Market Power Assessment and Mitigation in Hydrothermal Systems

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Abstract: the objective of this work is to investigate market power issues in bid-based hydrothermal scheduling. Initially, market power is simulated with a single stage Nash-Cournot equilibrium model. Market power assessment for multiple stages is then carried through a stochastic dynamic programming scheme. The decision in each stage and state is the equilibrium of a multi-agent game. Thereafter, mitigation measures, specially bilateral contracts, are investigated. Case studies with data taken from the Brazilian system are presented and discussed.

Keywords: Game theory, Hydroelectric-thermal power generation, Power generation economics

I. INTRODUCTION

Electricity utilities all over the world have been undergoing radical changes in their market and regulatory structure. A basic trend in this restructuring process has been to promote competition in generation and participation of private agents in the energy production process. In most cases, the restructuring process has replaced traditional expansion planning and operation procedures, based on centralized optimization, by market-oriented approaches.

While there seems to be a general agreement concerning the advantages of decentralized investment decisions, the operational efficiency of free markets in electrical systems is based on the assumption that no generator has the ability to make bids that all alone will artificially increase spot prices. This may not be the case in real life. Because electricity demand has a low price elasticity, changes in supply can alter spot prices. Coordination problems can also take place in hydrothermal systems with decentralized dispatch, specially when two or more utilities share hydro plants in the same river cascade [5]. However, it is not the objective of the present work to address such problems.

The work is organized as follows. In section II the concept of market power in hydrothermal systems is introduced. Market power is then simulated in a static model through a Nash-Cournot equilibrium model. In Section III the basic concepts of hydrothermal scheduling, in particular the concepts of tradeoff between immediate and future opportunity costs, and the calculation of expected future cost functions using stochastic dynamic programming (SDP) are presented. The bidding scheme for hydro systems is then formulated as a time-reversed dynamic programming problem. The approach will be illustrated with a case study with data taken from the Brazilian system, where the bid-based dispatch will be compared with the least cost dispatch. Section IV analyzes the use of bilateral contracts as an instrument to minimize market power. The conclusions are presented in Section V.

II. MODELLING MARKET POWER

A. Introduction

An agent is said to have market power whenever it has the ability to influence the market price independent of the remaining agents' actions. In Wholesale Energy Markets, the objective of market power is to raise system spot prices, either through modified bid prices or constraints on the amount of energy being offered. Market power can be exercised by individual agents or through *collusion*, in which a set of agents "conspire" to drive prices up. In this work, only the first case will be discussed.

B. Concentration Indices

Market power in different industries has traditionally been analyzed through *concentration indices*, such as the popular Hirschmann-Herfindall index (HHI), given by the sum of the squares of the agents' % market share. The underlying assumption for the use of HHI for market power analysis is that it is directly correlated to market concentration. The main drawback is that the ability to exercise market power in electricity markets may depend on other factors other than concentration. The use of concentration indices in energy markets has been criticized in [1,2]. The authors argue that indices do not capture agent actions such as constraining energy production or demand elasticity. Because indices don't provide information about market variables, such as price sensitivity with respect to hydro energy production, the use of an oligopoly equilibrium model is proposed. It will be used as an alternative tool in analyzing market power.

C. Proposed Approach: Market Simulation

The straightforward method for calculating market power impacts in electricity markets is by simulating the operation of these markets and directly measuring the market prices and firm's revenues as the strategic bidding or capacity withholding is carried. Two classical approaches in modeling the gaming aspect of strategic bidding are [3]: (a) the *Bertrand model*, where agents have fixed production capacities and compete through prices; and (b) the *Cournot model*, where agents decide on quantities and market price is defined through an inverse demand function. In this study, we have used a Cournot model, more adequate for long-term studies involving quantities of energy used or stored in reservoirs. Bertrand models are usually applied in the shorter-term [3].

The Nash-Cournot approach assumes that strategic firms employ quantities. Each strategic firm decides its production level supposing it knows the energy output by the remaining strategic firms. The market scheme is thus simulated through a game: the first strategic firm chooses its profit-maximizing output under the assumption that the production of the other

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strategic firms is known. This is repeated for each strategic firm, that resets its output levels based upon the most recent decisions of the others, until a Nash equilibrium, where no firm can profit from changing its output levels given the output of all other strategic firms.

D. Price Makers and Price Takers

The first step in modeling the market consists in identifying the set of N agents with potential market power, known as *price makers*. We will assume that each price maker has a variable operating cost $c(i)$, $i = 1, .., N$.

There are M additional agents, known as *price takers*, which do not have the power to influence spot price. We will assume that the price takers have a quadratic operating cost $\delta(\mathrm{O}) = (\mathrm{O}^2 / 2\alpha)$, where O is the total energy production of the price takers and α is a scalar parameter. From this assumption, given a market price p, the price taker production O can be obtained by setting their marginal production cost equal to the market price. In turn, the marginal production cost is given by the derivative of $\delta(\mathrm{O})$ with respect to O. It follows that the price taker production is a linear function of the spot price p, i.e. $\mathrm{O}(p) = \alpha p$.

E. Profit Maximization

Let D and p be the total system demand (assumed to be inelastic) and spot price, respectively. As discussed, price takers' production will be $\mathrm{O}(p)$. As a consequence, the price makers will meet the residual demand $\mathrm{D_r}$:

$$\mathrm{D_r} = \mathrm{D} - \mathrm{O}(p) = \mathrm{D} - \alpha p \tag{2.1}$$

Let $\mathrm{E}(i)$, $i = 1, ...,$ N represent the energy offered by each price maker. The total price maker production is given by:

$$\mathrm{Q} = \sum_{k=1}^{\mathrm{N}} \mathrm{E(k)} \tag{2.2}$$

Inverting (2.1) spot price can be related to the total price maker production Q:

$$p(\mathrm{Q}) = (\mathrm{D}-\mathrm{Q}) / \alpha \tag{2.3}$$

According to (2.3), the absence of price-takers only takes place when the market price is zero. In this case, the market power that will be derived next is somewhat silly.

Assuming that there are price takers in the market, the profit of the price maker i, given the production of the remaining N-1 price makers, is:

$$\mathrm{R(i)} = [p(\mathrm{Q}) - c(i)]\mathrm{E}(i) \tag{2.4}$$

The energy $\mathrm{E}^*(\mathrm{i})$ that maximizes $\mathrm{R}(i)$ is obtained by making $\partial\mathrm{R}(i)/\partial\mathrm{E}(i) = 0$. Substituting the expressions for Q and p(Q) into this derivative, we have:

$$2\mathrm{E}^*(\mathrm{i}) = \mathrm{D} - \alpha\, c(i) - \sum_{\mathrm{k}\neq\mathrm{i}}^{\mathrm{N}} \mathrm{E(k)} \tag{2.5}$$

F. Nash-Cournot Equilibrium

Expression (2.5) determines the energy production that maximizes revenues for agent i, assuming that the production of all other agents is known. The difficulty is that all agents are simultaneously trying to maximize their own profit without knowing the remaining agents' decisions. The Nash-Cournot equilibrium provides a solution to this problem: it shows that agents will reach a "standoff" situation where no agent can unilaterally increase its revenue by changing its production.

Expression (2.5) is a linear system of N equations (revenue maximization for each agent) and N unknowns (their respective energy production). This set of equations can be rewritten in a matrix form:

$$\boldsymbol{M} \quad \boldsymbol{E} \quad = \quad \boldsymbol{R}$$

$$\begin{bmatrix} 2 & 1 & 1 & ... \\ 1 & 2 & 1 & ... \\ ... & 1 & 2 & 1 \\ 1 & 1 & ... & 2 \end{bmatrix} \begin{bmatrix} \mathrm{E}(1) \\ \mathrm{E}(2) \\ ... \\ \mathrm{E(N)} \end{bmatrix} = \begin{bmatrix} \mathrm{D} - \alpha.\mathrm{c}(1) \\ \mathrm{D} - \alpha.\mathrm{c}(2) \\ ... \\ \mathrm{D} - \alpha.\mathrm{c(N)} \end{bmatrix} \tag{2.6}$$

As shown in [1], the equilibrium production of each agent is obtained by solving $\boldsymbol{M}^{-1}\boldsymbol{R}$. The elements of the $\boldsymbol{M}^{-1}$ are:

$$M^{-1}(i,j) = \begin{cases} \dfrac{N}{N+1}, i = j \\ -\dfrac{1}{N+1}, i \neq j \end{cases}$$

Therefore, the equilibrium production $\mathrm{E^e(i)}$ for agent i is:

$$\mathrm{E^e(i)} = \frac{D - N\alpha c(i) + \alpha \sum_{k\neq i} c(k)}{N+1} \tag{2.7}$$

The total price maker energy production $\mathrm{Q^e}$ is given by,

$$Q^e = \sum_{k=1}^{N} E^e(k) = \frac{ND - \alpha \sum_{k=1}^{N} c(k)}{N+1} \tag{2.8}$$

Equation (2.8) is then used to determine the system spot price p(Q) (see (2.3)) and to determine agent's revenue $\mathrm{R}(i)$ (see (2.4)). In the special case where all price makers have the same operating cost c, (2.8) reduces to:

$$\mathrm{E^e(i)} = [\mathrm{D} - \alpha\, c]/(\mathrm{N}+1) \tag{2.9}$$

The total equilibrium production $\mathrm{Q^e}$ is therefore:

$$\mathrm{Q^e} = [\mathrm{N}/(\mathrm{N}+1)]\,[\mathrm{D} - \alpha\, c] \tag{2.10}$$

Expression (2.10) will be used to illustrate the difference between the Nash-Cournot equilibrium solution and the ideal least-cost result, discussed next.

G. Least-Cost Solution

The least-cost dispatch can be formulated as:

$$\mathrm{Z} = \mathrm{Min}\,[\delta(\mathrm{D}-\mathrm{Q}) + c\mathrm{Q}] \tag{2.11}$$

where δ (D-Q) is the operating cost of the price takers when they supply the residual load D-Q and Q is the price maker production. The price maker production Q that minimizes overall production cost is obtained by making ∂Z/∂Q=0 which leads to :

$$Q^c = [D - \alpha c] \tag{2.12}$$

The spot price is then given by:

$$p_c = \frac{D - Q^c}{\alpha} = \frac{D - (D - \alpha c)}{\alpha} = \frac{\alpha c}{\alpha} = c \tag{2.13}$$

H. Measuring Market Power

Comparing the Nash-Cournot and least-cost solutions (2.10) and (2.12), we see that $Q^e < Q^c$. This means that price makers tend to decrease their energy production to "force" an increase in spot price. Table 2.1 shows the difference between equilibrium and least-cost solutions as a % of the later value.

Table 2.1 - Nash-Cournot versus Least-Cost Production

N	1	2	3	5	10	∞
Ratio (% of LC)	50	67	75	83	91	100

As expected, the equilibrium and least-cost solutions converge as the number of agents *N* increases, i.e. as more competition is introduced. Table 2.2 shows a similar comparison for the system spot price.

Table 2.2 - Nash-Cournot versus Least-Cost Spot Price

N	1	2	3	5	10	∞
Ratio (% of LC)	300	233	200	167	136	100

III. MARKET POWER IN HYDROTHERMAL SYSTEMS

A. Hydrothermal Scheduling Process

The market power discussions so far were based on a *static* market model, where operating or bidding decisions in each stage are taken without reference to the next stages. This time decoupling is reasonable for thermal systems, but cannot be applied to hydro systems. The reason is that hydro plants can store energy from one period to the other, which introduces a relationship between the operative decision in a given stage and the future consequences of this decision.

The operator is faced with the options of using hydro today, and therefore avoiding complementary thermal costs, or storing the hydro energy for use in the next period. If hydro energy is used today, and future inflows are high - thus allowing the recovery of reservoir storage - system operation will result to be efficient. However, if a drought occurs, it may be necessary to use more expensive thermal generation in the future, or even interrupt load supply. If, on the other hand, storage levels are kept high through a more intensive use of thermal generation today, and high inflows occur in the future, reservoirs may spill, which is a waste of energy and, therefore, results in increased operation costs. Finally, if a dry period occurs, the storage will be used to displace expensive thermal or rationing in the future.

B. Immediate and Future Costs

The optimal scheduling decision is obtained minimizing the sum of the immediate and expected future cost functions, as illustrated in Fig. 3.1.

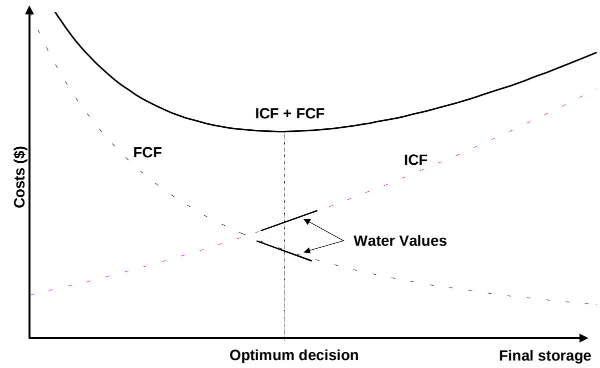

Fig. 3.1 - Immediate and Future Costs versus Final Storage

The immediate cost function - ICF - is related to thermal generation costs in stage *t*. As the final storage increases, less water is available for energy production in the stage; as a consequence, more thermal generation is needed, and the immediate cost increases. In turn, the future cost function - FCF - is associated with the *expected* thermal generation expenses from stage *t*+1 to the end of the planning period. We see that the FCF decreases with final storage, as more water becomes available for future use. Reference [4] describes the hydrothermal scheduling problem in details.

C. The Stochastic DP Recursion

The FCF is recursively calculated by a stochastic dynamic programming (SDP) scheme, which calculates for each stage and state (set of reservoir storage) the decision that minimizes the sum of immediate and future costs. As shown in Fig. 3.1, this is also where the derivatives of ICF and FCF with respect to storage (water values) become equal. This scheme is described next:

a) for each stage *t* (typically a week or month) define a set of *system states*, for example, reservoir levels at 100%, 90%, etc. until 0%.

b) start with the *last* stage, T, and solve the *one-stage hydrothermal dispatch problem* (see [4]) assuming that the initial reservoir storage corresponds to a given storage level, for example, 100%. Because we are at the last stage, assume that the future cost function is zero. Also, because of inflow uncertainty, the hydro scheduling problem is successively solved for *S* different inflow *scenarios*, in that stage. The procedure is shown in Fig. 3.2.

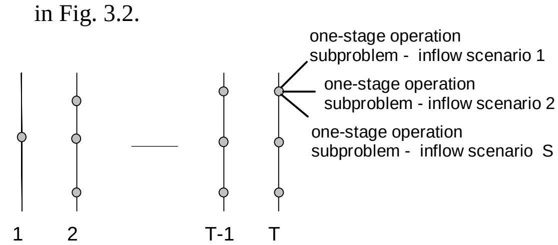

Fig. 3.2 - Optimal Strategy Calculation - Last Stage

c) Calculate the expected operation cost associated to storage level 100% as the mean of the S one-stage subproblem costs. This will be the first point of the expected future cost function for stage T-1, i.e. $\alpha_T(v_T)$. Repeat the calculation of expected operation costs for the remaining states in stage T. Interpolate the costs between calculated stages, and produce the FCF $\alpha_T(v_T)$ for stage T-1. The process is then repeated for all selected states in stage T-1, T-2 etc. as illustrated in Fig. 3.3. Note that the objective is now to minimize the immediate operation cost in stage T-1 plus the expected future cost, given by the previously calculated FCF.

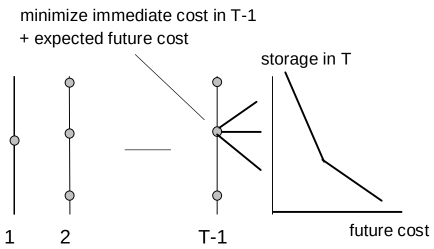

Fig. 3.3- Operation Costs for Stage T-1 and FCF for stage T-2

The final result of the SDP scheme (a)-(c) is the set of future cost functions $\alpha_{t+1}(v_{t+1})$ for each stage t. Note that the calculation of this function requires the representation of *joint* system operation, with full knowledge of the storage state and inflows of all hydro plants in the system - the FCF is a *non-separable* function of hydro plant states.

D. Dynamic Market Simulation Approach

The simulation of a hydrothermal system with hydro plants as price makers using a Cournot market model is analogous to the minimum cost simulation. Ref. [7] is one of the first works on modelling hydro operation in deregulated markets using Dynamic Programming. In our SDP model, for each stage (t=T,T-1,…1), storage level (0%, ..., 100%) and hydrological scenario, we simulate the bidding process dynamic for the hydro plants as a non cooperative game. Each plant tests an amount of energy produced (turbined inflow) that maximizes the sum of its immediate revenue with an expected value of its future revenue, supposing it knows the bidding decisions of its “rivals”. The game ends when a situation of equilibrium point is obtained, the Nash equilibrium. It reflects a situation that no plant has the incentive to modify its energy production because such decision would incur in a decrease of revenues. The SDP recursion proceeds therefore like the same scheme of the SDP described in the previous section, just containing an additional procedure whose purpose is to simulate the competitive process between the hydro plants. Reference [1] has the details on the implementation of this extended SDP. Fig. 3.4 illustrates step (b) of the traditional SDP scheme adapted to consider the bidding scheme:

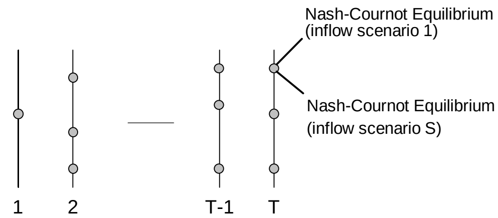

Fig. 3.4 – Optimal Decisions – last stage

It is also important to observe that while there are individual future benefit functions for each plant in the Cournot model, the minimum cost model has a single future cost function for the whole system (function of the storage state of all hydro plants in the system), as the objective of the operation is the minimization of total system costs.

E. Case Study

Previous concepts will be illustrated in a case study with operating data taken from the Brazilian Southeast system. The price maker agents are two hydro plants, A and B, whose characteristics are shown in Table 3.1. Price takers comprise 23 thermal plants, totaling 8210 MW of installed capacity.

Table 3.1 – Hydro Plant Characteristics

Name	Capacity (MW)	Max. Storage (Hm^3)	Production Coeff. ($MWh/m^3/s$)
A	1312	22950	0.745
B	4082	34432	0.383

The Nash-Cournot SDP recursion was calculated for a planning horizon of 3 years with monthly steps. Five additional years were added to the end of the horizon, in order to avoid the emptying effect of the reservoirs. Once the future revenue functions were calculated by the extended SDP scheme, system operation was simulated for 1000 streamflow scenarios. Nash equilibrium was reached in most of the iterations. However, in some of them we experienced multiple Nash equilibria. In these situations, the selected equilibrium was the one that had the highest revenues for both hydro plants. When it was not possible to choose such points, because different plants "preferred" different equilibria, we randomly chose any of the multiple equilibria obtained. This choice was made in 4% of the iterations.

A least-cost operating policy with subsequent simulation was carried out with the same data and for the same streamflow scenarios to allow the measuring of market power. Fig. 3.5 shows the expected monthly spot prices in Brazilian R$/MWh for the Nash-Cournot and least-cost simulations along the planning period. We observe that the hydro plants were able to substantially increase the system spot prices.

Fig. 3.6 shows the total hydro energy production for the Nash-Cournot (competitive) and least-cost cases. The inflow energy is also plotted. We observe that the hydro plants not only reduce their production but also decrease the water transfers from wet to dry seasons.

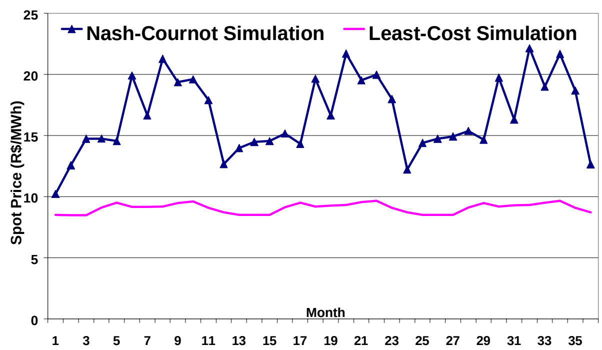

Fig. 3.5 – Nash-Cournot and Least-Cost Spot Prices

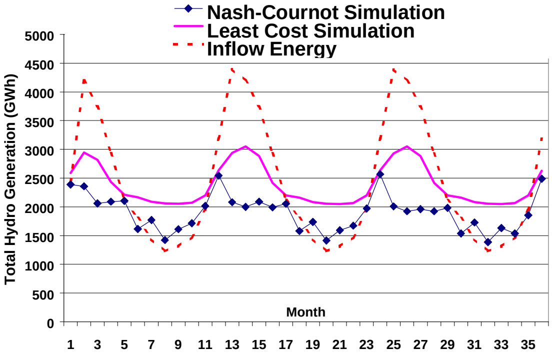

Fig. 3.6 – Nash-Cournot and Least-Cost Hydro Generation

IV. MITIGATORY MEASURES ANALYSIS

Given the negative effects of market power to society, regulators must be able to evaluate mitigating options, such as demand elasticity, competition, price caps, etc. In this work we will analyze the use of long-term bilateral contracts between generators and loads to minimize market power.

A. Price Volatility in Hydrothermal Systems

An important obstacle observed in the practical implementation of those market-oriented schemes in hydrothermal systems is the *uncertainty* of revenues from WEM sales. Predominantly hydro systems such as Brazil's present a fairly small short-term volatility but an extremely high mid-term volatility. Given that most of the plant's financial obligations are fixed (e.g. personnel, loan payment etc), this revenue volatility affects the plant's financial balance and its rate of return. The reason for the reduced short-term volatility is that system reservoirs can easily transfer hydro energy from off-peak to peak hours, thus modulating load supply and equalizing prices. The reason for mid-term volatility is that predominantly hydro systems are designed to ensure load supply under adverse hydrological conditions, which occur very infrequently. As a consequence, most of the time there are temporary energy surpluses, which imply in very low spot prices. However, if a very dry period occurs, spot prices may increase sharply, and even reach the system rationing cost. Due to reservoir storage capacity, these low-cost periods not only occur frequently but can last for a long time, separated by higher-cost periods, caused by droughts [4,5]. As a consequence, price distribution in each month is very skewed. Simulations with the Brazilian system show that there is a probability of 70% that prices in a given month are below average and a probability of 40% that they're actually zero. In contrast, there are a few simulated scenarios where spot price exceeds $300/MWh.

In order to hedge against the very high price volatility in hydrothermal systems, generators have the incentive to sign bilateral contracts. These contracts, as will be seen in the next section, can greatly reduce the risks of having market power. Some generation companies located in countries with significant hydro participation, specially in Central and South America do have some of their energy sold directly to the spot market. Therefore, although reduced, the potential for market power is not eliminated.

B. Bilateral Contracts

A forward contract defines that some asset will be delivered at a given time in the future at an agreed price and in a defined location[6]. Suppose that a generator/load pair has a x MWh bilateral contract priced at $\$p_c$/MWh for month t. When this month arrives, the actual generator production is E MWh, the actual consumption is D MWh and the system spot price is $\$p$/MWh. The net generator revenue R_g and load payment P_d are given by:

$$R_g = pE + (p_c - p)x \qquad (4.1)$$

$$P_d = p\,D + (p_c - p)x \qquad (4.2)$$

The first term of (4.1) and (4.2) represents the generator revenue (load cost) resulting from the sale (purchase) of its production (consumption) in the spot market. The second term represents the contract settlement, where the generator receives (load pays) for the contracted energy amount, valued at the *difference* between spot and contract prices. Note from (4.1) that the more the generator is contracted, the more it is indifferent to the spot price. Therefore, the use of bilateral contracts can be an interesting regulatory instrument to minimize market power.

C. Modeling Bilateral Contracts

Bilateral contracts can be included in the market power model from section II by replacing the expression (2.4), which gives the revenue of a strategic agent, by an expression similar to (4.1) that incorporates the bilateral contracts in its revenue. Following the previous notation, for a generator i, this expression is given by:

$$R(i) = p(Q)E(i) - c(i)E(i) + x_i[p_c(i) - p(Q)] \qquad (4.3)$$

From (4.3), expressions for total price maker production Q^m and spot price p^m can be easily derived, using the same methodology of section II. In particular, when all price makers have the same operating cost c, and same amount of bilateral contracts x, these expressions are given by:

$$Q^m = \frac{N}{N+1}(D - \alpha c + x) \qquad (4.4)$$

$$p^m = \frac{D - Nx + \alpha Nc}{\alpha(N+1)} \qquad (4.5)$$

Expression (4.4) shows that the total energy production of the price makers increases with the amount of contracts and spot price decreases (4.5). In the special case where the agents are fully contracted ($x = E(i)$), Q^m = D-$\alpha\,c$ which is equal to the expression (2.12), that gives the total price maker production obtained in the least cost dispatch.

D. Market Simulation with Bilateral Contracts

The use of bilateral contracts to reduce market power in hydrothermal systems was also analyzed through SDP. The Nash-Cournot equilibrium was simulated through an extension of the SDP approach, for which each agent tries to maximize the sum of spot and contract revenues. This issue was analyzed with data from the case study 2.4. Fig.4.1 shows three curves: expected monthly spot prices in Brazilian

R$/MWh for the planning horizon for: i) least-cost dispatch, ii) the Nash-Cournot *with* contracts and iii) the Nash-Cournot *without* contracts.

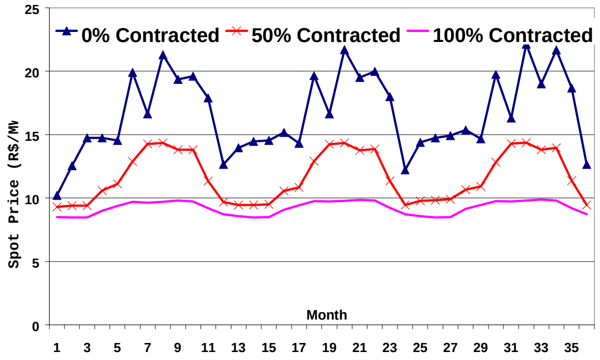

Fig. 4.1 – Nash-Cournot and Least-Cost Spot Prices

Once more, it can be seen that spot prices decrease as the amount of contracts signed by the generators increases. In particular, when generators are 100% contracted, spot prices match those obtained in the least cost dispatch. Figure 4.2 presents the total production of hydro plants in the Nash-Cournot and least-cost cases.

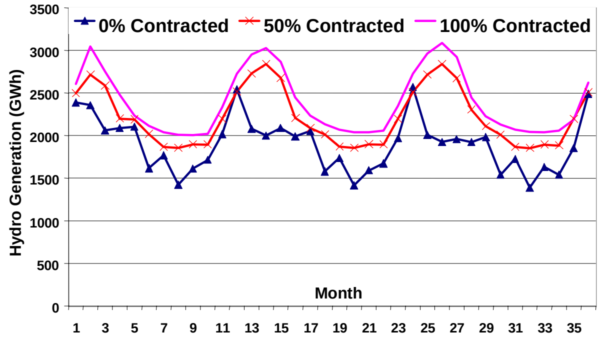

Fig. 4.2 – Nash-Cournot and Least-Cost Hydro Generation

V. CONCLUSIONS

- One obstacle to the efficient implementation of competitive environments is market power. Simulations with an analytical *static* market model with strategic producers show that the total output produced is smaller from the least-cost solution by a factor of $N/(N+1)$. As more agents are introduced in this market (making the market more competitive), the Nash-Cournot solution converges to the least cost solution. With a large number of agents both spot prices and total output produced are similar to the values obtained in a least cost dispatch.

- In a *dynamic* market model, where the hydro plants try to maximize the sum of their immediate and future revenues, the problem was handled through an extended SDP scheme. It was shown that the strategic hydro plants increased spot prices by decreasing the water transfers from wet to dry seasons.

- The use of bilateral contracts as an instrument to reduce market power was also analyzed. It was shown that, both in the static and dynamic market models, market power is reduced as the total amount of contracts for generators increases. Contracts are expected in hydro based systems because of high mid-term price volatility.

VI. REFERENCES

[1] Barroso, L.A.N.– *Competitive Schemes in Hydrothermal Systems: Strategic Behavior of Agents in a Market Environment*; M.Sc Thesis, IM/UFRJ, May 2000.

[2] Borenstein, S.; Bushnell J. and Knittel, C. – *Market Power in Electricity Markets: Beyond Concentration Measures*, PWP-059R, UCEI, February 1999

[3] Fudenberg, D. and Tirole, J.– *Game Theory*, MIT Press, Fifth Printing (1996)

[4] Pereira, M.; Campodónico,N.; Kelman,R. – *Long term Hydro Scheduling based on Stochastic Models*, Proceedings of EPSOM ’98, Zurich, September 1998.

[5] Kelman, R.– *Competitive Schemes in Hydrothermal Systems: Economic Efficiency and Strategic Behaviour*; M.Sc Thesis, COPPE/UFRJ, August 1999.

[6] Hunt, S.; Shuttleworth G.– *Competition And Choice in Electricity*, Wiley, 1996

[7] Scott,T.;Read,E.– *Modelling Hydro Reservoir Operation in a Deregulated Electricity Market*, ITOR 3 (3-4):243-253, 1996

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