0.9
Lig	5	600	150	-	0.8	1.41	0.33	0.8	0.9	0.95
LigIgcc	5	600	150	-	0,8	1.50	0.08	0.9	0.8	0.9
Ngcc	5	500	50	-	0.95	0.17	0.19	0.8	0.9	0.95
Hydro	4	100	10	-	0.4	-	-	-	-	-
Wind	2	80	10	48,000	0.3	-	-	-	-	-
Geo	4	50	10	1,000	0.85	-	-	-	-	-
Solar	2	20	5	500,000	0.25	-	-	-	-	-

the power plants, operating and maintenance costs of each type of CCS technology, are given in Table 4.4 [33,35,36]. We assume that the internal electricity usage of CCS technologies is linear with respect to the amount of carbon captured, and it is equal to 0.233 kWh per ton of carbon captured [3]. Moreover, transportation and storage cost of captured carbon is taken as $10 per ton of carbon captured and transported [37].

All data related to price and cost are given in American Dollars (USD) in 2014 with the most recent available data. Note that we obtain some of the data after investigations with engineers in industry. The cost data obtained from international reports [36] have been adjusted according to price differences between countries. For renewable energy resources, there is an incentive scheme according to Turkish Law No:5784, which includes the price subsidies provided for electricity generated from renewable energy sources. Therefore, we use this feed-in tariff for renewable energy sources as given in Table 4.4. Since the quality and accuracy of used data are important determinants of the optimal policy, we apply sensitivity analysis by generating different scenarios based on the first year's electricity price, including the subsidies given to renewable energy plants, carbon price and the interest rate. Moreover, we analyze the optimal strategy under different portfolio balance restrictions. Our analysis and results are provided in the following section.

Table 4.4. Cost data for power plants and CCS technologies.

$\boldsymbol{u}$	PE_{u0} (\$ $\times 10^6$/MW)	PF_{f0} (\$$\times 10^6$/MW)	IC_{uPre} (\$$\times 10^6$/MW)	IC_{uPost} (\$$\times 10^6$/MW)	IC_{uOxy} (\$$\times 10^6$/MW)	IC_{uNo} (\$$\times 10^6$/MW)	OMC_u (\$/MWh)	OC_{uPre} (\$/ton)	OC_{uPost} (\$/ton)	OC_{uOxy} (\$/ton)
Hc	54	50	-	3.6	3.850	1.7	4.9	2.24	2.24	2.51
HcIgcc	54	50	3.625	-	3.875	2.5	10.1	5.64	5.64	2.79
Lig	54	50	-	3.6	3.850	1.7	4.9	2.28	2.28	2.56
LigIgc	54	50	3.625	-	3.875	2.5	10.1	5.64	5.64	2.79
Ngcc	54	35	-	1.0	-	0.5	2.3	0.35	0.35	3.33
Hydro	73	-	-	-	-	1.8	6.05	-	-	-
Wind	73	-	-	-	-	1.5	1.20	-	-	-
Geo	105	-	-	-	-	2.5	6.85	-	-	-
Solar	133	-	-	-	-	3.25	2.85	-	-	-

4.1.2. Base Scenario Results

In this section, we analyze the optimal investment strategies by using base scenario data and present the results.

In the base scenario, we take the interest rate as 5%. The electricity price for thermal power plants is fixed to its initial value throughout the planning horizon. We assume that the feed-in tariff of electricity generated from renewable energy resources lasts for 10 years; and after 10 years, the price becomes equal to the regular price of electricity generated from other resources, which is compatible with the current law. The fuel prices are fixed to the initial year throughout the planning horizon, as well. As a reminder, the first year values are given in Table 4.4. We take the carbon price as $30 and fix throughout the planning horizon. The reason why we fix these values to the first year's values over the planning horizon for the base scenario is to clear of the model from forecasting errors as much as possible, since these forecasting errors may add more uncertainty to the results. We analyze the effects of these parameters through applying sensitivity analysis. We present the results in the following part of this section.

Table 4.5. Parameter values for the base scenario.

Parameter	**Value**	
r	5%	
PE_{ut}	PE_{u0}	$\forall t \in T$, $u =$Lig, LigIgcc, Hc, HcIgcc, Ngcc
	PE_{u0}	$t = 0, \ldots, 10$, $u =$ Hydro, Wind, Geo, Solar
	$PE_{Lig,0}$	$t = 11, \ldots, 30$, $u =$ Hydro, Wind, Geo, Solar
PF_{ft}	PF_{f0}	$\forall f \in F, t \in T$
$p_t^{CO_2}$	$30	$\forall t \in T$
$\kappa^{min} - \kappa^{max}$	5% − 10%	
γ_{ut}	50%	$\forall u \in U, t = 10$
	40%	$\forall u \in U, t = 20$
	35%	$\forall u \in U, t = 30$

The minimum market share that the company aims to reach is determined as 5% at the end of planning horizon, and the maximum limit on the market share, which is given by the government to the company, is set to 10%. Moreover, we apply portfolio balance constraints for the 10th, 20th and 30th years to the values are 50%, 40%, and 35%, respectively. These values are taken as the same for all types of power plants. Currently, there is no carbon trading market in effect in Turkey; however, Turkey signed Kyoto Protocol on 26th of August in 2009 [38]. Although currently Turkey does not have any commitments on the reduction of the emissions of GHGs, a mandatory carbon trading mechanism is expected to be put in effect in Turkey in near future because of the compliance with EU laws and signed protocols. Monitoring of GHGs and Emissions Trading Branch was founded under Climate Change Department of Ministry of Environment and Urbanization. One of the duties of this branch is "monitoring GHGs and performing national and international coordination studies, forming politics and strategies, and preparing legal legislation in carbon trading context." Since there is no effective emission trading system in operation, it is not determined yet how to assign cap values to the companies. In this study, we assume that the company entering the energy market will be assigned to a cap value that is equal to the total emission value of a medium-sized electricity generation company, which is taken as 2 million tons. Furthermore, this cap value is assumed to be decreased by 3% every following year. We summarize the parameter values for base scenario in Table 4.5.

We implement the formulation on GAMS 23.7.3, and use Cplex 12.3 as the solver. We solve the mixed-integer linear programming model with the base scenario parameter values, and obtain the optimal investment decisions. All instances are solved to optimality within a minute. The results are given in Table A.1 in Appendix. We also present the cumulative optimal added power plant capacities in terms of time periods as a line chart in Figure 4.1. From both the table and the figure, we observe that investing in a Geo power plant at the annual maximum level every year until the investments reach at their maximum potential is optimal. As a remark, the potential of Turkey for Geo is limited to 1000MW. In addition, investing in power plants at their annual maximum level every year starting from the first year until year 25 is optimal. The reason why the model gives up to invest in Wind power plants after 25th years is to guarantee that the portfolio balance constraints are satisfied. The same situation is observed in investment decisions for Hydro power plant. The optimal strategy is to invest at their maximum level on Hydro power plants by starting from the first year,

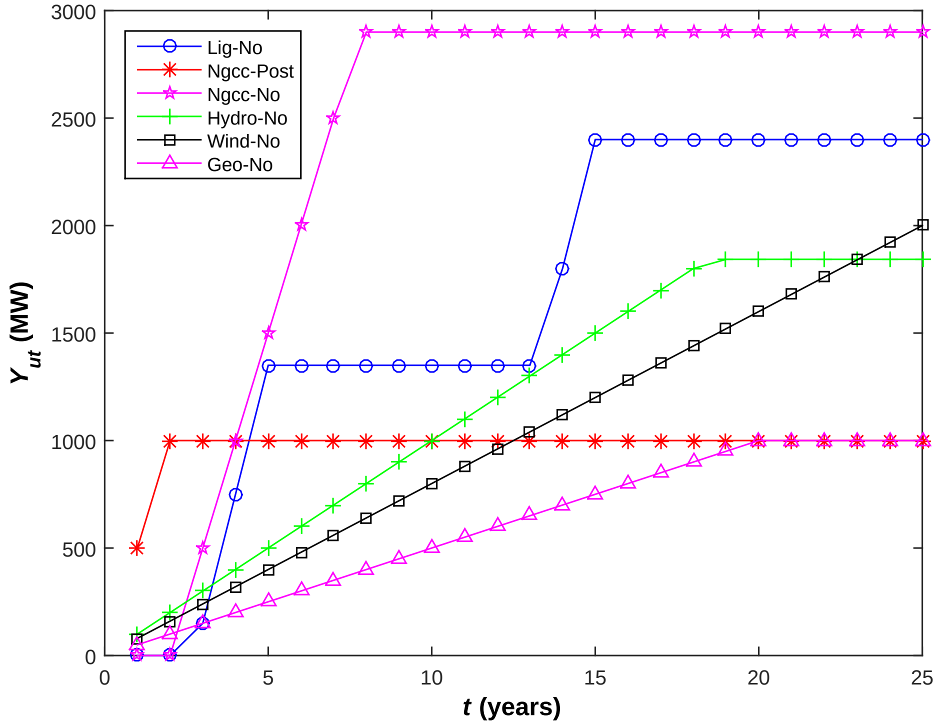


Figure 4.1. Cumulative investment amounts for the base scenario.

and continuing until year 18, and invest at the maximum possible value in year 19 such that the portfolio balance constraints are satisfied. Another observation is that Ngcc power plants investment is the most profitable option in terms of the cost of investment and capacity factor. As seen from Figure 4.1, the maximum of total investments is realized for Ngcc with no CCS technology, which is 2900MW. These investments are realized starting from year 3 until year 8. On the other hand, investing up to the annual upper limit on Ngcc with CCS technology of postcombustion is optimal in first two years. Moreover, it is noticed that investing on Lig power plants in years 3, 4, 5, 14 and 15 are in the optimal decisions. The investments in years 3 and 14 are under the annual upper limit given to this power plant type. Therefore, we see from these investments that the reason for the model to invest in Lig power plants is to guarantee portfolio balance constraints for the other more profitable options.

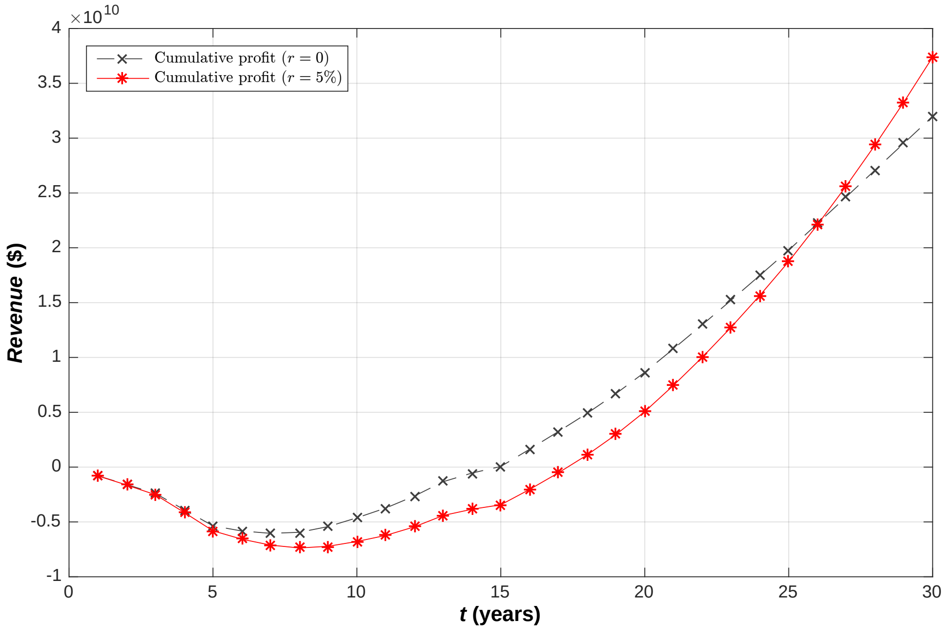


Figure 4.2. Cumulative profit curve for different interest rate values.

In Figure 4.2, we plot the cumulative profits realized throughout the planning horizon, where the red solid line shows the cumulative profit using the base scenario's interest rate, $r = 5\%$ and the black dashed line shows cumulative profit assuming zero interest rate. As seen from Figure 4.2, the simple payback period, which is calculated for interest rate, $r = 0\%$, is 15 years whereas the discounted payback is 18 years. Due to the carbon prices used in the model, payback periods are a bit higher than the industrial average. This result indicates that carbon pricing mechanism diminishes returns in the power generation industry.

4.1.3. Sensitivity Analysis

In this section, we perform sensitivity analysis based on certain parameters of the deterministic model. These parameters are carbon credit price, electricity price, portfolio balance ratio and interest rate. We create scenarios for these parameteres and provide results of analysis in the following sections.

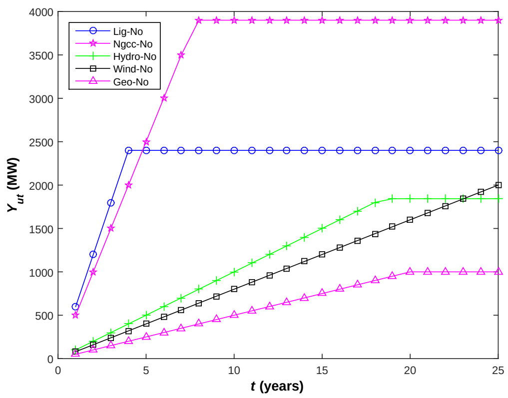
<u>4.1.3.1. Carbon Credit Prices.</u> The first parameter that we aim to analyze its effect on the optimal decision is the carbon credit price. For this purpose, we create ten scenarios for carbon credit price, and provide them in Table 4.6. In all these scenarios, we assume that the carbon credit price is fixed to the initial value throughout the planning horizon.

Table 4.6. Parameter values for the scenarios related to carbon price.

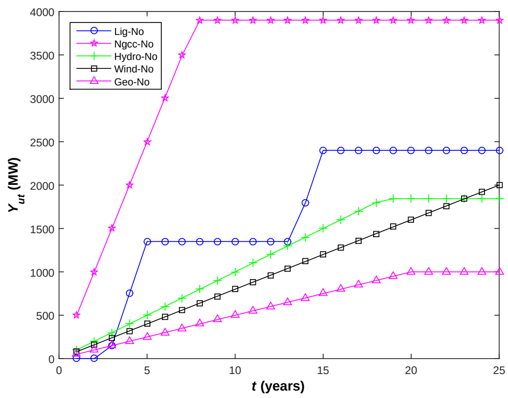
Scenario Name	$p_t^{CO_2}$	Scenario Name	$p_t^{CO_2}$
CO_2-1	10	CO_2-6	60
CO_2-2	20	CO_2-7	70
CO_2-3	35	CO_2-8	80
CO_2-4	40	CO_2-9	90
CO_2-5	50	CO_2-10	100

We give the optimal investment decisions in terms of carbon credit price scenarios in Table A.2 in Appendix. The cumulative optimal investment amounts over the planning horizon with respect to these scenarios are given in Figure 4.3.

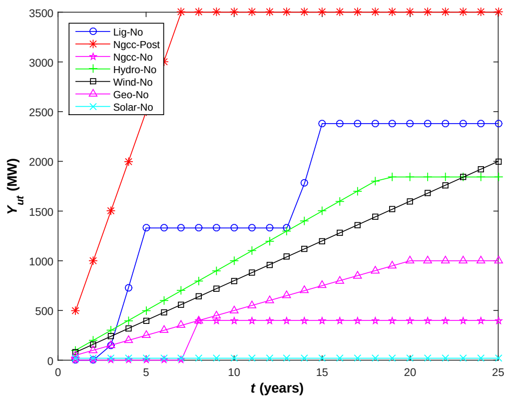
As the most profitable option is the Ngcc, the maximum investment is put on these plants. As it can be seen from Table A.2, when the carbon credit price is low, such as \$10 and \$20, making investment on Ngcc with no CCS technology added is optimal. On the other hand, as the carbon credit price increases, investing in Ngcc with postcombustion CCS technology plants becomes optimal. For carbon credit prices between \$10 and \$80, Lig with no CCS technology investments are optimal. When carbon credit price becomes \$90 and \$100, Lig with postcombustion CCS technology enters the optimal solution; and when carbon credit price becomes \$100, Lig with no CCS leaves the optimal solution. In short, if the carbon credit price becomes \$100, which is almost not possible according to today's carbon markets since it is so high, the optimal solution includes investments either for renewable energy sources or CCS technology added thermal power plants because carbon emission cost dominates the other parameters. When the carbon emission costs become higher, investing in renewable energy sources and installing CCS technology become optimal.



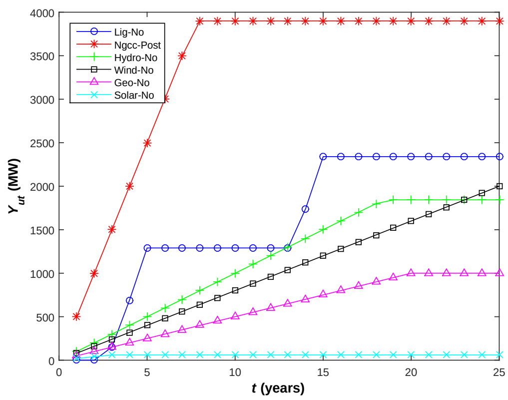
(a) $P_t^{CO_2} = 10$



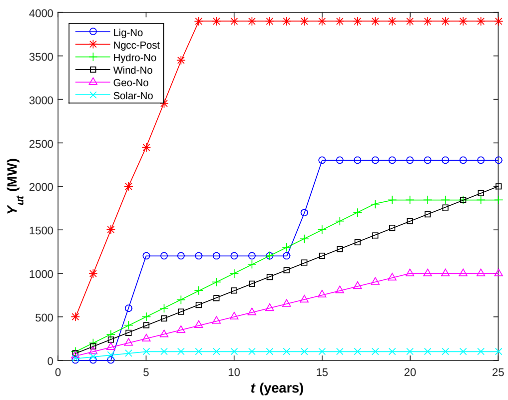
(b) $P_t^{CO_2} = 20$



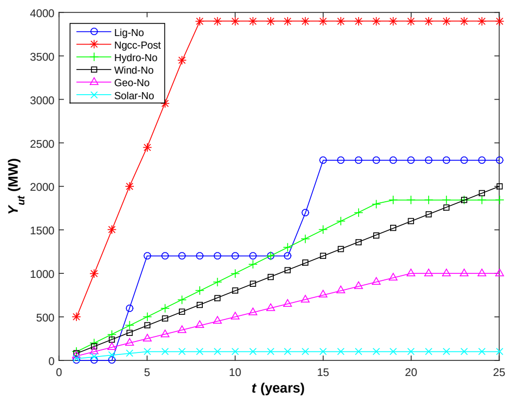
(c) $P_t^{CO_2} = 35$



(d) $P_t^{CO_2} = 40$

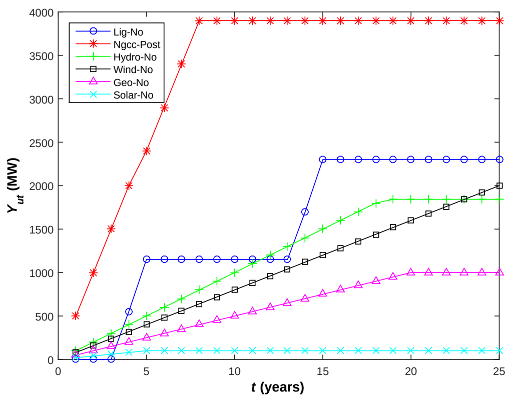


(e) $P_t^{CO_2} = 50$

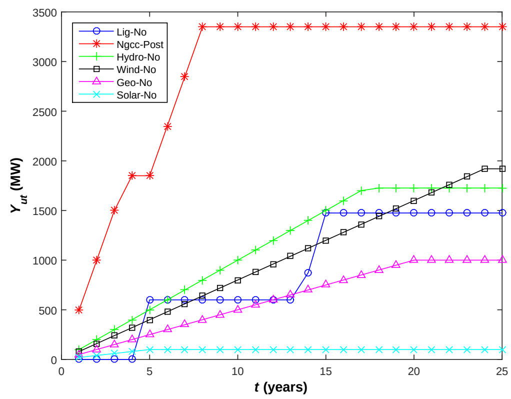


(f) $P_t^{CO_2} = 60$

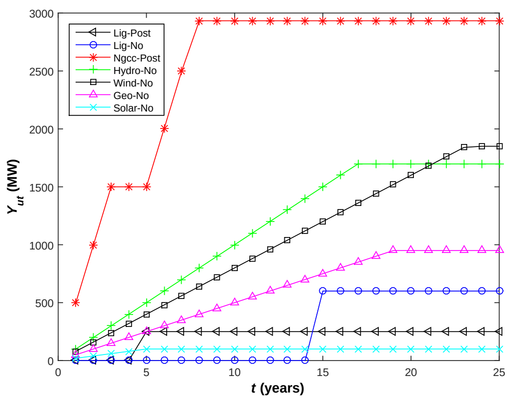
Figure 4.3. Cumulative investment amounts for different carbon price scenarios.



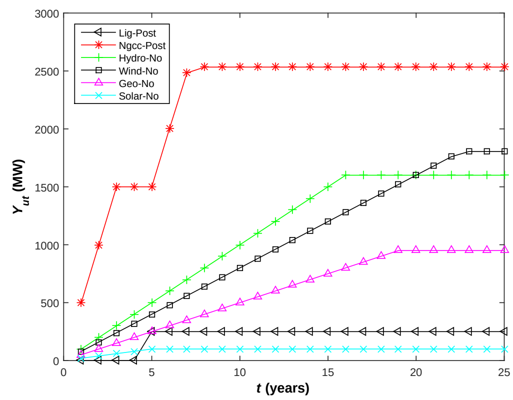
(g) $P_t^{CO_2} = 70$



(h) $P_t^{CO_2} = 80$



(i) $P_t^{CO_2} = 90$



(j) $P_t^{CO_2} = 100$

Figure 4.3. Cumulative investment amounts for different carbon price scenarios (cont.).

The results show that CCS technology investment starts to compansate cost of carbon emission after a certain carbon credit price, which is \$30 for our case. On the other hand, we conclude that the optimal investment decisions are not significantly sensitive to the carbon credit price for Hydro, Wind and Geo power plants. Even without high carbon prices, investing on these renewable energy resources are optimal as there are upper limits on every source, which prevent fully investing on the most profitable options, and as there are portfolio balance constraints, which force the model to include renewable energy resources into the portfolio. When the carbon price is low, \$10 and \$20, there is no Solar investment. As the carbon price gets higher, Solar investments enter the optimal solution, and these investments reach their maximum value at a carbon price of \$40. For prices between \$50 and \$100, they are fixed to 60MWs, which means high carbon prices do not force the model to invest on Solar energy after it reaches its highest possible value to balance the portfolio since the investment cost for Solar energy is high compared to other sources.

<u>4.1.3.2. Electricity Prices.</u> Another parameter whose effect on optimal decisions we analyze is electricity prices. For this purpose, we create six different scenarios for electricity prices and give them in Table 4.7. For scenarios PE-1 through PE-5, we assume that the subsidy given to the electricity generated using renewable energy sources is valid only for the first 10 years. After ten years, all prices for the electricity generated from any type of resource are equal. For scenario PE-6, only for Solar, the subsidized prices are valid for the first 20 years.

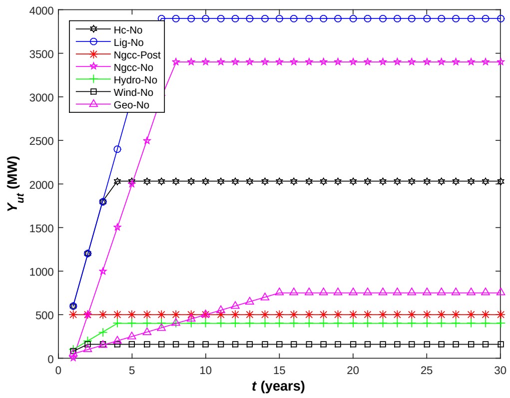
We obtain optimal investment decisions with respect to the scenarios created for electricity price. We provide these results in Table A.3 in Appendix. We also provide the cumulative investment amounts over the planning horizon for each electricity price scenario in Figure 4.4. As it can be observed from Table A.3 and Figure 4.4, Hc power plant investment is optimal only for the scenarios (PE-1, PE-2 and PE-3) in which electricity prices increase in the future with a predetermined ratio. As a reminder, in the base scenario, where the electricity prices are taken as constant over the planning horizon, investing in Hc power plants is not optimal at all. Similar situation occurs for

Table 4.7. Parameter values for scenarios related to electricity price.

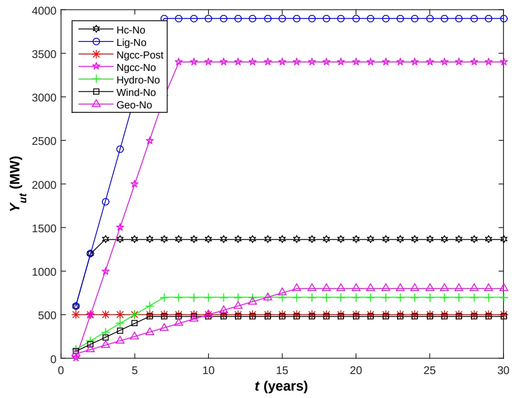
Scenario Name	PE_{ut}
PE-1	$PE_{u,t-1} + 3$, $\forall t \in T$
PE-2	$PE_{u,t-1} + 3$, $\forall t \in \{1, \ldots, 10\}$
	$PE_{u,t-1} + 2$, $\forall t \in \{11, \ldots, 20\}$
	$PE_{u,t-1} + 1$, $\forall t \in \{21, \ldots, 30\}$
PE-3	$PE_{u,t-1} + 3$, $\forall t \in \{1, \ldots, 10\}$
	$PE_{u,t-1}$, $\forall t \in \{11, \ldots, 20\}$
	$PE_{u,t-1} + 3$, $\forall t \in \{21, \ldots, 30\}$
PE-4	$PE_{u,t-1} - 1$, $\forall t \in T$
PE-5	$PE_{u,t-1} - 1$, $\forall t \in \{1, \ldots, 20\}$
	$PE_{u,t-1}$, $\forall t \in \{21, \ldots, 25\}$
PE-6	PE_{u0} and subsidized price for solar energy is valid for first 20 years the planning horizon

Lig power plants with one exception. Lig power plant investment exist in PE-6, where the subsidy given to the electricity generated from Solar plants continues for the first 20 years and all other electricity prices are fixed to their initial level. In this scenario, making investment on Lig power plants becomes optimal as in the base scenario.

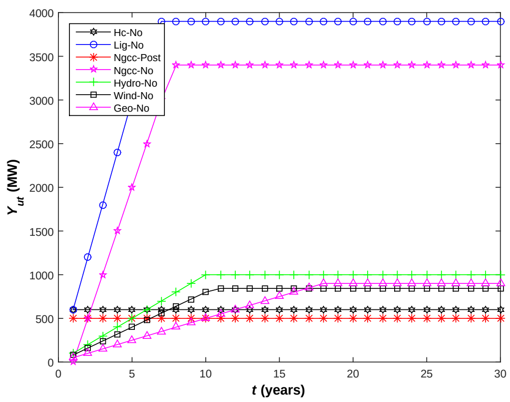
In addition to the Hc and Lig power plants investment analysis, Ngcc power plant investment is optimal for all scenarios. The electricity prices become close to the subsidized electricity prices given to renewable energy resources since electricity prices increase with time. This leads to lower investments in renewable energy sources, which can be observed in scenarios PE-1, PE-2 and PE-3. When the scenarios in which electricity prices decrease are investigated, it is seen that all types of investments decrease, except investments to Wind and Hydro power plants. These results can be explained with the subsidized electricity price given to these sources in the first 10 years. Solar energy investments enter the optimal solution only when the subsidized electricity prices generated from Solar energy continues longer than the subsidies given to other renewable energy sources (in PE-6).



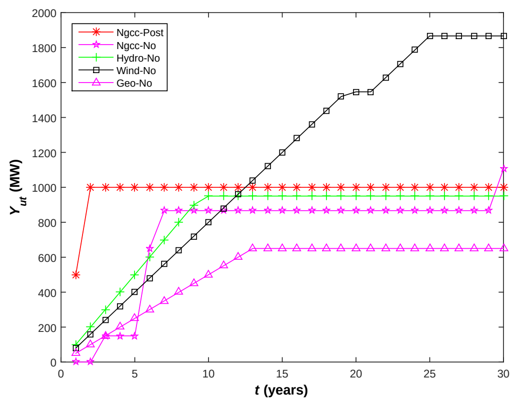
(a) Scenario PE-1



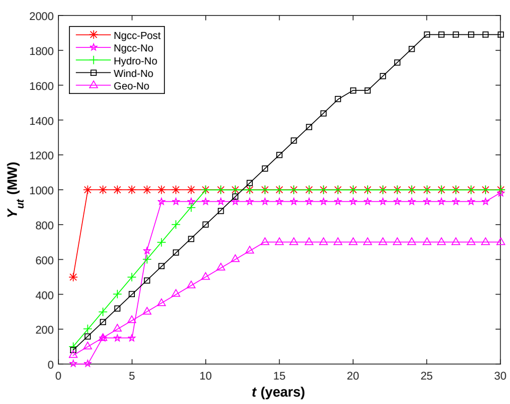
(b) Scenario PE-2



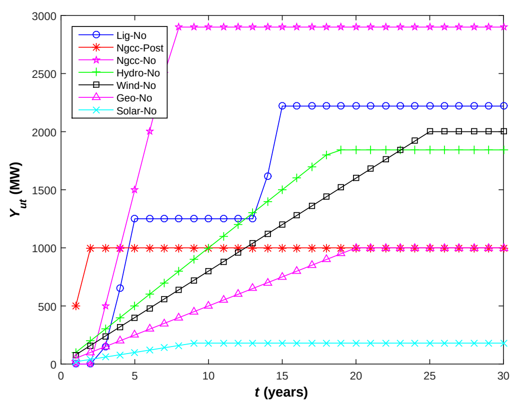
(c) Scenario PE-3



(d) Scenario PE-4



(e) Scenario PE-5



(f) Scenario PE-6

Figure 4.4. Cumulative investment amounts for different electricity price scenarios.

4.1.3.3. Portfolio Balance Ratios. Another parameter that we are interested in analyzing its effect is the portfolio balance ratios. We create scenarios for γ_{ut} values and provide these scenarios in Table 4.8.

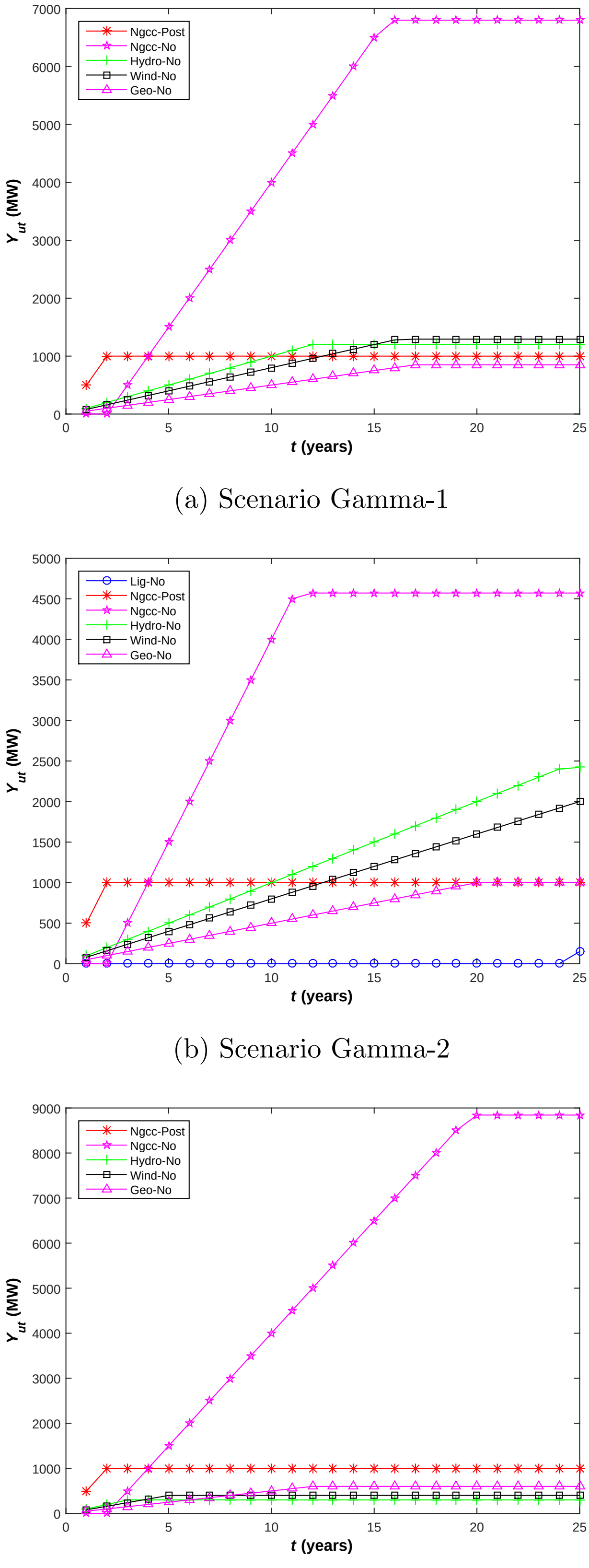
Table 4.8. Parameter values for scenarios related to portfolio balance constraint.

Scenario Name	γ_{u10}	γ_{u20}	γ_{u30}
Gamma-1	0.8	0.75	0.7
Gamma-2	0.8	0.75	0.5
Gamma-3	1	1	1

Optimal investment for all scenarios are provided in Table A.4 in Appendix, and the cumulative investment amounts over the planning horizon are given in Figure 4.5. In scenario Gamma-3, there are no portfolio balance constraints since all γ_{ut} values equal to one. The model is expected to select the most profitable investment options and invest fully until another constraint becomes tight. Since Ngcc power plants are the most profitable investment options, the model invests fully on Ngcc power plants starting from the first year until year 19. In year 20, the model does not invest at the annual maximum level since the market share constraint enforced by the government prevents any more investments on Ngcc. Investing on Hydro is profitable only if it is realized in first three years. Similar situation occurs for Wind for five years, and for Geo for 12 years.

In scenario Gamma-1 and Gamma-2, the portfolio balance constraints are enforced. It can be seen from Table A.4 that, in these scenarios, the investment amounts for Wind, Hydro and Geo power plants are greater than investment for these power plants in scenario Gamma-3. As portfolio balance constraints becomes restrictive as in the scenario Gamma-2, which is the most restrictive scenario, the optimal investment mixture includes different types of investments such as Lig power plants.

4.1.3.4. Interest Rates. We are also interested in investigating the effect of interest rate. We create four different scenarios for the annual interest rate and provide them in Table 4.9.



(a) Scenario Gamma-1

(b) Scenario Gamma-2

(c) Scenario Gamma-3

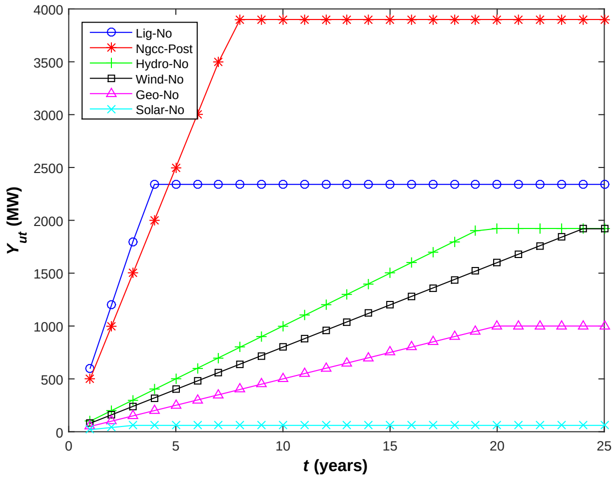
Figure 4.5. Cumulative investment amounts for different portfolio balance scenarios.

Table 4.9. Parameter values for scenarios related to interest rate.

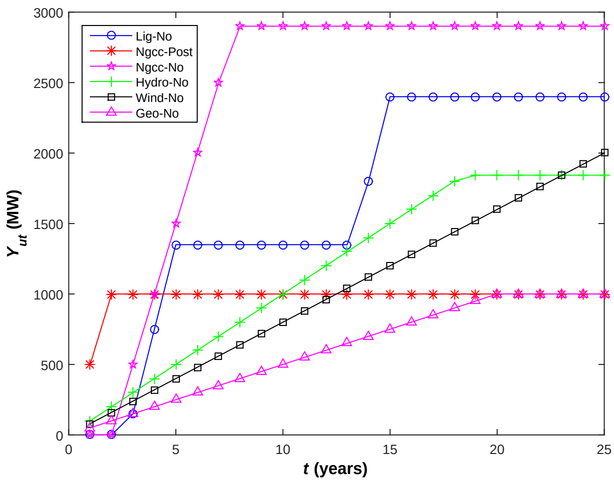
Scenario Name	r_t
r-1	%3 $\forall t \in T$
r-2	%8 $\forall t \in T$
r-3	%10 $\forall t \in T$

The resulting optimal investment decisions for scenarios are provided in Table A.5 in Appendix. Moreover, the cumulative investments in terms of time periods for these scenarios are given in Figure 4.6. Due to the fact that the costs and prices do not change throughout the planning horizon, i.e. they are equal to the inital values throughout the years, the net present value of the gains obtained from generating and selling electricity decreases as the interest rate increases. For scenario r-1, in which the interest rate is at its lowest value (3%), Solar energy power plant investment enters the optimal decision. However, Solar energy power plant investment is not optimal for other scenarios since the gains obtained from Solar energy do not compensate its high installation cost and low capacity factor. Furthermore, as the interest rate increases, the total investment throughout the planning horizon decreases because the net present value of the gains decreases.

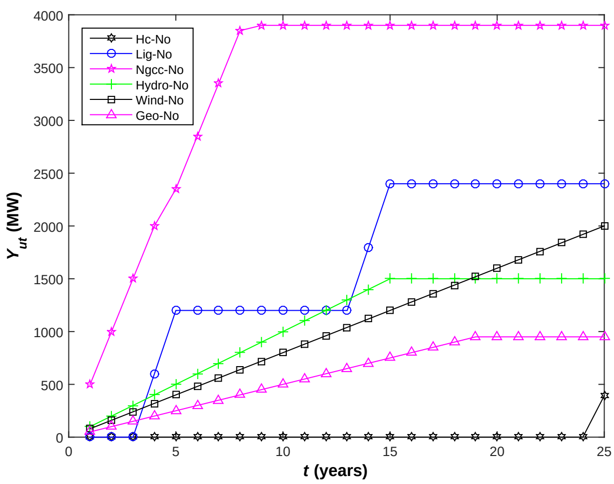
Comparing the base scenario and other settings that we tested for sensitivity, we observe portfolio balance and market share constraints affect the model's behavior. In real life, while portfolio balance constraint is determined by the company, market share constraint is determined by external party such as government. Similarly, the parameters, which are electricity prices, carbon prices and interest rate, should be estimated carefully while the investment strategies are determined. Accordingly, we include these conditions so as to make this model applicape for a private electricity generating company and obtain reasonable results. The sensitivity analysis results indicate that the optimal investment decisions are consistent with the expected outcomes.



(a) $r = 3\%$



(b) $r = 8\%$



(c) $r = 10\%$

Figure 4.6. Cumulative investment amounts for different interest rate value scenarios.

4.2. Stochastic Optimization Model Results

In this section, we investigate our multi-stage stochastic programming approach to model an investment planning model for a private electricity generating company in a carbon-constrained environment.

4.2.1. Related Data

The abbreviations and explanations used for power plant types given in Table 4.1 and CCS technology types given in Table 4.2 are valid for this section. Moreover, the parameters that are given in Table 4.3 and Table 4.4 are also valid for multi-stage stochastic optimization model. We take electricity and fuel price values in Table 4.4 as base year values while we generate scenarios. Note that the prices of electricity generated from renewable energy sources for the first ten years are taken as the values given in Table 4.4 because of subsidies given for applied on renewable energy sources.

In this section, we assume that there are two types of market through which we can sell the generated electricity: day-ahead market and bilateral contracts. The electricity prices differ according to the type of the market used. In Turkey there are three load blocks: (1) day (6am–5pm), (2) peak (5pm–10pm), and (3) night (10pm–6am). The electricity prices depend on the load block type during which the electricity is sold at the day ahead market or via bilateral contracts. Electricity prices realized in 2015 are used as the base year in the application. These prices are given in Table 4.10 and load block hours in Table 4.11.

Table 4.10. Electricity prices realized in 2015.

Electricity Market	**Day** ($)	**Peak** ($)	**Night** ($)
Bilateral	54	59.34	44.14
Day Ahead	54	57.88	38.31

Table 4.11. Load Block Hours.

Day (hrs)	**Peak** (hrs)	**Night** (hrs)
4015	1825	2920

There exists uncertainty about the carbon credit price. These carbon credit prices affect the price of electricity sold and the fuel cost. When the carbon credit price increases, the tendency to the new technology power plants and CCS technology increases, and this leads to rise in the price of electricity sold. Furthermore, the increase in carbon price causes decrease in demand for fuel due to decrease in generation from thermal power plants. Hence, this leads to fall in the fuel prices, namely fuel costs. By taking this relationship into consideration, we generate different scenarios. While creating these scenarios, we consider different policies that may be introduced by the government. In these scenarios, we first decide on the carbon credit price under the assumption that it will change based on the policy that the government will follow on carbon regulations. We assume that there will be an adaptation period, so there will be no change in carbon prices in first 5 years. After 5 years, there will be two options that the carbon prices will either continue on the same level or increase in order to urge carbon mitigation. After this period, new policies will be introduced that the carbon prices will continue on the same level, become more restrictive or softer according to carbon emission level of the country. Then, we decide on the electricity price and the fuel cost which are affected by the change in carbon credit price.

In this scope, we form a scenario tree which differs with respect to carbon credit, electricity and fuel prices. The generated scenario tree is given in Figure 4.7. We use three-stage stochastic optimization tree that includes 100 scenario paths. There are 111 branches in total, which include one branch at the first stage, ten branches at the second stage and a hundred branches at the last stage because of the fact that each branch of the second stage divides into ten branches. There are 1105 scenario nodes in these branches in total which is comprised of 5 nodes at the first stage, a hundred nodes (ten nodes for each branch) at the second stage, and a thousand nodes (ten nodes for each branch) at the last stage. Note that in the Figure 4.7, the dotted lines represent the intermediate scenario nodes in the branches.

While the scenario tree is formed, two extreme policies, at the top and bottom branches, are generated. Then, the possible scenarios in between these two extreme policies are created. Since we do not expect to have a major change in the carbon emission policy of the country in the first 5 years, we assume the carbon prices, hence the electricity price and fuel costs, will be stable at their current levels. This situation can be observed from both Figure 4.7 and Figure 4.8. After 5 years, i.e. in the second stage, we generate ten possible policies (with equal probabilities) regarding that the government may enforce. Therefore, based on these policies the scenario tree is separated into ten branches in the second stage. We assume that the carbon emission regulations will not be enforced at the top branch of second stage (nodes between 2,0,1,5 and 2,0,1,9); therefore, at this branch the carbon price will be stable during the second stage at its current value, which is \$30/ton. On the other hand, considering the situation that the government will enforce strict carbon regulations, we determine the carbon credit price as \$50/ton at the bottom branch. In the remaining branches of the second stage, carbon credit price is uniformly distributed between \$30/ton and \$50/ton regarding that the goverment may introduce different policies. In year 10, which is the last year of the second stage, each scenario branch is separated into ten different branches, resulting in 100 scenario branches at the last stage. At the top branch, starting with node (3,1,11,10), considering that the government will not enforce any regulations at all and the carbon credit price will drop to \$20/ton. At the very bottom node of the last stage, (3,10,110,10), the carbon credit price is taken as \$70/ton considering that the government strictly enforces the carbon regulations. In the intermediate scenario branches, carbon credit price is uniformly distributed between \$20/ton and \$70/ton so as to allow investigating results of different possible scenarios. As a remark, we assume that the carbon price is equal to its level in the first node of every path in each stage.

The generated scenarios for the carbon credit price are shown in Figure 4.8 so as to give information about the proposed relative change of the carbon credit prices with respect to years. As it is observed, there is no change in the carbon credit prices in the first 5 years. After 5 years, the scenario path is seperated into ten different branches, which represent scenario paths. Bottom path assumes that the carbon emission regulations will not be enforced, hence the carbon price will be stable during the second stage at its current value; and top path assumes that the government will enforce carbon regulations, so the carbon credit price will increase. In other paths in this stage, we distribute the carbon price evenly between its lowest and highest values. In year 10, each scenario path is separated into ten different paths, resulting in 100 scenario branches (the third stage). At the bottom path, we assume that the government will not enforce any regulations at all, and the carbon price will decrease; and at the top path, the carbon regulations are strictly enforced, resulting in increased carbon price. In the intermediate scenario branches, we again generate carbon price evenly between its highest and lowest values.

The equations, which are from Equation 4.1 to Equation 4.9, represent how we calculate the carbon prices in the scenario tree.

Table 4.12. Number of branches.

Notation	**Value**
b_1	1
b_2	10
b_3	100

Table 4.13. Predetermined Carbon Price Values.

Notation	**Value**
P_1	20
P_2	30
P_3	40
P_4	50
P_5	70

1st Stage :

$$CP_0 = P_2 \tag{4.1}$$

2nd Stage:

$$CP_1 = CP_0 \tag{4.2}$$

$$CP_k = CP_{k-1} + \frac{P_3 - P_2}{\frac{b_2}{2} - 1} \quad \forall k = 2, ..., 5 \tag{4.3}$$

$$CP_6 = CP_5 \tag{4.4}$$

$$CP_k = CP_{k-1} + \frac{P_4 - P_3}{\frac{b_2}{2} - 1} \quad \forall k = 7, ..., 10 \tag{4.5}$$

3rd Stage:

$$CP_{11} = P_1 \tag{4.6}$$

$$CP_k = CP_{k-1} + \frac{P_3 - P_1}{\frac{b_3}{2} - 1} \quad \forall k = 12, ..., 60 \tag{4.7}$$

$$CP_{61} = P_4 \tag{4.8}$$

$$CP_k = CP_{k-1} + \frac{P_5 - P_4}{\frac{b_3}{2} - 1} \quad \forall k = 62, ..., 110 \tag{4.9}$$

We create data sets for electricity price and fuel cost based on the carbon credit prices regarding the assumptions of [32]. In other words, considering the relationship between carbon credit, electricity and fuel prices, if the carbon credit price is stable, we take the electricity price and fuel cost as stable at their current levels. On the other hand, when the carbon credit price increases, we expect to have decreased demand for fossil fuels, which in turn will decrease the fuel cost, and increase the electricity prices

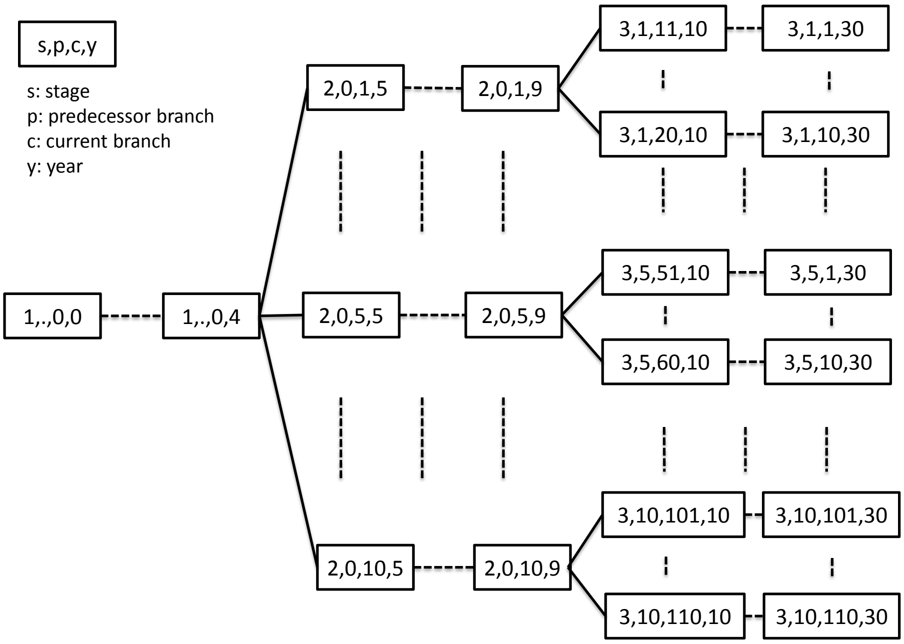


Figure 4.7. Scenario tree.

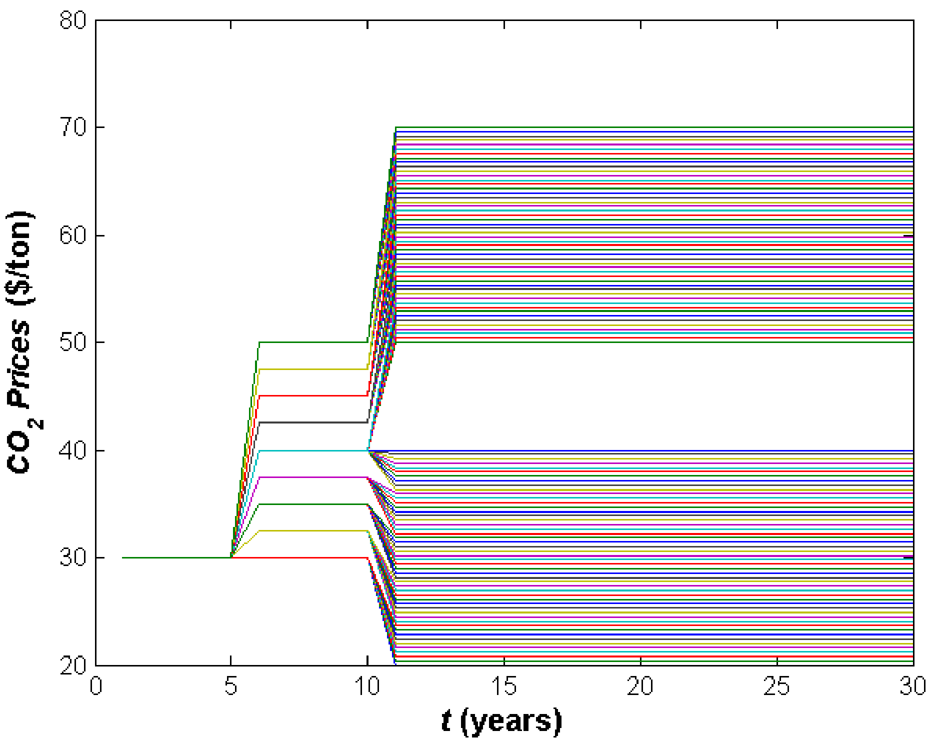


Figure 4.8. Carbon credit price scenarios.

due to the investment on expensive generation units and the high carbon prices. The opposite is true for the fuel cost and the electricity price when the carbon credit price decreases. Assuming that in the second stage the percentage increase in electricity prices (and the same percentage decrease in fuel cost) is uniformly distributed between 0.25% and 2%. In the third stage, the percentage decrease applied in electricity prices (and same percentage increase in fuel cost) is uniformly distributed between 2% and 0.25%, while the percentage increase applied in electricity prices (and same percentage decrease in fuel cost) is uniformly distributed between 0.25% and 3%. According to these assumptions, we generate data sets. Note that these percentage changes are applied at every scenario node on a branch to calculate the relative node's values based on the predecessor node's values.

The equations, which are from Equation 4.10 to Equation 4.30, stand for calculations of electricity price scenarios.

1st Stage:

$$PE_{0n} = PE_1 \quad \forall n = 1, .., 5 \tag{4.10}$$

2nd Stage:

$$R_k = R_{k-1} + \frac{LR - IR}{b_2 - 3} \quad \forall k = 2, ..., 10 \tag{4.11}$$

$$PE_{1n} = PE_{05} \quad \forall n = 1, ..., 5 \tag{4.12}$$

$$PE_{k1} = PE_{05} \times (1 + R_k) \quad \forall k = 2, ..., 10 \tag{4.13}$$

$$PE_{kn} = PE_{kn-1} \times (1 + R_k) \quad \forall k = 2, ..., 10 \quad \forall n = 2, ..., 5 \tag{4.14}$$

3rd Stage:

The ratios, which applied on the each node of the third stage, are calculated as follows:

$$R_{11} = IR_1 \tag{4.15}$$

$$R_k = R_{k-1} - \frac{IR_1 - LR_1}{b_2} \quad \forall k = 12, ..., 20 \tag{4.16}$$

$$R_{21} = IR_2 \tag{4.17}$$

$$R_k = R_{k-1} - \frac{IR_2 - LR_2}{b_2} \quad \forall k = 22, ..., 30 \tag{4.18}$$

$$R_k = 0,25 \quad \forall k = 31, ..., 40 \tag{4.19}$$

$$R_k = IR_i \quad \forall k = i * b_2 + 1 \quad \forall i = 4, ..., 10 \tag{4.20}$$

$$R_k = R_{k-1} + \frac{LR_i - IR_i}{b_2} \quad \forall k = (i * b_2 + 2), ..., (i + 1) * b_2 \quad \forall i = 4, ..., 10 \tag{4.21}$$

According to these ratios, electricity prices for the third stage are calculated as follows:

$$PE_{k1} = PE_{15} \times (1 - R_k) \quad \forall k = 11, ..., 20 \tag{4.22}$$

$$PE_{kn} = PE_{kn-1} \times (1 - R_k) \quad \forall k = 11, ..., 20 \quad \forall n = 2, ..., 10 \tag{4.23}$$

$$PE_{k1} = PE_{25} \times (1 - R_k) \quad \forall k = 21, ..., 30 \tag{4.24}$$

$$PE_{kn} = PE_{kn-1} \times (1 - R_k) \quad \forall k = 21, ..., 30 \quad \forall n = 2, ..., 10 \tag{4.25}$$

$$PE_{k1} = PE_{35} \times (1 - R_k) \quad \forall k = 31, ..., 40 \tag{4.26}$$

$$PE_{kn} = PE_{kn-1} \times (1 - R_k) \quad \forall k = 31, ..., 35 \quad \forall n = 2, ..., 10 \tag{4.27}$$

$$PE_{kn} = PE_{kn-1} \times (1 + R_k) \quad \forall k = 36, ..., 40 \quad \forall n = 2, ..., 10 \tag{4.28}$$

$$PE_{k1} = PE_{i5} \times (1 + R_k) \quad \forall k = i * b_2 + 1 \quad \forall i = 4, ..., 10 \tag{4.29}$$

$$PE_{kn} = PE_{kn-1} \times (1 + R_k) \quad \forall k = (i * b_2 + 2), ..., (i + 1) * b_2 \quad \forall i = 4, ..., 10 \tag{4.30}$$

Note that the ratios are same with the ratios, which are used in coal price calculations. The formulation is also valid for coal price calculations but the only difference is that plus and negative signs before the ratios will change inversely. As mentioned earlier, coal price and electricity price are inversely related. The curves of electricity and coal prices data are given in Figure 4.9 and Figure 4.10 for each scenario in terms of years, respectively. To make it clear, we generate electricity price scenarios only for the day load block which is same for both bilateral and day-ahead selling types that can be seen in Table 4.10. In order to calculate electricity prices for the peak and night load blocks with respect to selling types, we multiply these values by the ratios generated from the base values given in Table 4.10. As we mention, we apply same ratios to electricity prices and fuel prices by taking the relationship between these prices into consideration. This situation can be observed from Figures 4.9 and 4.10 that the figures are symmetric. In fact, the shape of the curves gives information about how we create scenarios. We only represent figure for coal price scenarios since the shape of the curves will be same for the rest of fuel types and selling types due to the fact that we apply same increase/decrease percentage for each fuel type and each selling type.

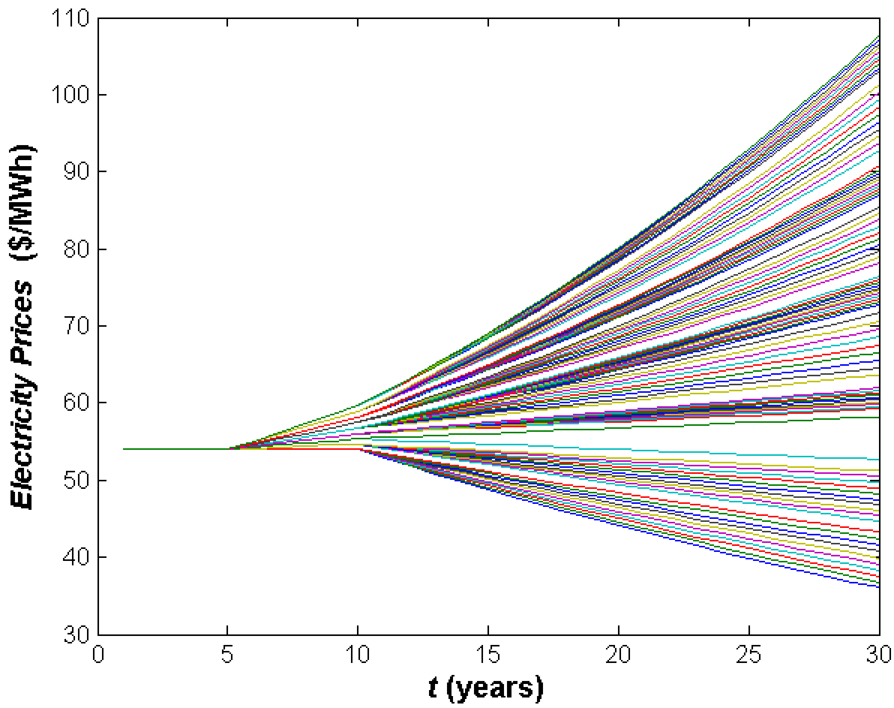


Figure 4.9. Electricity price scenarios.

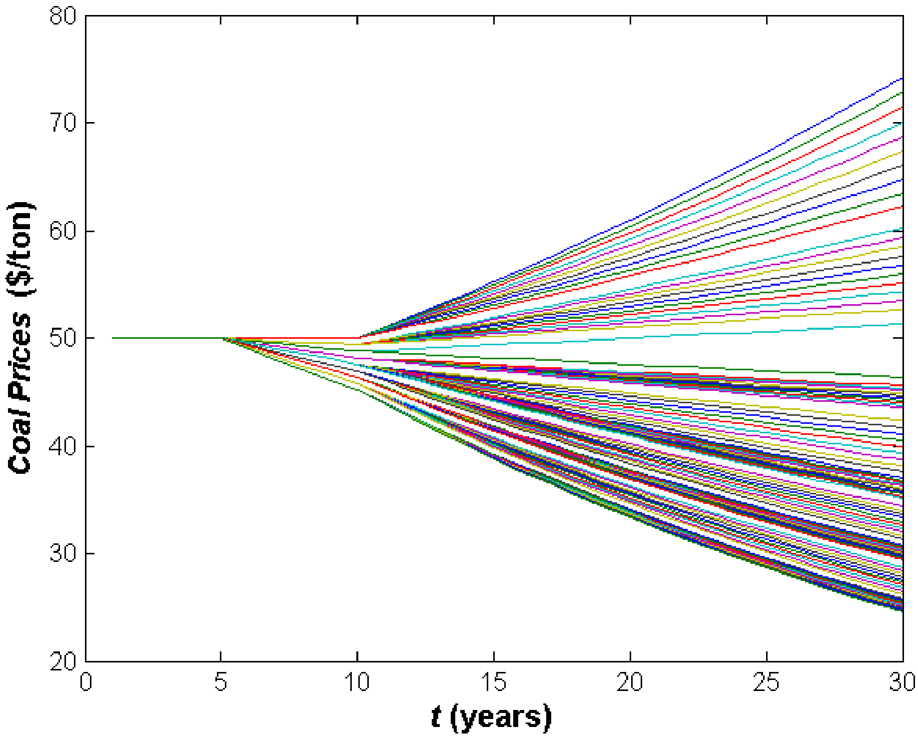


Figure 4.10. Coal price scenarios.

4.2.2. Analysis and Results

We implement the mixed-integer linear program by using programming language C# on Visual Studio on a machine with Intel Xeon 2.27 GHz CPU, 24 GB RAM and Windows 2008 Server R2 operating system, and used Cplex 12.3 as the solver. The model is solved to optimality within several minutes.

We present the results and the analysis of the implemented model in the following parts.

4.2.2.1. Investment. The optimal added capacity decisions for each year for some selected scenarios are given in Figure 4.11. In order to clarify Figure 4.11, we should note that year 0 in x-axis corresponds to 2015 and year 19 corresponds to year 2034. We omit the remaining years since there are no positive investments for these years in the optimal solution. The values of first 5 years are same for all scenarios. Starting from year 5, which is the starting year of the second stage, the first column represents "soft"policy, taking part in top branch, where the carbon regulations are not enforced, the second column represents a "middling" scenario, where the carbon credit prices are close to the initial price; and finally, the last column represents "restrictive" policy, taking part in bottom branch, where the carbon regulations are strictly enforced.

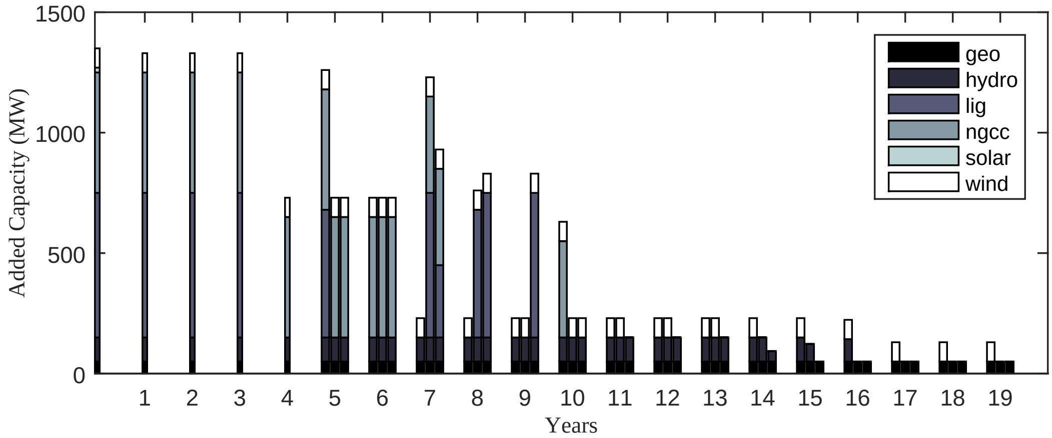


Figure 4.11: Added capacity for each year for different branches in scenario tree.

In the first stage, the highest investment is realized at Lig power plants and investment in Ngcc, Hydro, Wind, Geo and Solar power plants follow Lig, except year 4 where investing on Lig plant is no longer optimal. On the other hand, if carbon credit price does not increase, Lig plants investments are in optimal solution for year 5, while investing in Lig plants become optimal for 7th and 8th years of middling scenario and for 7th, 8th and 9th years for restrictive scenario. After year 10, Lig plants does not exist in the optimal solution for all scenarios. When we analyze Ngcc plants investments, we see that it is optimal to invest at the maximum annual investment limit for the first 6 years independent of the policy adopted. In year 7, positive investments in these plants can be observed for middling and the restrictive scenarios. Furthermore, these plants enter the optimal solution only for soft carbon policy in year 10. After this point, it is not optimal to invest in Ngcc plants.

Investment on Geo plants is occured at its annual maximum possible value independent of the policy adopted, which means it is always optimal to invest on Geo plants since the investment cost is smaller when compared to high feed-in tariff applied for electricity generated at Geo plants. For Hydro plants, we observe a similar pattern with Geo. The only difference is that there are no Hydro investments for years 17, 18 and 19, for all scenarios, and the amount of investment decreases for restrictive scenario starting from year 14, because of the portfolio balance constraints enforced by the company. Wind investments follow very similar pattern with Hydro plants, except that in the restrictive scenario, these investments leave the optimal solution after year 11. Main reason is that the total investment amount over the planning horizon for the restrictive scenario is lower than the other scenarios. These results show the effectiveness of incentives provided for renewable energy resources.

The investment decisions in Solar plants follow a different pattern with respect to other renewable energy sources, where it is only optimal to invest on Solar power plants in the first year if current carbon prices do not increase. This observation is not predictable. However, when we analyze the investment decisions, we see that in the soft scenario, so as to invest on more profitable options with high amount of investments and at the same time satisfying the portfolio balance constraints requires to have positive investment for Solar power plants.

4.2.2.2. Selling Type. We also investigate the electricity sold for different policies. Since the electricity prices are higher for bilateral contracts, the amount of electricity sold via bilateral contracts achieves the possible maximum value. Note that these prices also include incentives for prices of electricity generated from renewable energy sources.

As it can be observed from Figure 4.12, the amount of electricity sold at day ahead market is at its minimum value for peak load block when the carbon cost has the lowest value, represented by "Soft" including the branches 0, 1 and 11. The amount of electricity sold is at maximum value at day ahead market for night load block for the extreme policy with the highest carbon price, which is represented by "Restrictive" including the branches 0, 10 and 110. Note that the middling scenario is represented by "Middling" including the branches 0, 6 and 61. These values depend on the stability of the day-ahead market. As we expect, selling via bilateral contract is at a possible maximum value because it is more profitable. In short, the results are in line with our expectations.

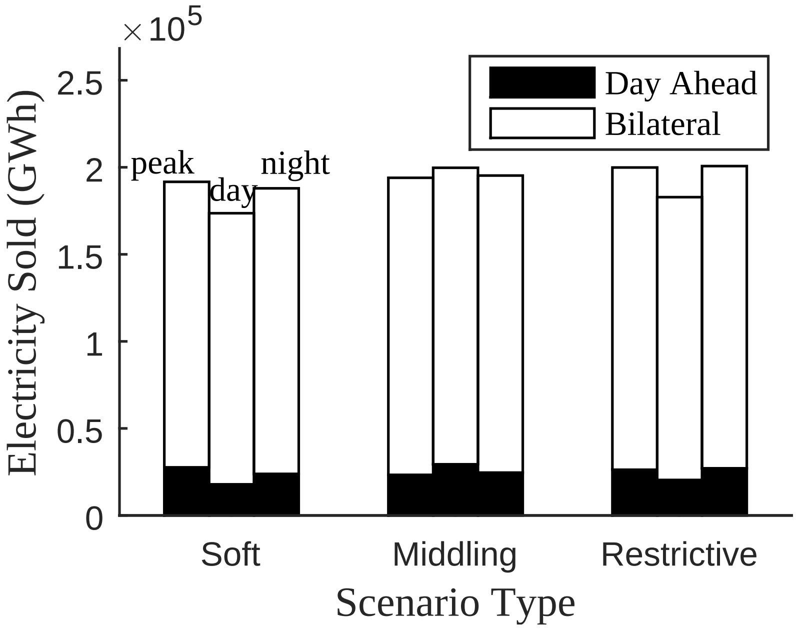


Figure 4.12: Electricity sold for different policy scenarios.

<u>4.2.2.3. Profit.</u> In order to analyze the effect of investment risk on the objective value, some basic concepts of stochastic programming are applied to our model and their results are compared [32]. Firstly, the expected value (EV) problem is solved that we take average of scenario nodes for each year and solve the model again for 30 years, i.e. one scenario node for each year. After that, we calculate the expectation of the expected value (EEV) by taking the resulting decisions of EV problem as decisions of original model scenarios nodes with respect to years. Note that the expected stochastic solution (ESS) is the objective value of the developed stochastic model in the thesis. Then, we obtain the value of stochastic solution (VSS) by substracting EEV from ESS. VSS shows the possible gain from the solving stochastic model [39]. On the other hand, the expected value of perfect information (EVPI) represents the maximum amount that the problem owner would be willing to pay in return for complete and accurate information about the future. In other words, it measures the loss of profit because of the presence of uncertainty [39]. To obtain EVPI, we calculate the expectation

under perfect information (EPI) that we solve the original problem for each scenario path, where one scenario path is comprised of scenario nodes of 30 years, and take the average of these resulting objective value of 100 scenarios. Subsequently, we get the expected value of perfect information (EVPI) by substracting ESS from EPI. The results of these calculations are given in Table 4.14.

Table 4.14. Expected profits over the planning horizon.

ESS ($\times 10^9$)	EPI ($\times 10^9$)	EEV ($\times 10^9$)	EVPI ($\times 10^6$)	VSS ($\times 10^9$)
22.74	22.75	17.83	7.10	4.91

EVPI = EPI – ESS
VSS = ESS – EEV

As seen from Table 4.14, the maximum value of the profit is attained under perfect information since it represents perfect foresight and it is so difficult to reach in real life. As it is expected, the minimum profit is obtained for EEV. This is because the EEV does not allow for adaptation to extreme scenario realizations. In constrast, the EEV does not include flexibility to uncertainty that will be revealed in following years. VSS shows us how much worse a deterministic model performs in real life when we used deterministic model instead of a stochastic one. Regarding VSS, we would get 4.91% worse in terms of expected profit.

5. CONCLUSION

In this thesis, we study a generation expansion planning problem for a private electricity generating company that aims to enter to a partially regulated market by making investments on generation units. The GEP problem has an importance for the decision-makers in the partially regulated electricity market. We develop a mixed integer linear programming model which determines the optimal size, time and technology types of generating units through a predetermined planning horizon. The aim of the model is to maximize the net present worth of the profit obtained while satisfying the constraints which arise from the nature of the problem. We assume that the company generates and sells electricity in a market where cap and trade system is in operation. Therefore, there is a cap value assigned to the company and the company can sell and buy carbon credits based on its emission levels and the cap value. The company has also the option of investing on CCS technologies to obey the carbon restrictions. Because the company operates at a partially regulated environment, the government may put some upper limits on the total investment amount in order to prevent monopoly. Moreover, the company may want to reach a certain investment percentage in the market. Another important part from the company's point of view is to have a balanced portfolio by investing on different options to manage the risk associated with each type of investment. All these aspects are included in the model developed.

Firstly, we model the problem using the deterministic electricity prices, carbon prices, portfolio balance ratios and interest rates. Then, we propose a multi-stage stochastic programming approach so as to incorparate the uncertainty in the electricity prices, fuel costs and carbon prices. We model these uncertain parameters via scenarios. In this part of the study, we include the fact that the electricity generated is sold either via bilateral contracts at a predetermined price or at a day ahead market at a price determined the day before.

We apply the deterministic and stochastic model to a hypothetical private company operating in Turkey. In the deterministic model, since the data affect the results heavily and most data may change in the future, we create scenarios for the most important parameters: electricity prices, interest rate, portfolio balance constraint and carbon prices. We perform sensitivity analysis and obtain results for each scenario. On the other hand, in the stochastic model, we develop a scenario tree based on electricity price, carbon price and fuel cost. We analyze the optimal investment decisions for both models. For the purpose of quantifying the improvement amount in reply for adopting a stochastic approach, we also calculate the value of the stochastic solution (VSS) for the stochastic model.

Our experimental results of the deterministic model show that time, type and amount of power plant investments highly depend on electricity prices, carbon prices, portfolio balance ratios and interest rates. Therefore, it would be so important that these parameters should be calculated very carefully with the methods. On the other hand, the results of stochastic model indicate that incentives provided for renewable energy resources are effective in the investment decisions. We conclude that the results are consistent with the expected outcomes. This shows that both models are suitable for being used for determining the strategy of the firm under a set of assumptions. In addition, our VSS analysis proves that stochastic programming approach is essential since it significantly contributes to the solution quality when various scenarios are taken into consideration.

As a future work, we may extend our analysis by including any constraint related to the transmission network of the country/region. With the introduction of the transmission network to the problem, the electricity sold will be constrained by transmission capacities, which may decrease the amount of electricity sold, and hence, decrease the total added capacity. The selling and buying prices of carbon credits are set equal to each other in the current situation. Analyzing the effect of the difference between these prices also left as a future study. In addition, current model does not include retrofitting option, which may be included in the future work.

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APPENDIX A: DETERMINISTIC MODEL RESULTS

Table A.1. Investment decisions for base scenario.

Y_{ult} (MW)		t																								
u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
LIG	no			150	600	600									450	600										
NGCC	post	500	500																							
NGCC	no			500	500	500	500	500	400																	
HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					

Table A.2. Investment decisions for scenarios related to carbon price.

	AC_{ult} (MW)		t																								
	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
CO_2-1	LIG	no	600	600	600	600																					
	NGCC	no	500	500	500	500	500	500	500	400																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
CO_2-2	LIG	no			150	600	600									450	600										
	NGCC	no	500	500	500	500	500	500	500	400.05																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
CO_2-3	LIG	no			150	580	600									450	600										
	NGCC	post	500	500	500	500	500	500	500	400																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20																								

Table A.2. Investment decisions for scenarios related to carbon price (cont.).

	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
CO_2-4	LIG	no			150	540	600									500	600										
	NGCC	post	500	500	500	500	500	500	500	400.05																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20	20	20	20	20																				
CO_2-5	LIG	no				600	600									450	600										
	NGCC	post	500	500	500	500	450	500	500	450.05																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	42.85						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20	20	20																						
CO_2-6	LIG	no				600	600									500	600										
	NGCC	post	500	500	500	500	450	500	500	450.05																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20	20	20																						

Table A.2. Investment decisions for scenarios related to carbon price (cont.).

	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
CO_2-7	LIG	no				550	600									550	600										
	NGCC	post	500	500	500	500	400	500	500	500																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20	20	20																						
CO_2-8	LIG	no					600									275	600										
	NGCC	post	500	500	500	350		500	500	500																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	26							
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	SOLAR	-	20	20	20																						
CO_2-9	LIG	no															600										
	LIG	post					250																				
	NGCC	post	500	500	500			500	500	433																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	98								
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	10	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50						
	SOLAR	-	20	20	20																						
CO_2-10	LIG	post					250																				
	NGCC	post	500	500	500			500	483	50																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100									
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	45		
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50						
	SOLAR	-	20	20	20																						

Table A.3. Investment decisions for scenarios related to electricity price.

	AC_{ult} (MW)		t																									
	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	30
PE-1	HC	no	600	600	600	233																							
	LIG	no	600	600	600	600	600	600	300																				
	NGCC	post	500																										
	NGCC	no		500	500	500	500	500	500	500	400																		
	HYDRO	-	100	100	100	100																							
	WIND	-	80	80																									
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50												
PE-2	HC	no	600	600	163																								
	LIG	no	600	600	600	600	600	600	300																				
	NGCC	post	500																										
	NGCC	no		500	500	500	500	500	500	500	400																		
	HYDRO	-	100	100	100	100	100	100	100																				
	WIND	-	80	80	80	80	80	80																					
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50											
PE-3	HC	no	600																										
	LIG	no	600	600	600	600	600	600	300																				
	NGCC	post	500																										
	NGCC	no		500	500	500	500	500	500	500	400																		
	HYDRO	-	100	100	100	100	100	100	100	100	100	100																	
	WIND	-	80	80	80	80	80	80	80	80	80	80	43																
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50									
PE-4	NGCC	post	500	500																									
	NGCC	no			150		500	217																					238
	HYDRO	-	100	100	100	100	100	100	100	100	100	50																	
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	27		80	80	80	80	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50														
PE-5	NGCC	post	500	500																									
	NGCC	no			150		500	282																					50
	HYDRO	-	100	100	100	100	100	100	100	100	100	98																	
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	50		80	80	80	80	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50													
PE-6	LIG	no			150	500	600									370	600												
	NGCC	post	500	500																									
	NGCC	no			500	500	500	500	500	400																			
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43								
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50							
	Solar	-	20	20	20	20	20	20	20	20	20																		

Table A.4. Investment decisions for scenarios related to portfolio balance constraint.

	AC_{ult} (MW)		t																								
	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Gamma-1	NGCC	post	500	500																							
	NGCC	no			500	500	500	500	500	500	500	500	500	500	500	500	500	300									
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100													
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	13								
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50								
Gamma-2	LIG	no																									150
	NGCC	post	500	500																							
	NGCC	no			500	500	500	500	500	500	500	500	500	72													
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	22
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
Gamma-3	NGCC	post	500	500																							
	NGCC	no			500	500	500	500	500	500	500	500	500	500	500	500	500	500	500	500	500	343					
	HYDRO	-	100	100	100																						
	WIND	-	80	80	80	80	80																				
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50													

Table A.5. Investment decisions for scenarios related to interest rate.

	AC_{ult} (MW)		t																								
	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
r-1	LIG	no	600	600	600	540																					
	NGCC	post	500	500	500	500	500	500	500	400																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	23					
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
	Solar	-	20	20	20																						
r-2	LIG	no			150	600	600									450	600										
	NGCC	post	500	500																							
	NGCC	no			500	500	500	500	500	400																	
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	43						
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50					
r-3	HC	no																									393
	LIG	no				600	600									600	600										
	NGCC	no	500	500	500	500	500	500	500	500	50																
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100										
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50						
r-4	HC	no																									521
	LIG	no					600									425	600										
	NGCC	no	500	500	500	250		500	500	500																	
	HYDRO	-	100	100	100	100	100			100	100	100	100	100	100	100	100										
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80			80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50										

APPENDIX B: STOCHASTIC MODEL RESULTS

Table B.1. Investment decisions for selected three scenarios.

	AC_{ult} (MW)		t																			
	u	l	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Soft	LIG	no	600	600	600	600		530														
	NGCC	post	500	500	500	500	500	500														
	NGCC	no							500				400,05									
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	92,95			
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
	Solar	-	20																			
Middling	LIG	no	600	600	600	600				600	530,75											
	NGCC	post	500	500	500	500	500	500	500	400,05												
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	72,875				
	WIND	-	80	80	80	80	80	80	80	80	80	80	80	80	80	80						
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
	Solar	-	20																			
Restrictive	LIG	no	600	600	600	600				300,05	600	600										
	NGCC	post	500	500	500	500	500	500	500	500	50											
	HYDRO	-	100	100	100	100	100	100	100	100	100	100	100	100	100	100	42,9					
	WIND	-	80	80	80	80	80	80	80	80	80	80	80									
	GEO	-	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
	Solar	-	20																			

Table B.2. Amount of electricity sold in terms of block hours for selected three scenarios.

	b	Sold-BI	Sold-DA
Soft	peak	164.025,176	27.635,972
	day	155.743,214	17.881,71
	night	164.025,176	23.893,744
Middling	peak	170.650,93	23.327,433
	day	170.339,23	29.399,433
	night	170.650,93	24.616,733
Restrictive	peak	173.605,258	26.282,835
	day	162.456,283	20.398,89
	night	173.605,258	27.098,835