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Forecasting of electricity prices with neural networks

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Abstract

During recent years, the electricity energy market deregulation has led to a new free competition situation in Europe and other countries worldwide. Generators, distributors and qualified clients have some uncertainties about the future evolution of electricity markets. In consequence, feasibility studies of new generation plants, design of new systems and energy management optimization are frequently postponed. The ability of forecasting energy prices, for instance the electricity prices, would be highly appreciated in order to improve the profitability of utility investments.

The development of new simulation techniques, such as Artificial Intelligence (AI), has provided a good tool to forecast time series. In this paper, it is demonstrated that the Neural Network (NN) approach can be used to forecast short term hourly electricity pool prices (for the next day and two or three days after). The NN architecture and design for prices forecasting are described in this paper. The results are tested with extensive data sets, and good agreement is found between actual data and NN results. This methodology could help to improve power plant generation capacity management and, certainly, more profitable operation in daily energy pools.

Keywords: Electricity prices; Energy prices forecasting; Energy management; Economics; Neural network

1. Introduction

Some European countries have recently completed their energy market deregulation. At present, the liberalized energy markets have led to a new free market where utilities, retailers and qualified end users daily launch demands and offers. By means of a trading system, the final electricity price is fixed. However, in economic studies performed for feasibility of new power plants, ancillary equipment, or for optimizing the installations management or even production planning, a new uncertainty parameter appears related to the evolution of market prices. Although the equilibrium price depends on specific electricity market rules, there are also other factors affecting the offer and demand prices, causing electricity prices to vary.

A key consequence derived from the electricity market rules is that the hourly electricity prices depend greatly on the demand. The electricity demand presents hourly, daily and seasonal oscillations, being also

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influenced by the economic activity and the gross domestic product (GDP) of the country. The monthly demand variation is caused, in part, by the seasonal evolution in climatic conditions that causes a different final electricity usage. The climate influence and other related factors are essential in order to determine the final electricity price that may fluctuate depending on the season and day and hour. The price variation may adversely affect utility incomes and final user costs. Therefore, it may be advisable to use prediction tools to take into account these variations in order to optimize the related equipment performance and to maximize utility profits.

In the literature, several papers that aimed to forecast demand evolution are easily found. On one hand, prediction of the short term energy consumption could allow the utilities to improve their cash flow [1]. On the other hand, a long term energy consumption forecasting has been reported [2] that could help utilities plan the next year's investments [2], but it is rare to find papers related to this subject in the literature. Researchers use assorted methodologies to develop these forecasting tools, from techniques trying to simulate complex demand waves by addition of simple waves [3] to highly developed statistical techniques that simulate non-linear behaviour [4]. The use of neural networks (NN), as the most representative technique of artificial intelligence (AI) or soft computing, is located between both techniques, since its conceptual simplicity does not avoid extraordinary results when used as a forecasting tool.

The main objective of the present paper is to examine the feasibility of NN systems in predicting the future values of electricity prices in a deregulated market using historical prices data and the prediction date. The paper is organized as follows. A description of the design and NN architecture is given in Section 2, including NN training and selection of input and output data for the set of NN simulations. Next, simulation results are discussed in Section 3, and finally, conclusions are given in Section 4.

2. NN applied to electricity pool prices forecasting

NN are soft computing techniques that emulate the biological connection between neurons. They are able to reproduce some functions of human behaviour, i.e., learning and reproduction of trends. NN are formed by a finite number of layers with different computing elements called neurons. The neurons are interconnected, building up a network. The design and structure of the connection arrangement determine the type and objectives of the NN. While radial basis neurons are applied in pattern recognition, perceptron multi-layer feedforward NN are usually used to reproduce temporal and future series. They provide good solutions to non-linear modeling of time series [5,6] and are adequate to forecast tendencies [7,8].

Since electricity price evolution exhibits non-linear behaviour, two different methods can be used to reproduce it. First, increasing the number of hidden layers allows increasing the degrees of freedom, and therefore, a wiggling effect could be obtained if necessary. However, this option could lead to over fitting. An alternative method consists of the use of intermediate layers with sigmoid neurons, where wiggling continues to be possible but with a lower number of degrees of freedom. To avoid discontinuities, the output layer contains lineal neurons.

Although the possibility of relating inputs and outputs by NN without knowing the internal relations is highly valued (black box models), it is also possible to build "grey box" models with NN. They are intermediate between "black box" models (any relation between inputs and outputs is ignored) and "white models" (all the connections between inputs and outputs must be expressed using equations) [9]. Previous analyses about input influence ranking are demonstrated to be essential for a correct and reliable operation of the simulator.

The methodology applied to develop NN could be theoretically divided into four stages: structure or architecture design, training, validation and use. Independent resolution of each stage is impossible in practical terms. From each stage, conclusions about how to improve the NN are extracted, frequently indicating the necessity of changing parameters of the previous steps. This operation causes exhaustive iterative work before establishing the definitive parameters of the NN. On line training is hardly advisable because quick and robust responses are not assured because of the impossibility of accurate and rigorous validation.

2.1. NN design and structure

The final aim of the developed NN is the simulation of the 24 h electricity pool prices that will be obtained the next day. Hence, the 24 outputs of the NN are defined.

Sometimes, NN models are described as a ‘‘black box’’ because they do not require any information about the functional relationships between variables. However, it is really important to introduce all the available qualitative information in the NN structure design. This paper pays special attention to the inputs selection. Irrelevant inputs have been reported to cause over fitting in the NN [6,9–11]. All the variables involved in electricity pool prices have been considered for the simulation. For example, in the present case, in order to distinguish between labour or festive days, the input ‘‘week day’’ adopts values between 1 and 7 (considering Monday as day number 1). With the aim of considering the weather influence and the population behaviour of the energy demand, the input ‘‘month’’ is introduced with values in the interval of 1–12 (starting from January). Normalization of the input and output data is a fundamental pre-treatment to be performed over the available data, which implies the transformation of the usual values into a new interval ranging from -1 to 1.

Electricity prices are influenced by a wide spectrum of situations derived from the deregulated market behaviour. Some of them can be taken into account in a way similar to the utilities current operation, an unexpected weather change or a power plant failure. However, these influences are difficult to evaluate numerically. Others are unpredictable and impossible to be introduced in the NN design. One solution is to simulate the expected maximum, medium and minimum prices for the day in three NN, with some actual previous values as inputs. In this case, 10 previous price values are taken into account in the NN design. The results are used as inputs to the main NN. Summarizing, there are five selected inputs: ‘‘week day’’, ‘‘month’’, ‘‘maximum value’’, ‘‘medium value’’ and ‘‘minimum value’’.

Two basic structures have been reported in the literature on the way of connecting inputs with outputs, The MIMO architecture (*Multi Input Multi Output*) and the MISO architecture (*Multi Input Single Output*). The MIMO architecture consists of a single NN where all the outputs are simulated at the same time with multiple inputs. This kind of NN architecture notably simplifies the NN development. However, since problems may arise, the results must be carefully validated. Given that outputs can depend on different inputs, or they can even depend on the same inputs but in a different way, the convergence strategy to calculate the weights and biases in the training process and the adjustment of an output over the rest can be irregularly favored. Use of the MISO architecture avoids those problems [5], but the same number of NN as the outputs must be developed.

The architecture proposed to simulate the hourly electricity pool prices is of the intermediate type. An analysis of the influence of the inputs on every output is made. Since the ranking of importance of each input in each output is established, the outputs can be grouped according to the most relevant input for simulation. Obviously, given that there are five inputs, five groups, called the most relevant input, appear. Four groups of outputs are simulated with the MIMO NN, while the fifth group is simulated with a MISO NN because only a single output is included.

The analysis of the influence of the inputs is time consuming and iterative, but it can be made using the NN’s own procedures. Five individual preliminary trainings are made for each output. An input is eliminated from each one and the mean square error (MSE) of the training process is registered. The higher is the influence of the absent input in the training, the higher is the MSE value, and the more important is the eliminated input variable to solve the problem [12]. Fig. 1 shows the results of the previous analysis results and indicates the input variables that most influence the electricity price. A noteworthy coherence with reality is disclosed. The electricity pool price in the hours included in the ‘‘weekday’’ set is known to depend strongly on labour days (9 a.m.) and weekends (1 and 2 a.m). ‘‘Month’’ is related to the peak demand caused by heating in the winter, which is not produced in the summer.

The general structure of the developed NN is shown in Fig. 2. Auxiliary NN used to forecast the maximum, medium and minimum values are also included. These NN are designed with 10 preceding values. It has been verified that including more data does not contribute to better forecasting. The possibility of feedback with the NN’s own generated values, allowing long term predictions, is an additional advantage of this kind of NN. This long term prediction must be strictly validated. In the case of electricity pool prices simulation, only a maximum period of 3 days between the actual day and the predicted day are being considered.

Once the elemental structure of the NN has been established, the next stage is to determine the number of hidden layers and the number of hidden neurons corresponding to each NN. The number of hidden neurons establishes the degrees of freedom of the NN. Obviously, the increase in the number of hidden neurons and, consequently, in the degrees of freedom, means more accuracy in the NN’s adjustment to the training data.

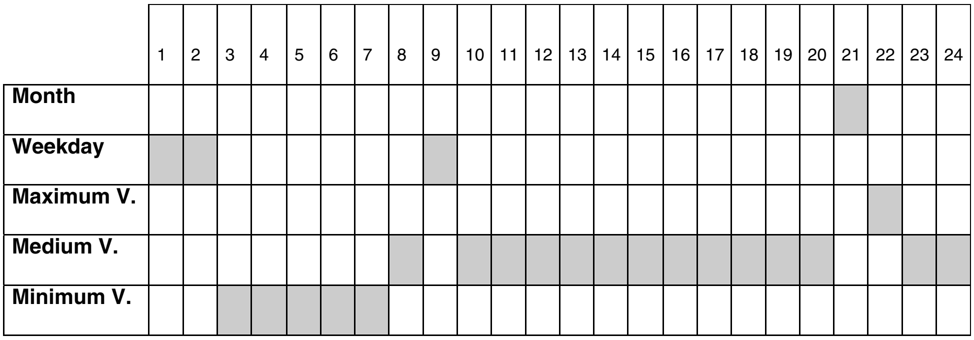

Fig. 1. Main input variables in the hourly electricity pool price.

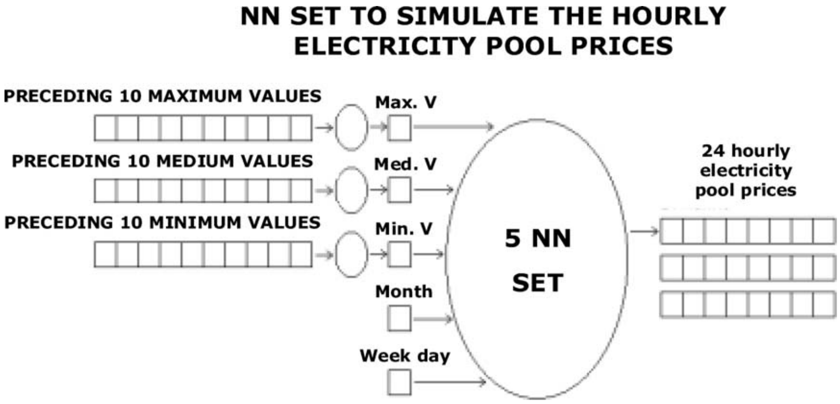

Fig. 2. NN general structure to simulate the hourly electricity pool prices.

However, over fitting can occur if the NN could memorize the training data. When the degrees of freedom are reduced, the NN improves its ability to generalize at the expense of the loss of detail in future simulations. Reaching equilibrium between both extreme situations is essential. The research effort is focused on the increase of details without unnecessary complexity [13]. The optimum number of neurons is determined in the training stage after successive trainings with different numbers of neurons.

2.2. NN training

NN training is an essential stage, since the implicit knowledge in the available training data is stored in the NN by neuron training. The recommended training method for the feedforward NN is called back propagation.

Available data to train and validate the NN include the years 1998, 1999, 2000, 2001 and 2002. Training with a given proportion of the total available data (for example, 75%), randomly selected, is reported to produce the best results in the validation stage. However, the aim of the model development in this paper is not only to obtain a correct simulator of the hourly electricity prices but also to establish a strong NN structure and define the robustness of a simulator of these characteristics. Hence, the data from 1998 to 2000 are used to train, while the data from the years 2001 and 2002 are used to validate.

The number of neurons is fixed in this stage using a constructive method. The training starts with a hidden neuron, after that, more neurons are added, one by one, and the training is repeated until the MSE improvement is less than 10% with respect to the MSE obtained in the previous training. This methodology avoids neurons that do not bring more information to be included. The final number of neurons of each NN is presented in Fig. 3.

	NN name	Outputs	Hidden neurons	Output neurons
Principal	Month set	21 h	3 neurons	1 neurons
	Week day set	1, 2, 9 h	3 neurons	3 neurons
	Maximum price set	22 h	2 neurons	1 neuron
	Medium price set	8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 23, 24 h	4 neurons	14 neurons
	Minimum price set	3, 4, 5, 6, 7 h	2 neurons	5 neurons
Secondary	Maximum price forecasting	Maximum price	3 neurons	1 neuron
	Medium price forecasting	Medium price	3 neurons	1 neuron
	Minimum price forecasting	Minimum price	3 neurons	1 neuron

Fig. 3. Neuron number in each NN of the global system.

A total number of 50 neurons are necessary to forecast the hourly prices of the next day. For long term forecasting, 12 neurons must be added for every new day, because more iterations are needed to solve the secondary NN.

2.3. NN validation

Every NN has been individually validated during the training stage, so the next stage is focused on validation of the whole NN system. There are two fundamental validation tests. Given the inputs, the first test consists of comparing the output generated by the NN compared to the actual values. When the validation inputs are the same as those used for training, the validation is called the re-substitution test. On the contrary, when the inputs come from data not used to train, the second validation type is called the resistance test. In both cases, the validation is evaluated by considering the differences that appear between the actual outputs and the simulated ones. The discrepancy can be more or less severe, showing the NN performance behaviour. Basically, the main potential error sources are three [11,14]:

- *Over fitting error:* it appears when the training adjustment is excessive. There are unnecessary degrees of freedom, meaning that more hidden neurons are used than required. Reducing the training data number, the NN memorizes them. This behaviour is produced when satisfactory results in the re-substitution test are observed, although the resistance test is not adequate. A NN with this feature has lost its generalization ability.
- *Bias error:* it is the opposite parameter. The degrees of freedom are reduced, and hence, the generalization ability is considered to have been excessively favored. The validation of the NN makes a considerable error in the re-substitution test as well as in the resistance test.
- Finally, the *noise* is an error associated with the data registration. In this case, it is not considered.

Once the validation criteria for the NN prices simulator are established, the results are presented in the following section.

3. NN simulation results

Re-substitution tests are made at the same time as the training process. A set of 1085 data has been used to train and to make the first validation. Evaluation of the re-substitution and resistance tests has been graphically made. The hourly data percentage reproduced with a smaller error than some error limits is shown in Figs. 4–8. Three different error limits have been fixed in order to observe their evolution. In the re-substitution test, the

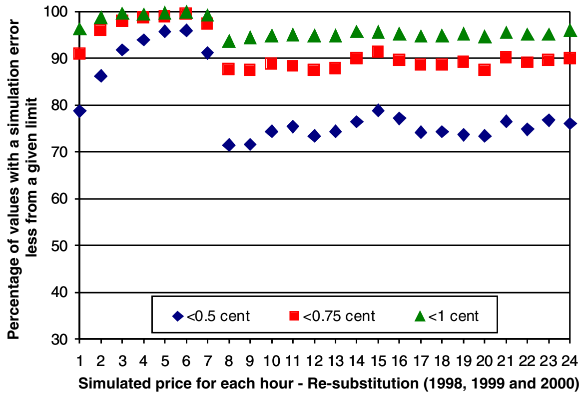

Fig. 4. Re-substitution error, as data percentage with an error less than a given limit.

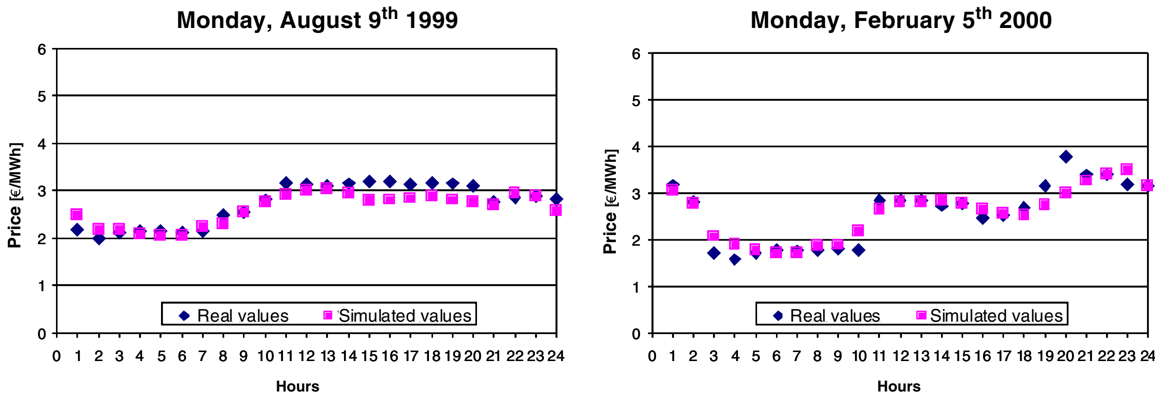

Fig. 5. Daily profiles of actual and forecasted hourly pool prices. Resistance test results.

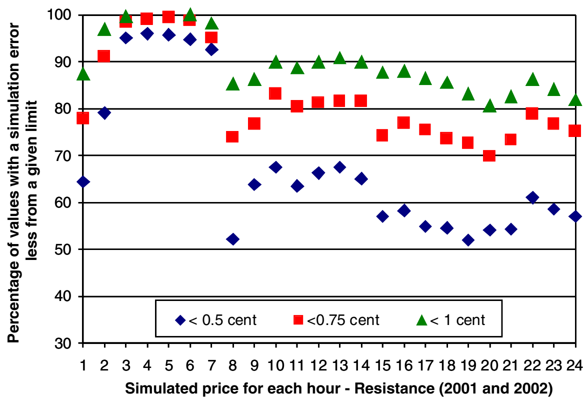

Fig. 6. Resistance error, as percentage of data with an error less than a given limit.

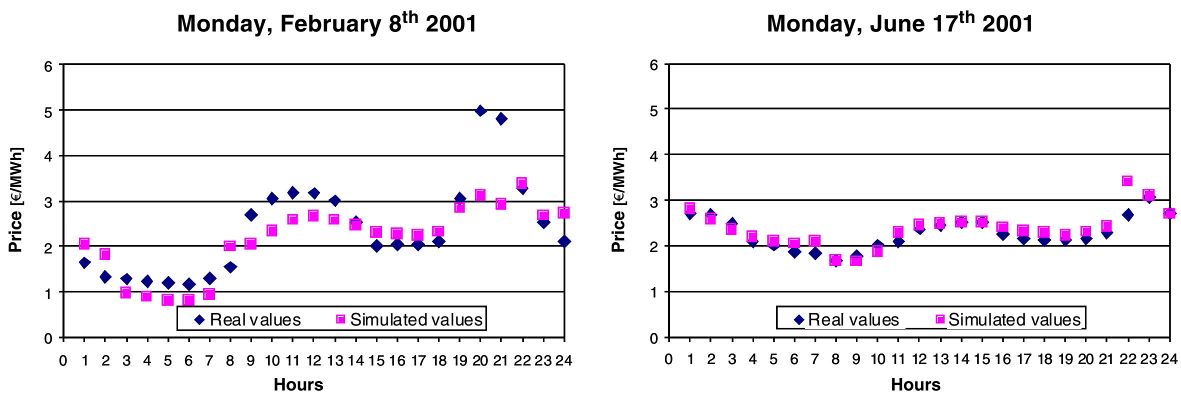

Fig. 7. Daily profiles of the actual and forecasted hourly pool prices.

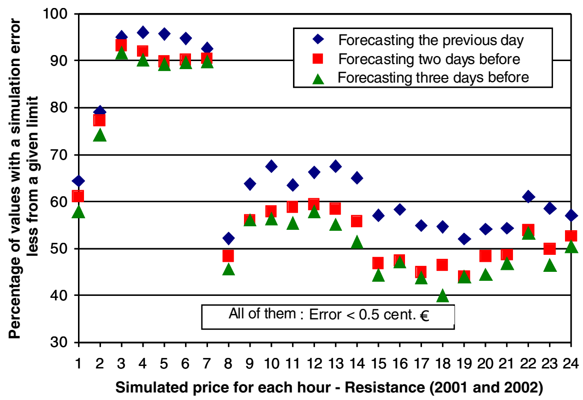

Fig. 8. Resistance error, as percentage of data with an error less than 0.5 c€ (one, two or three days of anticipation).

results are really positive. With the strictest error limit (less than 0.5 c€), more than 70% of the training data are simulated with errors below this error. With a less strict condition (error less than 1 c€), the percentage of valid simulation is over 90%.

The comparison between the actual prices evolution and the forecasted ones (resistance test) can be clearly shown in a daily graph (Fig. 5). Prices are registered in two randomly selected days, a summer labour day (Monday, August 9, 1999) and a winter non-labour day (Saturday, February 5, 2000). The combination of both price profiles demonstrates how the simulation follows the daily price evolution. However, typical characteristics related to the generalization ability of the NN also appear. The most significant feature associated with the simulation technique is the trend to smooth the curves, although the actual evolution was sharp. This feature can be even positive in other applications, for example in supervision systems where the deviation caused by the curves smoothing is considered as an error source. This behaviour is positive because any particular price peak is eliminated from forecasting.

Another example of resistance test results is shown in Fig. 6. They have the same features as those shown in Fig. 4. The data are slightly worse, but with the least strict limit (1 c€), the correct values are almost always near 90%. It should be pointed out that the inputs are completely unknown for the NN in this case. The resistance test results reveal a new problem. At first sight, it would be a good idea to use a NN trained with the data of previous years to reproduce the actual year prices, but a problem derived from the electricity prices augmentation is expected. NN simulators reach their best performance when they are used to interpolate data or to simulate situations close to training ones. However, it is reported that the NN simulators are not able to extrapolate for other situations. Since 2001–2002 prices are higher than those of the 1998, 1999 and 2000 years, the NN based simulator is expected to extrapolate data, given that the new inputs are out of the training input range. As expected, the simulator produces slight deviations.

Two days of the year 2001 have been randomly selected to compare the hourly actual and forecasted price profiles, which are shown in Fig. 7. The days are a winter labour day (Thursday, February 8, 2001) and a summer non-labour day (Sunday, June 17, 2001). The actual and forecasted prices are similar, and the data trends follow approximately the same curves. The same feature related to the generalization ability is observed in the resistance test. It is clearly seen that the average error is negligible and the particular errors are located at the price peaks.

3.1. Long term forecasting

Validation of the resistance of the NN price simulator has been made in order to study the possibility of forecasting the prices with two or three days of anticipation. A resistance test has been made using the inputs of the years 2001 and 2002. The results appear in Fig. 8. Once more, the results are obtained using new inputs (2000 and 2001 data) and the commented deviations are shown. The comparison has been made with the strictest condition (error less than 0.5 c€). The evolution of the error is similar to the previous days forecasting. It could be concluded that the principal problem is not the longer term forecasting but the error derived from the extrapolated input range. The results of a forecasting made three days before are admissible when they were compared with the prediction made just the day before.

4. Conclusions

Since electricity market deregulation, the knowledge of the electricity pool prices is fundamental to manage properly the energy systems based on electricity. Advanced simulation and forecasting systems have been frequently used to forecast the electricity demand in a short, medium or long term. Nevertheless, the use of comparable systems applied to forecast electricity pool prices has not been reported in the literature, although both problems seem to be related.

This paper demonstrates that NN can be suitably used to realize forecasting tasks, given its ability of simulating complex and non-linear processes and its capacity to forecast. The results show that the price is simulated with an error less than 1 c€ in 85% and less than 0.75 c€ in 75% of the simulations. Long term forecasting shows that 50–60% of the data are predicted with errors below 0.5 c€. The characteristic NN internal opacity is reduced, taking as input those variables that really influence the problem. It has been verified that the fragmentation of the initial problem into several elemental sub-problems favours coherent NN utilization.

The NN application to electricity pool prices forecasting performed in this paper proves that the training is possible. Simultaneously, the weak points of such a computational simulation have been revealed. Firstly, a slight deviation has been identified in the simulation of 2002 prices as compared to 2001 prices. The reason is the loss of reliability caused by the use of inputs out of the training range. Therefore, it is concluded that this kind of computational model should be revised every year in order to warranty its reliability. Finally, the typical NN trend to smooth the appearance of any simulation, avoiding sharp jumps, derives from a precision lost in the price simulation. Stacking NN methods could be a way to resolve these problems. A group of NN will be used to identify price peaks and others could be trained to simulate the typical error in these hours. The addition of the original forecasting price and the typical error will produce a more adjusted price.

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