# ELECTRICITY GENERATION INVESTMENT PLANNING UNDER UNCERTAINTY: A REAL OPTIONS APPLICATION FOR TÜRKİYE

by

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## ABSTRACT

## ELECTRICITY GENERATION INVESTMENT PLANNING UNDER UNCERTAINTY: A REAL OPTIONS APPLICATION FOR TURKEY

This thesis presents an investment planning model that integrates learning curve information on renewable power generation technologies into a dynamic programming formulation featuring real options analysis. The model recursively evaluates a set of investment alternatives on a year-by-year basis, thereby taking into account that the flexibility to delay an irreversible investment expenditure can profoundly affect the diffusion prospects of renewable power generation technologies. Price volatility is introduced through stochastic processes for the average electricity price and for input fuel prices. Demand for peak-load capacity is assumed to be increasingly price-elastic, as the electricity market deregulation proceeds, and linearly dependent on the extent of market opening. The empirical analysis is based on data for the Turkish electricity supply industry. Apart from general implications for policy-making, it provides some interesting insights about the impact of uncertainty on the diffusion of various emerging renewable energy technologies.

# ÖZET

## BELİRSİZ ŞARTLAR ALTINDA ELEKTRİK ÜRETİMİ YATIRIM PLANLAMASI: TÜRKİYE İÇİN BİR REEL SEÇENEKLER UYGULAMASI

Bu tezde öğrenme eğrisi ve dinamik programlama formulasyonunu birleştiren bir yatırım planlama modeli sunulmaktadır. Yıl bazında yatırım alternatifleri değerlendirilerek geri dönüşü olmayan bir yatırım harcamasının yatırımı erteleme esnekliği olduğunda nasıl etkileneceği incelenmiştir. Girdi maliyetleri ve elektrik fiyatındaki değişkenliği modele yansıtabilmek için stokastik prosesler kullanılmıştır. Piyasanın özelleştirme süreci ilerledikçe talebin fiyat esnekliğinin artacağı varsayılmıştır. Modelin çözümünde Türkiye enerji piyasasına ait veriler kullanılmıştır. Genel olarak yatırım politikalarına ışık tutmakla beraber, tez sonuçları belirsizliğin yenilenebilir enerji türlerine olan etkilerini ortaya koymaktadır.

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| | |
|---|---|
| ARMA | Auto Regressive Moving Average |
| BOO | Build Operate Own |
| BOT | Build Operate Transfer |
| CAPM | Capital Asset Pricing Model |
| CC | Combined Cycle |
| CDM | Clean Development Mechanism |
| CHP | Combined Heat Power |
| DCF | Discounted Cash Flow |
| EMRA | Energy Market Regulatory Authority |
| FBC | Fluidized Bed Combustion |
| GBM | Geometric Brownian Motion |
| GDP | Gross Domestic Product |
| GHG | Green House Gas |
| GT | Gas Turbine |
| IEA | International Energy Agency |
| JI | Joint Implementation |
| LR | Learning Rate |
| NPV | Net Present Value |
| O&M | Operating and Maintenance |
| OS | On Shore |
| PR | Progress Ratio |
| PV | Photovoltaic |
| R&D | Research and Development |
| RET | Renewable Energy Technologies |
| RO | Real Options |
| TEAŞ | Turkish Electricity Generation Transmission Co. |
| TEDAŞ | Turkish Electricity Distribution Co. |
| TEİAŞ | Turkish Electricity Transmission Co. |
| TEK | Turkish Electricity Authority |
| TETAŞ | Turkish Electricity Trading and Contracting Co. |

| | |
|---|---|
| TEÜAŞ | Turkish Electricity Generation Co. |
| TOR | Transfer of Operating Rights |
| TPES | Total Primary Energy Supply |

# 1. INTRODUCTION

In Turkey the demand for energy has been increasing eight percent on the average annually for the last two decades [1]. Naturally this necessitates huge capital investments. The difficulty in public financing is among the drivers for deregulating the electricity market in Turkey. There are some other reasons that trigger deregulation, including the inefficient running and management of public utilities, the desire to remove subsidies from the energy sector and make them available for other public expenditures, and the prospect to generate substantial income for the public budget by selling the utilities [3].

Several steps have been taken since the 1980s to establish a privatized electricity market in Turkey. In 1984, private investors had been given the opportunity to operate in the generation, transmission, and distribution of electricity. This arrangement could not achieve a breakthrough in privatization since the Constitution banned the ownership of electricity generating companies by private parties. For this reason, until 1997 a partial privatization was achieved through BOT (Build Operate Transfer), TOR (Transfer of Operating Rights) or auto production models. In 1993, the vertically integrated public utility TEK (Turkish Electricity Authority) was split into TEAŞ (Turkish Electricity Generation Transmission Co.) and TEDAŞ (Turkish Electricity Distribution Co.). In 1997, BOO (Build Operate Own) was constructed as a new model for privatization. According to this model the ownership of the plant was retained by the private investor. These were the preliminary steps for the actual reform process that has started in February 2001 with law 4628 aiming "*to ensure the development of a financially sound and transparent electricity market operating in a competitive environment under provisions of civil law and the delivery of sufficient, good quality, low cost and environment-friendly electricity to consumers and to ensure the autonomous regulation and supervision of this market.*" [4] To achieve this objective firstly the electricity sector has been further unbundled. TEAŞ was separated into TEİAŞ (Turkish Electricity Transmission Co.), TEÜAŞ (Turkish Electricity Generation Co.), and TETAŞ (Turkish Electricity Trading and Contracting Co.). Secondly, except the transmission of electricity (which can be regarded as a natural monopoly), competition was introduced to all other fields and privatization opened the way to real competition in these fields. Lastly, an independent regulatory authority EMRA (Energy Market Regulatory Authority) was established in 2001 [5].

Competition in the electricity market complicates investment planning as uncertainty in energy prices and demand arises as a side-effect of deregulation. In a state owned monopolistic market environment prices are quite stable. They are based on average costs to let electricity companies recover their expenditures. Also, there exists full information about the market. All the demand in each region is supplied by one utility, so it is straightforward to forecast the demand. Under these circumstances where uncertainty is not a major fact to be considered, short and midterm forecasting and optimization is easily done by traditional hard modeling approaches. From load scheduling to maintenance planning, demand forecasting and investment planning, well-known operational research tools such as linear and integer programming can be successfully applied. But in a deregulated market the data which is the main input of the above models becomes highly uncertain. It seems that operations research tools still can be valid in the short term in a deregulated market with the use of a gaming approach. But in the medium and long term, other approaches capable of addressing the uncertainty need to be employed. Business Dynamics, Competitive Analysis, Real Options (RO) and Scenario Analysis are the major tools that can be used for long term decision making under uncertainty [6]. The Real Options theory has been successfully employed to evaluate irreversible investment decisions under uncertainty. Case studies and examples of applying the RO approach to energy industry investment problems can be found in Ronn [7], among others. Applications of the RO approach to investment planning in the electricity sector, however, have only started to penetrate the literature in recent years and, therefore, are still very limited in number. Frayer/Uludere [8], for instance, conduct a RO analysis on two generation assets in a regional market under volatile electricity prices. In contrast, Keppo/Lu [9] make use of the RO approach, in order to introduce uncertainty for the electricity price, which is assumed to be affected by the investment behavior of a large producer. Botterud [10] studies three different decision support models for long-term generation capacity investment planning in restructured electricity markets, one of which is based on RO theory. Botterud/ Korpås [11] investigate the adequacy of power generation capacity in liberalized electricity markets and how/what regulatory mechanisms could ensure sufficient electricity supply, using a real options approach. Prospects for the diffusion of renewable energy technologies (RETs) are also affected by the high level of uncertainty. The adoption and diffusion of new RETs are subject to developments that bring down unit generation costs to a level where these technologies can actually compete with conventional technologies. Such developments can be conveniently represented by learning curves, which indicate the exponential reduction in the unit cost (e.g. measured in $ per MW of installed capacity) that can be expected as their cumulative production volume increases [12].

In this thesis, a dynamic programming model has been developed employing the real options approach to investment planning in the electricity sector. Learning curve information for renewable energy technologies has been integrated to the model.

This thesis is composed of seven chapters. In the following chapter the renewable energy technologies and learning rates will be covered. Firstly the general use of learning curves and the learning curve formulation will be discussed. Secondly the individual learning curves for renewable technologies will be given and finally the last subsection discusses the renewable energy potential of Turkey. The third chapter is Literature Survey part of this thesis. Literature survey mainly focuses on two concepts; one is Real Options (and related to it uncertainty), and the other is the learning rates for renewable technologies. The fourth chapter is the Methodology part. In the methodology chapter there is a brief description of real options at the beginning and the discussion of dynamic programming formulation used in model formulation. The second subsection is about the stochastic processes used in the thesis for price and cost estimations. The next chapter is composed of the description of the model. The dynamic programming formulation and the integration of learning curve concept is analyzed in this section. Also the constraints of the model are discussed. The sixth chapter is empirical analysis. In the first subsection model calibration is discussed. The cost and price estimation results are displayed in this section. Then the scenario assumptions are discussed. The following subsection explains the model results for five different scenarios. Also the learning results of renewable technologies are analyzed. Finally, the results of the sensitivity analysis made for different parameters of the model are discussed. The last chapter concludes the whole thesis and the results of the thesis are analyzed and further improvements that can be made related to this thesis are stated.

# 2. LEARNING CURVES AND RENEWABLE ENERGY TECHNOLOGIES

This chapter discusses renewable energy technologies and learning curves. The first subsection deals with learning curves and progress ratios. The derivation of the learning curve from historical data is explored and factors that affect the learning rate are discussed. The second subsection briefly describes the generation process of electricity from renewables. The technologies considered are wind, solar, biomass and geothermal. In the last subsection the renewable energy potential of Turkey will be discussed.

## 2.1. Learning Curves

Learning curves, sometimes synonymously also referred to as 'progress curves' or 'experience curves' indicate the development of marginal or average unitary cost as a function of cumulative production or capacity. They are an empirical artifact rather than a theoretically well-founded concept. Observed learning curve effects can have many reasons, including technological progress, learning-by-doing, reduction in input factor prices or financing cost, or improvements in organizational efficiency. Note, however, that when empirically estimating learning rates, it can sometimes be difficult to strictly disentangle cost reductions that arise from learning effects from those caused by other impacts, such as economies of scale or economies of scope. Hence, if such additional cost-influencing factors are not appropriately controlled for, there is some danger that learning rates may actually be over- or underestimated. Commonly, *progress ratios* or *learning rates* are used to express estimated unit cost decreases as a constant percentage for each doubling of experience.

Learning curves allow for projections of future cost reductions that are based on the extrapolation of historical trends, and in recent years have become popular also in the energy research literature and as a guide for policy-makers. In energy and climate models alike, learning curves have been employed with increasing frequency, in order to account for cost reductions due to technology-related learning. At the same time, there seems to be a severe lack of discussion about the appropriateness of model specifications and estimation techniques in learning curve studies. As a matter of fact, the choice of both model specification and estimation technique can have a strong influence on the learning rate estimates obtained. In spite of such uncertainties learning curves are considered as a useful tool in modeling technological change in energy supply systems [12].

A methodological issue regarding learning curve estimation is the relationship between cost and price. In an ideal case production costs should be used to construct the learning curve but usually the price data is available. However, price does not only depend on the production costs but also on marketing strategy, demand, competition, subsidies etc. Figure 2.1 describes the relationship between the evolution of price and cost with respect to time [13].

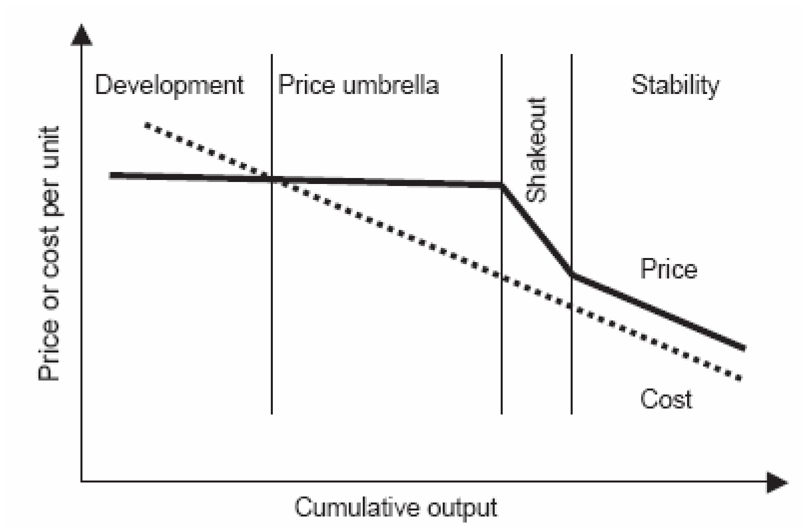



Figure 2.1. Evolution of price and cost with respect to time [13]

There are four phases depicted in the figure. In the first phase a manufacturer introduces a new product (e.g. a Solar PV Module, a Wind Mill etc.) with a price lower than its cost in order to create a market. In the second phase because of scale economies and learning effects (learning by doing, R&D) the production costs decline and there becomes a gap between the price and cost. In this umbrella phase the profit margins of the manufacturer increase and other firms start to enter the market and competition induces further price decrease in the third phase. Finally when the product becomes mature the prices and costs become stable. In the figure only in the last phase the slope of production cost and price is equal. So only at the last phase it shall be used to construct a learning curve.

Another methodological issue is the dynamics of progress. Obviously there can not be a continuous decrease in the costs and the progress rate may increase with time as the product becomes mature. However, learning curve formulation does not include time as a variable. Only the change in cumulative capacity determines the future costs. Doubling of cumulative capacity may take a very long time for a mature technology with respect to a new one and in this time period knowledge depreciation may occur and lead to lower progress rate which is not accurate. Figure 2.2 shows how progress ratio changes as technology become mature [13].

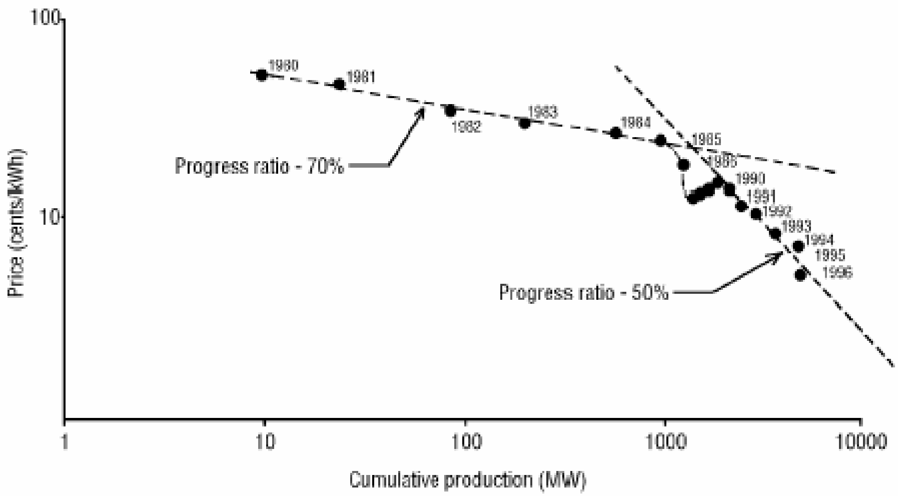



Figure 2.2. Change in progress ratio as technology becomes mature [14]

Organizational learning is another issue related to learning curves. Kobos et al. describe how organizational learning occurs as shown in Figure 2.3 [15].

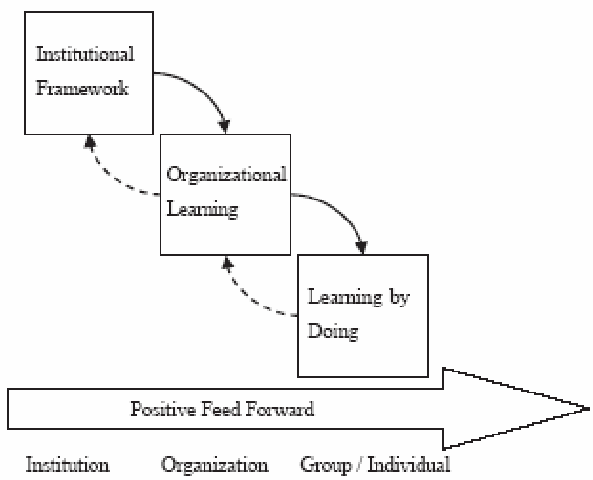



Figure 2.3. A dynamic process of organizational learning [15]

The solid arrows in the figure show the flow of knowledge spillover and the dashed arrows represent the feedback. The feedbacks both enhance quality control and also reinforce the standardization of knowledge stock. For instance a knowledge spillover can be a job training given by the organization. The feedback generated from spillover might be suggestion and discussions made to the management about the training program. In the same manner workers learn how to finish a job in a shorter time with less defects and the managers can gain experience by analyzing the results of their past decisions.

The most widely used formulation for learning curves is as follows [16]:

$$C_{Cum} = C_1 * Cum^b \tag{2.1}$$

for each doubling of cumulative production ( or capacity) $Cum_2$=2$Cum_1$;

$$\frac{C_{Cum_1} - C_{Cum_2}}{C_{Cum_1}} = 1 - \frac{C_1 * (2Cum_1)^b}{C_1 * Cum_1^b} = 1 - 2^b \tag{2.2}$$

$$PR = 2^b \tag{2.3}$$

$$LR = 1 - 2^b \tag{2.4}$$

Here, $C_{Cum}$ is the cost per unit, and $C_1$ is the cost of the first unit produced (unit is the capacity of the technology or the electricity produced from the technology). *Cum* is the cumulative production; *b* is the experience index; *PR* is the progress ratio and *LR* is the learning rate.

The progress ratio (PR) represents the rate at which costs decline each time the cumulative production (or capacity) doubles. The learning rate (LR) is its complement, computed as 1-PR. For example, if PR = 0.8 then costs are reduced by 20 per cent (LR = 0.2) to 80 per cent of the former level for each doubling of cumulative production or capacity. Here we can simply replace two by three if the cumulative capacity triples. Two is just a convention.

In this thesis we make use of learning curves for RETs, in order to take into consideration that these technologies, due to their greater potential for cost reductions (higher learning rates, less prone to environmental taxation), are expected to successfully compete with conventional technologies at some time in the future. Such competitiveness, a prerequisite for the transition towards a more sustainable energy system, depends on the cumulative production or cumulative installed capacity, both of which are assumed to reflect the total experience gained up to a certain point in time. This allows us to model the prospects for renewable energy technology adoption and diffusion in the light of declining unit costs, which can provide useful insights to policy-makers on how to design RET promotion policies or to achieve/safeguard a desired technological composition of the power generation sector [12].

## 2.2. Renewable Energy Technologies

Biomass is a general term for organic materials like plants, trees and crops. Biomass energy is gathered from the conversion of biomass into heat, electricity and liquid fuels. There are many ways of producing energy from biomass, the ones which are commonly used in electricity generation are Biomass Direct Combustion, Biomass Gasification, Biomass Pyrolysis, Anaerobic Digestion, Landfill Gas, Physical-Chemical Conversion and Fermentation & Hydrolysis [17]. Some of these conversion techniques are much more developed with respect to others. So estimates of technical potential and cost development of biomass energy mostly depends on the conversion technology. Figure 2.4 below shows a typical learning curve for the electricity production costs of Swedish Biofueled CHP plants for the period of 1990-2002 [18].

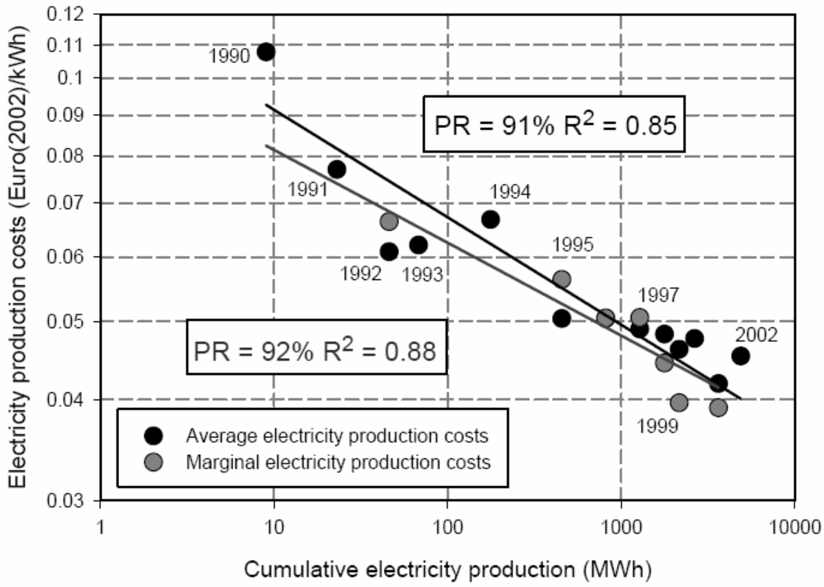



Figure 2.4. Learning curve of Swedish biofueled CHP plants [18]

Solar energy is produced using two main techniques solar photovoltaic and solar thermal power. Solar modules are semiconductor devices which convert sunlight into direct-current electricity. The progress in PV modules goes on with the collaborative effort of private and public sectors especially in Japan, Europe and Asia. In the last few decades PV module prices have declined and its efficiency has increased, Figure 2.5 shows the module price trend in US [17].

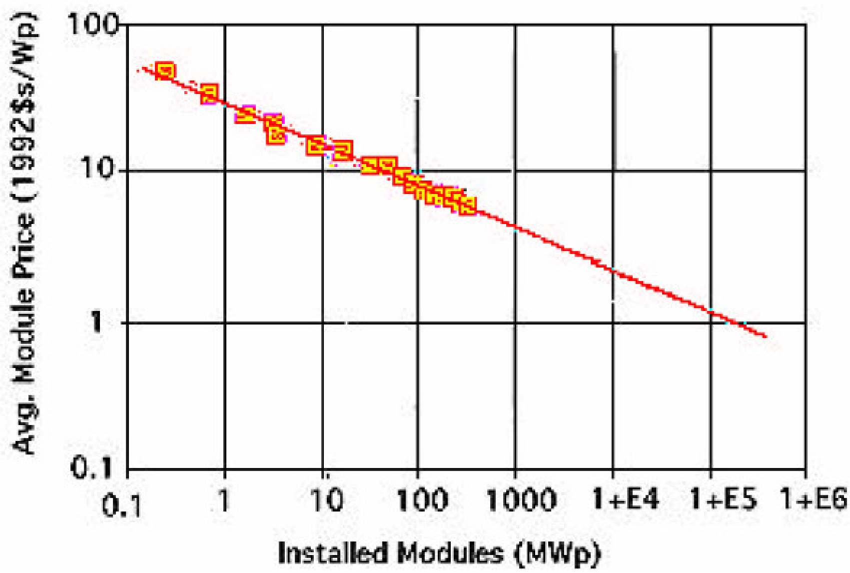



Figure 2.5. Learning curve of PV Modules in US [17]

Wind energy has been the fastest growing  renewable energy form, global installed capacity has increased from about two gw to over 31 gw between 1991 and 2002. In this period the prices of wind turbines and the cost of electricity generated from wind turbines has naturally decreased [17]. Figure 2.6 shows the decline in costs for UK (1992-2001) and Spain (1990-2001).

As in the case of Biomass, there are many different techniques of generating electricity from geothermal technology. Their price competitiveness with respect to conventional technologies differ from each other. The expansion of geothermal energy depends on its cost competitiveness. Available cost projections or a learning curve for geothermal technology could not be found.

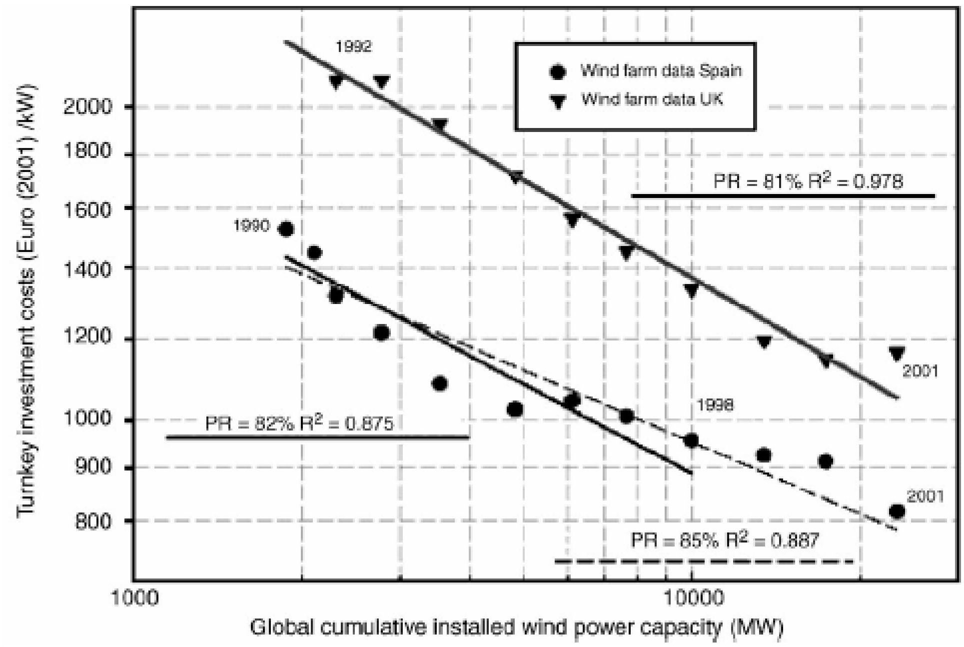
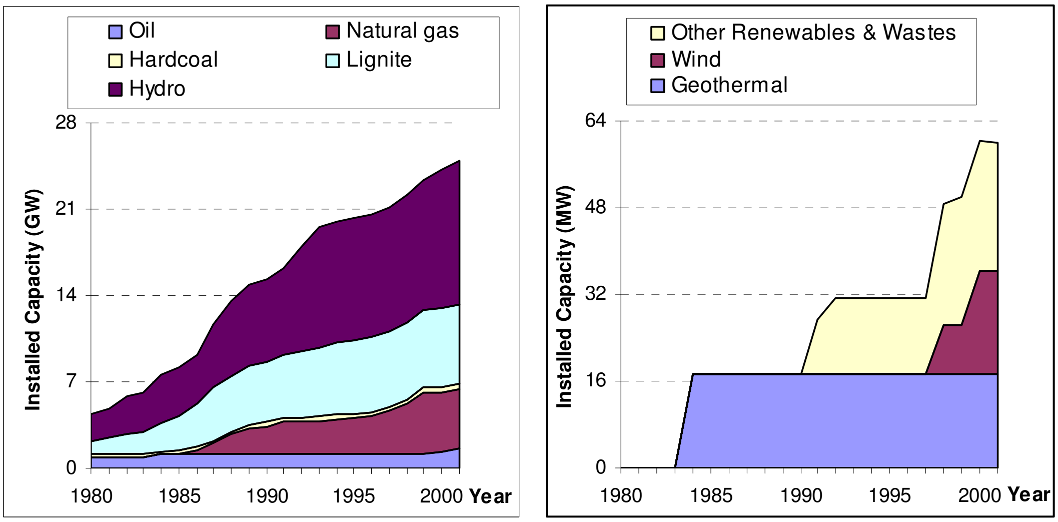



Figure 2.6.  Learning curve of wind turbines in UK and Spain [13]

## 2.3.  RETs In Turkish Electricity Supply Industry

Turkey is endowed with large renewable energy potentials, which taken together constitute the second-largest domestic energy resource after coal. Regarding total energy use, currently about two thirds of total renewable energy production is supplied by biomass and animal wastes (5.97 Mtoe), and one third by hydropower (2.89 Mtoe). About 0.5 per cent of total primary energy supply (TPES; 78.4 Mtoe as of 2002) come from geothermal, wind and solar energy resources. In 2002 renewables accounted for 8.9 per cent of TPES, of which biomass had the largest share (67.7 per cent) (see also Table 2.1) [12].

In electricity generation, renewables accounted for 26.1 per cent (33.84 TWh) in 1999 (20 per cent in 2001, 26 per cent in 2002), of which hydroelectric energy was absolutely dominating (99.5 per cent). The composition of installed hydropower capacity as of the end of year 2001 is as follows: 97.4 per cent storage power plants (with a dam), 1.6 per cent run-of-river power plants, and one per cent natural lake power plants. Natural gas accounted for 40 per cent of total power generation in 2001, coal for 31 per cent, and oil for about nine per cent [61]. Figure 2.7 (panel (a)) depicts installed capacities in the Turkish electricity supply sector by energy source. Renewable energy sources other than hydropower account for a negligibly small share of total power generation capacity, namely 0.24 per cent as of year 2001. A closer look at the composition of the non-hydro renewables is provided in panel (b) of Figure 2.7. The reported geothermal capacity of 17.5 MW corresponds to that of the Kizildere plant, currently the only operating geothermal power plant of Turkey [12].




(a) Fossil & hydro total (b) Non-hydro renewable

Figure 2.7. Decomposition of electricity generating capacity in Turkey, 1980-2001 [12]

Renewable electricity potentials (theoretical, technical, economic) by energy source and currently and expected future installed capacities are reported in Table 2.1, compiled from various sources. Of particular interest for the analysis are the economically feasible renewable energy potentials, which have been estimated at 196.7 TWh/a for biomass energy, 124 TWh/a for hydropower, 102.3 TWh/a for solar energy, 50 TWh/a for wind power, and 22.4 TWh/a for geothermal energy [12].

For a developing country like Turkey, which exhibits rapidly growing energy demand levels that have to be met under severe and changing budget constraints, it is of great importance that the most cost-effective energy resources are developed first. Presently, many RETs do not fall into this category due to comparatively high power generation costs. Therefore, diffusion of new RETs is typically not included in reference energy projections for Turkey, made by means of energy modeling applications. Even energy policy modeling studies with particular emphasis on pollution mitigation do not consider the possibility that RETs might become economically attractive in the foreseeable future. However, together with environmentally adverse impacts caused by intensive fossil fuel use and related high levels of GHG emissions, the widespread development and use of RETs is becoming increasingly vital for sustainable development. Rapid diffusion of RETs, which in recent years has got within reach not least due to cost reductions achieved through learning and scale economies, will also help to cover the rapidly growing energy needs of Turkey [12].

The annual rate of electricity demand growth in Turkey is expected to increase by eight-ten per cent until 2010. According to IEA forecasts, an increase in the installed electric generation capacity by some 30 GW until 2010 and additional 45 GW until 2020 will be needed compared to 2000 levels, equivalent to an investment requirement of approximately US$ three-four billion annually in generation, transmission and distribution systems [62]. The latest IEA country report on Turkey [61] criticizes that commercial renewable energy applications remained limited due to insufficient promotional measures, but acknowledges recent regulatory and promotional measures as positive developments. Turkish energy policy-makers indeed welcome further diffusion of RETs for the fact that it would reduce the reliance on imported fuels and at the same time enhance the country's energy supply security. A renewable energy law has passed in the Turkish parliament in May 2005, which provides regulated feed-in tariffs for electricity from RES. In particular, the law foresees a guaranteed purchase price of the equivalent of the previous year's average wholesale price in Turkey (corresponding to 6.9 US-ct/kWh in 2004) for a period of seven years for electricity generated from renewable energies sources. Primarily it supports wind, small hydro and geothermal power generation, but additionally also includes references to support solar, biomass, biogas and wave energy, and plans for targeted support of renewables [12].

Table 2.1. Renewable electricity potentials and current & expected RET installations in Turkey [12]

| Energy source | Theoretical potential | Technical potential | Economic potential | Current (2001) installation | Expected contribution / Policy goals | | |
|---|---|---|---|---|---|---|---|
| | | | | | 2005 | 2010 | 2020 |
| Hydro power | 49 GW<br>430 TWh | 216 TWh | 35 GW<br>125 TWh | 11.6 GW<br>24 TWh | 14.8 GW<br>48 TWh | 65 - 85 TWh Goal:<br>100 per cent of potential | 29 - 35 GW<br>98 -110 TWh |
| Wind power | 88 GW<br>>400 TWh | 83 GW -<br>124 - 166 TWh | 10 - 20 GW<br>50 TWh | 18.9 MW<br>62.4 TWh | 643 MW | 0.6 - 4 GW | 1 GW |
| Geothermal power | 4.5 GW tot. | 2.0 GW | 22 TWh | 17.5 MW<br>89.6 GWh | 0.04 - 0.15 GW<br>22 TWh | 0.3 - 0.5 GW<br>44 TWh | 0.6 - 1 GW<br>96 TWh |
| Solar PV | 102 TWh proven | | 102 TWh | 0.3 MW | | Goal:<br>40 MW (PV) | 9 TWh |
| Biogas | 12 - 23 TWh | | | 5.4 MW | 10 MW (Biogas-Waste) | | |
| Biomass | 197 - 372 TWh | | 197 TWh | 91 MW | | 86 TWh | 87 TWh |
| Total RET | | | | 104 TWh | | 25 GW | 30 GW |

# 3. LITERATURE SURVEY

This section is divided into two subsections. The first one provides a literature review on studies dealing with the uncertainty in energy markets and making use of real options theory. The second subsection reviews studies that handle the learning curve and progress ratio concepts in energy systems with emphasis on renewable energy technologies.

## 3.1. Real Options and Uncertainty

Pineau/Murto [19] propose a dynamic stochastic Nash-Cournot model for the recently deregulated Finnish electricity market. In the model, firms have two strategies which are investments and production levels. Special emphasis is given to electricity demand growth rate, which is modeled as a stochastic variable.

Pommeret/Cruz [20] propose a stochastic model of irreversible investment under uncertainty with embodied technological progress. The main idea incorporated into the model is that firms do not only invest for capacity expansion but also to replace old machines. According to the author, in most models like Pindyck (1988) investment is only considered as a capacity expansion. This model shows that firms can even invest under bad economical conditions to replace their low efficiency machinery.

Winsen [21] describes how the real options methodology can be applied in Australia's National Electricity Market. The revenues of the generators received from their generation assets are similar to a payoff from a call option and these generation assets can be valued using real options techniques. The special emphasis is given to unique characteristics of electricity price distributions, for instance volatility. The study finally applies the real options methodology to the valuation of a hypothetical open-cycle gas-fired electricity generator.

Ishii/Yan [22] propose a model to determine how regulatory restructuring affect the investment behavior of firms. Because of regulatory uncertainty, a substantial option value is generated. This option value makes the firms to delay their investment in order to have more information. Higher uncertainty causes less aggregate generation investment. Then Ishii/Yan compare their model with two alternative models, expected Net Present Value and Forward Looking. Their application shows that Forward Looking model fits the data much better than Net Present Value.

Frauendorfer et al. [23] use sophisticated methods from finance as an alternative to options theory. First the major obstacles to pricing electricity options are identified. Subsequently, a simplified Black-Scholes valuation framework and Advanced Valuation Scheme is analyzed. The study claims that these are very useful for the valuation of simple European-style electricity derivatives. Lastly a stochastic programming framework is proposed to price path-dependent and American-style electricity options (like swing options).

Diwekar et al. [24] consider uncertainty in a different part of energy system and propose that in advanced power system designs the technical and economic uncertainties are not treated most of the time in preliminary cost and performance estimates. They also claim that economic uncertainties can affect the utilization and performance of the plant. Optimization, mixed integer non-linear programming and stochastic programming models are described and compared. The design of advanced coal based energy systems is used as a sample case.

Triki et al. [25] propose a multi-stage mixed-integer stochastic optimization model for optimally allocating capacity. According to the authors technical and bidding rules make capacity allocation of crucial importance in multi-auction electricity markets, and difficult to model and solve. Another claim is for large scale systems where computational tractability becomes a major challenge. A representative test problem is solved to test the validity and effectiveness of the model.

Deng [26] proposes several mean-reversion jump-diffusion models to describe spot prices of energy. He claims that, because of physical characteristics of energy commodities (e.g. the inability of long term storage, multiple jumps, regime switching) stochastic volatility should be incorporated into energy models to capture the nature of energy prices.

Fourier transform methods are used in each model. Finally a real options approach is constructed to value physical assets.

Goceliakova [27] proposes two real options representations of valuation models. These are unit commitment decision and ancillary services provision. He evaluates products other than energy dispatch (which is the only basis in traditional plant valuation) like ancillary services, which might increase a plant's value especially in a liberalized market. In the second representation, which uses data from Germany, the results show an increase in operating profit when ancillary services are considered.

Kann/Weyant [28] summarize the approaches for incorporating uncertainty in large scale energy models. Several models incorporating uncertainty are defined and compared. The assumptions and limitations of each model are clarified. Learning and the expected value of information concepts are also examined. Finally a brief table displays the attributes of the models: model name, model type, type of uncertainty analysis, uncertainties considered, key results and the owner of the model.

Bhanot [29] analyzes the purchase option of large manufacturers and corporations in the case of uncertain consumption. This option is implemented to satisfy immediate consumption needs because it is not possible to store electricity. Monte Carlo methodology is applied to solve the model. The results show that consumption uncertainty may affect the price of an option contract. The study proposes that the volatility and correlation with power prices are the attributes of uncertainty that can change the direction of effect on the price of an option.

Davis/Owens [30] use real options pricing techniques to optimize the level of renewable electric R&D expenditures in the United States. The uncertainty in fossil fuel prices and the uncertainty in learning rates of renewable energy is explored, which rises the question of to what extent the R&D expenditures might increase. The authors find that R&D funding level increases the value of renewable energy technologies' increase.

Venetsanos et al. [31] compare the net present value and real options methodologies in valuing a wind energy project in a deregulated market for the case of Greece. It is found that the NPV method offers not to invest in this project, whereas, because of uncertainty the value of option increases in the real options method. Also, the authors find that the short construction lead time of wind turbines can make investors respond rapidly to demand growth. This decreases the cost of idle capacity. The application shows that the project has a higher value and it is feasible to invest with RO methodology.

### 3.2. Renewable Energy Technologies and Learning Rates

There is great uncertainty and variation in learning rate estimates for renewable energy technologies. Suggested values for wind energy technologies for example vary eight-fold changing in the range of four per cent to thirty two per cent. A compilation of learning rates for different technologies from different studies is provided in Table 3.1.

Neij [32] analyzes the cost of wind generated electricity in the Danish electricity sector. The cost reductions related to wind turbines are described by learning curves. Results show that there will be a moderate decrease in the costs, but there is potential for high cost reductions. The reason for high reductions might be improved performance and low operating and maintenance costs in addition to decreased investment costs. According to Neij, by year 2020 the average cost of wind power will be decreased by 45 per cent and the annual market growth will be about 20 per cent in the ecologically driven scenario (which is five per cent higher with respect to current policy scenario).

Barreto/Kypreos [33] analyze the interaction between emission trading and technology learning. A compact multi-regional MARKAL model of the global energy system has been used for this analysis. According to the authors, like technological learning emission trading is also evolving and interactions between regions are increasing. The result of the study is that in a $CO_2$ constrained energy system increased emission trading might cause technological learning and this might fasten the diffusion of renewable energy technologies.

Table 3.1. Learning rate estimates from different studies

| Technology | Region | Time Period | Learning Rate | Reference /Data Source |
|---|---|---|---|---|
| Wind Power | US | 1985-1994 | 32 | IEA (2000) |
| Wind Power | EU | 1980-1995 | 18 | IEA (2000) |
| Wind Power | Germany | 1990-1998 | 8 | IEA (2000) |
| Wind Power | Denmark | 1982-1997 | 4 | IEA (2000) |
| Wind Power | US | 1981-1996 | 14,3 | Mackay/Probert (1998) |
| Wind Power | Denmark | 1982-1995 | 4 | Neij (1997) |
| Wind Power | Denmark | n.a. | 15 | Lund (1995) |
| Wind Power | Den., Ger., Spa., Swe. | 1981-2000 | 6-8 | Neij et al. (2003) |
| Wind Power | Denmark | n.a. | 15,3 | Milborrow (2002) |
| Wind Power | Den., Ger., Spa., Swe. | 1981-2000 | 4-11 | Neij et al. (2003) |
| Wind Power | Denmark | 1981-1995 | 20 | Andersen/Fuglsang |
| Wind Power | UK | 1992-2001 | 19 | Junginger et al. (2003) |
| Wind Power | Spain | 1990-2001 | 15 | Junginger et al. (2003) |
| Wind Power | Spain | 1990-1998 | 18 | Junginger et al. (2003) |
| Wind Power | Denmark | 1984-1999 | 8 | Karin Ibenholt (2002) |
| Wind Power | Germany | 1991-1999 | 8 | Karin Ibenholt (2002) |
| Wind Power | UK | 1991-1999 | 25 | Karin Ibenholt (2002) |
| Wind Power | US | 1981-1997 | 25,7 | Kobos et al. (2004) |
| Wind Power | OECD | 1981-1995 | 17 | Kouvaritakis et al. (2000) |
| Wind Power | California | 1980-1994 | 18 | Norberg-Bohm (1999) |
| Wind Power | Germany | 1990-1998 | 8 | Durstewitz (1999) |
| Wind Power | Denmark | 1982-1997 | 8 | Neij (1999) |
| Wind Power | USA | 1982-1987 | 20 | Nakicenovic et al. (1998) |
| Solar PV Modules | World | 1968-1998 | 20 | Harmon (2000) |
| Solar PV Panels | US | 1959-1974 | 22 | Maycock/Wakefield(1975) |
| Solar PV Modules | World | 1976-1992 | 18 | IEA (2000) |
| Solar PV Modules | EU | 1976-1996 | 21 | IEA (2000) |
| Solar PV Modules | US | 1975-2000 | 25,9 | Kobos et al. (2004) |
| Solar PV Modules | EU | 1985-1995 | 35 | IEA (2000) |
| Solar PV Modules | World | 1985-200 | 20 | McDonald/Schrattenholzer (2001) |
| Solar PV Modules | World | 1981-1995 | 20 | Nakicenovic et al. (1998) |
| Compact Fluorescent Lamps | US | 1992-1998 | 16 | Iwafune (2000) |
| Sony Laser Diodes | World | 1982-1994 | 23 | Lipman/Sperling (1999) |
| DC Converters | World | 1976-1994 | 37 | Rabitsch (1999) |
| Primary Forest Fuel | Sweden | 1975-2003 | 13 | Turkenburg et al. (2003) |
| Primary Forest Fuel | Finland | 1988-2001 | 11 | Turkenburg et al. (2003) |
| Biomass Fuelled CHP | Sweden | 1991-2002 | 23 | Turkenburg et al. (2003) |
| Biogas | Denmark | n.a. | 12 | Turkenburg et al. (2003) |
| Biomass | EU | 1980-1995 | 15 | IEA (2000) |
| Ethanol | Brazil | 1979-1995 | 20 | Goldemberg (1996) |
| Ethanol | Brazil | 1978-1995 | 22 | IEA (2000) |
| Nuclear Power Plants | OECD | 1975-1993 | 5,8 | Kouvaritakis et al. (2000) |
| Hydropower Plants | OECD | 1975-1993 | 1,4 | Kouvaritakis et al. (2000) |

Gross et al. [34] provide an overview of the leading renewable energy technologies which are wind, wave and tidal, photovoltaic and biomass energy. The study proposes that there are three key facts which affect the emerging of renewables. These are market growth, innovation (technological development) and policy. Each technology is analyzed according to these aspects. The result is there is much to do in photovoltaic and wave & tidal. Wind power is found to be the best alternative and biomass is a good one depending on the conversion technology.

McDonald/Schrattenholzer [35] claim that most of the estimated learning rates for energy technologies are not that much useful. The main reason is claimed to be the use of studies based on non-energy technologies and sparse results from a limited number of energy studies. The paper summarizes learning rates from different authors for different regions of the world. For each study an $R^2$ value is displayed to judge the reliability of the learning rate. For the Harmon's data the authors show that even high $R^2$ values may not be enough to prove the reliability of the learning rate because the data points chosen extensively affect the results.

Ibenholt [36] compares the wind energy learning curves of Denmark, Germany and the United Kingdom. He claims that special policies have to be established to increase installed capacity of wind power and this has been achieved in Denmark and Germany. The study states that the diffusion of wind power in the United Kingdom is hampered because of high level of competition and also it is concluded that applying technology push policies may increase prices instead of decreasing them as might be caused by learning. So the result is that, to some extent, cost effectiveness has to be considered.

Junginger et al. [13] propose a global experience curve for wind farms. They claim that generally the experience curves for wind turbines are region-specific and this situation causes problems for global assessments. In the paper, first the reasons of price reductions in wind turbines are discussed. Secondly, a new approach of establishing a global experience curve is presented. The resulting progress ratios lie between 71 per cent and 85 per cent. Geographical area, time frame and GDP deflator seriously affect the results. So, according to the authors it is more logical to propose a range instead of a specific progress ratio.

Harrison/Wallace [37] analyze the climate change impact on renewable energy. The study shows that a rise in $CO_2$ emissions may increase the diffusion of renewables but this case also creates an uncertainty over the future climate conditions. The impact of climate change is considered for three renewable energy technologies which are hydro, wave and wind. While some models claim that climate change will positively affect the renewable diffusion others argue the opposite. The variation in dealing with uncertainty in many factors affects the results drastically.

Isoard/Soria [38] model the respective contributions of learning by doing and returns to scale in the capital cost reduction patterns of two renewable technologies, namely PV and wind. Flexible returns to scale is analyzed. Causality analysis and econometric estimation of learning curves are performed. Results show that both technologies need initial support policies before taking advantage of scale productions.

Menanteau et al. [39] compare two schemes developed for promoting renewable energy. One way of promoting they put forward depends on quantities, especially setting up bidding systems. The other depends on prices, using feed-in tariffs. The aim in both schemes is the same, speeding up the technological learning process to make renewables competitive with conventional technologies. The results show that a system of feed-in tariffs is more efficient than a bidding system.

Barreto/Kypreos [40] propose an energy-systems optimization model ERIS. The investment costs in ERIS do not only depend on cumulative capacities as in the traditional learning curve but also on the knowledge stock. According to the authors, the knowledge stock function generally depends on R&D expenditures. The paper also considers the lag, time between R&D expenditure and the effect on productivity, and depreciation. It is found that past expenditures do not accumulate and become obsolete by time, of the R&D expenditures. The model optimally allocates the R&D funds between competing technologies.

Zwaan/Rabl [41] analyze the cost reductions for different PV technologies. The cumulative production needed for breakeven point is estimated for different levels of learning curve parameters. The results show that before 2020 PV cannot take a major place in electricity supply. Significant cost reductions are predicted by the authors if niche-market applications continue. In addition to this considering the damage costs of conventional technologies a considerable amount of electricity supply might be covered by PV after 2020.

Borenstein [43] examines the value of electricity generated by PV during different time intervals. It is mentioned that generally the average wholesale cost is used to value the electricity production of PV. For the case of California, the paper shows that PV produces most of its electricity at the peak demand periods. So the value of electricity increases in the range of 29 per cent - 48 per cent with respect to a flat-rate tariff. It is concluded that this result might encourage PV investments.

Bhandari et al. [44] examine the uncertainty in the generation output of renewables. To solve this uncertainty a generation duration curve is used with combined dispatch of fossil fuel and renewables. A genetic algorithm is used as a solution method because of the complexity of the problem. The results show that combined operation of renewables and fossil fuels give better results. In this case also managing the uncertainty related with renewables is easier.

Wiser et al. [45] compare the risk profiles of electricity contracts among renewable technologies and natural gas-fired power plants. 27 agreements made in California in year 2001 are analyzed to find a conclusion. The result is such that each one has its own risks and advantages associated with it. For instance gas-fired plants avoid short term demand risk while renewables are better at environmental issues. Hence the class of risks taken into account determines which one is less risky.

Tokimatsu et al. [46] discuss the role of nuclear energy in future energy systems under uncertainty. The study has two main points; one is the breakeven point for nuclear energy, the other is the future role of nuclear energy in energy systems and in the environment. The model LDNE is used to find the optimal energy supply structure while minimizing costs and also considering $CO_2$ constraints. The uncertainties dealt with are energy demand, $CO_2$ emission targets, capacity projections of nuclear energy and the discount rate.

Gritsevskyi/Nakicenovic [47] model technological learning and uncertainty in energy systems. The linear programming optimization model MESSAGE is used. In the study, future costs of all technologies are assumed to be uncertain and represented with a log normal distribution. The technologies are clustered and collective technological learning is applied. The result is such that technology learning with uncertainty will affect emerging technologies in the next few decades. However, it is found that in the long run after many doublings of cumulative capacity large investments will not be affected.

Kypreos [48] models the effects of greenhouse-gas emissions (MERGE) with endogenous technological learning (ETL). A heuristic algorithm approach is applied to solve the non-linear and non-convex MERGE model. The findings of the MERGE-ETL model are similar to the MERGE model for the first half of the century. Results show that the fossil fuel technologies will dominate the supply of electricity. But with increasing $CO_2$ emissions and with the impact of learning by doing, in the second half of the century low emission technologies (mostly renewables) come into scene.

Sözen et al. [49] forecast the solar potential in Turkey using an artificial neural network (ANN) approach. Meteorological data of 2000-2003 and 12 cities around Turkey is used in the model. The results show that ANN is a better technique with respect to classical regression methods in predicting the solar potential. Also results show promising potentials for some parts of Turkey where there are no monitoring stations.

Mattson [50] claims that it is not possible to predict future learning rates with certainty. In the paper uncertainty in learning is modeled with GENIE. The author claims that there may be alternative branches on the progress curve and the information of which branch is currently followed is not initially known. In the model PV cells and fuel cells assume learning uncertainty. Independently of each other they can have high or low learning rates. The results show that early commitment to renewables is a good strategy both in the high and low learning rates.

Gerlagh/Zwaan [51] propose the DEMETER model to define the relationship between greenhouse gas emission reductions and renewables. There are two scenarios Business as usual (BAU) and two degrees Celsius (2DC). The second scenario includes a temperature increase constraint of 2°C. The important part of the paper is the extensive sensitivity analysis made for many parameters. Three levels of learning are considered. In the scenarios with low and medium level, renewables do not emerge in near future. But at the high level, which is 0.3, by year 2020 renewables reach 20 per cent of the total energy supply.

Kobos et al. [15] analyze the US renewable energy policy by evaluating technological learning. The learning curve they construct consists of two parameters, learning by doing and learning by searching (knowledge stock). Sensitivities of learning rates to model parameters are analyzed for solar photovoltaic and wind turbine technologies. The results show that policy instruments play a key role for the adoption of these technologies.

Lorenzoni [42] analyzes the Italian electricity market after the deregulation process in 1999. The non-renewable origin electricity producers have to buy Green Certificates which is equal to two per cent of its production. This enforcement has increased the prices and the uncertainty of the investors about the amount of renewables to invest. This is a good policy example which supports the emerging of renewables.

# 4. METHODOLOGY

This chapter is subdivided into two subsections. The first one describes the Real Options approach and its difference to traditional Net Present Value (NPV) analysis. Also the dynamic programming formulation used in the current model formulation is discussed in this subsection. The second subsection describes the stochastic processes employed in modeling the uncertainty in Real Options applications with emphasis on the Geometric Brownian Motion (GBM).

The restructuring of energy markets, which aims at the introduction of competition and the increase in economic efficiency, is a process that generates various risks and uncertainties that impact the energy sector. As the level of risk and uncertainty increases, traditional deterministic discounted cash flow (DCF) modeling approaches used for capacity investment planning need to be complemented by other, more sophisticated methods, in order to deal with the potential fluctuations in both demand and price trajectories. The RO approach to investment decision planning provides an attractive opportunity to evaluate investment alternatives in power generation in a deregulated market environment. [12]

## 4.1. Real Options

The idea of RO has been adopted from finance. It questions the underlying assumptions of traditional capital budgeting methods and seeks gains from deferring an irreversible investment expenditure (in contrast to a “now or never” proposition implicit in traditional NPV analysis).

A main feature of the RO approach is the inclusion of the possibility of delaying an investment and evaluating the value of waiting as part of the decision-making problem, which allows for a much richer analysis than if this aspect is neglected. Besides, it may help to avoid erroneous conclusions from overly simplistic investment modeling, as it has been frequently criticized. The value of waiting can be explained as follows: If a company invests at time $t$, it gets the expected present value of the revenues minus the cost. In contrast, if it waits and invests at time ($t$+1), a *real option* might arise that, if exercised, yields a higher net profit but also the current profit flow is missed. In dynamic programming the sequence of investment decisions is broken up into two parts, one that addresses the immediate choice, and one that addresses all subsequent remaining decisions. For the case of a multi-period evaluation, this leads to a model formulation that can be solved recursively. The dynamic decision framework then allows to systematically comparing the expected net present values from immediate investment and from waiting to invest, respectively. The ability to introduce and value the temporal flexibility in an irreversible investment decision represents the main distinction between real options and a conventional decision analysis based on NPV calculations. Figure 4.1 depicts the resulting improvement when the value of waiting is considered. [12]

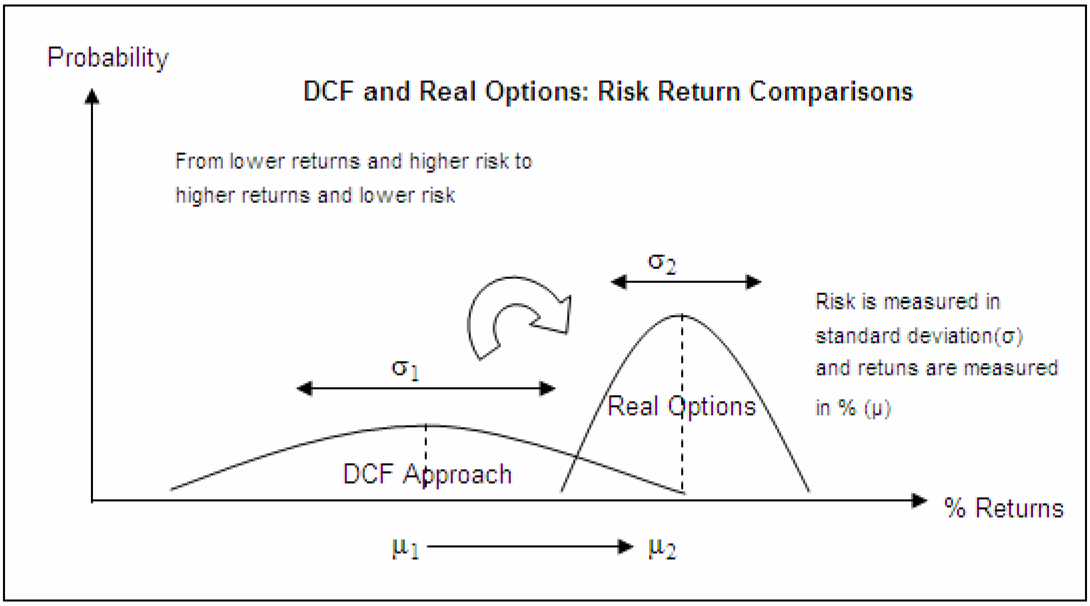



Figure 4.1. Comparison of DCF and Real Options [2]

The RO approach can be most conveniently translated into a mathematical model that can be used for analysis through a *dynamic programming* formulation. The dynamic programming formulation consists of two variables and the functions of these variables. The first variable is $x_t$ which describes the state of the investor at time $t$. $x_t$ might be a real number or a vector state of any dimension. The current state of the investor is known which is $x_t$ but the value of future states are random variables ($x_{t+1}$, $x_{t+2}$..). The value of the future states depend only on the current state because of the Markov Process property. The second variable is $u_t$ which is called control variable. At each time period there is a set of choices available to the investor. The resulting decisions determine $u$. If the decision is to invest or not, $u$ becomes a binary variable with value 0 or 1. But if the scale of the investment is also a choice for the investor then $u$ can be a continuous variable. The value of $u_t$ chosen can only depend on the information in the current period which is $x_t$. [12]

There are two terms in the formulation, one is the immediate profit flow and the other is continuation value. The immediate profit flow is stated as $\pi_t(x_t, u_t)$. So the immediate profit flow is a function of current state and the resulting decision depending on the current state. For instance if the investor decides to abandon the investment the immediate profit flow becomes zero. The continuation value is discounted using the discount rate $\rho$, i.e. the discount factor between any two periods is $1/(1+\rho)$. The sequence of $u_t$ is chosen in such a way that the sum of immediate profit flow and the discounted continuation value is maximized. Denoting the objective as $F_t(x_t)$ the resulting function is stated as:

$$F_t(x_t) = \max_{u_t} \left\{ \pi_t(x_t, u_t) + \frac{1}{1+\rho} E_t \left[ F_{t+1}(x_{t+1}) \right] \right\} \tag{4.1}$$

In period $t$ the continuation value is a random term so its expected value is taken into the formulation. Equation (4.1) is named the Bellman Equation or the fundamental equation of optimality. The principle of optimality resulting from this equation can be explained as follows: *An optimal policy has the property that, whatever the initial action, the remaining choices constitute an optimal policy with respect to the sub problem starting at the state that results from the initial actions.* In this formulation only the decision at the current period has to be chosen optimally which is $u_t$. The other choices are summed in the continuation value. [52]

### 4.2. Stochastic Processes

The Wiener Process (Brownian Motion) can serve as a building block for the derivation of a wide range of stochastic variables. There are three main characteristics of this process. Firstly it is a Markov process which implies that the probability distribution of the future states of the process depends only on the current state. The past values have no effect on the future values which can be defined as memoryless. Secondly the process has independent increments which mean the change in the process in disjoint time intervals are independent. Lastly the changes in the process are normally distributed in any finite interval of time and the variance increases linearly with time. The Wiener process can be stated formally as follows: if *z(t)* is a Wiener process then the increment of the process, *dz* is

$$dz = \varepsilon_t \sqrt{dt} \tag{4.2}$$

where $\varepsilon_t$ is a normally distributed random variable with zero mean and standard deviation of one.

If a drift term is added to a Wiener process the following formulation can be found:

$$dx = a(x,t)dt + b(x,t)dz \tag{4.3}$$

*dt*: is the drift rate
*dz*: increment of the Wiener process
*a(x,t)*: coefficient of the drift rate, a nonrandom function of the current state and time
*b(x,t)*: coefficient of the variance, a nonrandom function of the current state and time

The Geometric Brownian Motion is a special case of equation (4.3). If we replace *a(x,t)* with $\alpha x$ and *b(x,t)* with $\sigma x$ then we reach the following formulation ($\alpha$ and $\sigma$ are constants):

$$dx=\alpha\, xdt+\sigma\, xdz \tag{4.4}$$

if we take the term at the right to the parenthesis of *x* then we reach the notation of equation (5.6) in model description.

Geometric Brownian Motion is used in modeling securities prices, interest rates, wage rates, output prices and other economic and financial variables. In this thesis it is used to model the variable cost of fuels and the electricity price. Brownian motion tends to move far away from the starting point in the long run which is not realistic for some economic variables. Mean Reverting Process can also be used in modeling the prices of raw commodities. In the short run the prices of fuels might fluctuate randomly up and down, but in the longer run it seems to revert to a specific value. So the time horizon drastically affects the process that will be chosen. Pindyck's (1999) analysis on the long-run evolution of fossil fuel energy prices, for example, indicates that the state variables for fossil fuel prices follow non-stationary processes, and that a GBM process with a stochastically fluctuating drift term can be a useful approximation to the true underlying process. Ornstein-Uhlenbeck process will be described as an example of a mean reverting process which is stated as follows:

$$dx = \eta(\bar{x} - x)dt + \sigma dz \tag{4.5}$$

$\eta$ : the speed of reversion

$\bar{x}$ : the level $x$ tends to revert

If $\eta$=0 is substituted in equation (4.5), simple brownian motion is found. With higher $\eta$ values x tend to its normal value much fast. [52] The below figures depict the resulting sample paths of mean reverting process and a geometric brownian motion applications for electricity pricing in US.

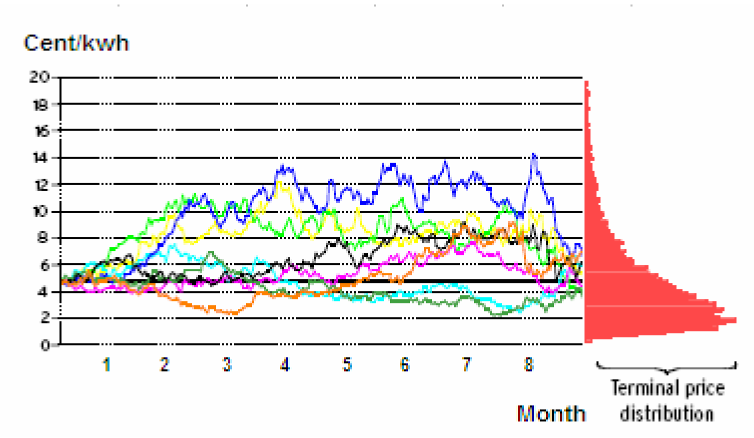



Figure 4.2. Geometric brownian motion application in electricity pricing [53]

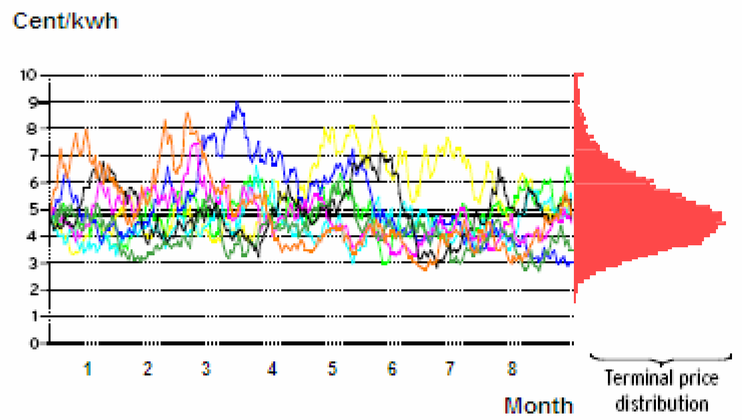



Figure 4.3. Mean reverting process application in electricity pricing [53]

# 5. MODEL DESCRIPTION

The dynamic programming model is structurally similar to a technology adoption model (Madlener et al., 2005) [63] recently developed to evaluate the economic rationality of historical power generation capacity investments in Turkey. However, the “historical” model has been modified with respect to several important aspects, in order: (1) to feature a real options analysis through a dynamic programming model formulation; (2) to account for construction lead times; (3) to consider a time-variant price elasticity of electricity demand (assumed to increase as the extent of market deregulation and competition increase); (4) to include non-stationary stochastic processes for the evaluation of fuel and electricity price uncertainties; and (5) to explicitly incorporate learning curve information for studying the prospects for the market diffusion of new RETs. The additional capabilities of the modified model version, esp. those mentioned under (1), (3) and (4), allow for the planning of “future” investment decisions. Feature (1) highlights the fact of a transition from the dynamic technology adoption linear programming model to a dynamic technology adoption sequential decision model. Feature (2), the inclusion of construction lead times, allows to capture the impacts of delivery lags on the investment decision, which is quite essential under irreversibility and uncertainty, among others. The evaluation of the impact of stochastic price volatility, i.e. feature (4), is inevitable when studying competitive electricity markets, and has been a subject of various studies that make use of stochastic modeling. As opposed to the stationary auto regressive moving average process employed in the earlier (historical) model version, a non-stationary GBM process has been introduced in the present model, which is in accordance with empirical findings that have been reported in the literature. As the existence of a price-elastic demand can be considered a prerequisite for the success of electricity market liberalization, feature (3) is also indispensable for the representation of a gradual electricity market opening. Policy-makers are supposed to take the necessary steps and actions to increase the price elasticity of demand, which can be expected to rise as market deregulation progresses and competition is extended. Finally, feature (5) combines learning curve information and RO modeling in an empirical application as a particularly original contribution of this thesis, in order to explore the prospects for the diffusion of new RETs under electricity market restructuring and uncertainty. [12]

The dynamic programming model formulation accommodates a period-by-period evaluation of irreversible investment alternatives under uncertainty, and thereby features a real options analysis. In the following model description, variables are denoted by uppercase letters, and parameters and subscripts by lowercase ones. Capacity additions $X_{i,v}$ for each technology $i$ (indicating the plant type) of vintage $v$ (indicating the year at which the investment decision is taken) are evaluated at each time period $t$ to maximize the net present value: $NPV_t(X_{i,v=t})$

$$NPV_t(X_{i,v=t}) = \max \left\{ \begin{array}{l} \sum_i \sum_{z=t+lt(i)}^{t+lt(i)+el(i)} p_z (1+r)^{-(z-t)} L_{i,z,v=t}\ \theta_{i,z,v=t} \\ -\left\{ \forall \sum_i L_{i,z,v}\theta_{i,z,v} \geq d_z \mid \sum_i \sum_{z=t+lt(i)}^{t+lt(i)+el(i)} p_z (1+r)^{-(z-t)} \left\{ L_{i,z,v=t}\theta_{i,z,v=t} - d_z \right\} \right\} \\ -\sum_i \sum_{z=t+lt(i)}^{t+lt(i)+el(i)} vc_{i,z,v=t} (1+r)^{-(z-t)} L_{i,z,v=t}\ \theta_{i,z,v=t} \\ -\sum_i fc_{i,v=t} X_{i,v=t} \\ +\dfrac{1}{1+r} E_t\left( NPV_{t+1}(X_{i,v=t+1}) \right) \end{array} \right\}$$

(5.1)

where $p_z$ is the electricity price (modeled as a stochastic process, see below), $r$ is the real interest (discount) rate, $L_{i,z,v}$ stands for the load of plant type $i$ of vintage $v$ in year $z$, $\theta_{i,z,v}$ denotes the corresponding duration (in hours), and $d_z$ is peak power demand. $X_{i,v}$ is the capacity installed of plant type $i$ in year $v$. The variable and fixed costs are denoted by $vc_{i,z,v}$ and $fc_{i,v}$, respectively, $lt$ stands for lead time, and $el$ denotes economic lifetime of the generation plant. The first two terms on the right hand side represent the revenues from selling electricity. Here, the value of power generation in excess of peak demand, $d_z$, is subtracted from total revenues, as this amount cannot be sold in the market and, therefore, does not contribute to the revenues. Obviously, the first two terms provide the value of power generated and sold as a net effect. That is, $\sum_i \sum_{z=t+lt(i)}^{t+lt(i)+el(i)} p_z (1+r)^{-(z-t)} L_{i,z,v=t}\theta_{i,z,v=t}$ if $\sum_i L_{i,z,v}\theta_{i,z,v} < d_z$ and $\sum_i \sum_{z=t+lt(i)}^{t+lt(i)+el(i)} p_z (1+r)^{-(z-t)} d_z$ if $\sum_i L_{i,z,v}\theta_{i,z,v} \geq d_z$

The next two terms on the right hand side of equation (5.1) stand for the present values of operation and maintenance (O&M) and investment costs, respectively. The final term is the continuation value, defined as the sum of NPVs, expected at time $t$, that accrue from investing in later time periods. Here, the optimality of the remaining investment choices at vintage $v=t+1$, $t+2$, etc. is subsumed in the continuation value. Only the immediate investment decisions at $v=t$ are chosen optimally, and the model is solved successively using the dynamic programming technique, in order to determine the decisions for the latter periods by working forward (note that, similarly, one can also start at the end of the time horizon and work backward from a termination payoff). [12]

Plants are assumed to be put into operation immediately after the construction lead time, $lt(i)$, has elapsed. They are operated for a duration equal to their economic lifetime, $el(i)$, which is implicitly modeled by subscript $z$. The first three components of the objective function (revenues, variable costs, and fixed costs) are all related to the plants for which the investment decisions are given in year $t$. As the model is solved successively, the resulting choices are fixed in the next year $(t+1)$ and become part of the first constraint, depicted in Eq. (5.2), which accounts for the electricity generation from previously installed power plants. It ensures that total power generation is sufficient to meet peak load in year $z$, $d_z$:

$$\sum_i \sum_{v=z-lt(i)-el(i)}^{z-lt(i)} L_{i,z,v}\theta_{i,z,v} \geq d_z(1+m) \qquad \forall \ t + lt(i) + el(i) \geq z \geq t \quad (5.2)$$

where $m$ represents the reserve margin. The demand for electricity is assumed to be price-elastic and determined by the function

$$d_z(p_z) = \alpha \, p_z^{\varepsilon(z)} \qquad (5.3)$$

where $\alpha$ is a scale parameter, and $\varepsilon(z)$ denotes the price elasticity of electricity demand, which is assumed to be time-dependent, in order to reflect an expectedly increasing price elasticity as the market opening process continues.

The second constraint ensures that output from each plant (i.e. the amount of electricity generated) does not exceed available capacity:

$$L_{i,z,v} \leq a_i X_{i,v} \qquad \forall \ t + lt(i)+el(i) \geq z \geq t + lt(i)\,, \ v \leq t \quad (5.4)$$

where $a_i$ is the availability factor for plant type $i$, which refers to the percentage of time that a plant can be used, i.e. is not out of service due to maintenance or repairs. Similarly,

$$L_{i,z,v}\frac{\theta_{i,z,v}}{8760} \leq cf_i X_{i,v} \qquad \forall \ t + lt(i)+el(i) \geq z \geq t + lt(i)\,, \ \ v \leq t \quad (5.5)$$

where $cf_i$ is the capacity factor for plant type $i$. It measures the productivity of the plant, comparing its actual production with the amount of power the plant would have produced if it had run at full capacity for the whole year (average energy output of the plant divided by the maximum energy output of the plant).

Uncertainty is introduced for both input and output prices, i.e. the prices of fossil fuels and electricity. The projection of electricity prices is based on a Geometric Brownian Motion, a log-normal diffusion process with the variance growing proportionally to the time interval. The price increment $\Delta p_z$ is computed as

$$\Delta p_z = p_{z-1} \left(\mu \ \Delta z \ + \ \sigma \ \ \varepsilon\sqrt{\Delta z}\right) \tag{5.6}$$

where $\mu$ and $\sigma$ represent the mean drift rate and percentage volatility, respectively, $\Delta z$ indicates the (discretized) time increment, and $\varepsilon$ is a standard normal random variable, $\varepsilon \sim N(0,1)$. The variability in fuel prices is reflected analogously through a GBM process for variable costs:

$$\Delta vc_{i,z,v} = vc_{i,z-1,v} \left(\mu \ \Delta z \ + \ \sigma \ \ \varepsilon\sqrt{\Delta z}\right) \tag{5.7}$$

Finally, the learning curve information of renewable power generation technologies, is integrated as

$$fc_{i,v} = fc_{i,v=2000}\, CC_{i,v}^{-li} \qquad \forall \ i, v > 2000 \quad (5.8)$$

where $CC_{i,v}$ is the cumulative (installed) capacity of technology $i$ in year $v$. The parameter $l_i$ represents the learning index, which is determined from the progress ratio $PR$ (i.e. the rate at which the fixed cost declines whenever $CC$ doubles) as

$$PR = 2^{-li} \tag{5.9}$$

This concludes the model formulation.

# 6. EMPIRICAL ANALYSIS

The empirical analysis is based on data for the Turkish electricity supply industry. Starting with the base year 2000 the attractiveness of a set of power generation alternatives is evaluated over time, under conditions of increasing competition and decreasing unitary cost (learning curves) for new RETs over the next 20 years. The year-by-year evaluation of investment options takes into account that the ability to delay an irreversible investment expenditure can profoundly affect the prospects for the diffusion of different renewable power generation technologies. The historical data on costs and prices have been used to estimate the mean drift and volatility parameters of the GBM processes. The resulting cost and price estimations are exogenously entered into the model formulation.

## 6.1. Model Calibration

Operational and cost data of existing power plants, as well as electricity price data for the period 1970-2000 are taken from the statistical yearbook of the Turkish Electricity Transmission Corporation (TEİAŞ, 2002) which is shown in Table 6.1.

The mean drifts are found by regression analysis of the historical data. The slope of the linear regression lines in Table 6.2 are assumed to give the growth value for each technology and also price. The starting values are the values of year 2000.

The case of electricity prices, however, forms an exception because of the change in market structure. As financial energy markets have not been established yet, there is a lack of data so the additional uncertainty due to competition is (arbitrarily) assumed to be 50 per cent. All drift and volatility assumptions are summarized in Figures 6.1 and 6.3, which illustrate the resulting stochastic trajectories. The projections depicted in Figures 6.1 and 6.3 are plotted as the average taken from a total of 5,000 randomized simulations that have been performed. For each technology and price the beta values are calculated to check if the number of simulations are adequate to conclude a result. The beta values found are given in Table 6.3 for three different levels of $\alpha$.

Table 6.1. Price and cost data

| Year | Hardcoal (cent/kwh) | Lignite (cent/kwh) | Nat. Gas (cent/kwh) | Oil (cent/kwh) | Geoth. (cent/kwh) | Hydro (cent/kwh) | Electricity Price (cent/kwh) |
|---|---|---|---|---|---|---|---|
| 1970 | 0,832 | 0,598 | | 0,918 | | 0,355 | 4,662 |
| 1971 | 0,887 | 0,543 | | 0,957 | | 0,361 | 5,721 |
| 1972 | 1,251 | 0,782 | | 0,945 | | 0,334 | 6,242 |
| 1973 | 1,391 | 0,869 | | 1,165 | | 0,730 | 8,826 |
| 1974 | 1,512 | 0,968 | | 2,684 | | 1,055 | 8,260 |
| 1975 | 1,777 | 1,178 | | 2,801 | | 1,001 | 7,464 |
| 1976 | 1,816 | 1,342 | | 2,609 | | 0,964 | 8,544 |
| 1977 | 2,544 | 1,563 | | 2,871 | | 1,124 | 8,976 |
| 1978 | 3,887 | 2,810 | | 2,651 | | 0,805 | 7,252 |
| 1979 | 4,048 | 2,137 | | 4,077 | | 0,491 | 7,870 |
| 1980 | 6,661 | 2,845 | | 5,470 | | 0,318 | 7,476 |
| 1981 | 6,636 | 2,854 | | 6,397 | | 0,207 | 6,449 |
| 1982 | 6,130 | 2,741 | | 6,161 | | 0,182 | 5,408 |
| 1983 | 5,103 | 2,852 | | 5,688 | | 0,228 | 5,855 |
| 1984 | 4,491 | 1,989 | | 4,818 | | 0,159 | 8,139 |
| 1985 | 4,183 | 2,411 | | 4,815 | | 2,017 | 7,920 |
| 1986 | 5,561 | 3,883 | 4,436 | 3,777 | 9,620 | 2,004 | 7,419 |
| 1987 | 4,947 | 4,419 | 5,398 | 3,249 | 8,047 | 1,742 | 7,046 |
| 1988 | 4,512 | 6,567 | 6,129 | 4,191 | 5,994 | 1,768 | 7,140 |
| 1989 | 6,684 | 4,421 | 3,430 | 4,465 | 8,183 | 1,991 | 8,275 |
| 1990 | 5,123 | 4,105 | 3,321 | 6,571 | 2,498 | 2,482 | 7,955 |
| 1991 | 4,624 | 3,853 | 2,839 | 10,513 | 3,052 | 2,692 | 8,761 |
| 1992 | 4,077 | 3,653 | 3,011 | 5,009 | 3,158 | 3,051 | 8,875 |
| 1993 | 4,186 | 4,026 | 3,182 | 3,712 | 3,090 | 2,672 | 5,013 |
| 1994 | 3,205 | 2,930 | 3,035 | 3,289 | 2,156 | 1,449 | 4,461 |
| 1995 | 4,165 | 3,563 | 3,485 | 4,646 | 1,975 | 0,126 | 3,716 |
| 1996 | 4,341 | 3,244 | 3,751 | 4,766 | 3,751 | 0,107 | 3,474 |
| 1997 | 4,233 | 3,219 | 4,281 | 4,234 | 1,928 | 0,111 | 3,199 |
| 1998 | 4,702 | 2,809 | 3,889 | 3,046 | 1,973 | 0,116 | 3,388 |
| 1999 | 4,367 | 2,987 | 3,853 | 3,137 | 2,460 | 0,157 | 3,730 |
| 2000 | 4,550 | 3,462 | 4,222 | 4,219 | 2,799 | 0,203 | 3,870 |

Table 6.2. Regression lines for generation technologies and price

| Technology/Price | Regression Line |
|---|---|
| Hardcoal | 2.289+0.104x |
| Nat.Gas | 4.340-0.057x |
| Geoth. | 7.640-0.449x |
| Lignite | 2.085+0.105x |
| Oil | 2.450+0.097x |
| Hydro | 0.750+0.016x |
| Price | 8.236-0.449x |

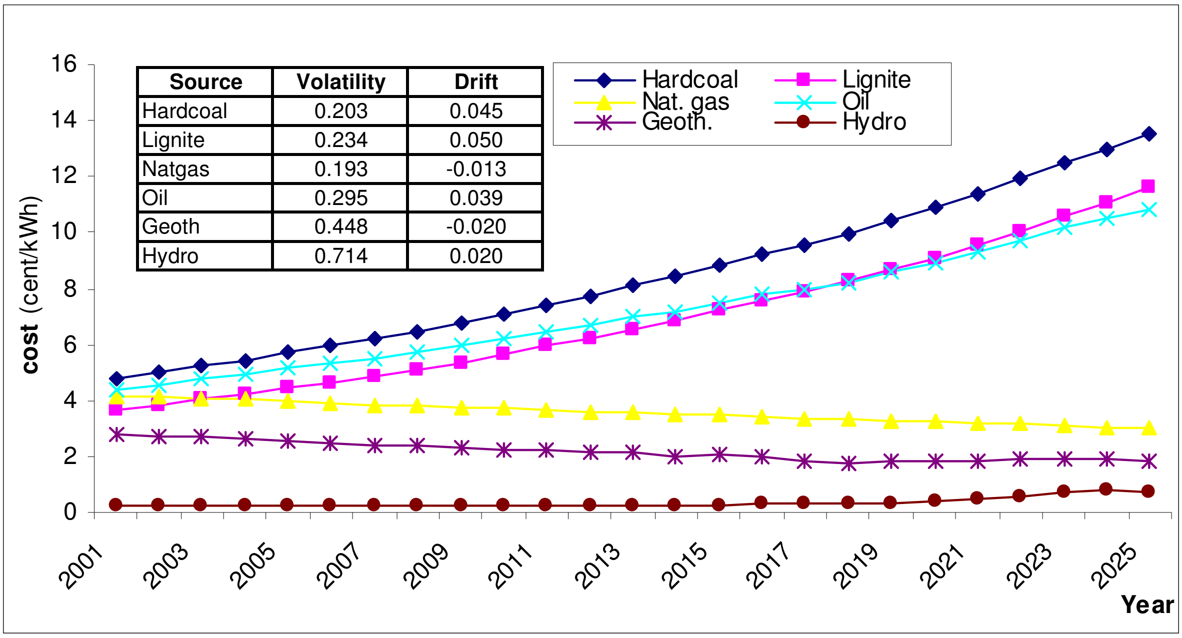



Figure 6.1. Variable cost projections for existing power generation technologies, 2001-2025

Table 6.3. Beta Values of each technology and price for 5,000 simulations

| Technology/Price | Beta Values | | |
|---|---|---|---|
| | α=0.005 | α =0.010 | α=0.025 |
| Hard Coal | 0.097607 | 0.088134 | 0.074266 |
| Natural Gas | 0.013001 | 0.011739 | 0.009892 |
| Geothermal | 0.022208 | 0.020053 | 0.016898 |
| Lignite | 0.088159 | 0.079603 | 0.067078 |
| Oil | 0.071449 | 0.064515 | 0.054364 |
| Hydro | 0.006256 | 0.005649 | 0.004760 |
| Price | 0.011272 | 0.010178 | 0.008577 |

As shown in Figure 6.1, the prices of fossil fuels except for natural gas increase. Indeed, on the one hand it is quite realistic to expect the prices of oil, lignite and hardcoal to rise in the coming decades, as these resources are getting scarcer and the substitution of alternative energy sources is accelerating. The use of natural gas, on the other hand, is becoming more and more common all over Europe. As a consequence, pipeline investments to develop the necessary infrastructure are expanding and the diffusion of natural gas continues, allowing for the exploitation of scale economies. Therefore, the suggested path with a slight reduction in the price of natural gas seems quite plausible. This path is also in agreement with the gas price projections used in the simulation model EUGAS [54]. Naturally, the variable cost components of the two existing renewable power generation options, geothermal and hydroelectricity are significantly lower than the fossil alternatives, since no fuel costs are involved. The volatility of hydropower cost seems to be high, but this is due to the large fluctuation of historical costs, which are themselves strongly affected by fluctuations in precipitation levels. The resulting variable cost projections seem very smooth for all technologies as if there exists no volatility but only a drift rate like a simple line formula. In the following figure the forecasts and five randomly chosen sample paths taken from 5000 simulations are depicted.

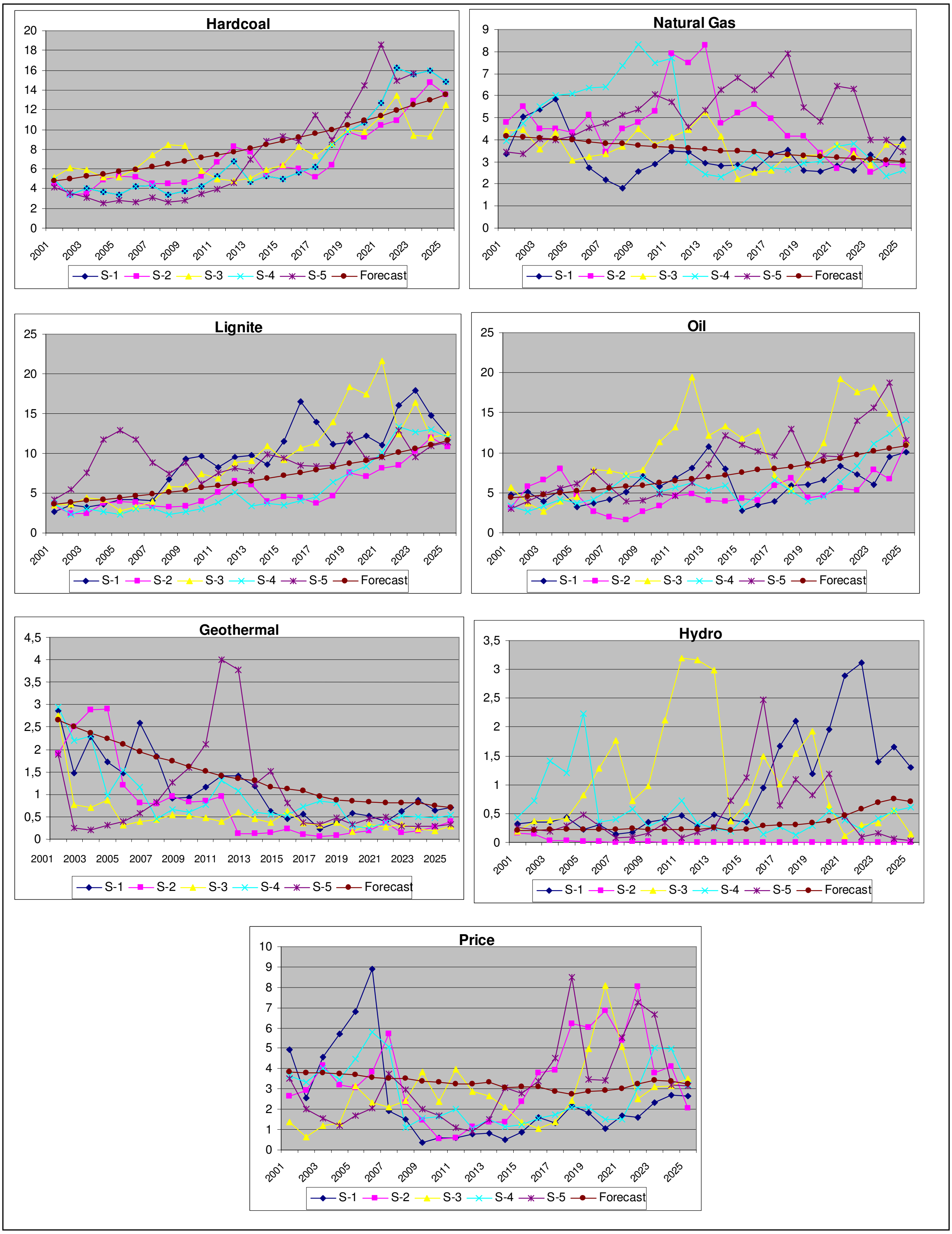
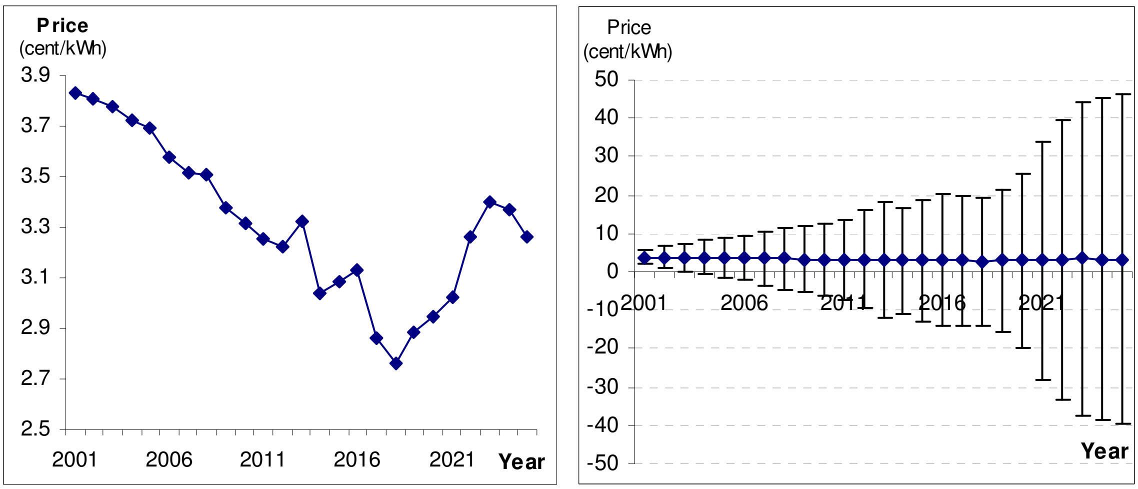



Figure 6.2. Sample paths for variable cost projections

The electricity price projections are depicted in Figure 6.3; panel (a) indicates the annual forecasts as an average of the simulations, while panel (b) depicts the standard deviations. The average price trajectory seems credible, as it is in line with the electricity market restructuring experiences in a number of countries. As presently Turkey faces an electric generation capacity surplus, the price of electricity would most probably go down in a competitive market environment, at least initially. In the longer term, one could expect it to approach its initial level. Another critical factor related to price projections is the responsiveness of electricity demand to changes in price. In electricity markets where consumers have either no choice of supplier, no ability to control their demand, or insufficient incentives to adjust their consumption, price elasticity of electricity demand can be assumed to be low, whereas in liberalized markets they can be assumed to rise [64]. Pilot installations of three-phase multi-tariff electricity meters have only just been started in Turkey, constituting an important concrete step towards increasing the price elasticity of electricity demand. Due to a lack of empirical evidence of what the price elasticity of electricity demand in Turkey may actually be in coming years, we have assumed linear growth for the price elasticity of electric energy, decreasing from -0.01 in year 2000 to -0.05 in 2025 for the most flexible scenario, and decreasing from -0.01 to -0.02 over the same period for the other scenarios (see below).




(a) Average (b) Error bands

Figure 6.3. Electricity price projections, 2000-2025

The assumed fixed costs and availability factors for the power plants and technologies modeled as candidates for new investment are based on MARKAL-MATTER data [55] and summarized in Table 6.4. Naturally, solar PV and wind turbines have particularly low capacity factors due to the intermittence of supply based on climatic conditions with high variances. It should be noted, however, that developments in energy storage systems can increase capacity factors and decrease levelized capital costs by storing energy from high power generation periods to be utilized later as a back-up in low generation periods. The global learning effects on renewables are considered in the MARKAL data.

Another critical issue is the choice of an appropriate discount rate. In the present analysis the risk-adjusted discount rate is assumed to be constant at five per cent, and refrained from trying to actually determine some risk-adjusted measure of expected return that could possibly be used as (an improved) discount rate [56]. In certain cases it may be possible to construct a risk-free portfolio, to determine its expected rate of return, and to equate that with the risk-free rate of interest to be inserted instead of a simple discount rate. However, for Turkey it will take a number of years until financial energy markets will develop and methods such as the capital asset pricing model (CAPM) can be applied to determine risk-adjusted interest rates for investments in the energy sector. Note that unless very restrictive conditions are being applied, a theory for determining the “correct” value of the discount rate does not exist. [52]

The assumed learning rates for the renewable energy technologies considered are 20 per cent for solar PV [57], 15 per cent for biomass [35], eight per cent for offshore wind turbines [58], and 10 per cent for onshore wind turbines [59].

Finally, Table 6.5 gives the emission factors used to find the resulting $CO_2$ emissions for each scenario. The emission factor for Biomass is zero because of the recirculation of the carbon principle.

Table 6.4. Candidate power generation technologies: costs, assumed availability factors, capacity factors, learning rates, and construction lead times [55]

| Technology | Inv. cost ($/kW) | Annual fixed O&M cost ($/kW) | Ava. factor | Cap. factor | Learning rate | Construction lead time (years) |
|---|---|---|---|---|---|---|
| Non-renewable | | | | | | |
| Coal FBC CHP plant | 3600 | 144 | 0.80 | 0.70 | 0.05 | 4 |
| Pulverized coal power plant | 1488 | 44.4 | 0.75 | 0.80 | 0.05 | 4 |
| Integrated coal gasification pow. pl. | 1260 | 64.8 | 0.75 | 0.80 | 0.05 | 4 |
| Oil fired power plant | 1032 | 28.8 | 0.75 | 0.80 | 0.01 | 3 |
| Natural gas CC power plant | 972 | 25.2 | 0.75 | 0.65 | 0.01 | 3 |
| Gas turbine CHP plant | 912 | 13.2 | 0.80 | 0.60 | 0.01 | 3 |
| Lignite fired power plant | 1728 | 44.4 | 0.75 | 0.75 | 0.01 | 4 |
| Integrated lignite gasif. power plant | 1920 | 37.2 | 0.75 | 0.45 | 0.05 | 4 |
| Nuclear LWR power plant | 2928 | 64.2 | 0.75 | 0.95 | 0.01 | 6 |
| Renewable | | | | | | |
| Biomass gasifier dedicated STAG | 2448 | 240 | 0.75 | 0.80 | 0.15 | 3 |
| Biomass gasifier SOFC* | 3120 | 312 | 1.00 | 0.80 | 0.15 | 3 |
| Biomass gas turbine CHP | 2040 | 51 | 0.80 | 0.80 | 0.15 | 3 |
| Solar PV | 6000 | 24.6 | 0.90 | 0.15 | 0.20 | 2 |
| Large onshore wind turbine | 1140 | 21.6 | 0.90 | 0.25 | 0.1 | 1 |
| Large onshore wind turbine storage | 1632 | 26.4 | 0.90 | 0.25 | 0.1 | 1 |
| Large offshore wind turbine storage | 2340 | 37.2 | 0.90 | 0.25 | 0.08 | 2 |
| Low head hydro | 3420 | 30 | 0.80 | 0.47 | | 10 |
| Medium and high head hydro | 2280 | 22.8 | 0.85 | 0.34 | | 10 |
| Hydro pumped storage | 3420 | 45.6 | 0.92 | 0.40 | | 10 |
| Geothermal power plant | 1236 | 31.2 | 0.70 | 0.90 | | 2 |

* available starting from 2010

Table 6.5. Emission factors for generation technologies

| Technology | $CO_2$ Emission Factor (KG $CO_2$/KWh) |
|---|---|
| Coal | 0,950 |
| Lignite | 0,950 |
| Fuel-Oil | 0,893 |
| Natural Gas | 0,484 |
| Geothermal | 0,091 |
| Wind | 0,010 |
| Hydraulic | 0,004 |
| Biomass | 0,000 |

The parameters defined above make up the reference scenario. In addition, the model has been calibrated under various other scenario definitions, allowing for further explorations of the diffusion prospects for new renewable energy technologies in the Turkish electricity market. The reference assumptions are kept as flexible as possible, in order to represent the natural evolution expected in a free market with minimum possible policy intervention. Instead of adopting the standard Business-As-Usual convention, the reference assumptions are therefore summarized under the nick *FLEX* (representing *flexibility*). Note that in scenario *FLEX* the maximum annual capacity addition limit for each technology is set at two GW (in order to avoid unrealistically high growth rates of certain technologies). The remaining scenarios are more restrictive, allowing for a maximum of one GW of additional capacity installation per technology and year (which seems to be a more realistic expectation when looking at historical capacity additions; cf. Fig. 6.4), and assuming a constrained increase in price elasticity from -0.01 to -0.02. In addition to such a *Non-Flex* scenario (*NF1*), two other non-flex scenarios are defined that include constraints on the adoption of natural gas combined cycle and wind power generation technologies. Scenario *NF2* incorporates a policy restriction that limits natural-gas-fired power generation capacity to a maximum of 40 per cent of total installed capacity. This is a rather realistic policy constraint, as Turkey does not possess natural gas reserves; besides, limiting import dependence is among the policy priorities of the energy decision-making community. The other non-flex scenario, *NF3*, enforces all the licenses granted by the Energy Market Regulatory Authority of Turkey for wind power generation facilities (totaling 928 MW). These license acquirements are not included under the reference assumptions, as they do not represent binding agreements. *NF4* includes a minimum bound on renewable energy source utilization, as required by the new renewable energy law in Turkey. Accordingly, in each year (starting from 2005), an amount equal to at least eight percent of total electricity generated in the previous year has to be composed of ‘new’ renewable energy sources (note that the large hydroelectric power plants in Turkey do not fall under the definition of renewable sources as defined in the law). In the last non-flex scenario, *NF5*, a constant price elasticity of electricity demand of -0.02 and no technology restrictions are assumed. The scenario assumptions are summarized in Table 6.6. [12]

Table 6.6. Scenario assumptions

| Scenario | Upper bound imposed on capacity addition per technology | Price elasticity (2000 → 2025) | Technology adoption restrictions |
|---|---|---|---|
| FLEX | 2 GW p.a. | -0.01 → -0.05 | No restriction |
| NF1 | 1 GW p.a. | -0.01 → -0.02 | No restriction |
| NF2 | 1 GW p.a. | -0.01 → -0.02 | Natural gas capacity share ≤ 40 per cent |
| NF3 | 1 GW p.a. | -0.01 → -0.02 | Wind turbine licensing |
| NF4 | 1 GW p.a. | -0.01 → -0.02 | Renewable Energy Law (8 per cent Renewables) |
| NF5 | 1 GW p.a. | -0.02 (const.) | No restriction |

## 6.2. Model Results

The model is written in GAMS and results have been obtained with the solver MINOS. A forward value iteration approach is used to solve the problem, implying 25 separate LP problems for each scenario that are solved successively. That is, starting from the base year 2000, a GAMS model is solved in each time period proceeding forward, once there is an adequate representation of the value function, such that the fundamental Bellman equation holds for each time period along the optimal path. Each LP model has a dimension of 27,612 constraints and 23,200 variables. Common to all scenarios, the model predicts the installation of new power plant capacities starting only after 2008. This indicates that the capacity currently available plus the plants just coming on line will be sufficient to meet the demand of the next three years. It is further observed that natural-gas-fired combined cycle power plants constitute the most attractive choice in all scenarios, followed by geothermal power for the first six-eight years, and then natural gas-fired CHP. The attractiveness of gas-based technology can be attributed to their comparatively low investment and O&M costs.

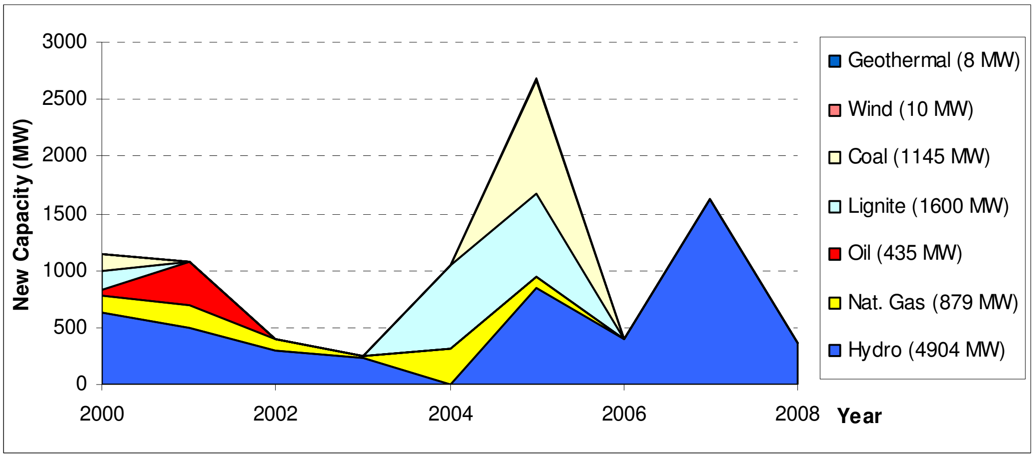



Figure 6.4. Capacity additions 2000-2008

In the reference scenario FLEX, Geothermal is the best generation alternative between 2010 and 2013. After 2013 to 2015 natural gas is superior to geothermal. In year 2015 the theoretical capacity of geothermal is reached and the model starts to install natural gas CHP plants as a substitute. The installed capacities in scenario FLEX are depicted in Figure 6.5. In this scenario the number of technologies installed are only three. The main reason for the limited technological diversification is the upper bound for installed capacities. The upper bound is two GW per year which is twice that of the upper bounds in other scenarios. Also the range of price elasticity of demand causes a moderate increase in electricity demand which is nearly 60 per cent of the demand in other scenarios and 75 per cent of the demand in scenario NF5. This also limits the variety of the technologies installed.

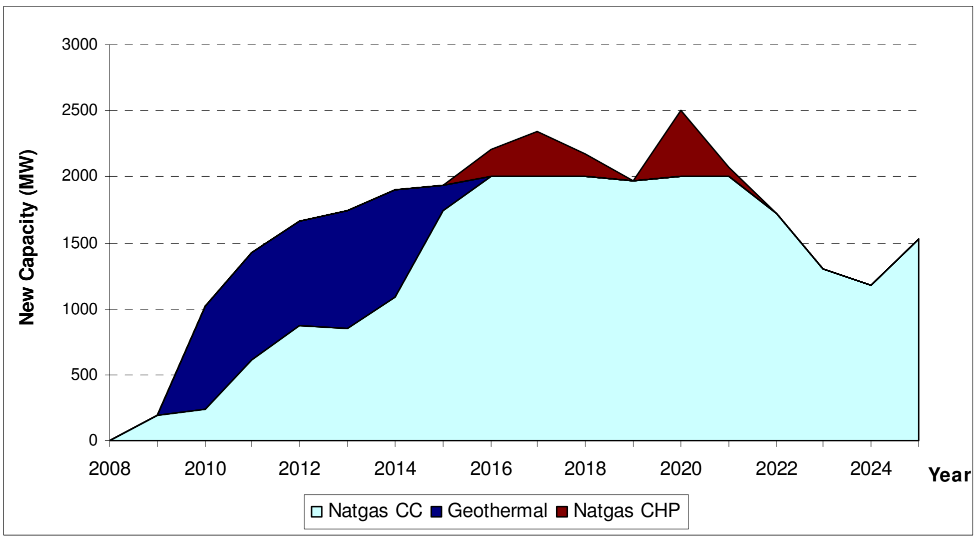



Figure 6.5. Capacity additions of scenario FLEX

The results of scenario NF1 are shown in Figure 6.6. Geothermal is the leading technology in scenario NF1. Between 2009 and 2012 the model installs geothermal plants at the upper bound. In year 2013 the theoretical capacity of geothermal is reached so it cannot be installed at its upper bound. After 2011 natural gas CC plants are also installed at the upper bound because of the rise in demand. Natural gas CC is the best alternative when model stops installing geothermal plants. Also in 2011 the model starts to install natural gas CHP plants to meet the demand. The second choice of the model is also a natural gas origined technology. In 2013 and 2014 the model installs oil plants. But in year 2015 biomass is superior to oil because of the rise in O&M cost of oil and also global learning of biomass which is included in the MARKAL cost data. After this point because of learning biomass becomes cheaper and its superiority to oil continues until 2025. Biomass also becomes a better alternative with respect to natural gas based technologies after year 2020 after the doubling of the cumulative capacity two times. In scenario NF1 the investment cost trajectory of Biomass GT CHP is depicted in Figure 6.11. The investment cost in year 2025 is nearly half of the investment cost in year 2015. After year 2020 the model installs small sized Coal FBC CHP plants because of the upper bound restrictions on other technologies to meet the excess demand.

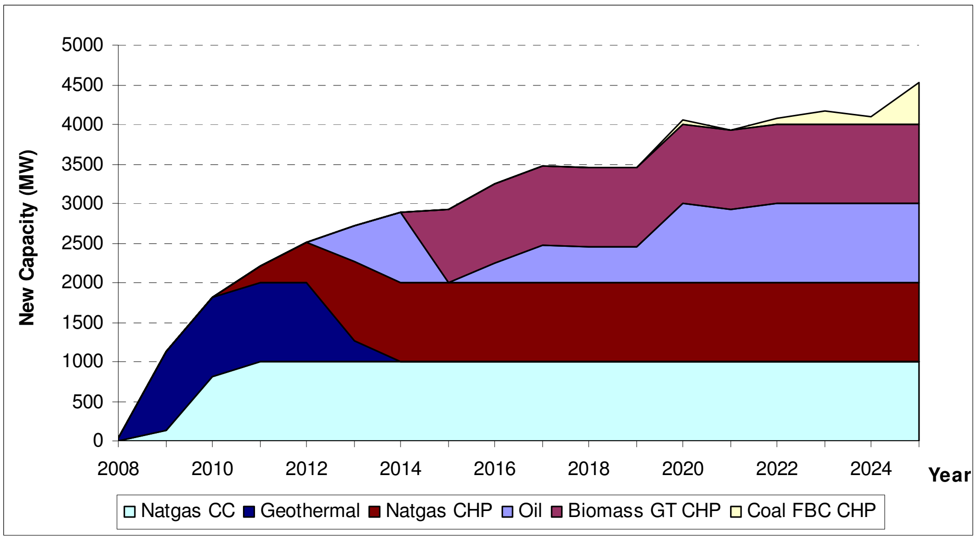



Figure 6.6. Capacity additions of scenario NF1

In scenario NF2 geothermal is again the leading technology at the beginning of the time horizon. It is installed at its upper bound until the theoretical capacity is reached. As in the case of NF1 the model starts to install natural gas CC plant at its upper bound in year 2011. In the same year the model starts to install natural gas CHP plants. Between 2013 and 2015 the natural gas based technologies are installed at the upper bound and also in this period the model starts to install oil plants. But after 2015 the capacity installed from natural gas CHP plants decrease because of the 40 per cent constraint on natural gas based technologies. This increases the amount of capacity installed from oil and coal CHP plants. Because after 2016 biomass is installed at its upper bound so the constraint on natural gas does not effect biomass learning. The only difference of the results from the previous scenario is after 2016; instead of natural gas CHP plants, oil plants and coal CHP plants are installed. The investment cost trajectory of biomass GT CHP is depicted in Figure 6.11. In this model the installment of coal FBC CHP plant starts earlier and the amount of capacity installed becomes higher. The reason is again the capacity restriction on natural gas. The capacity addition results of NF2 is depicted in Figure 6.7.

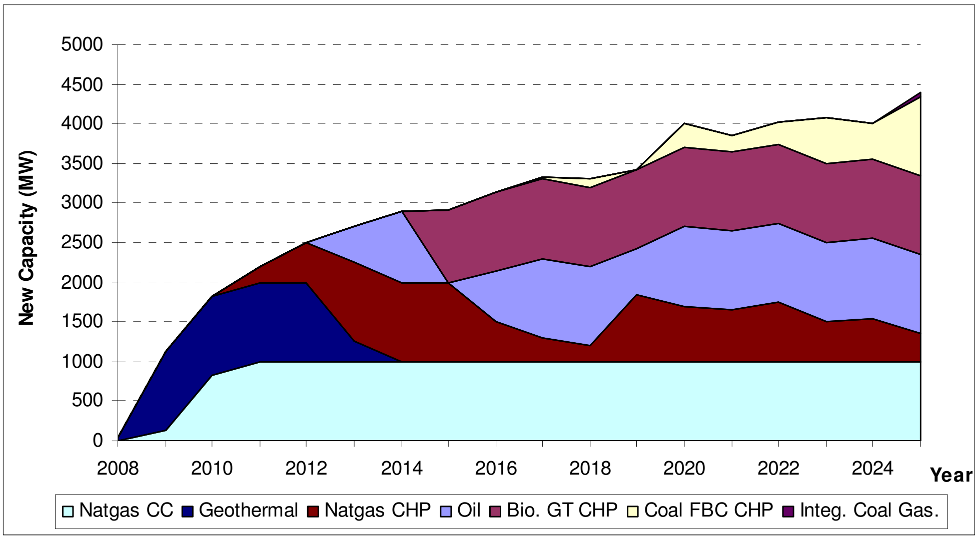



Figure 6.7. Capacity additions of scenario NF2

In scenario NF3 the results till 2020 are similar to the results of NF1. The amount of installed capacities from oil is lower in this model with respect to NF1 and NF2. The difference occurs because of the amount of installed capacity before 2008 is higher with respect to other scenarios so this installed capacities supply some portion of the demand in the following years. Biomass capacity additions are not affected as in the case of NF2 and they are similar to NF1's biomass capacity additions. So there is no change in biomass learning. In this scenario it is assumed that the investors who have taken wind turbine licenses have installed them in the respective years. So in 2007 the investment cost of wind turbine nearly becomes 50 per cent of the value in 2000. This learning effect is depicted in figure 6.8.

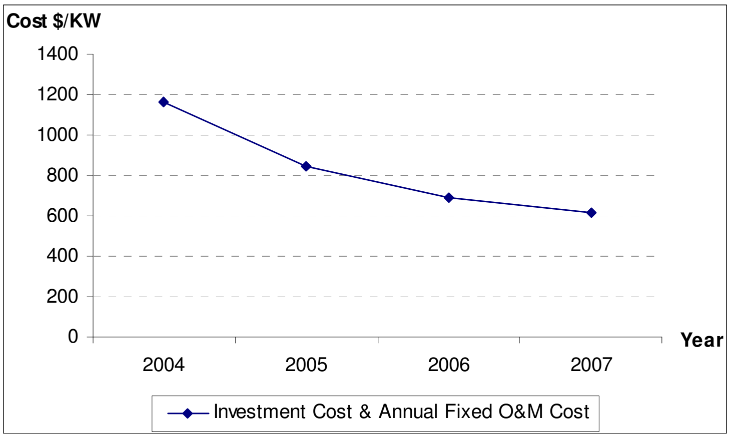



Figure 6.8. Learning effect of large onshore wind turbine in scenario NF3 (2004-2007)

In 2020 the first wind turbine is installed. At this point wind turbine is the fifth choice of investment. Because all other four technologies are at their upper bounds, in order to meet the demand wind turbine is installed. There becomes a slight decrease in investment cost from 2020 to 2024 because of learning. In year 2024 wind turbine becomes superior to oil. The capacity addition from coal based technology is lower with respect to NF1 and NF2 because of the wind turbine capacity additions. Only in year 2025 a small amount of capacity is installed from a coal based technology. This is the only model which includes three kind of renewable technologies and also the variety of installed technologies is highest. The results of scenario NF3 and the learning effect on wind turbine and biomass are depicted respectively in Figure 6.10, Figure 6.9 and Figure 6.11.

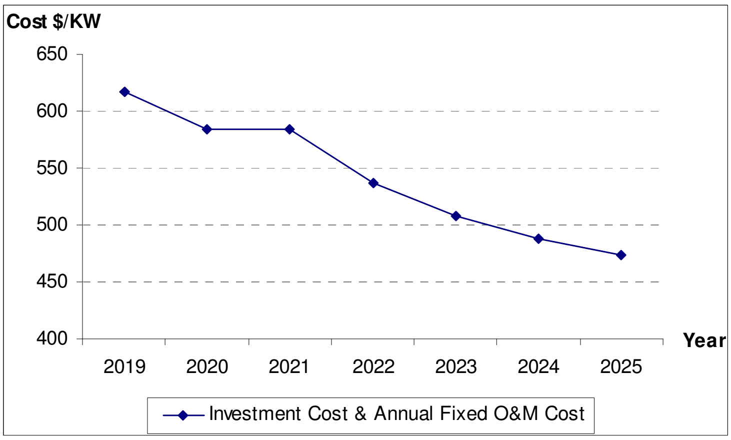



Figure 6.9. Learning effect of large onshore wind turbine in scenario NF3 (2019-2025)

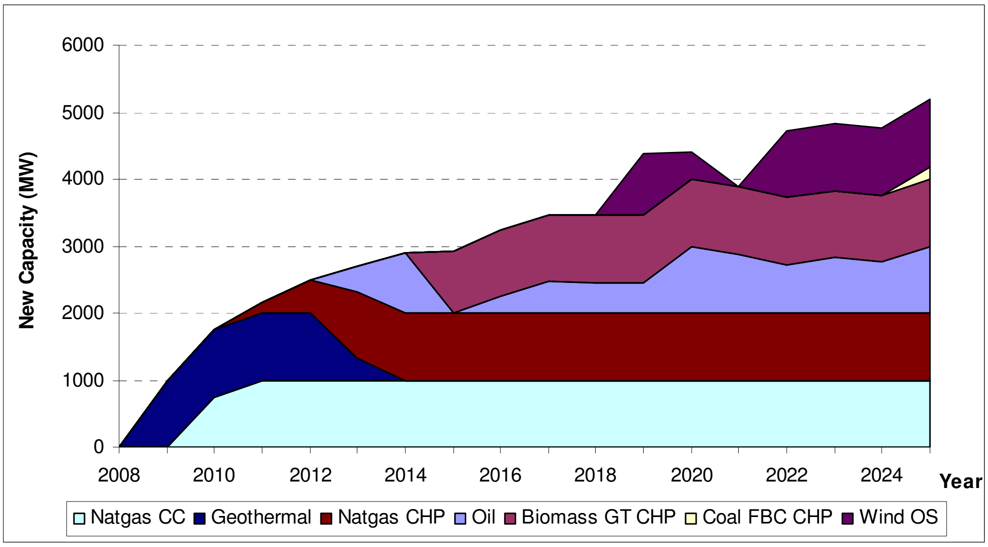



Figure 6.10. Capacity additions of scenario NF3

In scenario NF4 the restriction is at least eight per cent of the total load consumed after year 2005 is supplied by renewable technologies. The results of model NF4 is very similar to the results of model NF1. Because the model already supplies more than eight per cent of the total load consumed from renewable technologies between 2008 and 2013. Only in 2014 there is no capacity addition from renewable technologies. This year creates the difference between the model results of NF1 and NF4. In 2014 a small amount of capacity addition is made from biomass to satisfy the eight per cent restriction. From 2015 to 2025 the model again satisfies more than eight per cent of the load from the renewables. So we can say that the renewable quota of eight per cent becomes redundant. The installed capacities of model NF4 is depicted in figure 6.12. Figure 6.11 depicts the learning of biomass gas turbine CHP in scenarios NF1, NF2, NF3 and NF4.

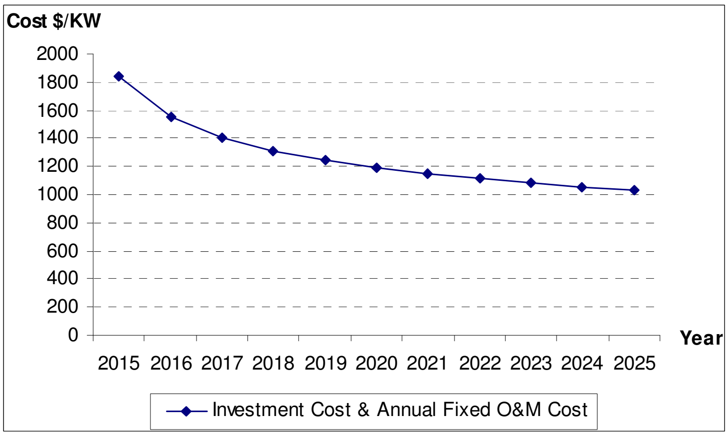



Figure 6.11. Learning effect of biomass GT CHP plant in scenarios NF1-NF2-NF3-NF4

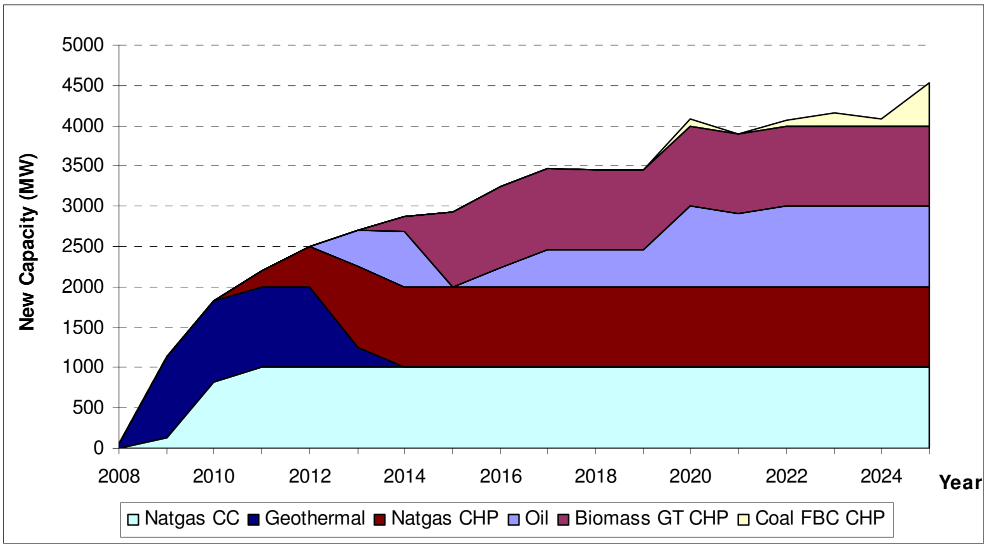



Figure 6.12. Capacity additions of scenario NF4

In scenario NF5 constant price elasticity of electricity demand of -0.02 is assumed and there is no technological restriction assumption. The results are similar to the results of NF1. But the demand values are lower with respect to NF1. This situation creates the difference between the results of the two models. The model starts to install plants in year 2010 which is two years later than NF1. Again this is the result of low demand values. Geothermal is the leading technology and natural gas CC becomes the best option after the theoretical capacity of geothermal is reached and after that natural gas CHP plants start to be installed as in the case of NF1. The capacity additions of oil becomes later because biomass becomes superior to oil in 2015 and it is not installed at its upper bound and this prevents the oil plant installation until 2017. The model installs no coal plant because the load supplied from other technologies is enough to satisfy demand. The installed capacities of model NF5 and the learning effect on Biomass are depicted in figure 6.13 and figure 6.14 respectively.

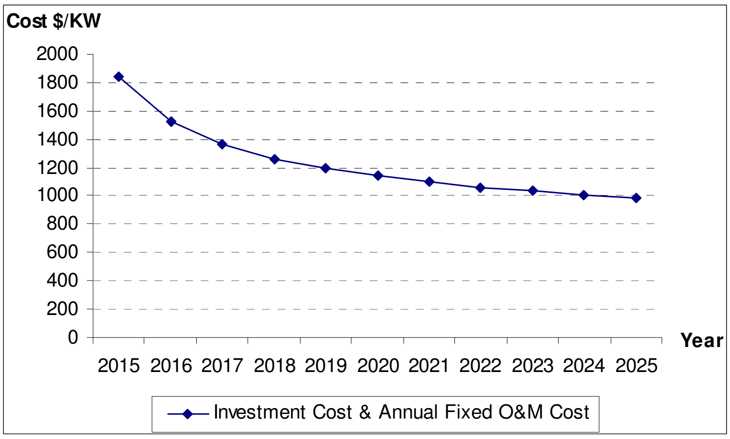



Figure 6.13. Learning effect of biomass GT CHP plant in scenario NF5

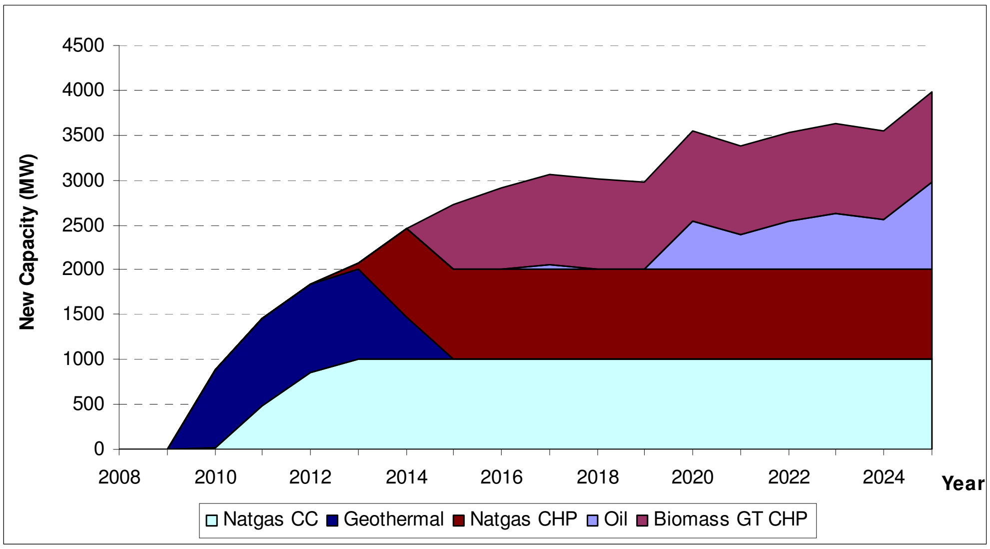



Figure 6.14. Capacity additions of scenario NF5

The share of renewables among new capacity additions is depicted in Figure 6.15. As can be seen there is considerable overlap between scenarios NF1, NF2, and NF4, in that the percentage share of renewable power capacity additions decrease from a very high level in the early years (as geothermal is increasingly outstripped by natural gas and later oil) and biomass starts to take a solid 25-30 per cent share after 2015 (which starts to slightly decline thereafter). Scenario NF5 only differs slightly, in that the peak (at nearly 100 per cent) is reached a bit later and the trough is a bit less pronounced, after which the share stabilizes at a somewhat higher level compared to NF1, NF2, and NF4. The effect of the wind power capacity additions in NF3 is eye-catching for the years 2022-2025. In other words, in the long run, scenario NF3 exhibits the highest renewable share of all scenarios at around 39 per cent by year 2025, after peaking in 2022 at slightly above 42 per cent. The inroad of wind power is apparently strongly driven by the learning effect that occurs as a result of the licensed wind turbine installations in earlier years, as it cannot be explained by the smooth positive drift in fossil fuel prices alone (cf. Fig. 6.1). This finding points out the profound effect that technological learning might have on the results, and shows that policies aimed at promoting renewable energy technologies – in the long run via learning – can induce a more widespread adoption than originally envisaged. [12]

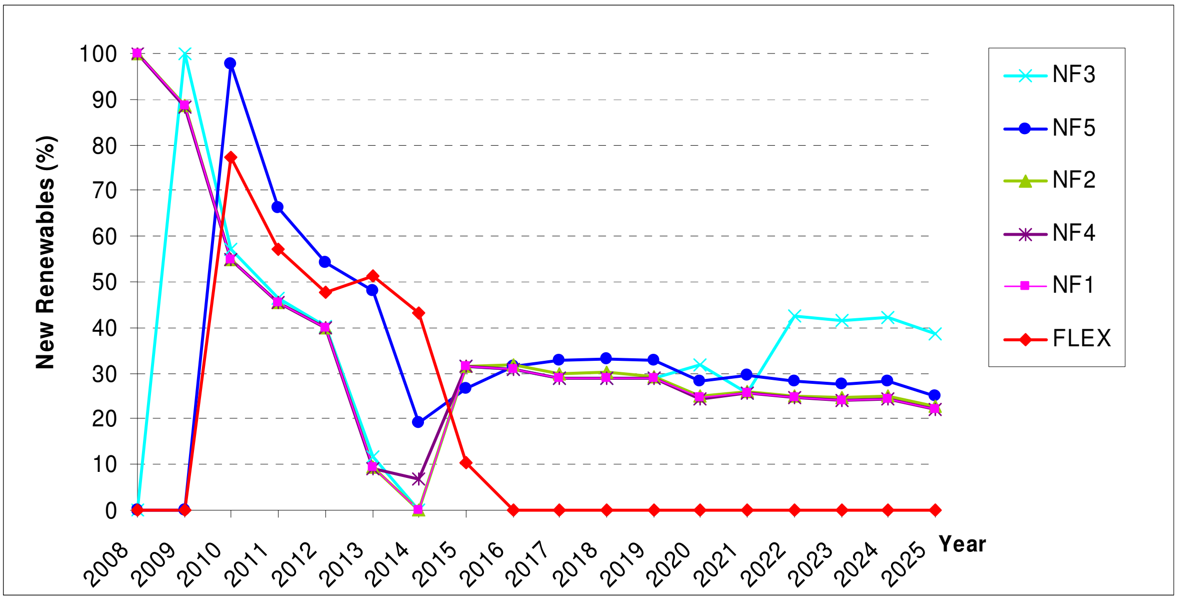
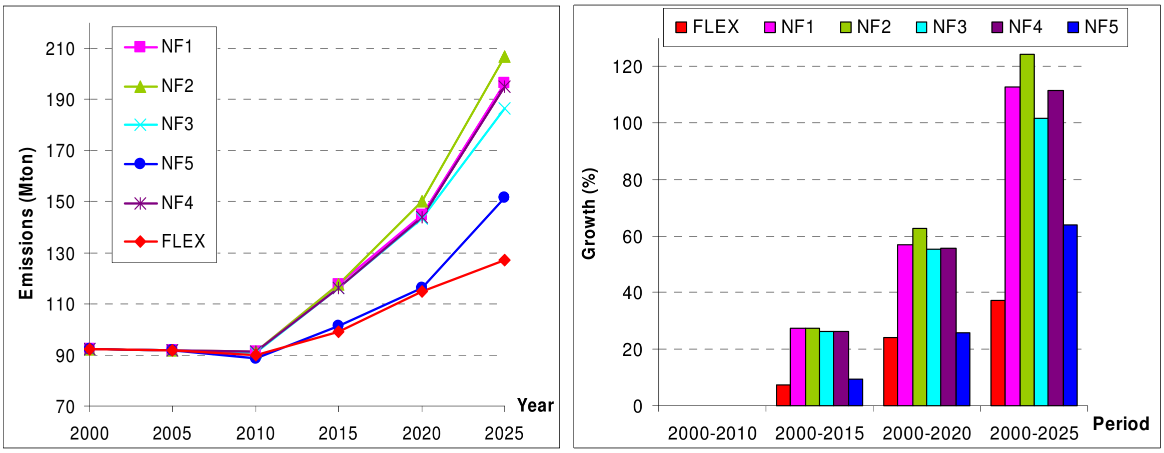



Figure 6.15. Percentage share of renewables among new capacity additions, 2008-2025

The development of $CO_2$ emissions is depicted in Figure 6.16 panel (a). It can be observed that, in the long run, the lowest emissions occur in scenario FLEX and the second lowest is scenario NF5. The comparatively low level of $CO_2$ emissions in scenario FLEX and NF5 can be explained by the low demand levels of these models. So these scenarios cannot be compared with the other ones. Scenarios NF1-4 follow each other rather closely until 2015, after which first NF2 and then NF1 and NF4 exhibit increasingly higher $CO_2$ emissions compared to NF3. It becomes evident from the results for NF2 that the bounds imposed on natural-gas-fired technology adoption lead to the highest emissions among all the scenarios considered. The lowest emission levels within the non-flex scenarios NF1-4 are monitored in scenario NF3, i.e. the wind turbine licensing scenario with the highest renewable share. The achieved $CO_2$ reduction in scenario NF3 (compared to the highest emission scenario NF2) amounts to some 21 Megatons (corresponding to a 10 per cent reduction) in 2025. The corresponding figures between scenarios FLEX and NF2 for 2025 are 80 Mt and 39 per cent, respectively. The growth in $CO_2$ emissions reaches considerable levels in the long run (e.g. in year 2025, the increase from 2000 levels ranges from 38 per cent in scenario FLEX to 124 per cent in scenario NF2), as depicted in panel (b) of Figure 6.16. [12]




(a) Levels (b) Growth

Figure 6.16. Development of $CO_2$ emissions, by scenario, 2000-2025

## 6.3. Sensitivity Analysis

In this section, the sensitivity of the model to certain parameters will be considered. The first parameter that will be considered is the discount rate. The model results are most sensitive to the discount rate in scenario NF5. In other scenarios the model results change at very high discount rates about 0,4. The discount rate of NF5 is increased to 0,2. In model NF5 the general investment preferences are actually the same as the original scenario. Again geothermal and natural gas are the best options to invest. But the investment choice between oil and biomass change. The model prefers to invest in oil in the period of 2015-2020 instead of biomass.

The second issue is the effect of the growth rates used in the estimation of the variable cost of the generation technologies. Two technologies are considered which are natural gas and oil. These technologies play a key role in the electricity markets all over the world. So two different scenarios are considered for each technology. Table 6.7 shows the growth levels used for the sensitivity analysis for each technology.

Table 6.7. Growth levels

| **Technology** | Low | High |
|---|---|---|
| Natural Gas | -0,043 | 0,017 |
| Oil | 0,009 | 0,069 |

When the natural gas growth rate is increased by three per cent the model prefers to install oil and biomass plants instead of natural gas based plants. After 2017 natural gas becomes cheaper with respect to oil because of the rise in oil prices. The model gives the same results after 2017. If the growth rate is decreased by three per cent the model prefers to install natural gas based technologies which becomes cheaper to geothermal energy. The geothermal investments are postponed for a few years. When the natural gas based technologies start to reach their upper bounds of one GW, geothermal investments take place. Again the investments after 2017 are not affected. Because when the theoretical capacity of geothermal is reached natural gas becomes the cheapest technology in the original scenario, in the case of sensitivity the same situation occurs.

The oil growth factor is also increased by three per cent and then decreased by three per cent. In the first case oil becomes cheaper with respect to natural gas and biomass until 2020. In this time period Oil investments are made at the upper bound of one GW. After 2020 the rise in oil prices cause biomass and natural gas investments more attractive. In the period of 2020-2025 the model finds the same results as in the case of original scenario. The oil investments start to decline and its gap is replaced by biomass. When the oil growth rate is increased by three per cent, the oil prices reach 22 cents around 2025. Because of the sharp increase in oil prices the model prefers to invest in coal based technologies and also the amount of investments to biomass increases. The coal based investments start in earlier years with respect to the original scenario with higher investment levels. There exist no oil investments in this scenario.

The third issue in sensitivity analysis is the effect of learning rates to the model results. There are two technologies with considerable learning rates that are installed in scenario results. These are Biomass Gas Turbine CHP and Large Onshore Wind Turbine with learning rates of 0,15 and 0,1 respectively. The following table displays the two levels of learning rates that are used for the sensitivity analysis.

Table 6.8. Learning levels

| Technology | Low | High |
|---|---|---|
| Biomass Gas Turbine CHP | 0,10 | 0,20 |
| Large Onshore Wind Turbine | 0,05 | 0,15 |

The results show increasing or decreasing biomass learning rate has no effect on the model results. Because biomass becomes cheaper with respect to oil after its first capacity addition in all scenarios and it is installed at its upper bound. Biomass becomes superior to natural gas in a shorter time in the case of higher learning rate but this does not affect the amount installed from these technologies.

The model is more sensitive to the learning rate of onshore wind turbine. At the low level the initial learning process between 2004 and 2007 does not decrease the investment costs enough to make onshore wind turbine a good alternative after 2020. The model installs no wind turbines at the low level of learning rate. At the high level the investment costs decrease drastically between 2004 and 2007. For this reason the model installs onshore wind turbines at the upper bound of one GW between 2009 and 2025. The following table summarizes the change in the capacity additions for each technology with respect to the base scenarios. The base scenario for the sensitivity of natural gas and oil is NF1, for onshore wind turbine NF3 and for the discount rate NF5.

Table 6.9. Summary of the sensitivity results

| | Natural Gas (MW) | | Oil (MW) | | Wind OS (MW) | | D.Rate(MW) |
|---|---|---|---|---|---|---|---|
| **Technology** | Low | High | Low | High | Low | High | D.Rate=0,2 |
| Natgas CC | 1.102 | -4.090 | -2.292 | 0 | 0 | -223 | 0 |
| Geothermal | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| NatgasCHP | 2.492 | -3.700 | -1.738 | 0 | 0 | -1.198 | 0 |
| Oil | -1.026 | 3.770 | 6.063 | -8.898 | 695 | -2.746 | 5.083 |
| Bio. GT CHP | -1.922 | 2.564 | -2.633 | 1.229 | 0 | -396 | -4.765 |
| Wind OS | - | - | - | - | -5.331 | 11.669 | - |
| Coal FBC | 0 | 0 | 0 | 5.924 | 772 | 0 | - |

Finally, to estimate the variable cost figures of generation technologies and the price of electricity instead of GBM, mean reverting process is applied to the scenario NF1. The parameters of the mean reverting process are acquired with the use of maximum likelihood estimation method [60]. The resulting cost trajectories of variable costs and the price is depicted in figure 6.17. The change in capacity additions is summarized in table 6.10.

Table 6.10. Change in capacity additions

| **Technology** | Mean Reverting Process (MW) |
|---|---|
| Natgas CC | -1.429 |
| Geothermal | -3.230 |
| Natgas CHP | -4.824 |
| Oil | 6.102 |
| Biomass GT CHP | -2.630 |
| Coal FBC | -124 |

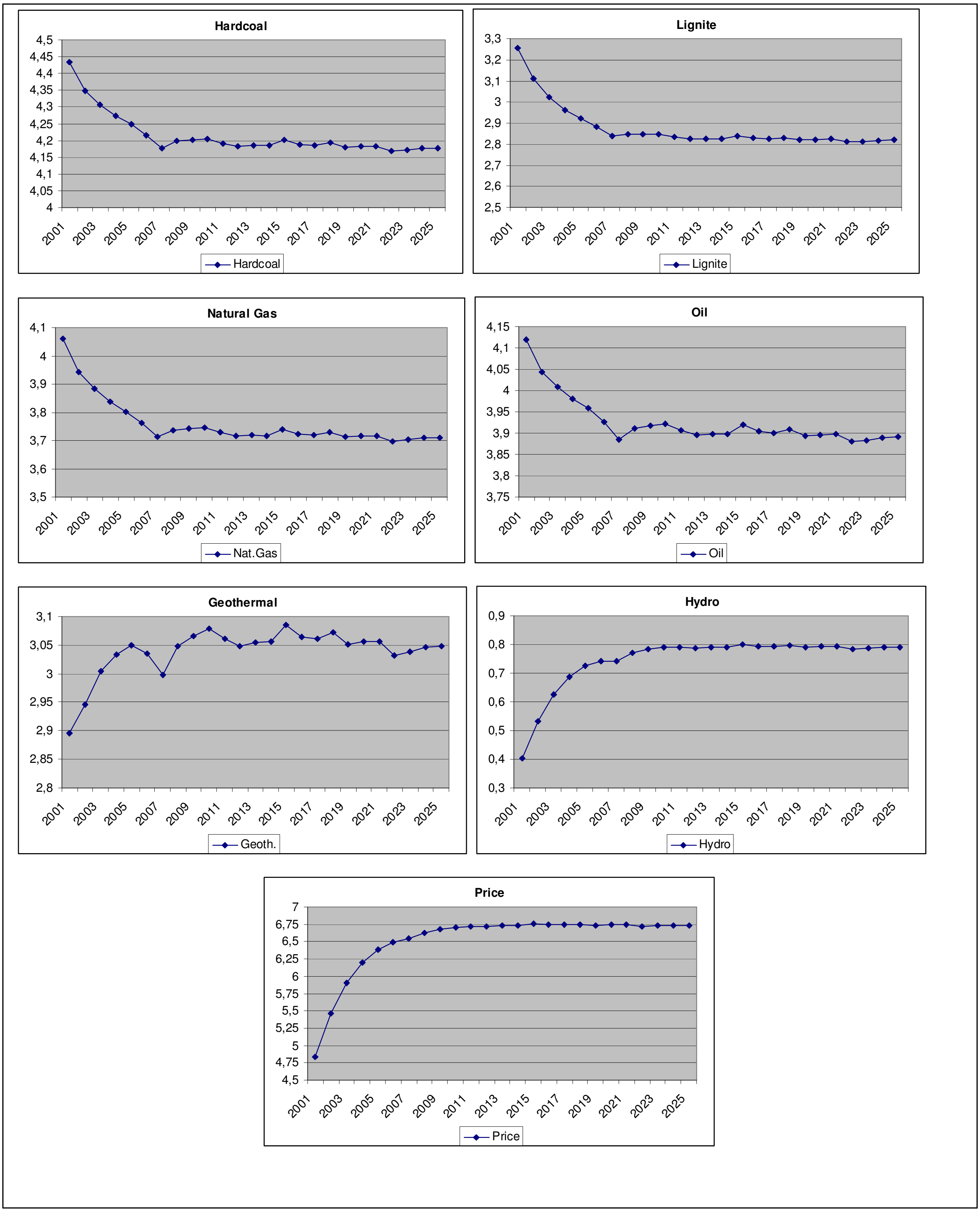



Figure 6.17. Cost & Price estimates with mean reverting process

# 7. CONCLUSIONS

In this thesis we have studied how learning curves for renewable energy technologies can be integrated into a dynamic programming model. The model built can guide optimal investment planning in the electricity supply sector and is based on the real options approach to investment. The model has been successfully applied to real data from Turkey. The results show that, due to existing excess power generation capacity, no capacity additions are needed up to the year 2008. Because of their relatively high costs, the diffusion of renewable energy technologies only occurs if targeted policies exist. The promotion of renewable energy technologies expands beyond the initial scope, due to an accelerated learning effect, through which the costs decline to a level at which they can successfully compete with non-renewable alternatives. This finding indicates the essence of technological learning, and points out the importance of policies aimed at increasing the share of renewable power generation. Indeed, the results indicate that particular aid is needed in excess of the new renewable energy law to affect the evolution of the technological structure of new electric capacity investments in the long run. In the absence of subsidies or other promotion policy instruments, market players can hardly be expected to invest in more expensive renewable energy technologies, especially in a liberalized electricity market environment. Financial incentives are needed in the short-term, in order to enable a more widespread adoption of renewable energy technologies in the longer run.

Incentives to finance investments in costly renewable energy technologies can, for example, be created through the operationalization of the flexibility mechanisms introduced by the 1997 Kyoto Protocol. In the case of Turkey, it could be expected that the wind power licenses held by the private sector may turn into real investments through project-based support by the clean development mechanism (CDM) or by joint implementation (JI). Turkey’s position with respect to CDM or JI projects is yet unclear. However, the model results and projected $CO_2$ emission growth rates show that allowances for increasing emissions, together with financial assistance for clean energy projects, is essential for a sustainable clean development of the country. Kyoto ratification should therefore bring Turkey into a position that features her to *host* CDM or JI projects. The possibility of hosting such projects would lead to a variety of different clean energy technology investments, as early project proposals indicate (Kumbaroğlu et al., 2004), might induce technological learning and thus far more emission reduction in the long run than initially anticipated.

A certain weakness of the model presented in this thesis is that electricity prices do not adjust to changing supply/demand conditions, and that data limitations prevented us from employing market-valuation principles in the RO modeling. Removing these two shortcomings seems to be a fruitful avenue for further research and model development, especially when applying the model to fully liberalized electricity markets where the demand/supply price mechanism plays a more important role. [12]

# APPENDIX A: MODEL RESULTS AND DATA SETS

Table A.1.Model results of scenario FLEX

| Year | Natgas CC_FLEX (KW) | Geoth_FLEX (KW) | Natgas CHP_FLEX (KW) |
|---|---|---|---|
| 2008 | | | |
| 2009 | 194.714 | | |
| 2010 | 233.797 | 788.557 | |
| 2011 | 611.634 | 816.170 | |
| 2012 | 870.588 | 792.338 | |
| 2013 | 847.970 | 892.554 | |
| 2014 | 1.083.996 | 820.808 | |
| 2015 | 1.738.597 | 200.000 | |
| 2016 | 2.000.000 | | 204.000 |
| 2017 | 2.000.000 | | 347.000 |
| 2018 | 2.000.000 | | 177.000 |
| 2019 | 1.972.000 | | |
| 2020 | 2.000.000 | | 499.000 |
| 2021 | 2.000.000 | | 66.800 |
| 2022 | 1.719.000 | | |
| 2023 | 1.298.000 | | |
| 2024 | 1.178.000 | | |
| 2025 | 1.533.000 | | |

Table A.2.Model results of scenario NF1

| Year | Natgas CC_NF1 (KW) | Geoth_NF1 (KW) | Natgas CHP_NF1 (KW) | Oil_NF1 (KW) | Biomass GT CHP_NF1 (KW) | Coal FBC CHP_NF1 (KW) |
|---|---|---|---|---|---|---|
| 2008 | | 44.660 | | | | |
| 2009 | 127.446 | 1.000.000 | | | | |
| 2010 | 818.672 | 1.000.000 | | | | |
| 2011 | 1.000.000 | 1.000.000 | 199.330 | | | |
| 2012 | 1.000.000 | 1.000.000 | 500.413 | | | |
| 2013 | 1.000.000 | 255.000 | 1.000.000 | 454.824 | | |
| 2014 | 1.000.000 | | 1.000.000 | 894.461 | | |
| 2015 | 1.000.000 | | 1.000.000 | | 922.016 | |
| 2016 | 1.000.000 | | 1.000.000 | 244.986 | 1.000.000 | |
| 2017 | 1.000.000 | | 1.000.000 | 471.251 | 1.000.000 | |
| 2018 | 1.000.000 | | 1.000.000 | 459.087 | 1.000.000 | |
| 2019 | 1.000.000 | | 1.000.000 | 456.000 | 1.000.000 | |
| 2020 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 61.100 |
| 2021 | 1.000.000 | | 1.000.000 | 917.000 | 1.000.000 | |
| 2022 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 71.600 |
| 2023 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 172.000 |
| 2024 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 93.500 |
| 2025 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 525.400 |

Table A.3.Model results of scenario NF2

| Year | Natgas CC_NF2 (KW) | Geoth_NF 2 (KW) | Natgas CHP_NF2 (KW) | Oil_NF2 (KW) | Biomass GT CHP_NF2 (KW) | Coal FBC CHP_NF2 (KW) | Integrated Coal Gas._NF2 (KW) |
|---|---|---|---|---|---|---|---|
| 2008 | | 44.660 | | | | | |
| 2009 | 127.446 | 1.000.000 | | | | | |
| 2010 | 818.670 | 1.000.000 | | | | | |
| 2011 | 1.000.000 | 1.000.000 | 199.328 | | | | |
| 2012 | 1.000.000 | 1.000.000 | 500.411 | | | | |
| 2013 | 1.000.000 | 256.000 | 1.000.000 | 453.889 | | | |
| 2014 | 1.000.000 | | 1.000.000 | 894.467 | | | |
| 2015 | 1.000.000 | | 1.000.000 | | 922.021 | | |
| 2016 | 1.000.000 | | 500.000 | 644.992 | 1.000.000 | | |
| 2017 | 1.000.000 | | 300.000 | 1.000.000 | 1.000.000 | 31.257 | |
| 2018 | 1.000.000 | | 200.000 | 1.000.000 | 1.000.000 | 99.080 | |
| 2019 | 1.000.000 | | 850.000 | 575.816 | 1.000.000 | | |
| 2020 | 1.000.000 | | 700.000 | 1.000.000 | 1.000.000 | 301.133 | |
| 2021 | 1.000.000 | | 650.000 | 1.000.000 | 1.000.000 | 196.695 | |
| 2022 | 1.000.000 | | 750.000 | 1.000.000 | 1.000.000 | 271.558 | |
| 2023 | 1.000.000 | | 500.000 | 1.000.000 | 1.000.000 | 572.046 | |
| 2024 | 1.000.000 | | 550.000 | 1.000.000 | 1.000.000 | 453.550 | |
| 2025 | 1.000.000 | | 350.000 | 1.000.000 | 1.000.000 | 1.000.000 | 42.611 |

Table A.4.Model results of scenario NF3

| Year | Natgas CC_NF3 (KW) | Geoth_NF 3 (KW) | Natgas CHP_NF3 (KW) | Oil_NF3 (KW) | Biomass GT CHP_NF3 (KW) | Coal FBC CHP_NF3 (KW) | Wind OS_NF3 (KW) |
|---|---|---|---|---|---|---|---|
| 2008 | | | | | | | |
| 2009 | | 982.938 | | | | | |
| 2010 | 745.761 | 1.000.000 | | | | | |
| 2011 | 1.000.000 | 1.000.000 | 159.831 | | | | |
| 2012 | 1.000.000 | 1.000.000 | 483.374 | | | | |
| 2013 | 1.000.000 | 317.000 | 1.000.000 | 387.976 | | | |
| 2014 | 1.000.000 | | 1.000.000 | 889.970 | | | |
| 2015 | 1.000.000 | | 1.000.000 | | 919.910 | | |
| 2016 | 1.000.000 | | 1.000.000 | 243.864 | 1.000.000 | | |
| 2017 | 1.000.000 | | 1.000.000 | 470.692 | 1.000.000 | | |
| 2018 | 1.000.000 | | 1.000.000 | 458.794 | 1.000.000 | | |
| 2019 | 1.000.000 | | 1.000.000 | 455.600 | 1.000.000 | | 929.660 |
| 2020 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | | 401.400 |
| 2021 | 1.000.000 | | 1.000.000 | 880.500 | 1.000.000 | | |
| 2022 | 1.000.000 | | 1.000.000 | 720.024 | 1.000.000 | | 1.000.000 |
| 2023 | 1.000.000 | | 1.000.000 | 829.609 | 1.000.000 | | 1.000.000 |
| 2024 | 1.000.000 | | 1.000.000 | 755.700 | 1.000.000 | | 1.000.000 |
| 2025 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 189.800 | 1.000.000 |

Table A.5.Model results of scenario NF4

| Year | Natgas CC_NF4 (KW) | Geoth_NF4 (KW) | Natgas CHP_NF4 (KW) | Oil_NF4 (KW) | Biomass GT CHP_NF4 (KW) | Coal FBC CHP_NF4 (KW) |
|---|---|---|---|---|---|---|
| 2008 | | 52.276 | | | | |
| 2009 | 131.542 | 1.000.000 | | | | |
| 2010 | 820.724 | 1.000.000 | | | | |
| 2011 | 1.000.000 | 1.000.000 | 200.438 | | | |
| 2012 | 1.000.000 | 1.000.000 | 500.970 | | | |
| 2013 | 1.000.000 | 250.000 | 1.000.000 | 459.711 | | |
| 2014 | 1.000.000 | | 1.000.000 | 689.681 | 192.094 | |
| 2015 | 1.000.000 | | 1.000.000 | | 922.072 | |
| 2016 | 1.000.000 | | 1.000.000 | 245.023 | 1.000.000 | |
| 2017 | 1.000.000 | | 1.000.000 | 471.263 | 1.000.000 | |
| 2018 | 1.000.000 | | 1.000.000 | 459.087 | 1.000.000 | |
| 2019 | 1.000.000 | | 1.000.000 | 455.814 | 1.000.000 | |
| 2020 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 86.242 |
| 2021 | 1.000.000 | | 1.000.000 | 904.414 | 1.000.000 | |
| 2022 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 65.282 |
| 2023 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 168.905 |
| 2024 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 91.976 |
| 2025 | 1.000.000 | | 1.000.000 | 1.000.000 | 1.000.000 | 524.663 |

Table A.6.Model results of scenario NF5

| Year | Natgas CC_NF5 (KW) | Geoth_NF5 (KW) | Natgas CHP_NF5 (KW) | Oil_NF5 (KW) | Biomass GT CHP_NF5 (KW) |
|---|---|---|---|---|---|
| 2008 | | | | | |
| 2009 | | | | | |
| 2010 | 20.023 | 863.782 | | | |
| 2011 | 490.731 | 968.659 | | | |
| 2012 | 848.102 | 1.000.000 | | | |
| 2013 | 1.000.000 | 1.000.000 | 82.536 | | |
| 2014 | 1.000.000 | 468.000 | 995.786 | | |
| 2015 | 1.000.000 | | 1.000.000 | | 728.552 |
| 2016 | 1.000.000 | | 1.000.000 | | 914.167 |
| 2017 | 1.000.000 | | 1.000.000 | 62.574 | 1.000.000 |
| 2018 | 1.000.000 | | 1.000.000 | 5.722 | 1.000.000 |
| 2019 | 1.000.000 | | 1.000.000 | | 973.408 |
| 2020 | 1.000.000 | | 1.000.000 | 540.168 | 1.000.000 |
| 2021 | 1.000.000 | | 1.000.000 | 386.217 | 1.000.000 |
| 2022 | 1.000.000 | | 1.000.000 | 534.532 | 1.000.000 |
| 2023 | 1.000.000 | | 1.000.000 | 632.273 | 1.000.000 |
| 2024 | 1.000.000 | | 1.000.000 | 551.708 | 1.000.000 |
| 2025 | 1.000.000 | | 1.000.000 | 981.194 | 1.000.000 |

Table A.7.Cost and price estimations for 2001-2025 (Geometric Brownian Motion)

| Year | Hardcoal (Cent/ Kwh) | Lignite (Cent/ Kwh) | Nat.Gas (Cent/ Kwh) | Oil (Cent/ Kwh) | Geoth. (Cent/ Kwh) | Hydro. (Cent/ Kwh) | Electricity Price (Cent/ Kwh) |
|---|---|---|---|---|---|---|---|
| 2001 | 4,760 | 3,640 | 4,172 | 4,391 | 2,644 | 0,208 | 3,831 |
| 2002 | 4,977 | 3,825 | 4,120 | 4,569 | 2,504 | 0,215 | 3,804 |
| 2003 | 5,214 | 4,028 | 4,077 | 4,766 | 2,374 | 0,221 | 3,781 |
| 2004 | 5,450 | 4,230 | 4,025 | 4,951 | 2,233 | 0,225 | 3,726 |
| 2005 | 5,701 | 4,447 | 3,977 | 5,152 | 2,110 | 0,230 | 3,690 |
| 2006 | 5,942 | 4,653 | 3,914 | 5,326 | 1,959 | 0,226 | 3,580 |
| 2007 | 6,185 | 4,865 | 3,848 | 5,506 | 1,835 | 0,230 | 3,515 |
| 2008 | 6,482 | 5,126 | 3,809 | 5,747 | 1,746 | 0,240 | 3,509 |
| 2009 | 6,762 | 5,367 | 3,753 | 5,938 | 1,609 | 0,229 | 3,374 |
| 2010 | 7,091 | 5,659 | 3,717 | 6,200 | 1,514 | 0,221 | 3,314 |
| 2011 | 7,400 | 5,932 | 3,664 | 6,429 | 1,419 | 0,218 | 3,252 |
| 2012 | 7,721 | 6,219 | 3,611 | 6,668 | 1,339 | 0,228 | 3,222 |
| 2013 | 8,097 | 6,562 | 3,576 | 6,992 | 1,310 | 0,255 | 3,324 |
| 2014 | 8,416 | 6,838 | 3,511 | 7,162 | 1,158 | 0,213 | 3,037 |
| 2015 | 8,832 | 7,218 | 3,480 | 7,504 | 1,119 | 0,223 | 3,084 |
| 2016 | 9,236 | 7,588 | 3,437 | 7,817 | 1,074 | 0,286 | 3,127 |
| 2017 | 9,555 | 7,860 | 3,358 | 7,933 | 0,945 | 0,303 | 2,865 |
| 2018 | 9,980 | 8,242 | 3,312 | 8,210 | 0,871 | 0,300 | 2,758 |
| 2019 | 10,437 | 8,670 | 3,272 | 8,580 | 0,859 | 0,333 | 2,883 |
| 2020 | 10,907 | 9,104 | 3,230 | 8,923 | 0,830 | 0,377 | 2,943 |
| 2021 | 11,395 | 9,558 | 3,187 | 9,280 | 0,805 | 0,467 | 3,026 |
| 2022 | 11,918 | 10,061 | 3,149 | 9,727 | 0,814 | 0,573 | 3,262 |
| 2023 | 12,468 | 10,584 | 3,111 | 10,156 | 0,801 | 0,684 | 3,402 |
| 2024 | 12,998 | 11,075 | 3,063 | 10,489 | 0,752 | 0,761 | 3,367 |
| 2025 | 13,549 | 11,589 | 3,016 | 10,830 | 0,697 | 0,713 | 3,265 |

Table A.8.Percentage share of renewables among new capacity additions

| Year | FLEX (per cent) | NF1 (per cent) | NF2 (per cent) | NF3 (per cent) | NF4 (per cent) | NF5 (per cent) |
|---|---|---|---|---|---|---|
| 2008 | 0 | 100 | 100 | 0 | 100 | 0 |
| 2009 | 0 | 89 | 89 | 100 | 88 | 0 |
| 2010 | 77 | 55 | 55 | 57 | 55 | 98 |
| 2011 | 57 | 45 | 45 | 46 | 45 | 66 |
| 2012 | 48 | 40 | 40 | 40 | 40 | 54 |
| 2013 | 51 | 9 | 9 | 12 | 9 | 48 |
| 2014 | 43 | 0 | 0 | 0 | 7 | 19 |
| 2015 | 10 | 32 | 32 | 32 | 32 | 27 |
| 2016 | 0 | 31 | 32 | 31 | 31 | 31 |
| 2017 | 0 | 29 | 30 | 29 | 29 | 33 |
| 2018 | 0 | 29 | 30 | 29 | 29 | 33 |
| 2019 | 0 | 29 | 29 | 44 | 29 | 33 |
| 2020 | 0 | 25 | 25 | 32 | 24 | 28 |
| 2021 | 0 | 26 | 26 | 26 | 26 | 30 |
| 2022 | 0 | 25 | 25 | 42 | 25 | 28 |
| 2023 | 0 | 24 | 25 | 41 | 24 | 28 |
| 2024 | 0 | 24 | 25 | 42 | 24 | 28 |
| 2025 | 0 | 22 | 23 | 39 | 22 | 25 |

Table A.9.Cost and price estimations for 2001-2025 (Mean Reverting Process)

| Year | Hardcoal (Cent/ Kwh) | Lignite (Cent/ Kwh) | Nat.Gas (Cent/ Kwh) | Oil (Cent/ Kwh) | Geoth. (Cent/ Kwh) | Hydro. (Cent/ Kwh) | Electricity Price (Cent/ Kwh) |
|---|---|---|---|---|---|---|---|
| 2001 | 4,435 | 3,255 | 4,062 | 4,120 | 2,896 | 0,404 | 4,835 |
| 2002 | 4,348 | 3,109 | 3,944 | 4,043 | 2,946 | 0,532 | 5,468 |
| 2003 | 4,306 | 3,024 | 3,884 | 4,010 | 3,004 | 0,626 | 5,908 |
| 2004 | 4,272 | 2,963 | 3,837 | 3,980 | 3,033 | 0,686 | 6,194 |
| 2005 | 4,248 | 2,921 | 3,803 | 3,958 | 3,049 | 0,724 | 6,382 |
| 2006 | 4,216 | 2,880 | 3,762 | 3,927 | 3,036 | 0,742 | 6,491 |
| 2007 | 4,177 | 2,838 | 3,712 | 3,884 | 2,997 | 0,743 | 6,543 |
| 2008 | 4,198 | 2,849 | 3,737 | 3,910 | 3,048 | 0,770 | 6,631 |
| 2009 | 4,202 | 2,848 | 3,741 | 3,917 | 3,066 | 0,783 | 6,678 |
| 2010 | 4,206 | 2,848 | 3,745 | 3,922 | 3,078 | 0,792 | 6,711 |
| 2011 | 4,192 | 2,835 | 3,728 | 3,906 | 3,061 | 0,789 | 6,714 |
| 2012 | 4,182 | 2,825 | 3,716 | 3,895 | 3,049 | 0,786 | 6,716 |
| 2013 | 4,184 | 2,826 | 3,718 | 3,898 | 3,055 | 0,790 | 6,727 |
| 2014 | 4,184 | 2,825 | 3,718 | 3,898 | 3,056 | 0,791 | 6,732 |
| 2015 | 4,202 | 2,839 | 3,739 | 3,919 | 3,085 | 0,801 | 6,756 |
| 2016 | 4,189 | 2,829 | 3,724 | 3,904 | 3,065 | 0,795 | 6,744 |
| 2017 | 4,186 | 2,826 | 3,720 | 3,900 | 3,061 | 0,794 | 6,742 |
| 2018 | 4,193 | 2,831 | 3,728 | 3,908 | 3,072 | 0,798 | 6,751 |
| 2019 | 4,179 | 2,821 | 3,712 | 3,893 | 3,051 | 0,791 | 6,737 |
| 2020 | 4,182 | 2,823 | 3,716 | 3,897 | 3,056 | 0,793 | 6,741 |
| 2021 | 4,183 | 2,823 | 3,716 | 3,897 | 3,056 | 0,793 | 6,741 |
| 2022 | 4,168 | 2,811 | 3,698 | 3,880 | 3,033 | 0,785 | 6,725 |
| 2023 | 4,171 | 2,814 | 3,702 | 3,883 | 3,038 | 0,787 | 6,729 |
| 2024 | 4,176 | 2,818 | 3,708 | 3,890 | 3,046 | 0,789 | 6,735 |
| 2025 | 4,178 | 2,819 | 3,710 | 3,891 | 3,049 | 0,790 | 6,736 |

Table A.10. $CO_2$ emissions data

| Year | FLEX (Mton) | NF1 (Mton) | NF2 (Mton) | NF3 (Mton) | NF4 (Mton) | NF5 (Mton) |
|---|---|---|---|---|---|---|
| 2000 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 |
| 2001 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 |
| 2002 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 |
| 2003 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 |
| 2004 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 | 92,316 |
| 2005 | 91,734 | 91,734 | 91,734 | 91,734 | 91,734 | 91,734 |
| 2006 | 91,419 | 91,419 | 91,419 | 91,419 | 91,419 | 91,419 |
| 2007 | 91,138 | 91,138 | 91,138 | 91,138 | 91,138 | 91,138 |
| 2008 | 90,384 | 90,384 | 90,384 | 90,384 | 90,384 | 90,384 |
| 2009 | 90,084 | 89,899 | 89,899 | 89,548 | 89,910 | 89,548 |
| 2010 | 89,770 | 91,196 | 91,196 | 90,644 | 91,213 | 88,644 |
| 2011 | 91,455 | 94,459 | 94,459 | 93,807 | 94,479 | 89,996 |
| 2012 | 93,855 | 98,488 | 98,488 | 97,792 | 98,509 | 92,334 |
| 2013 | 96,042 | 106,307 | 106,302 | 105,219 | 106,357 | 95,150 |
| 2014 | 96,293 | 114,120 | 114,114 | 113,005 | 112,968 | 97,703 |
| 2015 | 99,219 | 117,554 | 117,548 | 116,439 | 116,402 | 101,137 |
| 2016 | 100,589 | 119,630 | 120,700 | 118,509 | 118,479 | 101,776 |
| 2017 | 102,232 | 122,944 | 125,530 | 121,819 | 121,792 | 102,692 |
| 2018 | 107,336 | 130,079 | 134,423 | 128,953 | 128,928 | 107,167 |
| 2019 | 112,426 | 137,710 | 142,376 | 136,582 | 136,558 | 112,122 |
| 2020 | 114,787 | 144,839 | 150,240 | 143,329 | 143,843 | 116,171 |
| 2021 | 119,903 | 154,954 | 161,180 | 153,230 | 153,885 | 123,172 |
| 2022 | 122,576 | 164,504 | 171,342 | 160,690 | 163,395 | 129,543 |
| 2023 | 123,405 | 173,997 | 182,061 | 168,109 | 172,869 | 135,805 |
| 2024 | 126,651 | 185,748 | 194,916 | 177,844 | 184,611 | 144,342 |
| 2025 | 126,952 | 196,272 | 207,033 | 186,272 | 195,130 | 151,475 |

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