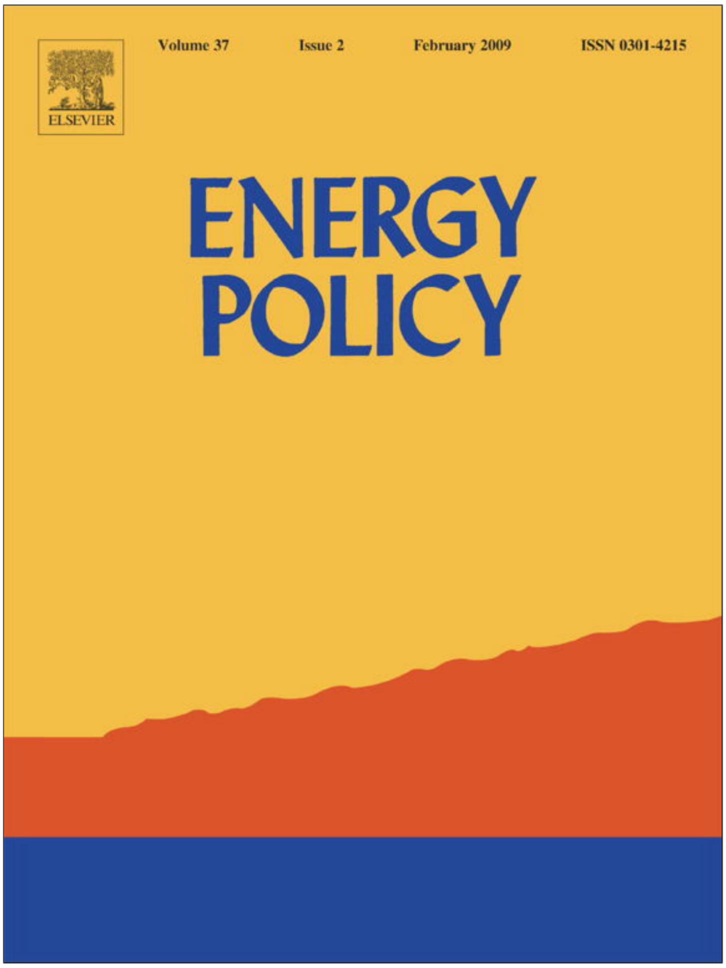
Volume 37
Issue 2
February 2009
ISSN 0301-4215
ELSEVIER
ENERGY
POLICY

Energy Policy 37 (2009) 560–569

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Estimating deficit probabilities with price-responsive demand in contract-based electricity markets ☆

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ARTICLE INFO

Article history:
Received 25 January 2008
Accepted 18 September 2008
Available online 18 November 2008

Keywords:
Price elasticity
Deficit
Demand

ABSTRACT

Studies that estimate deficit probabilities in hydrothermal systems have generally ignored the response of demand to changing prices, in the belief that such response is largely irrelevant. We show that ignoring the response of demand to prices can lead to substantial over or under estimation of the probability of an energy deficit. To make our point we present an estimation of deficit probabilities in Chile's Central Interconnected System between 2006 and 2010. This period is characterized by tight supply, fast consumption growth and rising electricity prices. When the response of demand to rising prices is acknowledged, forecasted deficit probabilities and marginal costs are shown to be substantially lower.

1. Introduction

Studies that estimate deficit probabilities in hydrothermal systems typically assume that the demand for electricity is perfectly inelastic. Yet there is substantial evidence that demand responds to price.[1] In this paper we show how to incorporate this fact when estimating deficit probabilities in contract-based electricity markets.[2] We conclude that ignoring the response of demand to changing prices can lead to substantial under or over estimation of deficit probabilities.

We make our point by estimating deficits in Chile's Central Interconnected System (SIC by its Spanish acronym) over 5 years starting in 2006. We use a stochastic dynamic programming model that incorporates hydrological uncertainty and estimates monthly deficit probabilities and marginal costs. We compare two scenarios: (a) with a consumption forecast made by the system's regulator, the National Energy Commission (NEC), which ignores the response of demand to changing prices; (b) with an adjusted NEC forecast which considers that consumers respond gradually to changing prices. Our results suggest that even a seemingly small demand elasticity makes a big difference when prices change substantially. Thus, studies that evaluate supply conditions or estimate deficit probabilities but ignore the response of consumers to changing prices can be quite misleading. Because prices tend to rise when capacity is tight, ignoring the response of consumers to price can lead to exaggerate the likelihood of a deficit.

Relatively few studies take account of the influence of prices on demand. One is Kirschen et al. (2000), who assumed that hourly wholesale prices are directly passed through to consumers and showed how the elasticity of demand can be taken into consideration when scheduling generation and setting the hourly price of electricity. Also, Bompard et al. (2000) showed that in an open access transmission regime, the independent grid operator can better manage congestion when loads respond to prices. Lijesen (2007) estimates the real-time elasticity of demand, finds that it is quite low and argues that this should stimulate investment in peak capacity, as scarcity rents should be high. On the other hand, Aires et al. (2002), in an application to Brazil, studied how distributors can use pecuniary incentives to reduce consumption when wholesale spot prices are high. Nevertheless, they assumed that households reduce peak consumption by 4%, regardless of the incentive offered by the distribution company. Last, Albadi and El-Saadany (2007) revises several experiences of utilities that have experimented with different demand-response programs.

☆ This paper was financed by AES Gener S.A. Nonetheless, its content is the exclusive responsibility of the authors and in no way commits AES Gener S.A. Galetovic gratefully acknowledges the hospitality of the Stanford Center for International Development and the financial support of Instituto Milenio, Project P05-004F.

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[1] The Lawrence Berkeley National Lab at the University of California undertook several research projects in recent years studying the response of demand to prices (see Heffner and Goldman, 2001; Goldman et al., 2002; Siddiqui et al., 2004 and Reiss and White, 2003)

[2] In contract-based electricity markets consumers pay a smoothed energy price which is set in a long-term contract and does not closely follow variations in the wholesale price of electricity. Normally, the contract price is indexed to inflation and fuel prices.

0301-4215/$ - see front matter
doi:10.1016/j.enpol.2008.09.079

A series of recent studies show that competition is more intense and electricity prices fall the more elastic is the demand for electricity. This result appears in Ruibal and Mazumdar's (2008) bid-based stochastic model which predicts wholesale electricity hourly prices in Bompard et al. (2007a, b) study of an oligopolistic electricity market; in Ahn and Niemeyer's (2007) Cournot analysis of the Korean electricity market; and in Chang's (2007) study of the intensity of competition in Singapur's electricity market.[3]

Most papers model the response of consumers to real-time pricing. Nevertheless, in contract-based markets like Chile and other Latin American countries consumers do not pay the real-time wholesale electricity price at which generators exchange energy, but a smoothed marginal cost forecast, normally indexed to state variables such as the level of reservoirs, fuel prices and inflation. It is also the case that households and small commercial consumers typically pay a regulated tariff that adds non-energy charges for capacity, transmission and distribution in a single monomic energy price.[4] Last, and perhaps more important, the price that consumers see in their bills varies at most once every month. Consequently, in this study we show how to adjust a demand forecast when consumers respond every month to changes in the price of energy. Because consumers adjust their consumption only gradually when prices change, we use a partial adjustment demand model.[5] Such a model yields the interesting implication that the elasticity of demand grows over time converging only gradually to its long-run level. Also, because the price that consumer pay varies once a month, we use monthly elasticities.

The rest of this paper is organized as follows. Section 2 describes the Chilean electricity market and shows how electricity prices are determined in Chile. Section 3 describes how to model the response of demand to changing prices. Section 4 describes the methodology. Section 5 presents our estimations of shortage probabilities in Chile. Section 6 concludes.

2. The Chilean electricity market

2.1. Market overview

The Chilean electricity market was radically restructured during the 1980s as part of sweeping market-oriented reforms that were massively introduced in Chile during the 1970s and 1980s. The initial step was the 1982 electricity law (see Ministry of Mining, 1982). As Bernstein (1988) shows, it functionally separated the provision of electricity in three distinct segments, generation, transmission and distribution. The law also introduced marginal cost dispatch, benchmark regulation in distribution (see Arellano (2008); Bernstein (1988); Moya (2002); Rudnick (1994); Rudnick and Donoso (2000); Rudnick and Raineri (1997)) and long-term contracts between generators and distributors at regulated and stabilized energy prices. This was followed in the late 1980s with a massive privatization of state-owned electricity utilities.

This regulatory framework has remained essentially unchanged since 1982, with specific changes introduced during the last couple of years to improve the regulation of transmission, strengthen conflict resolution mechanisms and substitute price regulation of consumer energy prices for competitive auctions.

Generators and consumers: The Chilean electricity market is in essence a financial contract-based market where generators sign long-term power and energy supply contracts. These contracts specify the volume and price for the sale of energy and power.

The 1982 law established two types of consumers. Free or unregulated consumers are those who demand more than 2 MW and they directly bargain over supply conditions and prices with generators.[6] Regulated consumers, on the other hand, are those who demand 2 MW or less.[7] They pay regulated power and energy prices set by NEC every 6 months in April and October and are supplied by distributors, who must sign long-term supply contracts with generators.[8]

Cost-based merit order dispatch and short-term marginal cost: In order to minimize the system's operation cost, generators must follow the instructions of the Economic Load Dispatch Center (CDEC by its Spanish acronym). CDEC centrally dispatches plants according to strict merit order to meet consumption at every moment, constrained to maintain the safety and reliability of service. The system's marginal cost is the running cost of the most expensive unit required to meet system demand at a given time and changes every half hour. Dispatch is completely independent of contractual obligations to supply energy. For this reason, each half hour a given generator is either a net supplier to the system or a net buyer. Net buyers pay net suppliers the system's marginal cost.

Capacity payments: Each generation unit is paid a monthly capacity payment based on their annual availability, whether they get dispatched or not.[9] The price of capacity, the so-called power node price, equals the capital cost of the peaking technology, a diesel turbine (see Appendix).

Transmission charges: *Every* 4 *years*: NEC fixes transmission charges for the use of the main high-voltage grid. These charges are assigned among generators and consumers according with their expected "use" of the grid; use is calculated with GGDF and GLDF factors. In case of regulated consumers, this cost is passed on as a postage-stamp charge.[10]

Value added of distribution (VAD): Each distribution company is granted an exclusive concession in a given geographical area. In exchange, it must supply electricity to all consumers. Every 4 years NEC calculates VAD following the efficient-firm standard coupled with yardstick competition (see Rudnick and Donoso (2000)). VAD is defined as the efficient cost of distributing 1 KW of peak power under maximum load conditions in the distribution system.[11] Distributors sign long-term contracts with generators, buy energy and power at the regulated node prices (see next section) and pass these directly to consumers.

2.2. Prices paid by consumers

Unregulated consumers (i.e., those who demand more than 2 MW), buy their electricity directly from generators and pay unregulated market prices for energy (p_e^m) and power (p_p^m). They

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[3] See also Lee and Ahn's (2006) analysis of electricity restructuring in Korea.

[4] The monomic energy price is the average cost of 1 kWh including the capacity payment. It is equal to $(e \cdot p_e + \pi \cdot p_p)/e$, where p_e is the price of energy, p_p is the price of power, e is the total amount of energy consumed, and π is the load during the peak hour of the year.

[5] The seminal study is Fisher and Kaysen (1962).

[6] Normally the contract term is 10 or more years. Energy and power prices are fixed in real terms and indexed to price indexes that track costs such as the Chilean and USA WPIs, fuel prices and the peso-dollar exchange rate.

[7] Consumers who demand between 0.5 and 2 MW can choose every four years between the regulated and free regime.

[8] After the passage of the so-called Ley Corta 2 (LC-2) in May 2005 (see Ministry of Economics, 2005), these contracts have a maximum term of 15 years and will be allocated in auctions to the lowest energy price bid.

[9] About capacity payments (see Oren, 2000 and Barrera and Crespo, 2003).

[10] See Galetovic and Muñoz (2006).

[11] See Rudnick and Raineri (1997).

Table 1
The elasticity of the demand for energy

Country	Study	One-year elasticity	Long-run elasticity
United States	Anderson (1973)	–	−1.12
Mexico	Berndt and Samaniego (1984)	–	−0.47
United States	Chang and Hsing (1991)	−0.36 to −0,13	−1.39
Greece	Donatos and Mergos (1991)	−0.21	−0.58
United States	Fisher and Kaysen (1962)	−0.15	–
United States	García-Cerrutti (2000)	−0.13	−0.17
UK	Houthakker (1962)	−0.89	
United States	Houthakker and Taylor (1970)	−0.13	−1.89
United States	Houthakker et al. (1973)	−0.9	−1.02
United States	Maddala et al. (1997)	−0.21 to −0.15	−1.03 to −0.22
United States	Mount et al. (1973)	−0.14	−1.2
Paraguay	Westley (1984)	–	−0.56
United States	Westley (1988)	–	−0.99
Costa Rica	Westley (1989)	–	−0.45

must also pay a per-kWh transmission charge τ. Thus, if λ_e are energy losses and λ_p are power losses, the total bill paid by consumer i is

$$E_i \cdot (\lambda_e p_e^m + \tau_i) + D_i \cdot \lambda_p p_p^m,$$

where E_i is i's energy consumption and D_i is i's load at the system's peak. Unregulated customers are typically connected to the transmission grid, and thus pay no distribution charge.

On the other hand, regulated consumers (i.e., those who demand 2 MW or less), may choose among any of the different regulated tariff options within their corresponding voltage level. The basic split is between high-voltage tariffs (AT by its Spanish acronym), and low-voltage tariffs (BT by its Spanish acronym).

Regulated consumers pay the regulated node price for energy (p_e^n) and power (p_p^n). In addition, these consumers are served by a distributor, and must pay their share of the value added of distribution. Last, they must also pay a per-kWh transmission charge, τ. Hence, their total bill is

$$E_i \cdot (\lambda_e p_e^n + \tau_i) + D_i \cdot \lambda_p p_p^n + \mathrm{VAD}_i.$$

Now when the price system was designed in 1982, hourly metering equipment was very expensive. Thus it was decided that small residential and commercial consumers would pay an energy-only price. To transform the per-KW power charge into an energy charge, a load-coincidence factor ψ is estimated and used. Similarly, to transform the per-KW VAD charge a so-called "responsibility" factor δ is used. Thus the total bill of a consumer with an energy-only meter is

$$E_i \cdot (\lambda_e p_e^n + \psi \lambda_p p_p^n + \tau + \delta \cdot \mathrm{VAD}_i).$$

Regulated energy and power node prices are set in April and October by NEC. The power node price p_p^n is equal to the annualized cost of a diesel peak turbine. The energy node price p_e^n is set by comparing the expected system marginal cost over the next 4 years with the average electricity price paid by unregulated consumers. The appendix explains in detail how this comparison is made.

3. The price elasticity of the demand for energy

In most cases the quantity demanded of a given good decreases as its price increases. Economists often linearize demand around a given point and summarize this response to price with the so-called elasticity of demand, defined as

$$\varepsilon = \frac{\Delta q / q_0}{\Delta p / p_0}.$$

The price elasticity of demand indicates the percentage change of the quantity demanded for a given percentage change in price. Because demand curves are downward sloping, this pure number is less than zero, unless demand is insensitive to price changes. In the remainder of this paper, it will be assumed that all prices and quantities have been normalized around a given equilibrium point (q_0, p_0).

Most if not all studies of the demand for electricity find that it is sensitive to price changes. Many also find that consumption responds gradually to price changes, presumably because when the price of electricity permanently changes, consumers do not change their appliances immediately but spread the adjustment over time.

Table 1 summarizes the results of a sample of studies that estimate the price elasticity of residential demand. It can be seen that long-run elasticities (elasticities that summarize the change in the quantity demanded after a long time has elapsed) range from −0.17 to −1.89. Short-run, 1-year elasticities go from −0.13 to −0.89.

Now in a study that estimates supply conditions and monthly deficit probabilities over the next couple of years one would like to explicitly account for the fact that consumption adjusts slowly to price changes. Moreover, one would also like to consider that this adjustment takes place month by month. The study by Benavente et al. (2005), which estimated the elasticity of demand for residential electricity in Chile, allows us to do this because it estimated a monthly partial adjustment demand model. They found that the price elasticity of demand is −0.055 after 1 month and −0.39 in the long run. That is, if tariffs are permanently raised by 10% in January, consumption falls by 0.55% in February and 3.9% in the long run after all adjustments have been made.

We now discuss how such a model can be used to adjust a demand forecast. Benavente et al. (2005) estimate that the monthly residential demand for energy is

$$\ln E_t = \ln A_t + 0.33 \ln E_{t-1} + 0.53 \ln E_{t-2} - 0.055 \ln p_{t-1} \tag{1}$$

where E is the quantity of energy consumed, p is the price of energy and all other factors that affect demand have been collapsed into the term A_t which will be assumed exogenous.

Function (1) indicates that the quantity of energy demanded during month t depends on energy consumption during the two preceding months, $t-1$ and $t-2$; and on the price of energy during month $t-1$.[12] The short-run, 1-month price elasticity of demand is −0.055.

[12] Consumers see the price of energy once a month when they receive their monthly bill, which reports the price during the previous month.

To see how the partial adjustment of demand works, assume that consumers are at their long-run optimum consuming $E=100$ when the price of energy is p and that A is constant. If the price of energy rises a little from p to $p+\Delta p$ in month 0, the quantity of energy consumed during the following month will be

$$\ln E_1 = \ln A + 0.33 \ln 100 + 0.53 \ln 100 - 0.055 \ln(p+\Delta p).$$

Next month the quantity consumed falls a little more to

$$\ln E_2 = \ln A + 0.33 \ln E_1 + 0.53 \ln 100 - 0.055 \ln(p+\Delta p),$$

and so on. Thus

$$\Delta E(1, p+\Delta p) = E_1 - 100$$

is the percentage change in consumption during the first month,

$$\Delta E(2, p+\Delta p) = E_2 - 100$$

is the total percentage change in consumption 2 months after the price change, and

$$\Delta E(n, p+\Delta p) = E_n - 100$$

is the percentage fall in consumption after n months. Consequently,

$$\frac{\Delta E(n, p+\Delta p)}{\Delta p/p}$$

is the price elasticity of demand n months after the price change and it can be shown that in this case

$$\lim_{n\to\infty} \frac{\Delta E(n, p+\Delta p)}{\Delta p/p} \approx 0.39,$$

which is the long-run price elasticity.

One might think that elasticities of the magnitude estimated by Benavente et al. (2005) are "small" in that they are considerably less than 1 in absolute value. Hence, a rather "large" price increase of 10% changes consumption only 0.55% during the first month, 2.7% after 1 year and 3.9% in the long run. Nevertheless, we will see that modest changes in consumption substantially affect deficit probabilities and generation costs. Consequently, such elasticities are not "small" for the problem at hand.

4. How to adjust a consumption forecast

We can now discuss how to use the demand function (1) to adjust a consumption forecast (E_0, E_1,… E_n) which ignores the effect of price on demand.

Note that given the known consumptions E_{-1} and E_{-2} the forecast E_0 can be assumed to be coming from the following evaluation of the demand function:

$$\ln E_0 = \ln A_0 + 0.33 \ln E_{-2} + 0.53 \ln E_{-1} - 0{,}055 \ln p_0,$$

where p_0 is the actual price in month $t=0$. Because E_{-1}, E_{-2} and p_0 are known, one can recover A_0 implicit in the forecast E_0. Similarly, because the forecast of consumption ignores the effect of price on demand, one can assume that E_0 satisfies

$$\ln E_1 = \ln A_1 + 0.33 \ln E_{-1} + 0.53 \ln E_0 - 0{,}055 \ln p_0,$$

and recover A_1. Following a similar procedure, one can obtain the whole sequence (A_0, A_1,…, A_n). Now given an exogenous price forecast (p_1, p_2,… p_n), it is straightforward to obtain the adjusted forecast (E_0, $\hat{E}_1$,… $\hat{E}_n$), which satisfies

$$\ln \hat{E}_1 = \ln A_1 + 0.33 \ln E_{-1} + 0.53 \ln E_0 - 0{,}055 \ln p_0$$
$$\ln \hat{E}_2 = \ln A_2 + 0.33 \ln E_0 + 0.53 \ln \hat{E}_1 - 0{,}055 \ln p_1$$
$$\vdots$$
$$\ln \hat{E}_{n1} = \ln A_n + 0.33 \ln \hat{E}_{n-2} + 0.53 \ln \hat{E}_{n-1} - 0{,}055 \ln p_n.$$

The adjusted forecast (E_0, $\hat{E}_1$,…, $\hat{E}_n$) can now be used to estimate deficit probabilities.

Note that in principle one should also consider that the change in consumption wrought by the change in price could lead to further adjustments in price, as energy suppliers move along an upward-sloping supply curve. Thus, using the adjusted demand forecast (E_0, $\hat{E}_1$,…, $\hat{E}_n$) one would have to recalculate equilibrium prices; these would then feed back into the consumption forecast and equilibrium prices are calculated again; and so on until the process converges.

In the particular case of Chile, determining the energy price in principle involves making a marginal cost forecast obtained from a hydrothermal dispatch model. Nevertheless, in our case one can safely ignore these feedback effects, as between 2006 and 2011 prices will evolve largely exogenously determined by the ceiling of a price band (see Appendix)

5. Dispatch model and results

We now present the results of a simulation that estimated monthly deficit probabilities over 2006–2011 in Chile's Central Interconnected System. The baseline case uses the consumption forecast, fuel prices and expansion plan used by the NEC when it fixed the node price in April 2006 (see National Energy Commission, 2006). We then adjust the consumption forecast following the procedure that we explained in the previous section, and recalculate deficit probabilities. We used the stochastic dynamic programming model Omsic, which was used until recently to dispatch plants in Chile's SIC. In what follows we briefly describe this model.

5.1. The dispatch model

The Chilean system is coordinated to minimize the expected cost of supply and outage cost. The CDEC centrally dispatches power plants in strict merit order, ranking them from lowest to highest operating costs until the amount of power demanded at

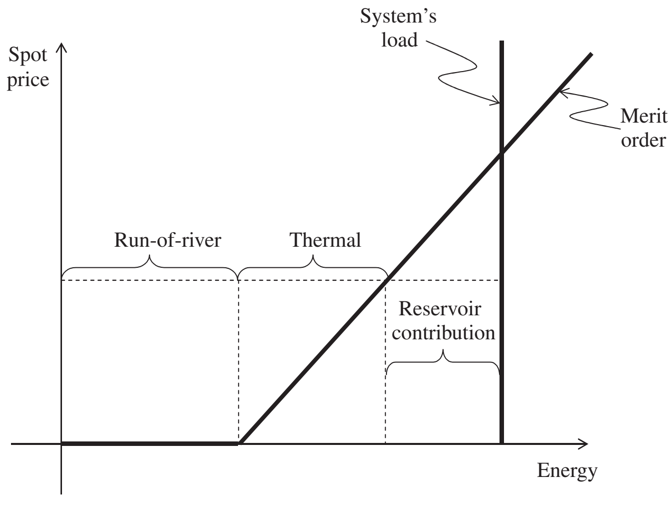

Fig. 1. Dispatch by merit order.

each point in time is covered. Thus, run-of-river hydroelectric plants are dispatched first. If the amount produced by run-of-river plants is insufficient to serve demand, thermal and reservoir hydro plants are activated in increasing order of operating cost. Last, the opportunity cost of reservoir water is calculated with a stochastic dynamic programming model at each instant and thermal plants are dispatched accordingly.

Regulation in Chile stipulates that CDEC orders are compulsory and independent of each firm's energy and power supply contracts. As a result, transfers are often made between generators to enable them to meet their commercial commitments, which are valued at the instantaneous nodal marginal cost. The spot price calculated hourly. The separation between dispatch and contracts allows the system to minimize short-run total production cost.

Dispatch rules are illustrated by Fig. 1. Run-of-river and thermal plants are ordered according to their variable cost of operation. It can be seen that the amount of electricity generated by thermal power plants at each point in time depends on system load, the availability of run-of-river hydroelectric generation, and the amount generated from water stored in reservoirs. The amount generated with reservoir water, in turn, is determined by equating the option value of water stored in reservoirs with the current cost of generation, which equals the variable cost of the most expensive thermal plant running. If that is so, reservoir water will exactly cover the difference between system load and thermal plus run-of-river generation.

Until recently, the system was operated with the dynamic programming model Omsic. This is the model used to perform our

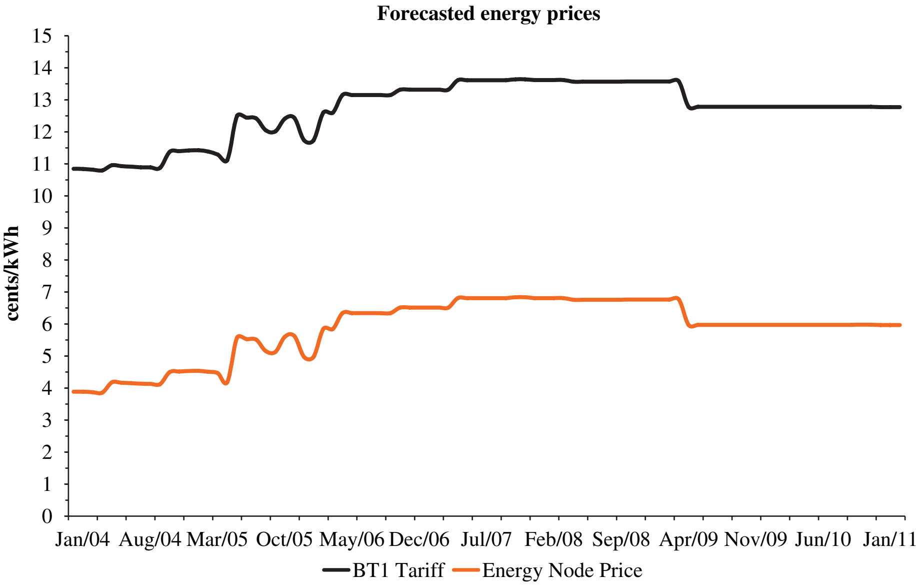

Fig. 2. Forecasted energy prices.

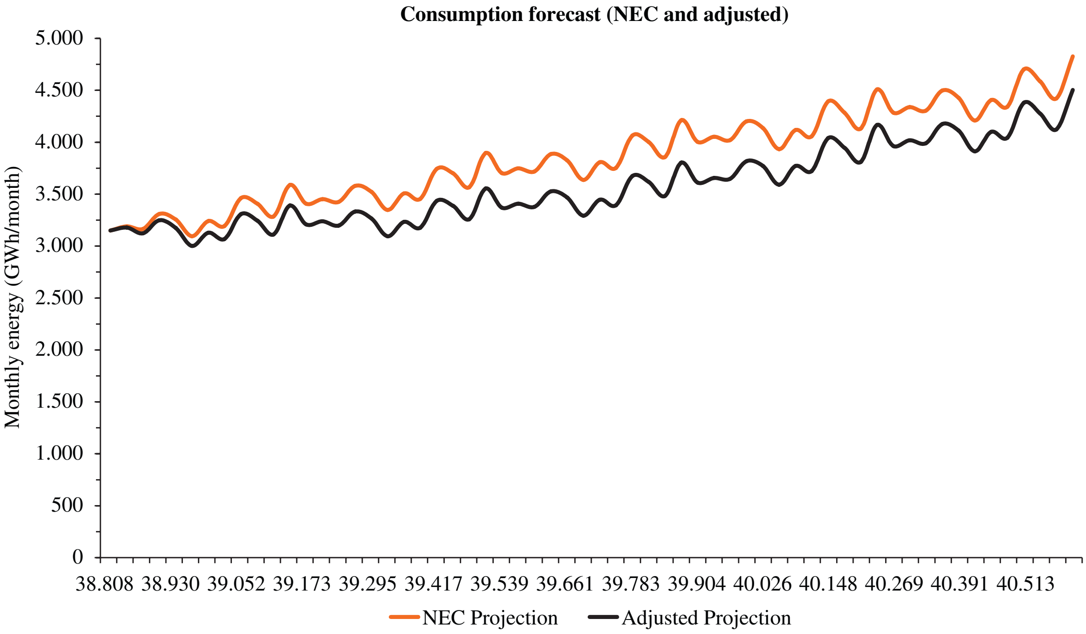

Fig. 3. Consumption forecast (NEC and adjusted).

simulations. In Appendix B we formally describe the model, the optimization and the simulations.

5.2. Results

Prices: Fig. 2 shows prices paid by consumers since 2004 and forecasted until 2011. The black line shows the monomic BT1 tariff, which is paid, as said before, by small residential and commercial consumers. The grey line shows the energy node price, which is paid by regulated consumers (mainly commercial and small industrial customers) and is the basis for many contracts with unregulated consumers. As said before, between 2006 and 2011 the energy node price, is a function of the monomic market price, which will evolve exogenously. For this reason, it will not be affected by the new consumption forecast.

As can be seen from Fig. 2, the price of energy has been rising since April 2004. Between March 2004 and April 2006, the BT1 tariff increased by 16%, while the energy price paid by regulated commercial and industrial consumers rose by 47%. This had a significant impact on demand growth: while until 2004 consumption had normally grown one or two points faster than the rate of growth of GDP, in 2005 it grew only 4.5%, while GDP grew by 6.2%. Note that energy prices are expected to level off from 2007 onwards.

Table 2
Forecasted consumption (NEC and adjusted)

	NEC[1,2]		Adjusted[3]	
	(1) Consumption (GWh)	(2) Rate of increase (%)	(3) Consumption (GWh)	(4) Rate of increase (%)
2006	38.412		37.774	
2007	41.443	7.9	38.823	2.7
2008	44.800	8.1	40.915	5.4
2009	48.250	7.7	44.075	7.7
2010	51.482	6.7	47.906	8.7

Sources: CNE (2006) and authors' calculations.
Notes: (1) Losses are assumed to be equal to 4.1% of power transmitted, the average recorded between 1996 and 2005. (2) NEC estimated consumption in 2006 at 38,480 GWh. We corrected this estimate with information on actual sales during the first quarter of 2006. (3) This is NEC's forecast adjusted for the fall in consumption wrought by higher energy prices, assuming short-and long-run elasticities as estimated by Benavente et al. (2005).

Quantities: In April 2006 NEC forecasted that energy consumption would grow at about 7% per year. Fig. 3 shows the monthly baseline consumption forecast made by NEC (grey line) and the adjusted forecast (black line). Both coincide in April 2006, which is the starting date.

Table 2 compares both forecasts. NEC estimated that consumption would grow by 7.9% in 2007 and 8.1% in 2008; our adjusted forecast gives much lower rates of growth: 2.7% in 2007 and 5.4% in 2008. Graphically, Fig. 3 shows the consequence of this difference: from 2008 onwards, the level of consumption is about 10% lower—some 300 GWh each month, or roughly the same as having an additional power plant available in the system.

Column 4 in Table 2 also shows that rates of growth are very similar in 2009 (both 7.7%) and 2010 (NEC: 6.7%; adjusted: 8.7%). The reason is that by then energy prices level off and the partial adjustment of consumption to higher prices is mostly completed. But note that, as Fig. 3 shows, the level of energy consumption is permanently lower.

The probability of a deficit: Fig. 4 compares monthly deficit probabilities with NEC's forecast (grey line) with deficit probabilities calculated with the adjusted forecast (black line). If the probability of a deficit in a given month is similar in both cases, then the figure only shows the black line.

Slower growth significantly affects the probability of a deficit. NEC's deficit probabilities are in general higher and during many months climb above 6% (that is, the simulation shows a deficit 6% of the time). By contrast, the simulation with the adjusted forecast indicates that deficit probabilities are most of the time lower than 3%. This is mainly due to the 300 GWh per month reduction in

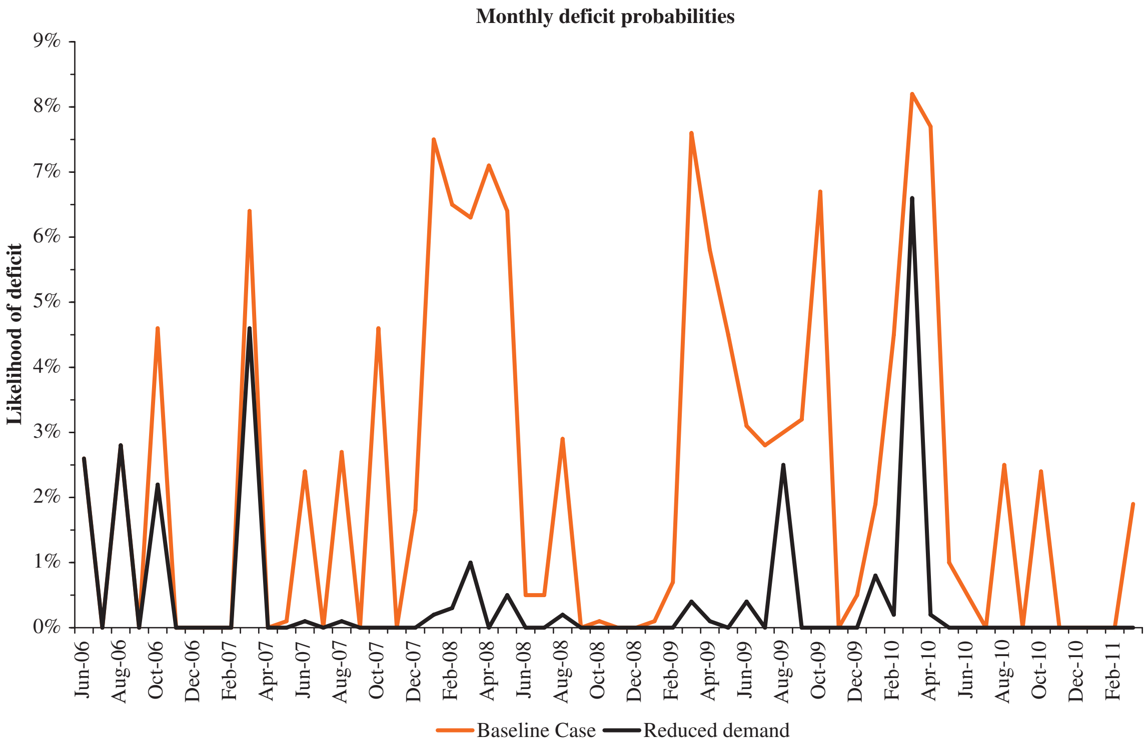

Fig. 4. Monthly deficit probabilities.

Table 3
Average system's marginal cost (Quillota bus, 220 kV)

	(1) Base case cents/kWh	(2) Adjusted demand cents/kWh	(3) Difference % = (2)/(3) (%)
2006	9.4	7.7	22
2007	11.4	8.1	41
2008	10.5	7.8	35
2009	11	8	38
2010	8.4	7	20
Average	10.2	7.7	32

Table 4
NEC and adjusted demand compared: additional thermal energy and generation cost

	Additional thermal energy		Additional generation cost	
	GWh	%	Million $	%
2006	1.079	9	117	28
2007	2.857	19	300	53
2008	4.339	26	388	52
2009	4.183	21	389	43
2010	3.544	15	273	30
Total	16.002	18	1.466	41

consumption which, as said before, is equivalent to an additional power plant in the system. The expected deficit is about six times larger when the effect of rising prices is ignored (258 vs. 34 GWh).

Marginal costs and the cost of system supply: Table 3 compares the system's marginal cost in both cases.[13] The average marginal cost is equal to 10.2 cents/kWh with NEC's forecast, 32% higher than the 7.7 cents/kWh average with the adjusted forecast.

Table 4 compares thermal energy and operating costs in both cases. With NEC's forecast thermal generation is 18% higher, and operating costs are 41% higher, a substantial amount.[14]

6. Conclusions

We have shown that ignoring the effect of price changes on the demand for energy can lead to substantial over or understatements of deficit probabilities, marginal costs and operating costs. In the case of Chile's SIC, an hydrothermal system, between 2006 and 2011 monthly deficit probabilities drop sharply from an annual average of 2.3% to just 0.4% once the effect of rising prices on demand is accounted for. Similarly, the size of the expected deficit falls from 258 GWh to just 34 GWh; the system's average marginal cost from 10.2 cents/kWh, to 7.7 cents/kWh (33%) and operating costs also fall by roughly 41%.

Appendix A. : Setting the regulated node price

In Chile distribution firms can buy energy and power from generators at regulated prices—the so-called energy and power node prices. Node prices are then passed through to consumers. NEC calculates both prices every 6 months in April and October.

Node prices are fixed in four steps. First, the so-called basic energy price and power node price are calculated. Second, these prices are combined into a monomic energy equivalent, to be compared with the monomic average price paid by unregulated customers according to actual contracts. Third, the monomic node price is calculated. It must fall within a band centered around the monomic market price. Last, the energy node price is obtained and fixed as the tariff paid by consumers. We revise each step in turn.

Step 1: Let $E(t)$ be the energy forecasted to be consumed at time t, $\mathrm{mc}(E(t);\theta)$ be the system's marginal cost at time t if the amount of energy produced is $E(t)$ and rainfall is θ; and let $r = 10\%$ be the real discount rate. Then the basic price of energy, p_e^b, is given by

$$p_e^b \cdot \int_0^4 E(t)e^{-rt}\,dt = E_\theta\left[\int_0^4 \mathrm{mc}(E(t);\theta)\cdot E(t)e^{-rt}\,dt\right], \tag{A1}$$

where E_θ is the expectation operator. Thus, the so-called basic price of energy is the average price that yields exactly the same revenue in present value as generators would expect to obtain if they would sell their energy at the system's marginal cost over the next 48 months (4 years).

In practice $\mathrm{mc}(E(t);\theta)$ is calculated using a hydrothermal dispatch model based on stochastic dual dynamic programming (SDDP) techniques.[15] The optimization is based on a forecast for energy and peak load consumption over the next 10 years. Given this consumption forecast, reservoir use is set to minimize the expected cost of supplying required energy and peak power. The givens of the problem are: the initial reservoir level; existing power plants; the optimal entry of power plants and forecasted trunk lines over the next 10 years; forecasted fuel costs; and the value of lost load (VOLL). Hydrological uncertainty, Θ, is modeled using historical statistics.

Now it follows from (A1) that

$$p_e^b = A \cdot E_\theta\left[\int_0^4 \mathrm{mc}(t;\theta)E(t)e^{-rt}\,dt\right]$$

with

$$A \equiv \left[\int_0^4 E(t)e^{-rt}\,dt\right]^{-1}$$

The power node price equals the cost of investing in a diesel-fired turbine meant to run at the system's peak hour. This cost equals the sum of I_t, the cost of the turbine, and I_ℓ, the cost of the transmission line needed to connect it to the high-voltage grid. Both are brought to a yearly equivalent assuming an 18-year recovery period, a system reserve margin α and a 10% real discount rate. Thus

$$p_p^n = (1+\alpha)\cdot\frac{1}{R}(I_t + I_\ell)$$

with

$$R \equiv \left[\int_0^{18} e^{-rt}\,dt\right]^{-1}$$

Step 2: The basic monomic energy-equivalent is calculated as

$$\bar{p}^b = p_e^b + p_p^n \cdot \frac{1}{\ell f}\cdot\frac{1}{h},$$

where ℓf is the system's load factor (assumed to be 74.4% in recent tariff reviews) and $h = 8760/12$ is the average number of hours per month.

[13] Marginal costs are computed at Quillota, one of SIC's main buses.
[14] Operating costs include the cost of outages when in deficit.
[15] See Pereira and Pinto (1991) and Power System Research Institute (2001).

Step 3: Next the basic monomic energy price is compared with the price band. Let

$$\Delta \equiv \frac{\bar{p}^b - \bar{p}^m}{\bar{p}^m},$$

the percentage difference between the market monomic price and the basic monomic price. Then, the monomic node price is determined by the following price band:

$$\bar{p}^n = \begin{cases} \bar{p}^m \times (1+\xi) & \text{if } \Delta > 0.05 \\ \bar{p}^b & \text{if } -0.05 \leqslant \Delta \leqslant 0.05 \\ \bar{p}^m \times (1-\xi) & \text{if } \Delta < -0.05 \end{cases}.$$

Thus, if $\bar{p}^b$ falls within a $\pm 5\%$ band centered around the observed monomic unregulated price, $\bar{p}^m$, then it is also the monomic node price. Nevertheless, assume $\bar{p}^b$ deviates by more than 5% from $\bar{p}^n$. Then, the monomic node price is equal to either the band's ceiling $\bar{p}^m \times (1+\xi)$ or floor $\bar{p}^m \times (1-\xi)$. The size of the adjustment factor ξ, in turn, depends on the size of Δ according to:

$$\xi = \begin{cases} 0.05 & \text{if } 0.05 < |\Delta| < 0.30 \\ 0.4 \times |\Delta| - 0.02 & \text{if } 0.30 \leqslant |\Delta| < 0.80 \\ 0.30 & \text{if } 0.80 \leqslant |\Delta| \end{cases}.$$

That is, the adjustment factor increases stepwise with Δ.

Step 4: The energy node price is, finally,

$$p_e^n = \frac{E \cdot \bar{p}^n - P \cdot p_p^n}{E}.$$

Regulated node prices are indexed monthly to track fuel prices, the level of reservoirs and local inflation. Nevertheless, since October 2006 the energy price is exclusively indexed to the average market price of the last few months.

Appendix B. A brief introduction to the Omsic model

Introduction: Dispatch in Chile's Central Interconnected System (SIC by its Spanish acronym) is run with a dynamic programming model. The center of this optimization is the Laja reservoir (Laja lake). When full, it holds enough water to generate about 7000 GWh, around one-sixth of annual consumption. Because the installed capacity of plant that runs with Laja water is 2500 GWh/year, energy can be stored for several years. A stochastic dynamic programming model operated by CDEC governs the hourly rate of use of Laja water. The model trades off the benefit of using water today and displace thermal generation, against the cost of not having water in the future and thus having to use thermal generation or ration consumers. The model's state variable is the current level of the Laja reservoir. The probability distribution of future hydrologies is modeled with 40 years of monthly past hydrologies (hence, there are 40 January hydrologies, 40 February hydrologies and so on, and $40 \times 12 = 4800$ monthly hydrologies in total). Each monthly hydrology is assumed to be an equally likely, statistically independent random draw. The output of the model indicates the amount of Laja water that should be used during each month and the shadow price of the remaining water. This shadow price is the system's marginal cost or wholesale spot price. Under normal conditions, the opportunity cost of water equals the operating cost of the most expensive thermal plant dispatched. If the model optimally predicts a shortage, the opportunity cost of water equals the outage cost.

In this appendix we describe the dynamic optimization and the simulation performed by the Omsic model. Omsic optimizes the use of reservoir water (optimization stage), and then simulates plant dispatch under different hydrologies (simulation stage). We describe each stage in turn.

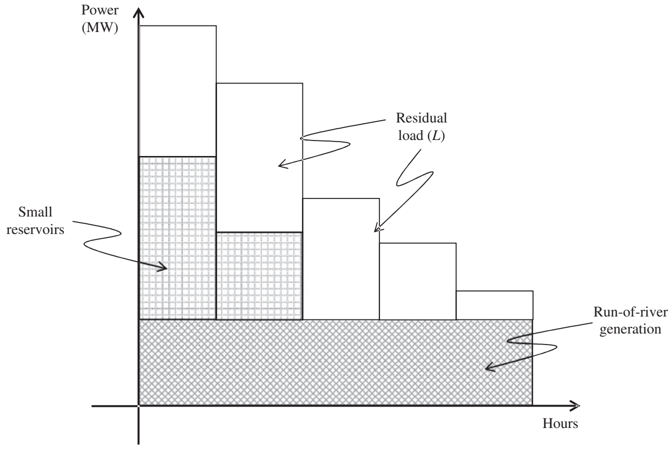

Fig. 5. Allocation of run-of-river and small reservoir water.

Stage 1: *Optimization*. The output of the optimization stage is a function that maps the state variable, the amount of water in the Laja reservoir as measured by its level, ℓ, to the monthly optimal use of water for each of the 40 hydrologies during each of the T months of the planning horizon (in this case, $T = 120$).[16] To run this optimization one needs a projection of each month's energy consumption; the entry dates of new generating plant; fuel prices; and the energy provided by each hydro plant under each hydrology each month. The model also divides monthly energy consumption in five demand blocks which follow the shape of the daily load curve. Last, the use of the water of lake Laja is optimized. We now describe this optimization

Step 1: Allocation of run-of-river and non-Laja reservoir energy.

The first step of the optimization stage is the allocation of run-of-river and non-Laja reservoir energy among the five demand blocks (see Fig. 5). On the one hand, run-of-river energy is assumed to spread evenly among the five blocks. On the other hand, water from four small reservoirs (Colbún, Cipreses, Canutillar and Rapel) is allocated to the peak block, and if these plants run at capacity during the peak block, the remaining water is allocated to the next block. The principle behind the allocation of small reservoir water is that one should strive to equalize the marginal cost of energy should across blocks, and this calls for using water from small reservoirs during peak hours.

Note that the allocation depicted in Fig. 5 is done 40 times for each month of the 10-year optimization horizon—that is, there are $40 \times 120 = 4800$ allocations.

Step 2: The optimal use of water in the Laja lake.

Whatever load remains unserved after run-of-river and small reservoir energy is allocated (the white area in Fig. 5, which we will call *residual load*) it must be supplied with energy generated in thermal plants or hydro plants that run with water of the Laja lake. A simple relation links thermal generation with the amount of water generated with water in the Laja lake: once the optimal flow of water extracted from the Laja lake is determined, thermal dispatch is obtained by following the merit order. To understand how the optimal flow of water extracted from the Laja lake is calculated, it is convenient to note that the optimization is based in an economic principle which is implemented with a specific computation method.

The principle has already been described: water in the Laja lake should be used until its marginal value today equals its marginal value tomorrow. It can be illustrated with a simple

[16] The level of the Laja lake is measured in meters over sea level (m.o.s.l.). When empty, the lake's level is 1310 m.o.s.l. When full, the lake's level is 1368 m.o.s.l.

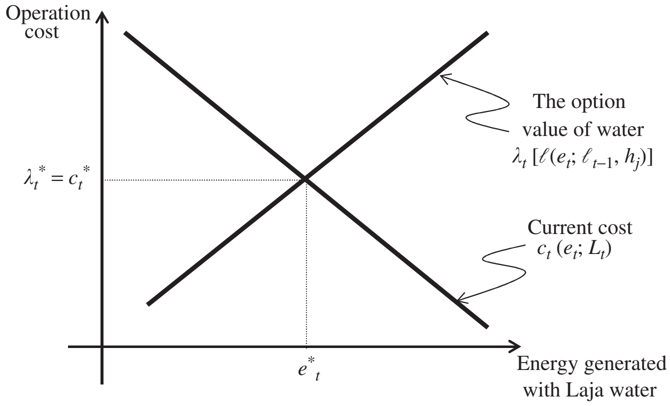

Fig. 6. The option value of water in the Laja reservoir.

graph, Fig. 6. On the one hand, the current-cost curve, c, depicts the current marginal operation cost. This curve is downward sloping because water displaces thermal generation which is dispatched in strict merit order. Its position depends on the size of the residual load which, in turn depends on the hydrology h. On the other hand, the option value of holding one additional kWh in lake Laja at the end of the current period, which we denote by λ, is an increasing function of the water currently used, call it e—if more water is used today, less water will be available in the future and more thermal generation will be needed.[17] λ is a function only of the state variable ℓ. But because the level at the end of the period depends not only on water use, but also on the current hydrology and the initial level of the lake, the position of this curve depends on the hydrology h and the initial level of the lake, ℓ_{t-1}. The optimal flow of water, call it e^*, is found at the intersection of both curves where the option value of water λ equals the current cost.

The method used to implement this principle is to solve a dynamic programming problem whose output is a set of matrices that indicate how much water is to be used each month for each level of the Laja lake and each hydrology. If the number of possible levels is ℓ, then the matrix is of order $\ell \times 40$, for there are 40 hydrologies each month. Because there are 120 months, it follows that there are 120 such matrices. Each component in a given matrix is a quantity of energy generated with the water of the Laja lake given ℓ and h.

The current-cost curve is easy to obtain. For a given residual load L (which in turn depends on the hydrology and the total load curve; see Fig. 6), a function relates the amount of Laja water and the operation cost of the most expensive thermal plant dispatched. Hence, a function also relates the current cost with the amount of energy generated with water in the Laja lake. Call this function $c_t(.;h_j)$, with $c_t(e_t,\ L_t)$ the current cost if e_t is generated with water in the Laja lake. Note that this function depends, in particular, on the consumption forecast.

On the other hand, function λ is the outcome of a dynamic optimization with one state variable, ℓ. At the end of month T, the level of lake Laja, ℓ, must be between 1310 m.o.s.l and 1368 m.o.s.l. For each level $\ell \in \{1310, 1311, \ldots, 1368\}$ the option value of water at the end of the planning horizon is computed.[18] This computation yields a function whose value evaluated at ℓ we will denote by $\lambda_T(\ell)$.[19] Function λ_T is decreasing in ℓ—the more water in the reservoir, the lower its option value.

[17] The value of water is the derivative of the standard Bellman equation.

[18] Note that there are 59 possible levels.

[19] This function is obtained from suitably extending the optimization n periods into the future, assuming that the option value of water is 0 in month $T+n$ and working the solution backwards.

Now let ℓ_{T-1} be the level of lake Laja at the end of month $T-1$, a_j be the inflow of water into the reservoir when the hidrology is h_j and let e_T be the extraction of water during month T. Then the level of lake Laja at the end of month T is

$$\ell_T = \ell_{T-1} + a_j - e_T.$$

Because a one-to-one function relates a_j with h_j, we can write

$$\ell_{T-1} + a_j - e_T \equiv \ell(e_T; \ell_{T-1}, h_j).$$

Thus the option value of water at the end of month T if the hydrology is h_j and e_T is extracted is $\lambda_T\lfloor \ell_T(e_T;\ell_{T-1},\ h_j)\rfloor$—variables affect the option value of water only through the state variable ℓ. Now for each pair $(h_j,\ \ell_{T-1})$ there exists $e^*{}_T(\ell_{T-1},\ h_j)$ such that

$$\lambda_T\lfloor \ell_T(e_T^*; \ell_{T-1}, h_j)\rfloor = c_T(e_T^*; L_T)$$

(where we have omitted the arguments in $e^*{}_T$). Therefore, the option value of water at T is

$$\lambda_T\lfloor \ell_T(e_T^*; \ell_{T-1}, h_j)\rfloor.$$

Now one can build two matrices: $[E_T\ell_{T-1},\ h_j)]$, which summarizes the energy generated with water in the Laja lake for each level-hydrology pair; and $[\Lambda_T(\ell_{T-1},\ h_j)]$, which summarizes the option value of water at the optimum for each level-hydrology pair. Each matrix is of order 59×40. Also, one can calculate the average option value of water for each level at the end of month T, which is equal to

$$\bar{\lambda}_T(\ell_{T-1}) = \frac{1}{40}\sum_{j=1}^{40} \lambda_T[\ell_T(e_T^*;\ \ell_{T-1},\ h_j)],$$

Note that $\bar{\lambda}_{T-1}$ is decreasing in ℓ because each $\lambda_{T-1}(.,h_j)$ is decreasing in ℓ. Note also that $\bar{\lambda}_T$ is a function of the state variable ℓ_{T-1} only. Hence one can define

$$\lambda_{T-1}(\ell_{T-1}) \equiv \bar{\lambda}_T(\ell_{T-1}),$$

Now the optimization for months 1, 2,…, $T-1$ can be done applying backwards induction exactly in the same fashion, by solving

$$\lambda_{T-1}\lfloor \ell_T(e_{T-1}^*;\ \ell_{T-2}, h_j)\rfloor = c_{T-1}(e_{T-1}^*;\ L_{T-1})$$

and so on. The result is a sequence of matrices $([E_t(\ell_{t-1},\ h)])_{t=1}^{T}$ and $([\Lambda_t(\ell_{t-1},\ h)])_{t=1}^{T}$. These matrices are used later for simulating the system's operation.

Example: Assume four lake levels and three hydrologies. The energy matrix in month t is

$$E_t(\ell_{t-1}, h) \equiv \begin{bmatrix} e_t^*(1,1) & e_t^*(1,2) & e_t^*(1,3) \\ e_t^*(2,1) & e_t^*(2,2) & e_t^*(2,3) \\ e_t^*(3,1) & e_t^*(3,2) & e_t^*(3,3) \\ e_t^*(4,1) & e_t^*(4,2) & e_t^*(4,3) \end{bmatrix},$$

where $e^*{}_t(1,2)$ is the optimal energy to be generated with water of the reservoir during month t if the level of lake Laja is ℓ_1 and the hydrology h_2. The second matrix is

$$\Lambda_t(\ell_{t-1}, h) \equiv \begin{bmatrix} \lambda_t(1,1) & \lambda_t(1,2) & \lambda_t(1,3) \\ \lambda_t(2,1) & \lambda_t(2,2) & \lambda_t(2,3) \\ \lambda_t(3,1) & \lambda_t(3,2) & \lambda_t(3,3) \\ \lambda_t(4,1) & \lambda_t(4,2) & \lambda_t(4,3) \end{bmatrix}.$$

Notice that both, hydrologies and lake levels are independent of t. Finally, the average option value of water, as function of level ℓ_i is

$$\lambda_{t-1}(\ell_{t-1}) \equiv \bar{\lambda}_t(\ell_{t-1}) = \frac{1}{3}\sum_{j=1}^{3} \lambda_t(\ell_{t-1}, h_j).$$

Stage 2: Simulation The sequence $(E[_t(\ell_{t-1},h)])_{t=1}^{T}$ tells how much water to use each month for any possible level, hydrology pair. Thus, given the initial level of lake Laja, ℓ_0, and a sequence of hydrologies $(h_t)_{t=1}^{T}$ one can simulate the operation of the system from the first to the last month computing, among others, monthly spot prices, quantities and deficits, this for each of the five demand blocks. To obtain a probability distribution of monthly spot prices, quantities and deficits one chooses randomly 1000 sequences $(h_t)_{t=1}^{T}$ and simulates each sequence.

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