Available online at www.sciencedirect.com

SCIENCE DIRECT®

Energy Economics 27 (2005) 139–163

Energy Economics

www.elsevier.com/locate/eneco

Modeling technology adoption as an irreversible investment under uncertainty: the case of the Turkish electricity supply industry☆

Reinhard Madlener[a,*], Gürkan Kumbaroğlu[b], Volkan Ş. Ediger[c,1]

[a]*Centre for Energy Policy and Economics (CEPE), Swiss Federal Institute of Technology Zurich, ETH Zentrum, CH-8092 Zurich, Switzerland*
[b]*Department of Industrial Engineering, Boğaziçi University, TR-34342 Bebek, Istanbul, Turkey*
[c]*Cumhurbaşkanlığı, Çankaya, TR-06689 Ankara, Turkey*

Abstract

This paper studies energy conversion technology adoption in the electricity supply sector from the perspective of irreversible investments under uncertainty and with a particular interest in environmental sustainability. We develop a dynamic technology adoption model that is firmly rooted in economic theory and that takes important determinants of optimal investment in available technologies (e.g., life cycle capital and operation cost) explicitly into account. Uncertainty is introduced for the demand for peak-load capacity, unit generation costs, and for the average electricity price. We test the model empirically by applying it to data for the Turkish power supply industry. The model-guided optimal investment schedule based on net present value considerations exhibits significant deviations from the actual investment outcome. We find that the increased adoption of natural-gas-fired power generation technologies in Turkey in recent years, while

---

☆ An earlier version of this article was presented at the 2003 International Conference on Policy Modeling (EcoMod 2003), 3–5 July 2003, and the EURO/INFORMS 2003, 6–10 July 2003, both held in Istanbul, Turkey.

* Corresponding author. Tel.: +41 1 632 0652; fax: +41 1 632 1050.

E-mail address: rmadlener@ethz.ch (R. Madlener).

[1] Volkan Ediger also teaches at the Geological Engineering Department, Middle East Technical University (METU), Ankara.

doi:10.1016/j.eneco.2004.10.007

contributing to environmental sustainability, has had doubtful merits from an investor's perspective.

JEL classification: C61; D81; E22; L94; O33; O52

Keywords: Technology adoption; Irreversible investment under uncertainty; Real options; Electricity supply; Dynamic optimization

1. Introduction

Increasing concern about the adverse socioeconomic and environmental impacts of current energy use patterns, in many cases coupled with staggering levels of fossil fuel import dependence, call for substantial changes in the energy technology and fuel mix towards a more sustainable energy supply system. Technology adoption and diffusion models (e.g., see Thirtle and Ruttan, 1987; Sarkar, 1998), both at the microeconomic and the aggregate level, can provide valuable insights for a better understanding of actual and required transitions in the energy-converting capital stock composition, related fuel consumption patterns, underlying investment decisions, and technological trajectories followed.

In this paper, we study energy conversion technology adoption in the electricity sector from the perspectives of irreversible investment under uncertainty and environmentally sustainable development. Particularly, we develop a dynamic technology adoption model that features elements from real options theory (Dixit and Pindyck, 1994) and apply it to detailed industry level time series cross-sectional data for Turkey (e.g., for installed capacities, unit generation costs, and input fuel and electricity consumption and prices). The model developed is firmly rooted in economic theory and rests on important determinants of investment in available technology options, such as (expected) capital and operation costs over the lifetime of a certain vintage of a specific technology.

Investment decisions in liberalized markets, in contrast to noncompetitive markets, are based on market-driven value maximization criteria. Because the profitability of investment projects is contingent upon input and output price variations, project values evolve dynamically over time. Therefore, it is optimal to invest in some physical asset ('real option') when the present value of the expected cash flow exceeds the cost of investment by a (strictly) positive amount that is at least equal to the compensation for the loss of forfeiting the real option.

Two alternative approaches are discussed in the literature to derive the optimal investment rule and the value of the optimal investment in a real asset. While *contingent claims analysis* is essentially rooted in the finance literature, *dynamic programming* starts from a given discount rate and considers the maximization problem of the expected value of discounted cash flows. The two methods are linked through the equivalent risk-neutral valuation principle, and although they make different assumptions about financial markets and the rates firms use to discount future cash flows, they yield identical results in many applications. In contingent claims analysis, one attempts to find some combination or portfolio of traded assets that will be an exact replication of the return and risk pattern pertaining to the investment project studied. In this paper, a dynamic programming approach is adopted and the timing of the irreversible investment formulated as an optimal stopping problem (e.g., see Karatzas and Shreve, 1991). In particular, we use a model that accommodates plant availability, load duration curves, and irreversibility of investment similar to those of Moreira et al. (2004) and Chaton and Doucet (2003). This allows us to analyze the investment decisions taken for different vintages of power generating technologies based on different energy resources.

The Turkish electricity supply industry provides the subject of our empirical analysis. Power plant expansion planning in Turkey has so far been based on the two main models MAED[2] and WASP[3], whose shortcomings have been discussed in various studies. For example, an investigation of historical MAED/WASP projections indicates that the model results have persistently overestimated electricity demand, as documented in Ediger and Tatlıdil (2002). Arıkan and Kumbaroğlu (2000) highlight the importance of the energy–economy feedback link that is missing in the MAED/WASP approach.

We discuss our model's characteristics and compare its predictions for the Turkish electricity sector with actual developments. We also assess the differences between model and actual outcome in terms of environmental sustainability indicators (i.e., greenhouse gas and pollutant emissions).

The remainder of the paper is organized as follows. Section 2 contains some general considerations regarding the adoption of electricity generating technologies. Section 3 introduces the literature and theoretical approaches considered; Section 4 describes and discusses the proposed model formulation; and Section 5 presents the empirical analysis and results from applying our model to the Turkish electricity-generating sector. Section 6 summarizes and concludes.

2. Electricity system capacity (expansion) planning and the adoption of power generation technologies

Because of the long lead times involved, capacity planning in the electricity supply industry has always been of paramount importance. Before market liberalization, such capacity planning was mainly undertaken to ensure that installed capacity plus net import capacities are able to meet electricity demand at all times. According to Ku (1995), power plant investment decisions are threefold: (a) what to build (choice and mix of technology); (b) how much to build (capacity); and (c) when to build (timing and sequencing). What to build is a matter of available technologies (and fuel resources), their performance characteristics, expected construction times and cost,

---

[2] Model for Analysis of Energy Demand, a simulation model that has been operated by the Turkish Ministry of Energy and Natural Resources since 1984.

[3] Wien Automatic System Planning, a linear programming model operated by TEAŞ, which uses the forecasts of MAED to determine the least cost electricity generation/capacity expansion plans.

expected operating lifetimes, expected fuel cost, and other factors. How much and when to build is a matter of demand projections, existing (over)capacity, the plant retirement schedule, financial constraints, and other factors. In the case of (partial) irreversibility of investment expenditures and uncertainty, how much and when to build is also affected by a firm's flexibility to postpone an investment and the related determination of the optimal investment timing as a function of the (real options) value of waiting.

In real life, capacity planning decisions also involve trade-offs between proven and new technologies, an evaluation of the costs and benefits of over- and undercapacity, and decisions on the postponement of investment decisions in anticipation of regulatory changes (Ku, 1995, p.51). Schedules for investments in the electricity generating capital stock may cover time periods of 40–50 years and are often strongly influenced by political considerations (e.g., use of domestic energy resources, supply security and diversification aspects, environmental protection).

Electricity supply capacity investments typically involve irreversible decisions with far-reaching consequences. These long-term policy implications can be captured using a computable general equilibrium model with sufficient technological detail in the electricity sector. While models using such a hybrid top–down bottom–up approach are superior for policy analysis (e.g., see Kumbaroğlu and Madlener, 2003), they are less relevant for investment planning, as they neglect uncertainties with potentially essential impact on the investment decisions to be taken. Investment planning in liberalized electricity markets poses new modeling challenges due to additional uncertainties as a by-product of market restructuring (Dyner and Larsen, 2001; among others). These may be critical determinants of investors' behavior. Furthermore, capacity additions of technologies that feature modular characteristics can be made in smaller units (e.g., gas turbines, wind turbines, PV), contrary to conventional technologies (e.g., large hydropower projects), influencing the valuation of risk (e.g., see Bar-Ilan and Strange, 1999; Murto, 2003). Finally, technological risk and uncertainty can also play an important role, making the valuation of investment options with respect to electricity supply very difficult (e.g., see Choi, 1994; Balcer and Lippman, 1984; Rosenberg, 1976).

3. Literature review and theoretical approaches considered

In this section, we will provide a short literature review on research that is closely related to ours and also discuss elements that have been used in applied research on optimal capacity planning in the electricity supply industry under irreversibility and uncertainty.

An early work on optimal capacity choice in the electricity supply sector under uncertainty is that of Brown and Johnson (1969). They assume homogeneous production technologies (that is, they disregard technological, operational, and economic differences) and restrict uncertainty to the electricity demand function.

Levin et al. (1985) study capacity expansion of electric power generation systems when input fuel prices are uncertain. They consider two different types of technologies (a peak and an off-peak unit) that meet power demand of a given target year and map the probability distribution of the installed capacity and the total cost for any distribution of fuel prices.

Kobila (1990), in a mathematically very rigorous manner, addresses the choice between hydro and thermal power generation in Norway under stochastic electricity demand. He expresses the cost of hydropower as an everlasting and irreversible capital investment, while for thermal power generation, he considers the variable fuel costs (of natural gas) only. The focus of the paper is on the optimal timing for switching from thermal to hydropower in supplying a given electricity demand level at minimum cost.

Pindyck (1993) studies irreversible investment decisions by incorporating, on the one hand, uncertainties related to physical difficulties in completing a power plant project (technical uncertainty) and, on the other hand, uncertainties related to construction input cost and construction cost affected by changes in government regulation. His empirical analysis focuses on decisions to start or continue investing in nuclear power plant projects in the U.S. during the early 1980s.

Chaton (1997) determines optimal investment in thermal power plants in a two-period model, given uncertainty in both input fuel prices and electricity demand. Her model explicitly takes the load duration curve into account for demand modeling. Recently, this model has been extended by Chaton and Doucet (2003) to three periods to account for the option of investors to delay planned investments, to endogenize plant availability (as a function of intensity of use over time), and to explicitly account for electricity trading.

Epaulard and Gallon (2000), using real options theory, study the investment choice between nuclear and natural-gas-fired power plants and compare the outcome with traditional net present value (NPV) calculations.

Murto (2003) provides a compilation of papers (doctoral thesis) on dynamic investment models under uncertainty with a main focus on energy markets. He covers several aspects of optimal capacity expansion modeling, including technological and revenue-related uncertainties, irreversible investment choices related to energy projects with different degrees of uncertainty, and the incorporation of game theoretic elements.

Keppo and Lu (2003) extend the theory of irreversible investment under uncertainty for the case of a large energy company, whose electricity production decision affects the price of electricity.

Finally, Moreira et al. (2004) study thermal power generation investments in Brazil by employing a stochastic dynamic programming approach and real options theory. They consider uncertainty in the load, the input fuel price, and other economic factors. The present paper adds to this literature.

4. Model formulation and discussion

4.1. Load duration curve and merit order

The demand for power is traditionally described by a *load duration curve* (LDC), i.e., by a graphical summary of demand levels with corresponding (nonchronological) time durations. In regulated markets, the LDC is typically used together with *screening curves* (in which, for comparing the generation costs of different technologies, annual revenue requirements are plotted as a function of capacity factors, CF) to determine the optimal mix of generation technologies. This procedure, also referred to as the *merit order approach*, is no longer applicable in a competitive market environment because of uncertainty (e.g., regarding cost and demand). Still, the LDC provides a useful summary of a year's worth of hourly fluctuations in electricity demand. A discretized LDC (i.e., one that is segmented into vertical sections) is shown in Fig. 1, which also illustrates the significance of some of the variables and parameters defined in the model that is developed and used in this paper. The LDC is further segmented into horizontal bands that represent technologies (denoted by the subscript j) allocated to meet certain load sections (bands).

The cost-based ranking of technologies in a merit order that may be employed for the optimal dispatching of power is illustrated in the example given in Fig. 1. The lowest cost technology is in use during all periods (of durations $\theta_1+\theta_2+\theta_3+\theta_4$), contributing L_1 kWh of power, whereas peak demand (of duration θ_1) is satisfied by the more flexible but also more expensive technologies (for low utilization rates) located at the top of the LDC, with contribution L_4. In the absence of competition, demand is inelastic, implying a fixed LDC. Therefore, the 'demand curve' (D_1, ..., D_4) indicates revenue per unit time. It defines the screening curve. The screening curve then shows the CF at which a different technology becomes cheapest and, hence, the CF in the LDC to schedule the optimal dispatching of the load (cf. Chaton and Doucet, 2003, Fig. 1). Anderson (1972) has reviewed early modeling studies employing this traditional technique to determine least cost investments in electricity supply. Note that this technique assumes a stable world that ignores the role of price in the determination of demand. In our model, we will also assume demand for electricity to be price *in*elastic. This can be justified by noting that the period studied is characterized by a monopoly which leaves only the

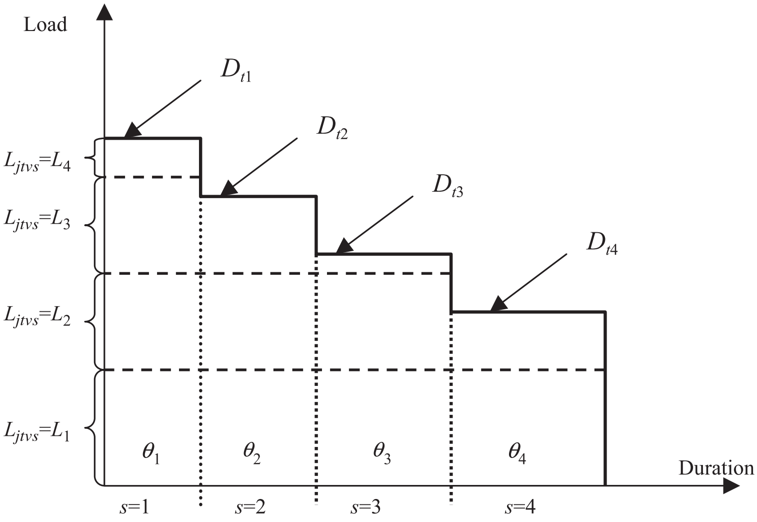

Fig. 1. A discretized load duration curve with horizontal bands.

curtailment of consumption as a reaction to a price increase (rather than switching to another supplier). Moreover, the monopoly concerned was not profit maximizing, thus aiming at a value of provision where price elasticity is low and where electricity rates (regulatory process) and output (disallowance to choose the profit-maximizing output level, as utilities must provide the electricity demanded at all times) both have an exogenous character. However, we explicitly take cost, price, and demand uncertainty into account in our model.

4.2. Objective function

In spite of the nonprofit nature of the Turkish electricity monopoly during the period 1970–2000 and to derive a benchmark, we use an objective function formulated in terms of expected net present value maximization. This is the expected discounted difference between revenues and fixed and variable costs that accrue from electricity production E_t(NPV). Formally, this may be expressed as

$$E_t(NPV) = \sum_{j=1}^{J}\sum_{\tau=1}^{T}\sum_{v=0}^{\tau}\sum_{s=1}^{S} E_{z_\tau}(P_\tau)L_{j\tau vs}\theta_s - \sum_{j=1}^{J}\sum_{v=1}^{T} fc_{jv}X_{jv} - \sum_{j=1}^{J}\sum_{\tau=1}^{T}\sum_{v=0}^{\tau}\sum_{s=1}^{S} E_{z_\tau}\left(vc_{j\tau v}\right)L_{j\tau vs}\theta_s \tag{1}$$

where fc_{jv} and $vc_{j\tau v}$, respectively, stand for the discounted fixed costs (capital investment)[4] and variable costs (operation and maintenance, O & M) of technology j with vintage v in year τ (note that we assume a year-by-year evaluation in our model). Hence

$$fc_{jv} = fc_j(1+r)^{-v} \text{ and} \tag{2}$$

$$vc_{j\tau v} = vc_j(1+r)^{-\tau}(1+r)^{-v} \tag{3}$$

where r is the real discount rate. $E_{z_\tau}(P_\tau)$ and $E_{z_\tau}(vc_{j\tau v})$ in Eq. (1) represent the expected values of electricity price and variable costs, respectively, for different states of nature z_τ. The installed capacity[5] of technology j, vintage v, is represented by X_{jv}, and $L_{j\tau vs}$ denotes the dispatched load of technology j, vintage v, operating in the sth section of the load duration curve in year τ; the load duration in each section being θ_s.

Timing of an irreversible investment under uncertainty matters. Hence, if a company has the opportunity to postpone an investment, this option should be appropriately valued

---

[4] Investments are viewed as sunk costs; that is, they cannot be recovered, say, if electricity prices fall and/or the investor wants to disinvest (e.g., dismantling of a dam). Similarly, the investment costs of existing plants are sunk and thus irrelevant for the present model. This *irreversibility* is a typical and reasonable assumption for electricity generation investments.

[5] For simplicity, we assume that capacity is perfectly divisible.

and included in today's investment decision. 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. Assume that when the company chooses the control variables u_t, representing its available choices at time t, it gets an immediate profit flow, $\pi_t(u_t)$. Expected optimal decisions after that will yield $E_t(NPV_{t+1})$, sometimes referred to as the *continuation value*. Hence, the optimal investment timing problem can be specified as

$$E_t(NPV) = \max_{u_t} \left\{ \pi_t(u_t) + \frac{1}{1+\rho} E_t(NPV_{t+1}), \right\}, \tag{4}$$

which corresponds to the *Bellman equation* or fundamental equation of optimality (e.g., see Dixit and Pindyck, 1994, Ch. 4). Quite obviously, 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* that, if exercised, yields a higher net profit might arise. Then it gets the continuation value $E_{t+1}(NPV)$, which has to be discounted by the factor $1/(1+\rho)$ for being comparable at time t with the immediate investment. The optimal choice is naturally the one that yields the larger outcome. For infinite planning horizons, each decision leads to a problem that looks like the previous problem, and the model can be solved recursively. In case of a fixed finite time horizon, T, one can start the optimization from a termination payoff and work backwards in solving the maximization problem. Such a dynamic decision framework allows to systematically compare the expected net present values from immediate investment and from waiting to invest. The ability to introduce and value the temporal flexibility in an irreversible investment decision represents the main distinction between real options and conventional decision analysis based on NPV.

The ability to delay an irreversible investment expenditure and invest at some later point in time, when a more profitable 'real' investment option can be realized with a certain probability, is incorporated into our model through the maximization of $E_t(NPV)$ over all time periods. That is, we specify our objective function as

$$\text{Maximize} \sum_t E_t(NPV)/(1+\delta)^t. \tag{5}$$

Hence, the model determines the timing of investments endogenously such that the discounted total of expected net present values is maximized. This implies that there is an implicit incentive to wait and invest in a future period if it is (expected to be) more profitable; that is, the model takes account of the value of waiting. This feature is in line with the real options idea, especially since uncertainties are explicitly taken into account in the dynamic decision-making process (see Section 4.3). However, it should be noted that we do not decompose the problem and employ a multistage recursive computation, as suggested by the dynamic programming approach, but instead implement a classical optimization approach that maximizes the NPV of all options dynamically under a specified set of constraints (see Section 4.4). Specifically, we solve the problem using MINOS, a reduced gradient method with quasi-Newton approximations to the reduced

Hessian (Murtagh and Saunders, 1980). It turns out that our modeling approach is satisfactory in terms of computational efficiency.

Closely related to the problem of waiting with an investment is that of choosing the optimal time to build (Majd and Pindyck, 1987) and the often unavoidable discrepancy between, on the one hand, the time an investment decision is taken, and costs start to occur, and on the other hand, the time revenues from an investment start to flow (e.g., see Alvarez and Keppo, 2002; Bar-Ilan and Strange, 1996). We do not consider the latter aspect in the present application due to the unavailability of the necessary data.

4.3. Modeling of uncertainty

The uncertainties arising from input and output price fluctuations are considered by computing their expected values as a discrete stochastic autoregressive moving average process of orders p and q, ARMA(p,q). Hence, we model the variation in (real[6]) input fuel prices (the only O & M costs considered) as

$$vc_{j,\tau} = \alpha_0 + \sum_{i=1}^{p} \alpha_i vc_{\tau-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{\tau-i}, \tag{6}$$

where α_0 and α_i are constants, with $-1<\alpha_i<1$, and $\varepsilon_{\tau-i}$ is a normally distributed random variable with mean zero. The variation in the (real) average electricity price and in peak load capacity (see Constraint no. 2 in the following section), respectively, is modeled analogously.

Obviously, NPV-maximizing optimal vintages are determined by the model, which is referred to as *optimal stopping*. The model formulation is completed with a set of demand and capacity constraints summarized in Section 4.4.

4.4. Constraints

The following three constraints, together with nonnegativity constraints for all variables except *NPV*, complete the model formulation.

Constraint No. 1

The available installed capacity must be sufficient to meet peak load demand almost always.

$$\sum_{j=1}^{J} \sum_{v=0}^{\tau} a_{jv} X_{jv} \geq E_{z_\tau}(D_{\tau s})(1+m) \quad s = 1, \tau = 1, \ldots, T \tag{7}$$

where a_{jv} is the availability factor for plant j and vintage v, and m denotes the reserve margin in percent (expressed as a decimal value).

---

[6] All prices, in the Turkish energy statistics expressed in US Dollars, have been deflated by using the US GDP deflator (2000=1) published by the US Department of Commerce, Bureau of Economic Analysis.

Constraint No. 2

Total plant output must be sufficient to meet instantaneous power demand levels on expectation.

$$\sum_{j=1}^{J}\sum_{v=0}^{\tau} L_{j\tau vs} \geq E_{z_t}(D_{\tau s}) \quad s = 1,\ldots,S \quad \tau = 1,\ldots,T \tag{8}$$

where the expected peak-load capacity requirement for each technology (hard coal, lignite, natural gas, oil, geothermal, and hydro), $L_{j,\max}$, is modeled as a stochastic process with an ARMA(p,q) model formulation, as already indicated above.

Constraint No. 3

Output from each plant cannot exceed available capacity.

$$(a)\ L_{j\tau vs} \leq a_{jv} X_{jv} \quad \forall j,\tau,s,v = 0,\ldots,t \tag{9}$$

$$(b)\ \sum_{s=1}^{S} L_{j\tau vs}\theta_s \leq b_j X_{jv} \quad v = 0,\ldots,\tau \quad \tau = 1,\ldots,T \tag{10}$$

where b_j is the load factor for technology j (the average production of the plant divided by its maximum).

5. Empirical analysis and model results

To empirically illustrate and assess our theoretical modeling assumptions and results, we apply the model formulation presented in Section 4 to the Turkish electricity supply sector, one of the most dynamically evolving in the world. To this end, we first analyze the development of electricity supply and use in Turkey.

5.1. Electricity demand and supply in Turkey[7]

Electricity supply considerations in Turkey have been strongly driven by a rapid growth on the demand side and the historical dominance of hydropower and fossil-fuel-based thermal power generation on the supply side (IEA, 2001b; Kaygusuz, 2002; Ediger and Kentel, 1999, among others; see also Fig. 4). Until recently, the Turkish electricity sector was dominated by a state-owned vertically integrated utility. It was unbundled in 1993 into the Turkish Electricity Generation and Transmission Company (TEAŞ) and the Turkish Electricity Distribution Company (TEDAŞ). TEAŞ is responsible for the operation of all state-owned plants, as well as transmission and imports and exports of electricity. In spite of a market opening

---

[7] This subsection is essentially based on IEA (2001b), as well as Ediger (2003a) and references therein. If appropriate, additional references are provided.

Table 1
Electricity balance of Turkey, 1950–2003

	1950	1960	1970	1980	1990	2000	2003*
Total installed capacity (MW)	407.8	1272.4	2234.9	5118.7	16317.6	27264.1	36283.1
Electricity generation (GWh)	789.5	2815.1	8623.0	23275.4	57543.9	124921.6	139245.0
Import surplus (GWh)	–	–	–	1341.2	732.2	3354.0	3255.0
Electricity consumption (GWh)	789.5	2815.1	8623.0	24616.6	56811.7	128275.6	142500.0

Data source: TEİAŞ (2002).
* Estimates.

process that was initiated as early as 1984, when foreign private investors were invited to play a role in the Turkish electricity supply industry[8], the major part of installed electricity generation capacity is still owned by TEAŞ. However, its share is gradually declining, and concessionaires, industrial autoproducers, and others are gaining market shares. In 2001, TEAŞ has been further split into EÜAŞ (generation), TETAŞ (trading and contracting), and TEİAŞ (transmission). Currently, in a new wave of reform, further market opening and unbundling is under way driven by the desire to introduce competition and prepare for EU accession and to meet certain requirements of IMF and World Bank support programs.

Electricity demand in Turkey has been growing at a remarkable average rate of 10.8% over the last 50 years, inducing annual investments in the generation, transmission, and distribution infrastructure in the order of US$ 4–5 billion. Installed generation capacity today is provided by some 350 power plants and is estimated to be around 36.3 GW in 2003 (Table 1). While only some 7% of the villages had grid access in 1970, this percentage increased to 61% by 1982 and to 99.9% by 1999 (IEA, 2001b).

Additions to installed capacity have come in bursts, as Fig. 2a illustrates. Fig. 2b shows the evolution of the energy sources and related technologies used in power generation, with hard coal almost entirely replaced (first by petroleum and then by hydropower) in the course of 40 years.

In the 1950s, the dominant fuel for power generation in Turkey was hard coal. Its share in total installed capacity declined gradually from 52.1% (212.6 MW) in 1950 to 27.4% (348.3 MW) in 1960. By that year, hydroelectric energy supply had reached a share in capacity of 32.4% (411.9 MW).

Turkish electricity generation rests on hydropower and fossil-fueled thermal power generation. The rise of hydropower started with the evaluation of technically and economically feasible hydropower potentials. Turkey's first hydroelectric power plant came online in 1956 (567 MW). Total installed capacity rose from 3.1 GW in 1982 to 11.2 GW in 2000. The remaining economic hydropower potential has been estimated to be about 20 GW (equivalent to an estimated construction cost of some US$ 30 bn, spread across some 330 additional plants). Investment planning in hydropower plants in recent

---

[8] A new law in 1984 opened the way for private participation in the electricity sector, facilitating the so-called Build–Operate–Transfer and Transfer-of-Operation-Rights contracts (see also p. 13). Full privatization featuring the transfer of plant ownership, however, could not follow by that time, as electricity was regarded as a public service in the constitution. A constitutional amendment in 1999 made privatization possible, and the regulatory framework to establish a competitive electricity market has been developed in late 2001.

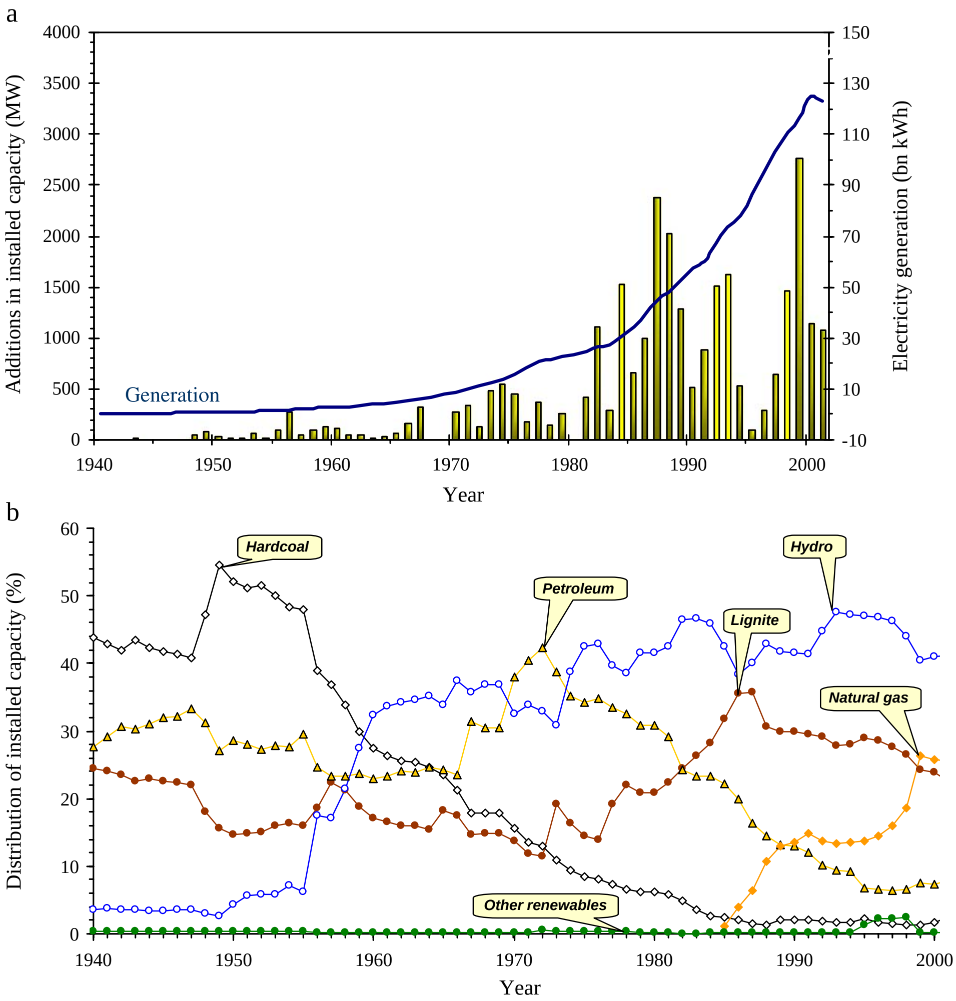

Fig. 2. (a) Additions in installed capacity (left scale) and power generation (right scale), 1940–2001. (b) Shares of installed capacity by energy source, 1940–2001 (modified after Ediger, 2003b,c).

years has been largely influenced by the huge South–East Anatolia Project (GAP), which combines hydropower use and increased irrigation by utilizing the water from the lower reaches of the Euphrat and Tigris rivers. The largest two hydropower plants in Turkey are Karakaya (1800 MW) and Atatürk (2400 MW). The Karakaya and Atatürk plants are part of the GAP project, which upon completion will comprise an installed capacity of some 7.5 GW, equivalent to about 22% of the total estimated economic hydropower potential of Turkey.

Since the 1970s, emphasis has been put on the development of domestic energy resources, especially on lignite and on hydropower but much less on other renewables (see

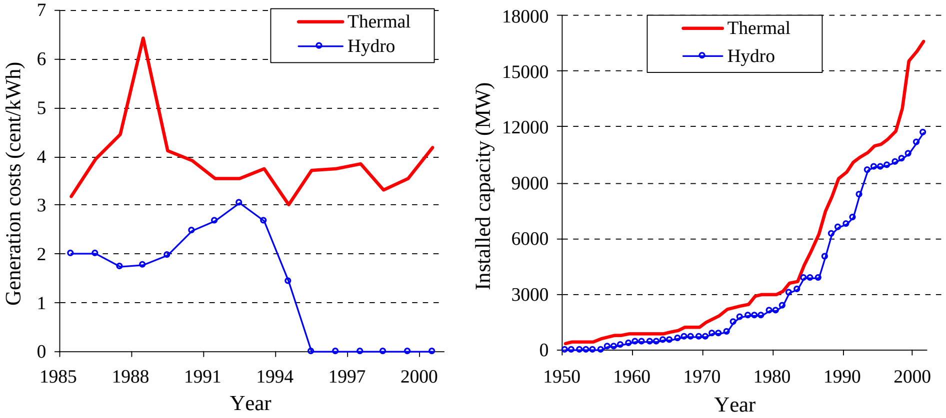

Fig. 3. Development of average thermal and hydropower generation cost (in real US cents/kWh), 1985–2000 (left panel), and installed capacity (in MW), 1950–2001 (right panel).

Ediger and Kentel, 1999 and, more recently, Evrendilek and Ertekin, 2003 for useful assessments of the renewable energy potentials in Turkey). The share of (largely domestically produced) lignite in electricity production increased from 19.1% in 1973 to 24.4% in 1982, rose further to 35.7% in 1987, and then declined again to 24.4% in 1999.

The rise of natural gas came in the 1970s although its share remained very modest until the 1980s. The share of natural-gas-fired power plants rose from 1.1% in 1985 to 26.4% in 1999, and the capacity added was in the order of 5 GW.

First privatization efforts were undertaken as early as in the 1950s when construction of power plants were initiated at a larger scale both by publicly owned and private enterprises operating under state concession. More extensive privatization in the electricity sector was initiated in 1984 with the first energy privatization law 3096 (also known as the 'BOT law') designed to enable private actors to build and operate electricity generation, transmission, and distribution systems. Law 3096 essentially foresaw two different types of contracts: Build Operate Transfer (BOT) contracts for planned projects and Transfer of Operation Rights (TOOR) contracts for existing facilities.[9] A further step in private participation followed 10 years later, in 1994, with the Build Operate Own (BOO) Law, through which the investors gained the right to the ownership of the plant. Typically, under a BOO, BOT, or TOOR contract, the state guarantees to buy a certain amount of the production at specified prices so that investors can recover their fixed costs. Despite these privatization efforts, in 2000, some 75% of the installed capacity in the electricity sector were still owned by the government.

The net electricity generation costs are presented in Fig. 3 (left panel) for thermal and hydropower. The costs for hydropower generation exhibit a sudden fall after the Atatürk

---

[9] BOT—the plant is constructed by private investors who transfer it to the state after an operation period of about 20 years; TOOR—a lease-type agreement is made with private investors who renovate and operate an existing plant.

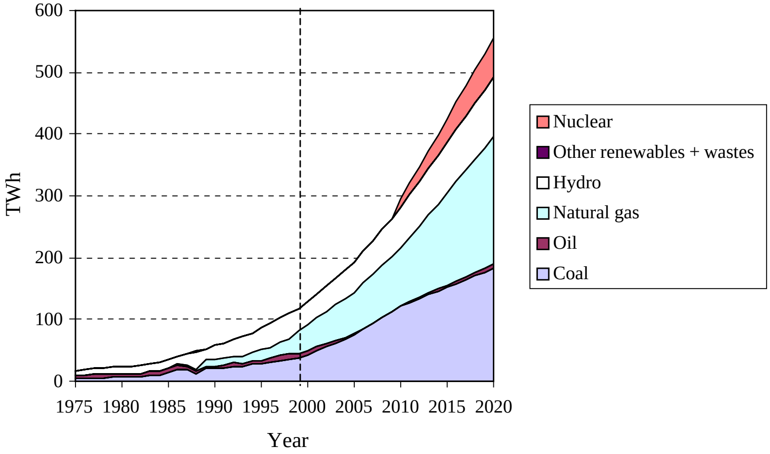

Fig. 4. Electricity generation by energy input source, 1975–1999, with projections until 2020. Data source: IEA (1989, 1993, 2001a,b).

power plant became operational in 1993. This is because the Atatürk plant has started to produce electricity at rather low cost (i.e., at a net operating cost of 0.03 cent (US) per kWh), replacing older and smaller hydro plants that were generating electricity at considerably higher cost (e.g., Keban at 6.2 cent/kWh, Botan at 10.9 cent/kWh, Bozyazi at 8.9 cent/kWh, and Denizli at 31.3 cent/kWh). However, note that the generation cost for hydroelectric energy depicted in the left panel of Fig. 3 are variable cost only.[10] The development of installed thermal and hydropower generation capacities is plotted in the right panel of Fig. 3. It shows the cumulative capacity effect of the structural changes reported in Fig. 2.

Fig. 4 illustrates the changing composition of total primary energy supply (TPES) in the electricity generation of Turkey from 1975 to 1999, with predictions from 2000 to 2020. As can be seen, it is expected that the share of hydropower will decrease, while the use of coal and nuclear power and, to a lesser extent, natural gas is expected to rise. New renewables are expected to emerge and start playing an increasingly significant role after 2010.

Research on greenhouse gas emissions of the Turkish electricity supply industry (essentially CO_2) is still rare. Most of the available energy-environment analyses (e.g., see Kumbaroğlu, 1997; Plinke et al., 1990; Taşdemiroğlu, 1992) have typically focused on SO_2 and NO_x emissions, as these pollutants, until recently, had caused the most severe adverse environmental impacts in Turkey. Kaygusuz (2003) and Demirbaş (2003) are two recent studies exploring greenhouse gas emissions in Turkey.

---

[10] The data depicted in Fig. 3 are based on TEAŞ (2001). The state-owned hydraulic works (DSI) is responsible for the development of hydroelectrical energy projects—after completion, the electricity generation company EÜAŞ starts to operate the hydropower plants, ignoring the construction costs specified by DSI in their cost accounting reports.

Modeling studies exploring the economic impacts of environmental constraints in Turkey (e.g., see Arıkan and Kumbaroğlu, 2001; Kumbaroğlu, 2003) typically do not explicitly capture the uncertainty inherent in input and output prices.

Utilization of renewable energy technologies except hydroelectricity is still quite limited, amounting to only 0.1% of installed capacity in 2000.[11] However, a considerable technical renewable energy potential exists in Turkey, amounting to some 495 TWh/year in total according to recent studies undertaken by Evrendilek and Ertekin (2003). In particular, these authors estimate the potential for biomass energy at 196.7 TWh, for hydropower at 124 TWh, solar energy at 102.4 TWh, wind energy at 50 TWh, and geothermal energy at 22.4 TWh per annum. Further discussions on the renewable energy potential and utilization in Turkey can be found in Ediger and Kentel (1999) and Kaygusuz and Sarı (2003), among others.

5.2. Model results

In the empirical model application, we explore investment decisions in electric generation capacity for the period 1970–2000, differentiating between various types of thermal power plants (i.e., fired by hard coal, lignite, natural gas, and oil) and hydro and geothermal power technologies of different vintages.

As a first step, we have estimated the parameters of the stochastic processes introduced in Section 4.3 for electricity price, variable cost, and peak load demand.[12] Particularly, for the exposition here, we assume that the variables considered are all stationary[13] and estimate various finite order ARMA(p,q) model specifications with p and q equal to 0, 1, and 2. Of the altogether eight different models for each stochastic variable, we have chosen the models which performed best in terms of parsimony and goodness of fit (Box–Jenkins approach) but also their forecasting ability. The model estimation and within-sample forecasting results obtained are shown in Table A.1 and Table A.2 in the Appendix. Fig. 5 shows the fitted and forecasted values for the average electricity price variable as an illustration.[14]

---

[11] The 0.1% renewable share includes geothermal and wind energy. Hydroelectric energy has a 41% share (11175 MW) in the total installed capacity of the year 2000.

[12] For the estimations described, we have used the econometrics software package EViews 4.1 of Quantitative Micro Software, Irvine, CA.

[13] We acknowledge the need for unit root (UR) testing to assess the stationarity properties of the variables studied. At the same time, however, it is quite clear that given the small number of available observations, these tests have a severe lack of power. As Table A.3 shows, the UR tests revealed that the peak-load capacity (PLC) for geothermal power and natural gas are (barely) integrated of order zero, $I(0)$, as the null hypothesis of a unit root is rejected, while from the tests, we conclude that fuel oil, hard coal, lignite (barely), and hydro PLC seem to be $I(1)$. With respect to unit generation cost (UGC), those of geothermal power and natural gas (note that the ADF and PP tests yield contradictory results) appear as $I(0)$ variables, while those of fuel oil, hard coal, lignite (barely), and hydropower UGC seem to be $I(1)$. Finally, for the average price of electricity, we find some (weak) evidence that it could be $I(1)$ as well. Given the very small sample sizes, however, we must caution against too much reliance on these results, as it is well known that it can be very difficult to distinguish between trend stationary and unit root processes in finite samples (e.g., see Campbell and Perron, 1991, p.157). For this reason, and because of a lack of space, we have refrained from pursuing any cointegration analysis here.

[14] Detailed results can be obtained from the authors upon request.

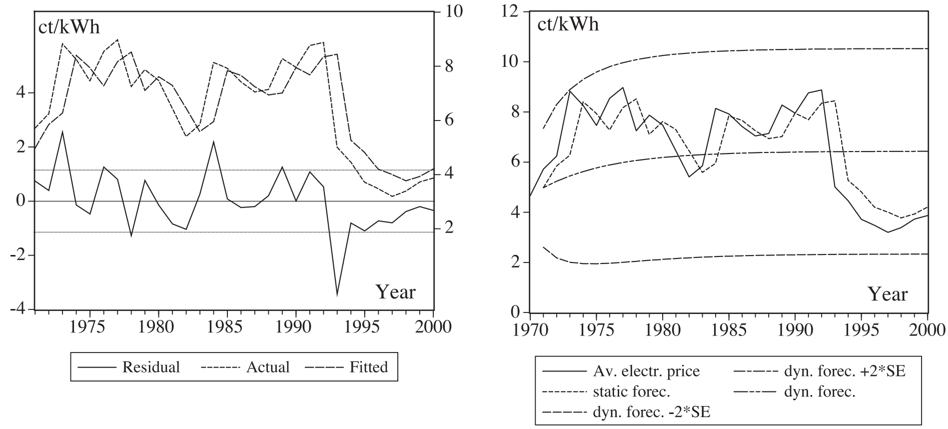

Fig. 5. Average electricity price development (real, in US cent/kWh). Actual, fitted, and residuals (left panel) and comparison between actuals and static one-step ahead and dynamic multistep ahead within-sample forecasts (right panel), 1970–2000.

The optimal investment model for power generation technology adoption in the electricity supply industry has been programmed in GAMS, and results have been obtained with the solver MINOS. Load factors, annual durations, and other reference parameters required for calibration are essentially based on TEAŞ (2001).[15]

The results yield technology selections that differ significantly from the actual choices made by policy makers and/or investors. This can be gleaned from Fig. 6, which presents the percentage deviation between model determined and actual total installed capacity levels for thermal and hydropower. As opposed to actual investment expenditures, the NPV-maximizing behavior of the model prefers to allocate more resources for the construction of hydropower plants than for thermal power plants in the 1970s and early 1980s but predicts the take-up of installation of large thermal power plants thereafter. Investments in hydropower rise in the 1990s, and the model-determined and actual installed capacities become almost equal in 2000, but the share of hydropower in total electric energy supply declines slightly as a result of the dominant increase in investments into thermal power generating technologies.

---

[15] Essential base case assumptions are as follows:

- The load duration curve is segmented into four sections (vertical bands) and six horizontal bands, accounting for hard-coal-fired, lignite-fired, natural-gas-fired, oil-fired, geothermal, and hydropower generation technologies.
- The maximum plant size (electric capacity) that can be constructed per year is 1500 MW for any technology.
- Natural gas and geothermal have been restricted such that they cannot be utilized before 1985 and 1984, respectively, when the necessary infrastructure became available.
- The deviation of aggregate total annual demand from actual values is subject to a tolerance level of +/−20%.
- Discount rate=8%, reserve margin=10%, availability factor=90% (uniform for all technologies).
- CO_2 emission factors are taken as 96.1 kg/GJ for hard-coal-fired, 108.4 kg/GJ for lignite-fired, 50.92 kg/GJ for natural-gas-fired technologies, and 73.74 kg/GJ for oil-fired technologies (factors based on TEAŞ, 1996).

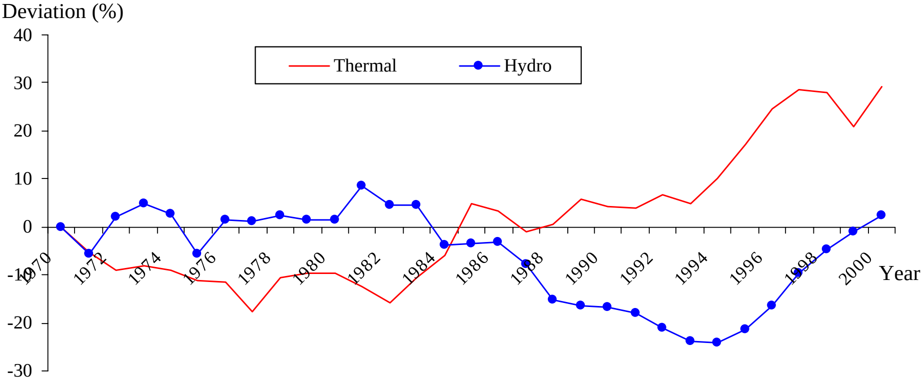

Fig. 6. Percentage deviation of NPV-maximizing investments in hydro- and thermal-based power generation technologies from actual ones, 1970–2000.

A closer look into the composition of thermal power, especially the development of natural-gas- and lignite-fired technologies, provides interesting findings. In contrast to the recent development with huge investments into natural-gas-fired technologies, the model prefers to utilize lignite-fired power generation technologies in significantly higher amounts, as illustrated in Fig. 7. Hence, model-derived choices deviate from real-life ones in that the oil and gas/solid fuels ratio becomes much lower in the case of NPV maximization. It should be underlined that a possible reason for this difference in preference is uncertainty. Natural gas is an imported energy source for Turkey, whereas lignites are domestic. Limited foreign exchange availability and economic instability from time to time have led to considerable fluctuations in natural gas prices. Hence, the model suggests investment in domestic fuel-fired technology whose operation costs are more stable.

Model-based and actual investments in hydroelectric power plants are quite close in the year 2000 (model-based investments accumulate to an installed capacity level that exceeds the actual capacity level by 6%), although there are some deviations in the timing of

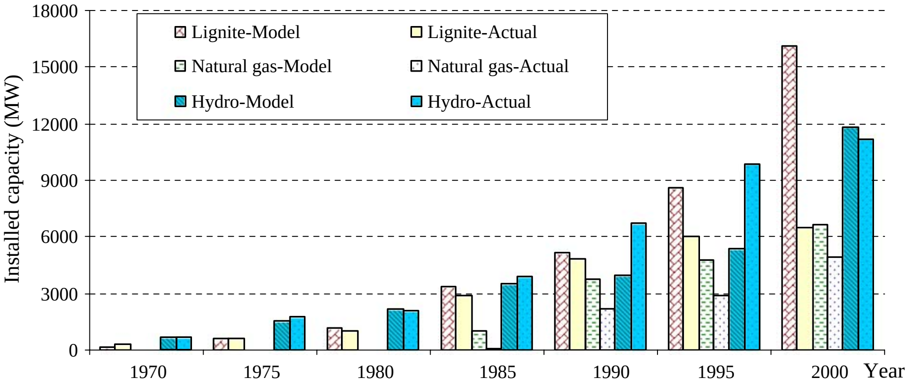

Fig. 7. Installed capacities: hydropower, natural-gas-, and lignite-fuelled technologies, 1970–2000.

capacity additions. Some 97.3% of the total actual hydropower capacity in the year 2000 is based on storage plants (with a dam), 2.3% on run-of-river plants, and 0.4% on natural storage plants (without a dam).

The actual investment behavior of decision makers in the electricity generation sector in recent years, i.e., to prefer natural-gas-fired power plants over coal-fired plants, has been more environmentally friendly than the NPV-maximizing investment decisions predicted by the model would have been, as the development of CO_2, SO_2, NO_x, and particulate emissions in Fig. 8 shows. It seems that, although Turkey has not signed the Kyoto Protocol on Climate Change yet, it has chosen an ecologically more sustainable path with less greenhouse gas emission that would have been chosen on a net present value maximization criterion alone. Besides environmental concerns, strategic considerations, political and societal priorities, and long-term international agreements, which are not incorporated in the present model, may be responsible for this deviation.

Environmental concerns have actually been a rather dominant driver. Especially in the early 1980s, winter months in major Turkish cities, especially in Istanbul and Ankara, were characterized by heavy air pollution (see also IEA, 2001b, Ch. 4). This certainly was a main motivation for policy makers to substitute natural gas as a relatively clean

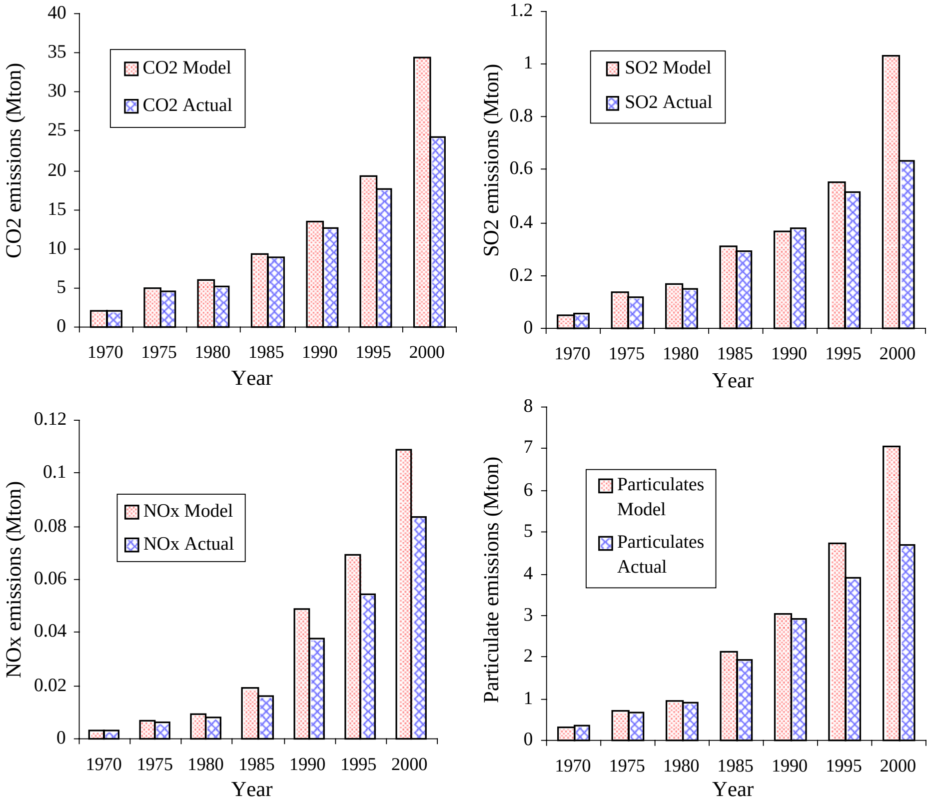

Fig. 8. NPV maximizing and actual pollutant emissions, 1970–2000.

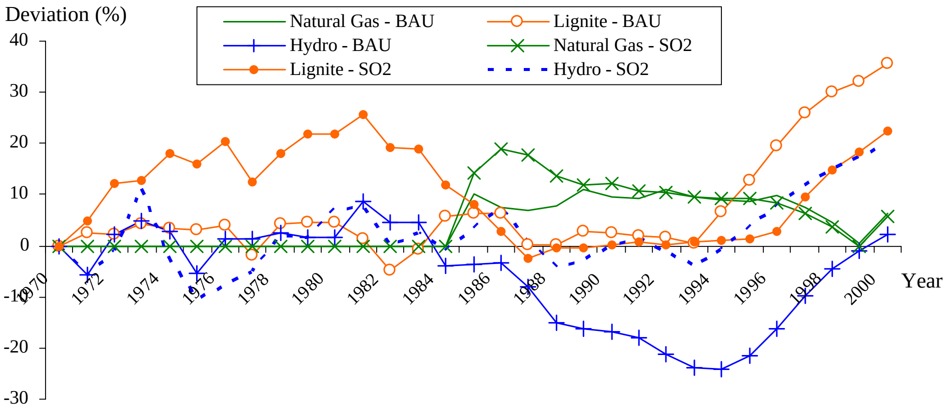

Fig. 9. Percentage deviation of NPV-maximizing investments (hydro, natural-gas-, and lignite-fired technologies) from actual ones; BAU and SO_2 Emission scenarios, 1970–2000.

fuel for low-quality and high-sulfur domestic coal (lignite) used in heating systems and electricity generation.[16] With the help of booming investments in gas-fired power generation technologies, Turkey has managed to effectively slow down growth in pollutant emissions. However, this path has at the same time significantly raised the dependence on imports of a country, which has only very limited foreign exchange and which relies on heavy foreign exchange inflows to finance the outstanding external debt (which has reached some US$ 114 bn or about 78% of GDP in 2001, e.g., see Orhangazi, 2002). Note that the NPV-maximization as formulated in Sections 4.2 and 4.3 does not take these macroeconomic uncertainties into account though.

5.3. Emission restrictions

Substitution of hard coal and even more so lignite may have been a consequence of restrictions on emissions introduced during the 1980s. To explore this impact on electricity supply investment behavior, we have imposed the actual CO_2, SO_2, and NO_x emission paths as upper bounds (with a 20% tolerance level) on the model solution. The three restrictions have similar effects; therefore, only the results for SO_2 (which has been the main source of air pollution in Turkey during the 1980s) are reported in Fig. 9. The emission restriction scenario is shown in comparison with the

---

[16] In 1998, when coal and lignite still accounted for about 32% of total electricity production in Turkey, the electricity sector emitted some 1.29 million tons of SO_2, 0.17 million tons of NO_x, and 0.14 million tons of particulate matter (IEA, 2001b, p.36). Electricity demand has been projected to increase by 250% until 2012, requiring some 41 GW of new generation capacity. Assuming that about a fifth of the additional capacity needed would be coal fired, this resulted in a doubling of the coal-fired capacity (ibid.). The additional SO_x, NO_x, and particulate emissions released would severely add to the emission problems predicted for automotive fuel use in transport.

reference run (business-as-usual scenario [BAU]) as the percentage deviation from actual investments.

Expectedly, restrictions on emission do reduce predicted investment in lignite-fired power generation technology, especially after 1994, bringing it down to a level close to the actual investment (Fig. 9). To substitute for coal-fired technology, the model does not shift to invest in additional natural-gas-fired technology but instead to utilize more hydropower. Accelerated investment in hydropower starts in the 1980s. The oil and gas/solid fuels ratio of the restriction scenario becomes quite close to its actual value. Overall, these findings support the argument that environmental concerns have been a main motivation in preferring natural gas instead of domestic lignites. Given these environmental restrictions, decision makers' investment behavior has been close to an NPV-maximizing path except for some minor fluctuations (which can be explained by the model's failure to cover various sociopolitical concerns).

6. Summary and conclusions

In this paper, we have applied a dynamic technology adoption model for the evaluation of irreversible investment options for electricity generating technologies, taking into account uncertainty, and vintage-specific life-cycle capital and operation costs. The consequences of electricity conversion technology choices for environmental sustainability have been a particular focus of our investigation.

In the case of Turkey, we find that historical investments strongly diverge from the prediction of the model, indicating that the actual choices are far off from what a net present value-based optimization model would suggest. In particular, there is an accelerated adoption of natural-gas-fired technologies in reality that limits the increase in pollutant emissions, which would otherwise occur from the utilization of domestic fossil fuel sources. Indeed, according to the model, investments in lignite-fired technologies should dominate in view of the lower volatility in lignite prices. Conversely, high volatility of natural gas prices (in domestic currency)—essentially due to Turkey's economic instability and limited foreign exchange availability—reduces the attractiveness of technologies using this imported fuel.

The explicit inclusion of macroeconomic uncertainty, expected technological change and learning, regulatory change, capital depreciation, and construction lead times into the formulation of the model are promising avenues for further improvement and testing.

Acknowledgments

We gratefully acknowledge helpful comments received from Ilhan Or, Yves Smeers, and several other participants at the EcoMod 2003 and EURO/INFORMS 2003 conferences in Istanbul, July 2003, as well as from Peter Zweifel, Socioeconomic Institute, University of Zurich. Any remaining errors and misconceptions are of course our own.

Appendix A.

Table A.1
Time series model estimation results

Variable	Unit generation costs						Peak load capacity						El. price
Technology, by energy input	Fuel oil	Hard coal	Lignite	Geothermal	Hydro	Natural gas	Fuel oil	Hard coal	Lignite	Geothermal	Hydro	Natural gas	Average electricity price
ARMA(p,q) model	p=1 q=0	p=1 q=0	p=1 q=0	p=1 q=1	p=2 q=1	p=1 q=1	p=1 q=0	p=1 q=0	p=1 q=0	p=2 q=1	p=1 q=0	p=1 q=0	p=1 q=0
α_0	6.305 (6.13)	6.330 (5.18)	4.215 (7.66)	2.439 (5.85)	1.699 (17.54)	3.800 (35.23)	788.031 (10.13)	244.919 (3.215)	−11244.01 (−0.43)	14.083 (136.38)	−490.348 (−0.19)	4123.654 (4.12)	6.435 (5.44)
α_1	0.671 (4.89)	0.800 (7.46)	0.649 (4.75)	–	1.758 (17.43)	0.475 (4.84)	0.727 (6.12)	0.904 (10.01)	1.014 (37.72)	0.542 (2.04)	1.085 (17.32)	0.817 (8.87)	0.822 (7.26)
α_2	–	–	–	0.660 (9.26)	−0.924 (−8.87)	–	–	–	–	−0.375 (−2.35)	–	–	–
β_1	–	–	–	–	−0.951 (−17.03)	−0.960 (−38.34)	–	–	–	−0.926 (−10.31)	–	–	–
β_2	–	–	–	−0.990 (−1307.41)	–	–	–	–	–	–	–	–	–
SSR	96.144	50.727	31.056	17.776	9.829	5.934	355943.8	40759.89	2371309	18.629	10605657	3392136	36.785
AIC	4.136	3.496	3.006	3.505	2.032	2.408	12.353	10.185	14.249	3.588	15.747	15.433	3.175
SBC	4.229	3.590	3.099	3.642	2.220	2.545	12.446	10.279	14.342	3.777	15.840	15.528	3.269
Q(4)	2.4 (0.50)	2.5 (0.47)	4.7 (0.19)	4.3 (0.12)	2.3 (0.13)	1.3 (0.52)	1.4 (0.72)	8.5 (0.04)	2.8 (0.43)	1.8 (0.19)	2.9 (0.41)	3.5 (0.32)	1.5 (0.69)
Q(8)	4.2 (0.76)	4.6 (0.71)	9.3 (0.23)	8.8 (0.18)	2.9 (0.71)	5.8 (0.44)	9.9 (0.19)	9.5 (0.22)	7.5 (0.38)	4.4 (0.49)	6.9 (0.44)	7.1 (0.42)	1.8 (0.97)

t-values (coefficient estimates) and p-values (Q-statistics) in brackets. SSR is the sum of squared residuals, AIC the Akaike Information Criteria, SBC the Schwarz–Bayesian Criteria, and Q(4) and Q(8) the Ljung–Box Q-statistics at lags 4 and 8 for the null hypothesis that there is no autocorrelation up to lag k.

Table A.2
Root-mean-squares forecasting errors (RMSFE)

Variable	Unit generation costs						Peak load capacity						Electricity price
Technology, by energy input	Fuel oil	Hard coal	Lignite	Geothermal	Hydro	Natural gas	Fuel oil	Hard coal	Lignite	Geothermal	Hydro	Natural gas	Av. el. price
ARMA(p,q) model	p=1 q=0	p=1 q=0	p=1 q=0	p=1 q=1	p=2 q=1	p=1 q=1	p=1 q=0	p=1 q=0	p=1 q=0	p=2 q=1	p=1 q=0	p=1 q=0	p=1 q=0
One-step	1.790	1.300	1.017	1.127	0.582	0.651	108.926	36.860	281.147	1.114	594.577	475.544	1.107
Multistep	2.345	2.163	1.256	1.482	1.252	1.244	176.122	81.491	555.436	1.325	2605.432	459.721	2.056

Table A.3
Unit root testing

Variable	ADF	PP	Variable	ADF	PP
*plc*_fueloil	−**2.303** [*c*,0] (0.1175)	−**2.439** [*c*,3] (0.1402)	Δ*plc*_fueloil	−5.417***[*c*,0] (0.0001)	−5.417*** [*c*,0] (0.0001)
*plc*_hardcoal	−1.402 [*c*,2] (0.5672)	−1.123 [*c*,2] (0.6936)	Δ*plc*_hardcoal	−2.613 [*c*,1] (0.1022)	−6.465*** [*c*,2] (0.0000)
*plc*_lignite	−2.320 [*c*,*t*;0] (0.4112)	−2.304 [*c*,*t*;1] (0.4193)	Δ*plc*_lignite	−**5.641***** [*c*,0] (0.0001)	−**5.635***** [*c*,2] (0.0001)
*plc*_geoth	−4.115*** [*c*,0] (0.0069)	−**4.084***** [*c*,1] (0.0073)	Δ*plc*_geoth	−5.172*** [*c*,*t*;1] (0.0056)	−17.345*** [*c*,*t*;14] (0.0001)
*plc*_hydro	1.362 [*c*,0] (0.9984)	1.755 [*c*,1] (0.9995)	Δ*plc*_hydro	−**5.430***** [*c*,0] (0.0001)	−**5.490***** [*c*,3] (0.0001)
*plc*_ngas	−2.772* [*c*,2] (0.0891)	−2.226 [*c*,2] (0.2058)	Δ*plc*_ngas	−**5.355***** [*c*,*t*;0] (0.0043)	−**12.133***** [*c*,*t*;13] (0.0000)
*ugc*_fueloil	−**2.398** [*c*,0] (0.1508)	−**2.314** [*c*,4] (0.1743)	Δ*ugc*_fueloil	−5.139*** [*c*,0] (0.0002)	−5.638*** [*c*,13] (0.0001)
*ugc*_hardcoal	−1.892 [*c*,0] (0.3312)	−2.009 [*c*,3] (0.2815)	Δ*ugc*_hardcoal	−5.673*** [*c*,0] (0.0001)	−5.665*** [*c*,2] (0.0001)
*ugc*_lignite	−**2.565** [*c*,0] (0.1112)	−**2.565** [*c*,0] (0.1112)	Δ*ugc*_lignite	−6.824*** [*c*,0] (0.0000)	−7.015*** [*c*,4] (0.0000)
*ugc*_geoth	−**11.109***** [*c*,3] (0.0000)	−3.642**[*c*,4] (0.0192)	Δ*ugc*_geoth	−5.360*** [*c*,0] (0.0012)	−5.360*** [*c*,0] (0.0012)
*ugc*_hydro	−2.210 [*c*,1] (0.2070)	−1.773 [*c*,1] (0.3859)	Δ*ugc*_hydro	−4.098*** [*c*,0] (0.0036)	−4.077*** [*c*,2] (0.0038)
*ugc*_ngas	−10.895*** [*c*,2] (0.0000)	−1.524 [*c*,4] (0.4927)	Δ*ugc*_ngas	−3.053* [*c*,1] (0.0581)	−3.764** [*c*,0] (0.0166)
P_{el}	−**2.698** [*c*,*t*;0] (0.2442)	−2.698 [*c*,*t*;0] (0.2442)	ΔP_{el}	−**4.999***** [*c*;0] (0.0004)	−4.992*** [*c*;2] (0.0004)

ADF—augmented Dickey Fuller test; PP—Phillips–Perron test; geoth—geothermal; ngas—natural gas. Square brackets: *c*—constant included; *t*—trend included; the number gives the lag length (ADF) or bandwidth (PP) used, respectively. Round brackets: MacKinnon (1996) one-sided *p*-values. For the ADF, the lag length has been chosen based on the SIC, and for the PP, the Newey–West method with Bartlett kernel for covariance weighting was used. ADF/PP test statistics printed in bold face means that all coefficient estimates in the test equation were statistically significant.

* At the 10% level.

** At the 5% level.

*** Significance is at the 1% level.

References

Alvarez, L.H.R., Keppo, J., 2002. The impact of delivery lags on irreversible investment under uncertainty. Eur. J. Oper. Res. 136 (1), 173–180.

Anderson, D., 1972. Models for determining least-cost investments in electricity supply. Bell J. Econ. Manage. Sci. 3 (1), 267–299.

Arıkan, Y., Kumbaroğlu, G., 2000. Geçmişten günümüze enerji modelleri (Energy models from past to the future). Proceedings of the 8th Turkish Energy Congress: Energy and Technology for Sustainable Development in the 21st Century. WEC Turkish National Committee, 9–20.

Arıkan, Y., Kumbaroğlu, G., 2001. Endogenising emission taxes; a general equilibrium type optimisation model applied for Turkey. Energy Policy 29 (12), 1045–1056.

Balcer, Y., Lippman, S.A., 1984. Technological expectations and adoption of improved technology. J. Econ. Theory 34 (2), 292–318.

Bar-Ilan, A., Strange, W.C., 1996. Investment lags. Am. Econ. Rev. 86 (3), 610–622.

Bar-Ilan, A., Strange, W.C., 1999. The timing and intensity of investment. J. Macroecon. 21 (1), 57–77.

Brown, G.M., Johnson, B., 1969. Public utility pricing and output under risk. Am. Econ. Rev. 59 (3), 119–128.

Campbell, J.Y., Perron, P., 1991. Pitfalls and opportunities: what macroeconomists should know about unit roots. In: Blanchard, O.J., Fischer, S. (Eds.), NBER Economics Annual 1991. MIT Press, Cambridge/MA.

Chaton, C., 1997. Fuel price and demand uncertainties and investment in an electricity model: a two-period model. J. Energy Dev. 23 (1), 29–58.

Chaton, C., Doucet, J.A., 2003. Uncertainty and investment in electricity generation with an application to the case of Hydro-Québec. Ann. Oper. Res. 120 (1), 59–80.

Choi, J.P., 1994. Irreversible choice of uncertain technologies with network externalities. RAND J. Econ. 25 (3), 382–401.

Demirbaş, A., 2003. Energy and environmental issues relating to greenhouse gas emissions in Turkey. Energy Convers. Manag. 44 (1), 203–213.

Dixit, A.K., Pindyck, R.S., 1994. Investment Under Uncertainty. Princeton University Press, Princeton.

Dyner, I., Larsen, E.R., 2001. From planning to strategy in the electricity industry. Energy Policy 29 (13), 1145–1153.

Ediger, V.Ş., 2003a. Development of the Power Generating Capacity of Turkey, unpublished mimeo.

Ediger, V.Ş., 2003b. Elektrik sektöründeki tarihsel yakz rekabetinin sistem dinamikleri-1 (System dynamics of historical fuel competition in the electricity sector-1). Petrogas 36, 60–64 (January).

Ediger, V.Ş., 2003c. Elektrik sektöründeki tarihsel yakz rekabetinin sistem dinamikleri-2 (System dynamics of historical fuel competition in the electricity sector-2). Petrogas 37, 62–67 (March).

Ediger, V.S., Kentel, E., 1999. Renewable energy potential as an alternative to fossil fuels in Turkey. Energy Convers. Manag. 40 (7), 743–755.

Ediger, V.S., Tatlıdil, H., 2002. Forecasting the primary energy demand in Turkey and analysis of cyclic patterns. Energy Convers. Manag. 43 (4), 473–487.

Epaulard, A., Gallon, S., 2000. The prospects of nuclear power in Europe's deregulated energy markets using real option theory to assess nuclear investment value. Proceedings of the 2000 European Conference of the International Association for Energy Economics (IAEE) "Towards an Integrated European Energy Market", Bergen/Norway, 31 August–2 September.

Evrendilek, F., Ertekin, C., 2003. Assessing the potential of renewable energy sources in Turkey. Renew. Energy 28 (15), 2303–2315.

IEA, 1989. Energy Balances of OECD Countries. 1986–1987. OECD/IEA, Paris.

IEA, 1993. Energy Balances of OECD Countries. 1990–1991. OECD/IEA, Paris.

IEA, 2001a. Energy Balances of OECD Countries. 1998–1999. OECD/IEA, Paris.

IEA, 2001b. Energy Policy of IEA Countries. Turkey 2001 Review. OECD/IEA, Paris.

Karatzas, I., Shreve, S., 1991. Brownian Motion and Stochastic Calculus. Springer Verlag, Berlin.

Kaygusuz, K., 2002. Sustainable development of hydropower and biomass energy in Turkey. Energy Convers. Manag. 43 (8), 1099–1120.

Kaygusuz, K., 2003. Energy policy and climate change in Turkey. Energy Convers. Manag. 44 (10), 1671–1688.

Kaygusuz, K., Sarı, A., 2003. Renewable energy potential and utilization in Turkey. Energy Convers. Manag. 44 (3), 459–478.

Keppo, J., Lu, H., 2003. Real options and a large producer: the case of electricity markets. Energy Econ. 25 (5), 459–472.

Kobila, T.Ø., 1990. The choice between hydro and thermal power generation under uncertainty, in: O. Olsen, J. Vislie (eds.), Recent modelling approaches in applied energy economics, International Studies in Economic Modelling. Chapman and Hall, Routledge, New York.

Ku, A., 1995. Modelling Uncertainty in Electricity Capacity Planning, PhD thesis, London: London Business School, February.

Kumbaroğlu, G.S., 1997. A model for long-term global air quality and development of efficient control strategies in Turkey. Eur. J. Oper. Res. 102 (2), 380–392.

Kumbaroğlu, G.S., 2003. Environmental taxation and economic effects: a computable general equilibrium analysis for Turkey. J. Policy Model. 25 (8), 795–810.

Kumbaroğlu, G., Madlener, R., 2003. Energy and climate policy analysis with the hybrid bottom-up computable general equilibrium model SCREEN: the case of the Swiss CO_2 Act. Ann. Oper. Res. 121 (1–4), 181–203.

Levin, N., Tishler, A., Zahavi, J., 1985. Capacity expansion of power generation systems with uncertainty in the prices of primary energy sources. Manage. Sci. 31 (2), 175–187.

MacKinnon, J.G., 1996. Numerical distribution functions for unit root and cointegration tests. J. Appl. Econ. 11 (6), 601–618.

Majd, S., Pindyck, R.S., 1987. Time to build, option value, and investment decisions. J. Financ. Econ. 18 (1), 7–27.

Moreira, A., Rocha, K., David, P., 2004. Thermopower generation investment in Brazil—economic conditions. Energy Policy 32 (1), 91–100.

Murtagh, B.A., Saunders, M.A., 1980. MINOS/Augmented User's Manual. Stanford University, Dept. of Operations Research, Stanford, CA, USA.

Murto, P., 2003. On Investment, Uncertainty, and Strategic Interaction with Applications in Energy Markets, PhD thesis, Helsinki University of Technology, Systems Analysis Laboratory, April.

Orhangazi, Ö., 2002. Turkey: bankruptcy of neoliberal policies and the possibility of alternatives. Rev. Radic. Polit. Econ. 34 (3), 335–341.

Pindyck, R.S., 1993. Investments of uncertain costs. J. Financ. Econ. 34 (1), 53–76.

Plinke, E., Haasis, H.-D., Rentz, O., Sivrioğlu, M., 1990. Analysis of energy and environmental problems in Turkey by using a decision support model. Ambio 19 (2), 75–81.

Rosenberg, N., 1976. Perspectives on Technology. Cambridge University Press, Cambridge.

Sarkar, J., 1998. Technological diffusion: alternative theories and historical evidence. J. Econ. Surv. 12 (2), 131–176.

Taşdemiroğlu, E., 1992. Air pollutant emissions due to energy utilization in Turkey. Energy 17 (1), 95–97.

TEAŞ, 1996. Elektrik Energjisi Üretiminde Çevre Faktörünün Incelenmesi (Analyzing the Environmental Factor in Electric Energy Production), Report No. TEAŞ-Ç 96-03-01.

TEAŞ, 2001. Türkiye Elektrik Üretim-İletim A.Ş. 2000 Yılı İstatistikleri (Turkish Electricity Generation-Transmission Year 2000 Statistics), Report No.: APK-379.

TEİAŞ, 2002. Türkiye Elektrik İletim A.Ş. 2001 İşletme Faaliyetleri Raporu (Turkish Electricity Transmission 2001 Annual Report), Report No. 475.

Thirtle, C.G., Ruttan, V.W., 1987. The Role of Demand and Supply in the Generation and Diffusion of Technical Change. Harwood Academic Publishers, Chur.