INFLUENCE OF ANN-BASED MARKET PRICE FORECASTING UNCERTAINTY ON OPTIMAL BIDDING

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Abstract - In today's deregulated markets, forecasting energy prices is becoming more and more important. In the short term, expected price profiles help market participants to determine their bidding strategies. Consequently, accuracy in forecasting hourly prices is crucial for generation companies (GENCOs) to reduce the risk of over/underestimating the revenue obtained by selling energy.

In this paper, the influence of the accuracy of ANN-based hourly energy price forecasting on the bidding strategy of GENCOs is assessed. First, a customized, recurrent Multi-layer Perceptron is developed and applied to the 24-hour energy price forecasting problem, and the expected errors are quantified. Then, price profiles are used to compute the optimal bidding of realistic GENCOs, and the influence of forecasting errors on both the bidding strategies and the expected revenues is studied.

Keywords - Artificial neural networks, energy price forecasting, competitive markets, optimal bidding

1 INTRODUCTION

THE new competitive Spanish Electricity Market has been in operation since 1998, and it is mainly based on two separated day-ahead markets [7]:

- The energy market, managed by the Market Operator (MO), where producers and consumers submit production and consumption bids (blocks of hourly energy and the corresponding price in Euros/MWh). The MO produces a market-clearing price and sets of accepted production and consumption bids for every hour. Constraint management is subsequently performed by the System Operator (SO), taking also into account the scheduled bilateral contracts and adjusting the result of the energy market to avoid transmission congestion. Furthermore, additional markets for minor adjustments are also performed on an hourly basis.

- The market for regulation reserves. Once the energy market and the subsequent constraint management procedure are finished, the SO establishes the requirements for operating reserves (an hourly band in MW up and down) that are needed for frequency control for each of the 24 hours of the following day. The reserve market allocates the bands among the generators that are capable of providing secondary frequency control by using generators' up and down bids which include the offered band (MW) and the price (Euros/MW). A market for additional energy reserves (power that can be provided within 15 minutes for a period of two hours) is also performed.

In this context, forecasting energy prices is extremely important. In the short term, expected price profiles, both in terms of energy and reserve prices, help market participants to determine their bidding strategies. Consequently, accuracy in forecasting hourly energy & reserve prices is crucial for generation companies (GENCOs) to reduce the risk of over/underestimating the revenue obtained by selling energy.

The motivation of this paper is twofold: First, two customized Multi-layer Perceptrons are developed and applied to the 24-hour energy and reserve price forecasting problems, respectively, and the expected errors are quantified. Secondly, price profiles are used to compute the optimal bidding of several realistic GENCOs, and the influence of forecasting errors on both the bidding strategies and the expected revenues is presented. The objective is to compute the commitment schedule and the hourly generation profile of the GENCO in order to maximize the expected benefit from selling both energy and reserve to the corresponding markets [2].

2 ANN-BASED MARKET PRICE FORECASTING

As stated before, this paper is not aimed at developing the best market price forecasting technique, but to assess how relevant the forecasting errors are, so far as the benefits of a GENCO are concerned.

The ANN approach has been chosen because of its successful performance in the load forecasting problem [3, 4]. Larger errors are expected in this case, however, as the influence of the load level on market clearing prices is only moderate, and other unpredictable factors play an important role in non-perfect oligopolistic markets.

Usually, it is mandatory for GENCOs to provide the secondary regulation service, for which there is an additional income. Therefore, in order to prepare the day-

ahead bid, an estimation of prices for this complementary service must be available, in addition to energy prices.

The study reported in this paper is based on the hourly Spanish energy and secondary regulation prices recorded from January 2001 to August 2001. As weekends and holidays constitute separate cases, only data corresponding to working days have been retained and analyzed.

Figures 1 and 2 show the hourly averages and standard deviations (s.d.) of both prices for the working days of March 2001, in cents of Euro per kWh and cents of Euro per kW respectively. Average spot prices larger than 2 cent/kWh take place during the morning and evening peak hours (10am-2pm and 8-10pm respectively). Except for a few valley hours, the s.d. of this price exceeds 20% of the mean value, reaching even 40% at 8pm and 9pm. Note that the s.d. of regulation market price is, in relative terms, much higher than that of the energy market price, which means that this factor is less predictable.

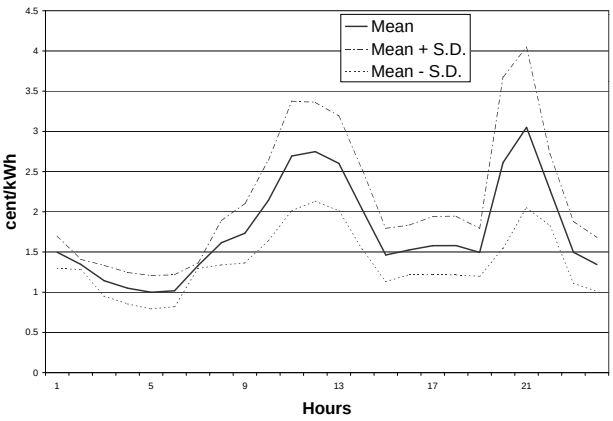

Figure 1: Hourly average of spot market prices for March 2001.

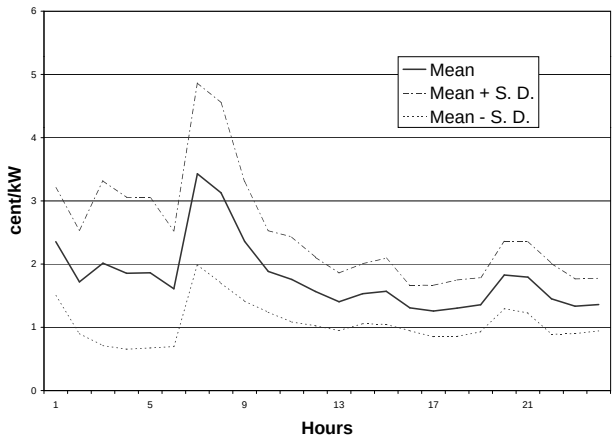

Figure 2: Hourly average of secondary regulation prices for March 2001.

Figure 3 represents the energy prices for two selected days of March 2001. The significant differences in the prices of the peak hours can not be explained by a change in the demand profile, probably revealing market power mechanisms.

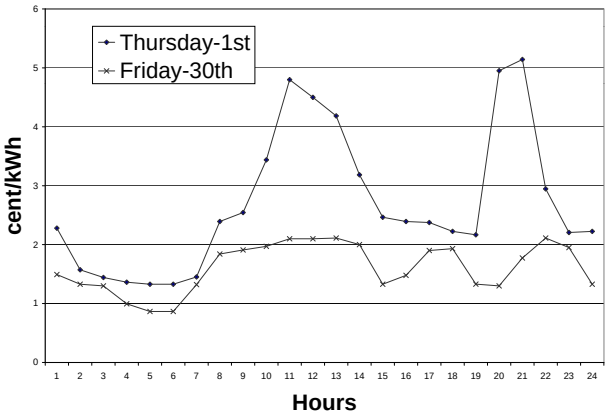

Figure 3: Evolution of energy prices for two days of March 2001.

2.1 Structure of the ANN

A brief description of the ANN adopted in this work is provided in this section (the reader interested in ANN background is referred to [5] and [6]).

An ANN is composed of a certain number of perceptrons organized by layers. Each perceptron has several inputs and a single output, whose value is a non-linear function of the inputs. Each perceptron's input is affected by a weighting factor, which must be determined during the training phase. Usually, an ANN is composed of three layers (input, hidden and output), where the outputs of a layer feed the inputs of the next layer.

The two main steps involved in the use of an ANN are:

- Determining its topology, which basically consists of defining the number of perceptrons in the intermediate hidden layer.
- Obtaining the input weighting factors for a given non-linear function (training process).

According to authors' previous experience, it is decided to feed the ANN with a shifting window of prices comprising 24 hours. This means that the input layer is composed of 24 perceptrons. As far as the number of output perceptrons is concerned, two possibilities have been evaluated [6]:

a) A single output whose value is dictated by the previous 24 hours. Under this scheme, very popular in load forecasting, the window is shifted one hour each time.

b) Twenty four outputs corresponding to the prices of a whole day, whose values are determined by those of the previous day. This implies that the window is shifted 24 hours each time.

Test results have shown better accuracy for scheme b), which is the only one considered in the sequel [6].

In order to fully define the ANN, it is necessary to determine the number of perceptrons in the intermediate layer and the number of days required for the training process. Figure 4 shows, for 12, 24 and 36 neurons in the hidden layer, the average forecasting error in the energy price

corresponding to the working days of February 2001, a representative month, versus the number of days used to train the ANN. As can be noted, 20 days are sufficient to train the ANN, the number of neurons not being so important. Similar conclusions are reached for the ANN devoted to forecasting the spinning reserve price. For the results presented below, 24 and 12 neurons in the hidden layer have been used to forecast the spot market energy and reserve service prices, respectively, and the actual prices of the 20 previous days are used to train the ANNs to predict the next day.

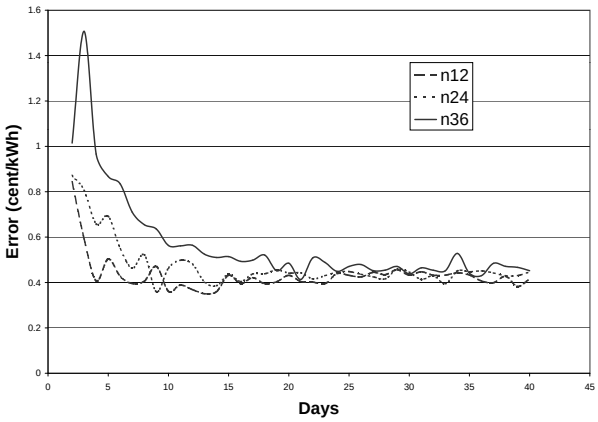

Figure 4: Average forecasting error in the energy price.

2.2 *Results*

About two months of the available period (January - February 2001) are used in several experiments to find out and tune the best ANN topology, while the remaining material (March-August 2001) is devoted to check the forecasting errors and to perform the market simulations of the second part of the paper.

Figure 5 presents the absolute value of the error of the forecasted spot market prices for the two days of March 2001 leading to the largest and smallest average errors.

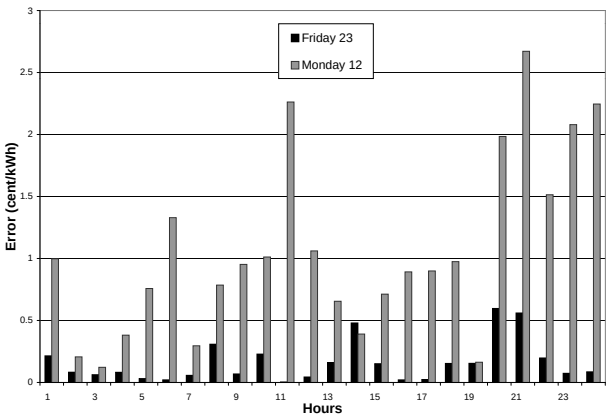

Figure 5: Absolute value of the error of the forecasted energy prices.

Figure 6 shows the hourly average of the forecasted energy prices corresponding to March 2001, as well as the resulting prediction errors (obtained by difference with the actual prices of figure 1). Note that the forecasting errors are larger during peak hours. Figure 7 provides the same information for the price of the reserve service.

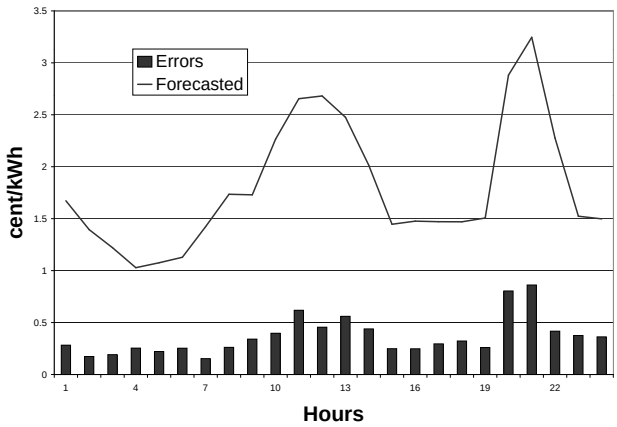

Figure 6: Hourly average of the forecasted energy prices (March 2001).

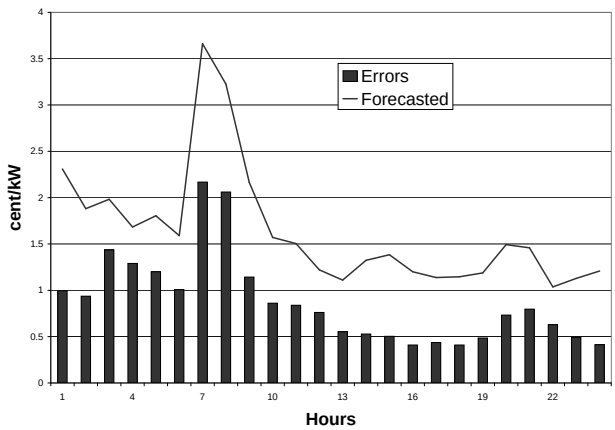

Figure 7: Hourly average of the forecasted reserve prices (March 2001).

Finally, tables 1 and 2 present the average and s.d. of actual prices, the average of forecasting errors and the maximum errors for Spring and Summer seasons. For the spot market price, the average error ranges from 12% (Summer) to 15% (Spring) of the hourly average price. As expected, the larger the s.d. of prices the higher the average forecasting error. Note that regulation price errors are rather high, obviously due to the influence of external factors such as unit failures on the reserve market.

	Daily Prices (cent/kWh)			
	Average real price	s. d.	Average absolute errors	Maximum errors
March-May	2.2588	0.7801	0.3464	2.671
June-August	3.5482	1.0597	0.428	2.0736

Table 1: Forecasting errors for the energy prices.

	Frequency Regulation Service (cent/kW)			
	Average price	s. d.	Average absolute errors	Maximum errors
March-May	0.7965	0.9864	0.5309	5.12
June-August	0.5986	0.4471	0.4916	4.49

Table 2: Forecasting errors for the reserve prices.

3 OPTIMAL BIDDING OPTIMIZATION PROBLEM

After obtaining the forecasted energy and reserve price profiles, the GENCO must determine the optimum commitment and hourly generation schedule in order to maximize the expected benefit from selling both energy and spinning reserve. In this paper, perfect competition is assumed, and, in consequence, no GENCO has the possibility of modifying the market clearing prices. After computing the optimal hourly generation scheduling based on the forecasted prices, the GENCO may choose to offer the scheduled energy at zero price to ensure that the offer will be accepted, or to offer the energy at marginal cost, as Game Theory recommends. If the GENCO has market power, the optimization problem must reflect its capability to modify the market-clearing prices by controlling the total amount of energy and reserve offered [8].

The optimal generation scheduling problem can be posed as a mixed-integer linear programming model as proposed in [2], allowing complex operating costs to be modeled, e.g., non-convex cost functions and exponential start-up and shut-down costs, along with operating constraints such as ramp limits.

3.1 Objective Function

The total benefit of a GENCO over a 24-hour scheduling period, given the energy and spinning reserve hourly prices, λ_t and μ_t respectively, is defined by

$$\begin{aligned} B_T &= \sum_{t=1}^{24} \lambda_t \cdot P_t + \mu_t \cdot (\overline{P}_t - P_t) \qquad (1) \\ &- \{C(P_t) \cdot U_t + UC(S_t) \cdot Y_t + DC \cdot Z_t\} \end{aligned}$$

where P_t is the average generated power at hour t, $C(P_t)$ is the operating cost, $\overline{P}_t$ is the available maximum power at hour t, S_t is the number of hours the thermal unit has been shut-down at the end of hour t, $UC(S_t)$ is the start-up variable cost, DC is a shut-down fixed cost, U_t, Y_t and Z_t are 0/1 variables which are equal to one if the thermal unit is committed at hour t, started-up or shut-down at the beginning of hour t, respectively.

3.2 Constraints

The maximization of the objective function is subject to the following constraints ($t = 1, \ldots, 24$):

- Upper and lower generation limits:

$$P^m \cdot U_t \leq P_t \leq P^M \cdot U_t \qquad (2)$$

- Maximum up and down ramps:

$$\begin{aligned} \overline{P}_t &= \min\{P^M \cdot (U_t - Z_{t+1}) + SD \cdot Z_{t+1}, \\ &\quad P_{t-1} + RU \cdot U_{t-1} + SU \cdot Y_t\} \qquad (3) \\ \underline{P}_t &= \max\{P^m, P_{t-1} - RD \cdot U_t\} \qquad (4) \end{aligned}$$

where $\underline{P}_t$ is the minimum generated power at hour t, P^M and P^m are the maximum and minimum power of the thermal unit, RU and RD are the maximum up and down ramps, SU and SD are the maximum start-up and shut-down ramps, respectively.

- Minimum up and down times:

$$\begin{aligned} (X_{t-1} - UT) \cdot (U_{t-1} - U_t) &\geq 0 \qquad (5) \\ (S_{t-1} - DT) \cdot (U_t - U_{t-1}) &\geq 0 \qquad (6) \end{aligned}$$

where X_t is the number of hours the thermal unit has been on at the end of hour t, and UT and DT are the minimum up and down times.

- Logic constraints:

$$\begin{aligned} Y_t - Z_t &= U_t - U_{t-1} \qquad (7) \\ Y_t + Z_t &\leq 1 \qquad (8) \\ X_t &= [X_{t-1} \cdot (1 - Y_t) + 1] \cdot U_t \qquad (9) \\ S_t &= [S_{t-1} \cdot (1 - Z_t) + 1] \cdot (1 - U_t) \qquad (10) \end{aligned}$$

The above model is solved by using the CPLEX optimization module under GAMS [1].

4 TEST RESULTS

The optimization model described in the former section is used in conjunction with the ANN-based forecasted prices to assess the benefits of two different GENCOS, whose main parameters are shown in table 3. Fuel costs have been scaled so that the incremental cost of generators equals the average market price and half the average price, respectively. Start-up costs are functions of the time the generator have been shut-down, with time-constants of 2 and 12 hours. Finally, start-up and shut-down ramp rates have been equalled to the normal up and down ramp limits, and no minimum up or down time constraints have been imposed.

The results reported below refer to March 2001, considered a representative month.

GENCO	Economical data	
	$C(P_t)$ (Euros/h)	UC (Euros)
Gas-turbine	$594.58 + 29 \cdot P_t$	$6541.7 \cdot (1 - \mathbf{e}^{-\frac{S_t}{2}})$
Coal-fired	$359.5 + 14.5 \cdot P_t$	$12588.6 \cdot (1 - \mathbf{e}^{-\frac{S_t}{12}})$

GENCO	Technical data			
	P^m	P^M	RU	RD
	(MW)		(MW/h)	
Gas-turbine	100	350	350	350
Coal-fired	100	350	50	50

Table 3: GENCOs main technical and economical data.

4.1 Case A: Conventional coal-fired generator

This unit takes several hours to fully start up and its fixed cost is high. However, its variable cost is about one half of the average market clearing price. In past regulated markets, this would have been a base unit usually working at rated power.

Figure 8 compares the total daily benefits obtained with forecasted prices with those that would have been obtained if actual prices had been known in advance. The monthly average difference is 7.7%, the largest deviation taking place on March 12 (please note that, as weekends are excluded from the analysis, this is day #8 in the figures). As shown in figure 5, this is also the day leading to the largest energy price forecasting error. Note that the benefit obtained with perfect information is always larger than or equal to the profit achieved from forecasted prices. This is not the case, however, when profits are analyzed at the hourly frame, because the objective function considers the daily period as a whole.

Figure 9 represents the hourly profit based on forecasted prices (right) and the scheduled energy (left) on March 1. Except for the valley hours, the unit maximizes its profit at rated power. Another exception arises at 7pm, when the income from the regulation service is so high that it is better for the unit to reduce the scheduled power. In order to assess the influence of the reserve income on the optimal bidding strategy, the experiment is repeated by ignoring this term in the objective function. As shown in figure 10, the profit decreases during some valley hours and at 7pm, in spite of the increased generated energy. However, this kind of units are not significantly influenced by this income component, as the profit reduction for the scheduling shown in figure 10 is only 2%.

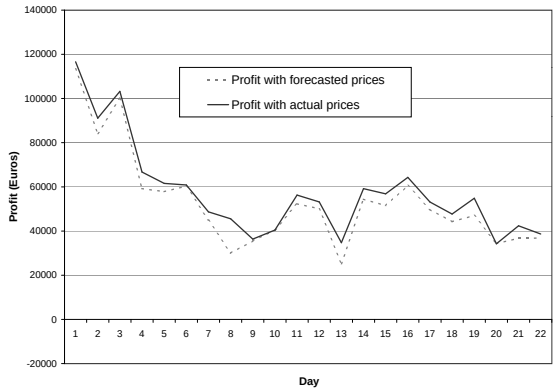

Figure 8: Total daily benefit of the coal-fired generator.

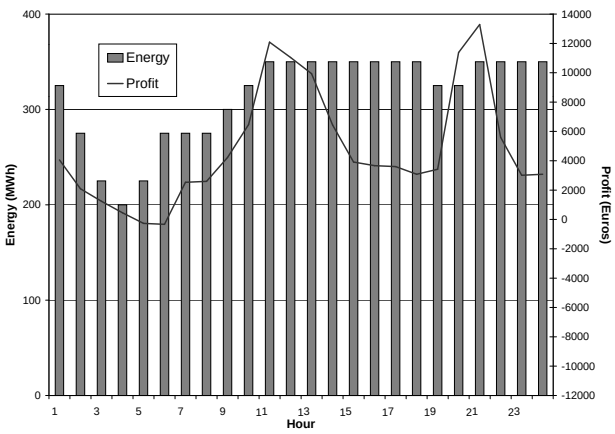

Figure 9: Hourly benefits and scheduled energy of the coal-fired unit.

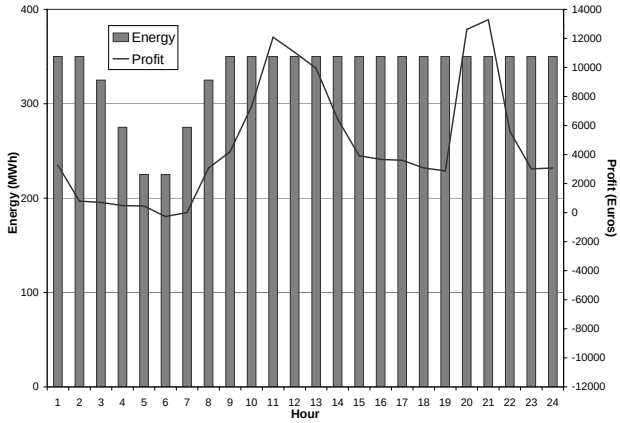

Figure 10: Hourly benefits and scheduled energy of the coal-fired unit. Reserve incomes not considered.

4.2 Case B: Gas-turbine generator

This is a fast-acting, high average cost unit whose optimal bidding strategy is quite different from that of Case A.

Figure 11, the counterpart of 8, shows that the profit attained with forecasted prices is very similar to that obtained if exact prices were available the day before, except for days #8, 13, 14, and 15. As discussed in Case A, unexpectedly high energy price forecasting errors are responsible for this deviation on March 12 (day #8). However, the large profit gap observed on days #13 to #15 is fully attributable to the extremely high uncertainty that took place in the reserve price during these days. This is confirmed by the fact that the net income is nearly indistinguishable from the one obtained with exact prices, when exact prices are adopted for the regulation service only (third series in figure 11).

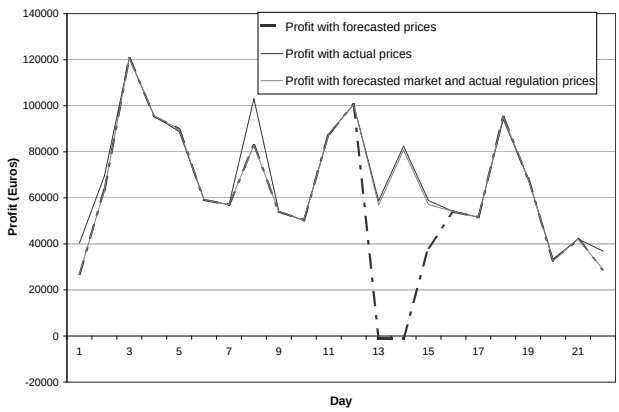

Figure 11: Total daily benefit of the gas-turbine generator.

As in Case A, the scheduled energy and profit achieved with forecasted prices on March 1 is shown in figures 12 and 13, with and without consideration of the income arising from the reserve service, respectively. Unlike in Case A, the profit difference between both situations is very important. When the objective function takes into account the regulation service income (figure 12), the unit is dispatched most of the time at minimum power. Only at peak hours does the energy price justify maximum power. Note

that the net income is negative from 4 to 7 am, in spite of which the unit is not shut-down. The total profit in this situation is 40300 Euros.

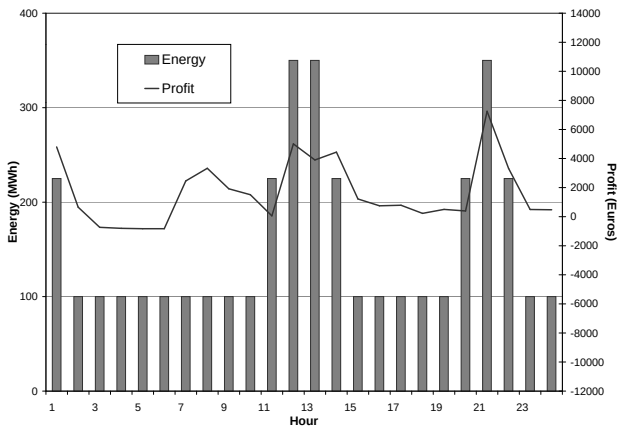

Figure 12: Hourly benefits and scheduled energy of the gas-turbine unit.

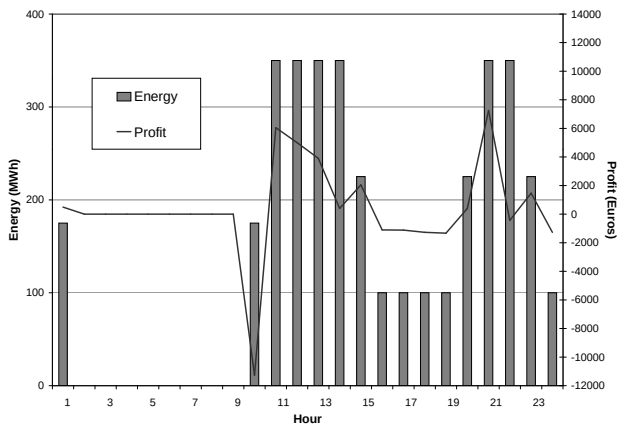

Figure 13: Hourly benefits and scheduled energy of the gas-turbine unit. Reserve incomes not considered.

When the regulation service income is ignored in the optimization model, the unit starts up only at 9am, and the total profit reduces to 10000 Euros. This suggests that about 3/4 of the net profit for this unit is due to the reserve income. Therefore, in cases like this, the uncertainty in the reserve clearing prices may have a significant influence on the overall profit.

5 CONCLUSIONS

This paper addresses the influence of the accuracy of ANN-based hourly energy price forecasting on the bidding strategy of GENCOs. First, two customized Multilayer Perceptrons have been applied to the 24-hour energy and reserve price forecasting problems, respectively, using real data of the Spanish energy and reserve markets. For the energy market price, the average error ranges from 12% (Summer) to 15% (Spring) of the hourly average price, errors being much higher in the reserve price forecasting, as expected. Secondly, forecasted price profiles have been used to compute the optimal bidding of two realistic GENCOs, a coal-fired generator and a gas-turbine plant, and the influence of forecasting errors on both the bidding strategies and the expected revenues have been presented.

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