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Applying Artificial Neural Networks to Forecast European Union Allowance Prices: The Effect of Information from Pollutant-Related Sectors

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Abstract: In this paper, we forecast the price of CO₂ emission allowances using an artificial intelligence tool: neural networks. We were able to provide confident predictions of several future prices by processing a set of past data. Different model structures were tested. The influence of subjective economic and political decisions on price evolution leads to complex behavior that is hard to forecast. We analyzed correlations with different economic variables related to the price of CO₂ emission allowances and found the behavior of two to be similar: electricity prices and iron and steel prices. They, along with CO₂ emission allowance prices, were included in the forecasting model in order to verify whether or not this improved forecasting accuracy. Only slight improvements were observed, which proved to be more significant when their respective time series trends or fluctuations were used instead of the original time series. These results show that there is some sort of link between the three variables, suggesting that the price of CO₂ emission allowances is closely related to the time evolution of the price of electricity and that of iron and steel, which are very pollutant industrial sectors. This can be regarded as evidence that the CO₂ market is working properly.

Keywords: European Union Allowances; price of CO₂ emission allowances; neural networks; forecasting

1. Introduction

The European Union Directorate-General for Climate Action (EU DG CLIMA) refers to the European Union Emissions Trading System (EU ETS) as a cornerstone of the EU's policy to combat climate change and its key tool for cost-effectively reducing greenhouse gas emissions [1]. The EU ETS was created in 2005 as a cap-and-trade system. The scheme includes only large stationary sources of emissions belonging to the most pollutant industrial sectors of the European economy—power plants, oil refineries, ferrous metallurgy, cement clinker or lime, glass (including glass fiber), ceramic products by firing, and pulp, paper, and board. Companies producing CO₂ emissions are supposed to effectively manage associated costs by buying or selling CO₂ emission allowances. They are allowed to trade allowances freely with one another within the EU. Therefore, the aim of the system is to ensure that overall emissions are reduced, as well as to encourage firms that can achieve the most efficient abatement costs to make cuts (European Commission, 2003).

The European rights to emit, the so-called European Union Allowances (EUAs), were asymmetrically distributed both in time and across sectors. The first phase (2005–2007) was a

trial period with a free allocation of allowances. Small-scale EUA auctioning for installations in specific sectors began during the second phase (2008–2012). In the third period, a further increase in auctioning at the expense of free allocation is expected [2]. Namely, at the end of 2019, the European Commission estimates that up to half of allowances may be auctioned throughout the period 2013–2020.

Economic theory suggests that the EU ETS can change the cost structure of enterprises, affecting their input mix choice, their optimal amount of production, or their investment decisions. Both current allowance prices and predicted EUA prices are critical for companies, and they can affect decarbonization investment decisions [3–6].

The question then arises: does the market price work properly? If so, the EU ETS could achieve its goal, that is, to give firms an incentive to move towards less fossil-fuel-intensive production. Time plays a crucial role in proper market operation, since external information could affect the price of CO₂ emission allowances depending on firms' capacity to change their input mix or decide on decarbonization investments. In the short run, EUAs might be perceived as financial assets due to the fact that companies are unable to adapt production to a change in fuel prices or to a new technical situation. In the long term, however, additional information could change agents' perceptions about prices based on firms' ability to adjust to a new environment. Therefore, predictions of the price evolution of CO₂ emission allowances are likely to be a valuable tool to help enterprises to make such decisions.

In this paper, we predict prices and analyze their accuracy over a wide time horizon ranging from 1 to 20 days. The tool selected to do this is a neural network. Neural networks take into account past data to forecast future prices. Additional information coming from sectors related to pollutant companies is then added to the forecasting model in order to find out whether it can explain (and reduce) errors in the forecasted future CO₂ prices. If additional variables improve the accuracy over a long period of time, this would suggest that the EU ETS is working properly, since firms would have enough time to manage production to change their decisions in view of allowance supply and demand or to make decarbonization investment decisions.

The tool used to forecast future allowance prices, neural networks, has been widely used in time series forecasting [7], as they are universal approximators [8], that is to say, they are able to reproduce the behavior of any dynamical system provided that a suitable network structure is defined.

Data from the second and third EU ETS phases were used to perform this study. This provides predictions for a large dataset in order to prove the robustness and accuracy of the forecasting process. In addition, the amount of sold and auctioned permissions has gradually increased over this time period. Therefore, the dataset is able to provide better market features. In contrast to other studies, we have used a dataset that includes Phase 3 EUA prices. This is an important and noteworthy difference with previous evidence based on the first CO₂ market phases, when grandfathering was the method used to assign permits.

The remainder of the paper is organized as follows. Section 2 sets out the model used to forecast future CO₂ prices, first with only past CO₂ prices, and then with additional information about pollutant sectors. Predictions are carried out using neural networks, an artificial intelligence tool designed to emulate brain structure. We describe the dataset and variables used. A Pearson matrix indicating relationships between variables is also shown and used to decide which exogenous variables the neural model should include. Section 2 concludes with a description of the performance indices used to measure forecasting accuracy. Section 3 presents and analyzes the numerical results. Section 4 outlines the conclusions.

2. Materials and Methods

2.1. Forecasting Model

In order to analyze EU ETS operation, academic literature has tried to identify the factors that shape the price of CO₂ emission allowances. Supply and demand components, such as number of

distributed allowances or expected emissions, can usually be expected to define the CO₂ price, but the allowance market can also be affected by macroeconomic or financial market shocks [9]. Several authors [10–15] have analyzed the relationship between EUA prices and their fundamentals (prices of gas, coal, oil...) or the link between CO₂ prices and the stock market returns of the power sector (one of the most polluting industries). They concluded that, in the short run, EUAs evolve like financial assets due to the time delay in their response to changes in fuel prices or to a new technical situation.

It is generally accepted that economic variables behave like nonlinear processes [16]. Non-linearity is rather troublesome when modeling the dynamics of time series describing the evolution of such economic variables [12,14,15,17]. To overcome this issue, several methods have been proposed in the literature [10,17]. The complex non-linear behavior of economic and financial time series is a problem for which neural networks are especially well suited. They have been widely used in time series forecasting [7], as they have proved to be reliable and accurate tools that are able to reproduce the behavior of complex dynamical systems. Since economic factors change over time and tend to vary with market volatility, neural networks are ideal tools for flexible nonlinear modeling.

Neural networks have been used to forecast energy (mainly electricity) and fuel demand and prices [18–23]. In most of these works, neural networks clearly outperform other tools, providing more accurate predictions. On this ground, they will be used in this paper to forecast future values of prices of CO₂ emission allowances.

A neural network is a mathematical algorithm that mimics brain structure [24]. It can approximate any system thanks to its capability to learn the system behavior from a dataset (a time series describing the time evolution of allowance prices for the problem at hand) by adjusting the values of a set of internal parameters (weights) during a training stage in which they are adaptively modified to reduce the error between predictions and actual values. In this training process, the neural structure, the number of layers and the neurons in each layer, must be also defined. Nevertheless, there is no way of deciding a priori which will be the most efficient structure. Therefore, different numbers of layers and neurons should be tested to find out which provide the most accurate predictions.

There are a number of neural models usually used to forecast times series, although feedforward neural networks (FFNNs) are the most widely used. FFNNs are a class of neural networks in which information flows without feedback from input to output. They have been proved to be universal approximators [8,25], as they can approximate any continuous function with one hidden layer, provided that it has enough neurons. The multilayer perceptron (MLP) is a member of this class and is one of the most popular neural models used for time series forecasting [7,21,23,26–28] because of its simplicity, robustness, and accuracy. In addition, it can be easily programmed using neural network simulation tools. The MLP is made up of an input layer, one or more hidden layers, and an output layer. Usually, however, only one hidden layer is used because, as mentioned above, this structure will be enough to approximate any system. Each layer has a variable number of neurons. The first is not an actual layer but the set of neural network input data. The hidden layer is the processing layer, where each neuron receives all the outputs of the previous layer (neural inputs). The output layer provides the network response. Again, each neuron receives all the outputs from the previous layer.

Each neuron computes the weighted sum of all the inputs it receives and a bias constant. The result is processed by a function that provides the neuron output:

$$y_k = \Psi \left(\sum_{j=1}^n w_{kj} x_j + \theta_k \right) \quad (1)$$

In the above expression, x_j represents the j th input to the k th neuron, w_{jk} is the strength (weight) of connections with neurons in the previous layer, y_k is the neuron output, and θ_k is a bias constant. $\Psi(\cdot)$ is an activation function that provides the network with a non-linear characteristic in order to

identify the non-linear behavior inherent to complex dynamics. In the hidden layers, it is usually the hyperbolic tangent or the logistic function:

$$\Psi(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

The activation function of neurons in the output layer is usually linear, and it therefore adapts the neural outputs of the hidden layer to the range of values of the variables processed by the neural network.

As stated above, the neural network's ability to approximate any system is provided by its learning capability. Therefore, it must be trained to learn the behavior of the respective system using a set of specific data. The data must be arranged in pairs of network inputs and desired outputs. As a result, every time an input pattern is presented to the network, it provides an output that must be compared with the desired response. The resulting error will be used to properly modify the neuron weights in order to minimize the error value. The well-known backpropagation algorithm [24] performs this process in MLPs. Once the neural network has been trained, it can be used to forecast data other than those used during training.

The definition of the network structure is a critical step in the training process. It is essential to select the right structure on two grounds. First, a network that does not have enough neurons will not be able to accurately reproduce the system dynamics and would not, therefore, be able to provide reliable forecasting. Second, a network with too many neurons will, at best, behave properly or, at worst, only learn the input patterns and not be able to generalize the knowledge acquired to predict non-learned patterns. However, it will have high or excessive computing load and memory requirements. Therefore, different structures must be trained to find out which provides the most accurate predictions.

The data used as network inputs do not necessarily have to be merely past examples of the data to be predicted. In fact, other data can also be used as neural inputs. For the problem at hand, this means that data different, albeit somehow related, to the price of CO₂ emission allowances may also be used. The question that then arises is the following: will predictions be improved if data related to variables affecting CO₂ emissions are also taken into account? Thus, it may be useful to find out whether, looking beyond short-term financial portfolio decisions, CO₂ prices are sensitive to fuel price changes or technological evolution.

Some works have pointed out that the use of such data in the forecasting model could improve prediction accuracy [29,30]. Therefore, variables linked to pollutant sectors could be used along with the prices of CO₂ emission allowances to feed a neural network model to forecast future values of this variable.

In order to answer the above question, this paper compares the forecasting accuracy of a neural network fed with only past data on prices of CO₂ emission allowances with the accuracy of other structures in which the network also receives data that could influence that price. A previous analysis of different time series related to the energy and raw material markets will be carried out to find out which could probably have a more significant influence on CO₂ emission allowance prices.

On the other hand, it can be assumed that, in cases where companies do not have enough time to react to changes in fuel prices or to new technical situations, including those additional variables in the forecasting model would not improve the prediction accuracy in the short run. The best option in such cases would be to use a set of past allowance prices only to forecast future prices because additional variables will not improve the model's predictive power. This assumption has been broadly studied in the efficient market hypothesis for the financial market [31]. This issue has major policy implications, as, in the short run, only unknown information or unexpected policies could affect company behavior. This defines the second aim of this research: find out the time horizon over which prices of CO₂ emission allowances may be influenced by additional variables including information about pollutant sectors.

2.2. Data Description

We have used 1834 data of daily future prices of CO₂ emission allowances from October 2009 to October 2016 to carry out this study (Figure 1). Previous works have used data from the first carbon market phase, when grandfathering was the method used to assign permits, or have included only the beginning of the auctioning period [32]. In this paper, EUA prices from Phase 3 have been included.

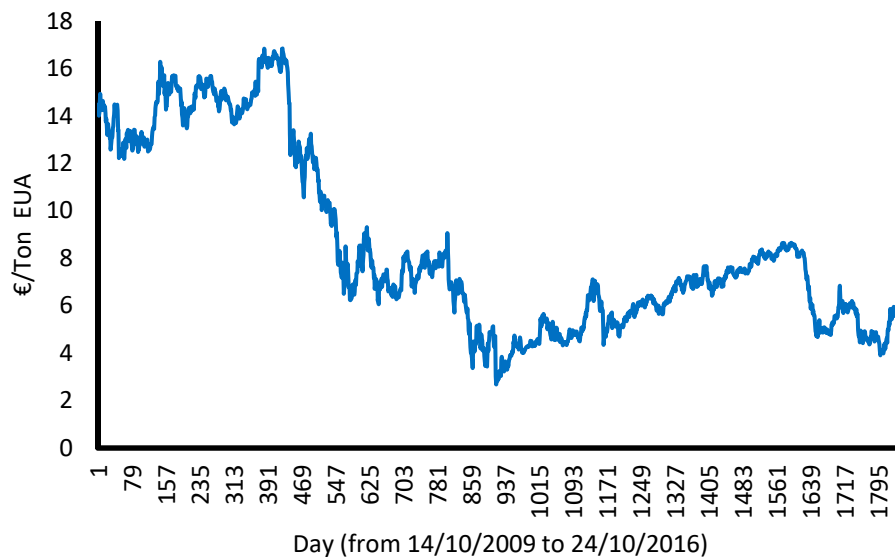


Figure 1. Time evolution of EUA prices (October 2009–October 2016).

In addition to daily prices of CO₂ emission allowances, other external variables that can affect those prices have been also used to study their possible influence on forecasting performance. They include fuel prices or stock market returns of emitters (changes in future profits due to higher or lower expected production can be linked to variability in EUA demand; accordingly, it could be linked to increases or reductions in EUA prices). These variables are summarized in Table 1.

Table 1. Variables analyzed to determine the influence of energy or raw materials on the forecasting accuracy of prices of CO₂ emission allowances.

| | Description | Source | Variable |
|---|------------------------|--------------------------------------|-------------------|
| EUA | CO ₂ prices | EEX–European Energy Exchange | F CO ₂ |
| EUROPE PRICE INDEX; Sectors Included in EU ETS | Electricity price | EUROPE-DS Electricity-PRICE INDEX | PI Elec |
| | Iron & steel price | EUROPE-DS Iron & Steel-PRICE INDEX | PI Iron |
| | Paper price | EUROPE-DS Paper-PRICE INDEX | PI Pap |
| | Chemical prices | EUROPE-DS Chemicals-PRICE INDEX | PI Che |
| | Oil and Gas prices | EUROPE-DS Oil & Gas Prod-PRICE INDEX | PI OG |
| Fuel Prices | Gas price | Natural Gas-Henry Hub | P Gas |
| | Oil price | Crude Oil Dated Brent | P Oil |
| | Coal price | Coal ICE API2 CIF ARA | P Coal |

The EUA price series (€/EUA) is the spot price of a ton of CO₂ quoted on the European Energy Exchange (EEX) in Leipzig, Germany. The natural gas price (\$/MMBTU) is the Henry Hub spot price, the coal price (\$/ton) is the API2 spot index (CIF ARA delivered to the Amsterdam/Rotterdam/Antwerp region), and the oil crude price (\$/BBL) is the Dated Brent. The European price indices related to the most polluting sectors included in EU ETS (electricity, iron and steel, paper, chemicals, and oil and gas production) have also been included. All data were extracted from the Thomson Reuters Datastream and Bloomberg Databases.

Only the variables with the biggest influence should be taken into account. Thus, we have to study the relationships of the variables in order to find out which variables could influence future prices of CO₂ emission allowances. Although there can be little doubt that such relationships really do exist (prices of energy sources or industries related to CO₂ emissions should have a fair amount of influence on allowance prices), their actual existence and the extent of their influence should be empirically proved.

The relationship between statistical variables is usually specified by the Pearson correlation coefficient, which measures the strength of the linear correlation between two variables. It takes values from -1 to $+1$, where a value close to 1 constitutes a positive correlation of the two variables (that is to say, they both increase or decrease in the same way and at the same rate), whereas a value close to -1 suggests an inverse relation (when one increases, the other decreases). Values close to 0 mean that there is no relationship between the variables. The value of this coefficient for variables x and y is obtained from

$$\rho_{x,y} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y} \quad (3)$$

where $\text{cov}(x, y)$ stands for the covariance of x and y , and σ_x and σ_y stand for their respective standard deviations. When we are looking for correlation coefficients between a set of variables, they can be arranged in a matrix structure to facilitate the comparison of their values. Table 2 shows the matrix for the price of CO₂ emission allowances and the other variables described above. Nevertheless, as only relationships between CO₂ prices and the other variables are meaningful for the analysis at hand, correlations between the other variables are not taken into account. Although there are clearly several relationships, their analysis is beyond the scope of this research.

Table 2. Matrix of the correlation coefficients of the analyzed variables.

| | CO ₂ F | Elec PI | Iron PI | Pap PI | Che PI | O-G PI | Gas P | Oil P | Coal P |
|-------------------|-------------------|---------|---------|--------|--------|--------|--------|--------|--------|
| CO ₂ F | 1.000 | 0.821 | 0.862 | −0.306 | −0.610 | 0.386 | 0.404 | 0.079 | 0.573 |
| Elec PI | 0.821 | 1.000 | 0.924 | −0.222 | −0.356 | 0.674 | 0.686 | 0.304 | 0.575 |
| Iron PI | 0.862 | 0.924 | 1.000 | −0.415 | −0.499 | 0.718 | 0.590 | 0.396 | 0.723 |
| Pap PI | −0.306 | −0.222 | −0.415 | 1.000 | 0.745 | −0.454 | −0.215 | −0.517 | −0.564 |
| Che PI | −0.610 | −0.356 | −0.499 | 0.745 | 1.000 | −0.098 | −0.101 | 0.019 | −0.361 |
| O-G PI | 0.386 | 0.674 | 0.718 | −0.454 | −0.098 | 1.000 | 0.594 | 0.875 | 0.766 |
| Gas P | 0.404 | 0.686 | 0.590 | −0.215 | −0.101 | 0.594 | 1.000 | 0.422 | 0.437 |
| Oil P | 0.079 | 0.304 | 0.396 | −0.517 | 0.019 | 0.875 | 0.422 | 1.000 | 0.746 |
| Coal P | 0.573 | 0.575 | 0.723 | −0.564 | −0.361 | 0.766 | 0.437 | 0.746 | 1.000 |

From Table 2, we find that the price of CO₂ emission allowances is positively correlated with the electricity and the iron and steel price indices. No other clear correlation appears. Note that, unexpectedly, there is very little relationship between future CO₂ and energy resources (gas, oil, and coal) prices.

Nevertheless, the strong correlation between CO₂ and electricity prices is hardly surprising. In fact, electricity generation is one of the most important activities affecting EUA prices: the wholesale electricity market and the EUA market are linked, since polluting power production technologies include their emission allowance costs in the short-term marginal kWh cost of electricity. In addition, the field of power generation has not received (except in exceptional cases) free emission allowances since 2013.

The high correlations with iron and steel price indices are not unanticipated either, bearing in mind that all steel- and iron-making processes not only demand a high amount of energy but also generate high CO₂ emissions.

Therefore, the analysis reported in this paper is confined to the possible influence of electricity price indices and iron and steel production.

Indices should be defined in order to measure the forecasting accuracy error. They will be used to find out how good a prediction is. This research uses four indices, those usually used in the literature to measure the accuracy of predictions: mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). They are calculated as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{A_i - F_i}{A_i} \right| \cdot 100 \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |A_i - F_i| \quad (5)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (A_i - F_i)^2 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (A_i - F_i)^2} \quad (7)$$

where A_i is an actual datum, F_i is its forecasted value, and N is the number of predicted data. These indices are widely used to study the accuracy of predictions. MAPE allows comparisons between different time series with different data ranges, whereas the other three can be used merely to compare the forecasting accuracy of different tools applied to the same data set, as they are scale-dependent.

All data used to forecast prices of CO₂ emission allowances were split into training (60%) and test (40%) sets. The first set was used to train the forecasting tool, whereas the last set was used to test its performance.

The programs developed in this work were programmed in Matlab R2012b (TheMathWorks, Inc., Natick, MA, USA) and run in a PC.

3. Results and Discussion

The neural model selected to forecast future prices of CO₂ emission allowances was the multilayer perceptron (MLP), because it has been widely used to forecast different kinds of time series and has been proven not only to provide very accurate predictions but also to regularly outperform predictions provided by other forecasting tools [19,21,27,33–35]. Accordingly, its performance will not in this paper be compared with forecasts provided by other tools. Besides, the main aim of this work is to analyze the time evolution of predictions of the price of CO₂ emission allowances. Its key objective is not, therefore, to find the most accurate forecasting tool, as all we need is a reliable and accurate prediction. As the MLP has been proven to be one of the best tools for providing reliable and accurate forecasts [23,26,36,37], it will be the only one used in this research.

Most works providing predictions of future values of a time series forecast a single data item. Therefore, the neural model used has only one neuron in its output layer. Nevertheless, there is no reason to stop a neural model from providing more than one prediction. Forecasting a set of sequential future data will provide a time evolution of prices that should allow enterprises to carry out better planning of their buy–sell decisions. This should be more useful than a single prediction of the following data. The key issue would then be to find out how many future data would provide reliable predictions, which could be confidently used to analyze their time evolution to extract information for buy–sell decision making.

Therefore, several MLPs providing different numbers of future predictions (that is to say, different numbers of neurons in the output layer) were tested to find out which provided the most reliable predictions. Reliability was set at a 10% error. This is a high value for achieving accurate predictions, especially when they are related to a short-term time horizon. Nevertheless, this value can be regarded as acceptable when several future predictions are provided, since a rough estimation of future values

could suffice in this case. From this perspective, the chosen error can be regarded as reasonable. After testing several numbers of future predictions, it was found that 20 always provided mean forecasting errors lower than 10%.

Along with the number of network outputs, the numbers of neurons in the hidden layer and past data to be used as network inputs were also tested to find out which structure provided the most accurate mean predictions. Only one hidden layer was used, because, as stated above, this is enough to guarantee that the network can efficiently approximate the time series behavior. The best performance was achieved with a network with three inputs and two neurons in the hidden layer.

Before training and use, the network data are usually preprocessed for transformation into a new series that could be more efficiently processed to achieve more accurate predictions. A number of works [33,38–41] have pointed out that splitting the time series into several sub-series, each of which retains a particular behavior of the original series, can improve forecasting accuracy. One of the simplest such decompositions is to split the time series into its trend and fluctuations. This results in two new series: one describing how the original series evolves over time and the other representing variations around that trend. This decomposition can be especially useful for long-term forecasting, that is to say, when a set of future data are to be predicted, because the trend series represents a more or less global behavior that can better describe the long-term evolution of the original time series.

The behavior of the time series of the price of CO₂ emission allowances, Figure 1, can be easily analyzed in such a way: small amplitude variations appear superimposed on a clearly changing trend. In order to split the two behaviors, the trend must first be extracted. This can be done using a smoothing process that removes variations. Several methods have been proposed for time series smoothing [42]. The moving average is one of the most commonly used, because of its simplicity. It transforms the original time series into another series whose elements are the weighted mean of a set of data (window) preceding and following that to be modified. Usually, only past values (along with the value to be smoothed) are used to calculate the mean because otherwise the causality principle of time series forecasting would not be preserved. The simplest form is a window with constant weights:

$$T[i] = \frac{1}{n}(C[i] + C[i-1] + \dots + C[i-(n-1)]) \quad (8)$$

where n is the size of the window. This value should be properly defined to provide a meaningful trend behavior. Too many data would define a series that represents only a rough approximation of the actual trend of the series, whereas too few data would retain variations that could mask that trend. Several window sizes were tested, and the best predictions were obtained with four data.

The fluctuations series is easily obtained by subtracting the trend from the original series. Once both trend and fluctuation series have been obtained they can be independently forecasted. Their predictions can then be added to forecast the original series.

Accordingly, the price of CO₂ emission allowance series was split into its trend and fluctuations, which were independently forecasted and then combined to provide the price forecasting. The resulting performance was very similar to that provided by a single neural network (direct forecasting of the price series). Nevertheless, we adopted this structure to carry out predictions, because, as we will see later, performance can be improved when trend and fluctuations of variables different from CO₂ are also considered as neural network inputs. The neural structures providing the best performance were the same as that obtained for directly forecasting the original time series (three inputs and two neurons in the hidden layer). Several other structures were also tested but prediction accuracy was not improved. Table 3 shows the error indices for 20-day predictions. An average error of predictions of all days is also provided.

Table 3. Prediction errors of prices of CO₂ emission allowances when only past values were used as network inputs.

| Days Ahead | MAPE | MAE | MSE | RMSE |
|------------|-------|-------|-------|-------|
| 1 | 2.469 | 0.159 | 0.040 | 0.200 |
| 2 | 2.945 | 0.187 | 0.058 | 0.240 |
| 3 | 3.336 | 0.212 | 0.073 | 0.270 |
| 4 | 3.770 | 0.239 | 0.096 | 0.310 |
| 5 | 4.188 | 0.265 | 0.117 | 0.342 |
| 6 | 4.579 | 0.290 | 0.137 | 0.371 |
| 7 | 4.957 | 0.314 | 0.161 | 0.401 |
| 8 | 5.335 | 0.337 | 0.184 | 0.429 |
| 9 | 5.706 | 0.360 | 0.209 | 0.457 |
| 10 | 6.129 | 0.388 | 0.234 | 0.484 |
| 11 | 6.457 | 0.409 | 0.261 | 0.511 |
| 12 | 6.815 | 0.431 | 0.291 | 0.539 |
| 13 | 7.164 | 0.454 | 0.319 | 0.565 |
| 14 | 7.482 | 0.473 | 0.344 | 0.587 |
| 15 | 7.797 | 0.493 | 0.373 | 0.611 |
| 16 | 8.067 | 0.510 | 0.398 | 0.631 |
| 17 | 8.407 | 0.530 | 0.425 | 0.652 |
| 18 | 8.726 | 0.549 | 0.454 | 0.674 |
| 19 | 9.031 | 0.566 | 0.481 | 0.694 |
| 20 | 9.339 | 0.584 | 0.510 | 0.714 |
| Means | 6.135 | 0.387 | 0.258 | 0.484 |

MSE and RMSE are good for detecting abnormal errors (too high or too low) because, as individual ones are squared (Equations (6) and (7)), their presence will highly influence the value of each index. On the other hand, both MAE and MAPE provide information regarding the mean value of errors, defining a sort of overall behavior. Taking into account these facts, it may be concluded from their analysis in Table 3 that very few abnormal errors appear in the predictions obtained, as the values of MSE and RMSE show a smooth increasing trend without anomalous changes. MAE and MAPE also show the same behavior. These facts suggest that the forecasting model is able to provide robust and reliable predictions whose accuracy decreases as the time horizon increases.

As pointed out above, we tested several time horizons and selected the longest providing forecasting errors lower than 10%: 20-day predictions. Note that models with shorter time horizons returned lower errors. The extreme case of only one prediction provided an average error of 1.75%, a value noticeably lower in one-day-ahead predictions than in 20-day predictions. This is hardly surprising because predictions made many days in advance are unavoidably less accurate. Therefore, long-term predictions that are all provided by a single network must inevitably influence the accuracy of short-term predictions as the training process needs to balance errors from each prediction in order to minimize the overall error; that is to say, training the network to reduce long-term error predictions will worsen the short-term predictions and vice versa. Therefore, the results shown in Table 3 can be regarded as useful for enterprises, as the model provides a reliable prediction of the time evolution of prices of CO₂ emission allowances in the following month (20 days ahead, because Saturdays and Sundays were not considered, as markets do not operate at weekends).

Once it has been proved that a neural network is able to provide reliable predictions of future prices of CO₂ emission allowances by using only past values of this variable, it is worth looking at whether or not accuracy can be improved by adding exogenous variables (that is to say, variables other than the one to be forecasted) to the network. As only the electricity and the iron and steel price indices are correlated with CO₂ emission allowance prices, they will be the only ones used as network inputs. The network providing the best performance (with three inputs and two neurons in the hidden layer) was used to find out whether or not adding these variables improves performance.

The results are reported in Table 4, which also clarifies that adding electricity prices and iron and steel prices to the model does not improve the performance achieved when only prices of CO₂ emission allowances were used. Not only are the average errors of all predictions slightly higher but also most of the individual ones (days ahead) are worse. Therefore, we can conclude that there is no point in including those exogenous variables in the model as it does not lead to any improvement in the forecasting accuracy and makes the network structure more complex. To simplify comparison between both models, we plotted their differential error (subtracting prediction errors including exogenous variables from prediction errors using prices of CO₂ emission allowances only) (Figure 2). Figure 2 shows that predictions with prices of CO₂ emission allowances only clearly outperform those with exogenous variables for all but the longest, time horizons, where there is an almost negligible improvement. As this plot provides a simple comparison between errors produced with different forecasting models, it is also used in the other cases studied in this paper.

Table 4. Prediction errors of CO₂ emission allowance prices when electricity prices and iron and steel prices are also used as input variables.

| Days Ahead | MAPE | MAE | MSE | RMSE |
|------------|-------|-------|-------|-------|
| 1 | 2.836 | 0.181 | 0.051 | 0.225 |
| 2 | 3.260 | 0.207 | 0.068 | 0.261 |
| 3 | 3.573 | 0.228 | 0.083 | 0.288 |
| 4 | 4.024 | 0.257 | 0.107 | 0.327 |
| 5 | 4.409 | 0.282 | 0.127 | 0.356 |
| 6 | 4.810 | 0.307 | 0.146 | 0.382 |
| 7 | 5.143 | 0.328 | 0.169 | 0.411 |
| 8 | 5.497 | 0.350 | 0.191 | 0.437 |
| 9 | 5.835 | 0.372 | 0.213 | 0.462 |
| 10 | 6.188 | 0.395 | 0.238 | 0.488 |
| 11 | 6.536 | 0.417 | 0.263 | 0.513 |
| 12 | 6.889 | 0.439 | 0.292 | 0.540 |
| 13 | 7.231 | 0.461 | 0.320 | 0.565 |
| 14 | 7.472 | 0.476 | 0.344 | 0.586 |
| 15 | 7.756 | 0.494 | 0.371 | 0.609 |
| 16 | 8.024 | 0.511 | 0.394 | 0.628 |
| 17 | 8.389 | 0.533 | 0.421 | 0.649 |
| 18 | 8.679 | 0.550 | 0.450 | 0.671 |
| 19 | 8.992 | 0.569 | 0.476 | 0.690 |
| 20 | 9.283 | 0.586 | 0.504 | 0.710 |
| Means | 6.241 | 0.397 | 0.261 | 0.490 |

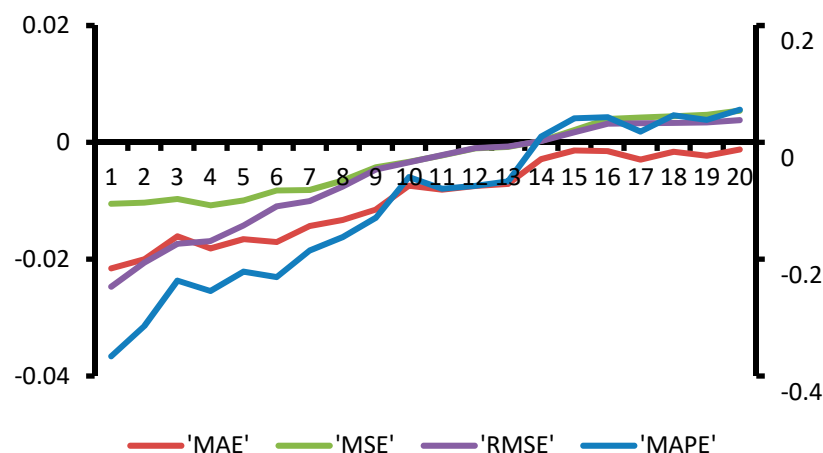


Figure 2. Differential errors between predictions when using prices of CO₂ emission allowances only and when exogenous variables (power and iron and steel sector prices) were added.

From these results, we can conclude that exogenous variables related to pollutant sectors have no influence on the forecasting accuracy of prices of CO₂ emission allowances. Moreover, they worsen short-term forecasting when included in the prediction model, providing an almost equal accuracy for long-term forecasts.

Nevertheless, the question that arises now is the following: could the forecasting accuracy be improved if only one of the exogenous variables is added to the prediction model? Besides, could it be improved if only trend or fluctuations are taken into account? To answer these questions, several configurations of input data were tested. They all consider prices of CO₂ emission allowances (split into trend and fluctuations) and different combinations of trend and fluctuations of the other two variables. All possible combinations were tested, although only combinations providing a significant improvement in forecasting accuracy are reported here.

The first model accounts for only one exogenous variable as a network input. The results for both predictions are shown in Table 5. Figures 3 and 4 also plot the differential errors in order to better compare the basic model with these two exogenous variables. When comparing errors in Tables 3 and 5, overall accuracy is found to be unchanged (when the power sector is considered along with prices of CO₂ emission allowances) or experiences a slight improvement (when iron and steel is included). Nevertheless, Figures 3 and 4 show that long-term predictions are clearly better when one exogenous variable is considered in both cases. The inclusion of exogenous variables clearly improves forecasting accuracy of prices in the last two weeks predicted. This improvement is offset by a worse accuracy for the first two weeks (as shown in Figures 3 and 4), hence the more or less similar average errors for all three cases.

Table 5. Prediction errors of prices of CO₂ emission allowances when electricity prices and iron and steel prices are also separately used as input variable.

| Days Ahead | Prices of EUA and Electricity | | | | Prices of EUA and Iron and Steel | | | |
|------------|-------------------------------|-------|-------|-------|----------------------------------|-------|-------|-------|
| | MAPE | MAE | MSE | RMSE | MAPE | MAE | MSE | RMSE |
| 1 | 2.585 | 0.165 | 0.042 | 0.205 | 2.451 | 0.154 | 0.039 | 0.197 |
| 2 | 3.013 | 0.191 | 0.059 | 0.243 | 2.981 | 0.188 | 0.059 | 0.242 |
| 3 | 3.370 | 0.213 | 0.074 | 0.272 | 3.406 | 0.217 | 0.076 | 0.275 |
| 4 | 3.804 | 0.241 | 0.097 | 0.312 | 3.856 | 0.247 | 0.100 | 0.316 |
| 5 | 4.206 | 0.266 | 0.118 | 0.343 | 4.278 | 0.274 | 0.119 | 0.345 |
| 6 | 4.605 | 0.291 | 0.138 | 0.371 | 4.709 | 0.300 | 0.139 | 0.372 |
| 7 | 4.979 | 0.315 | 0.161 | 0.401 | 5.050 | 0.322 | 0.161 | 0.401 |
| 8 | 5.347 | 0.338 | 0.184 | 0.429 | 5.422 | 0.344 | 0.180 | 0.425 |
| 9 | 5.709 | 0.361 | 0.209 | 0.457 | 5.711 | 0.362 | 0.202 | 0.449 |
| 10 | 6.117 | 0.387 | 0.234 | 0.483 | 6.033 | 0.382 | 0.224 | 0.474 |
| 11 | 6.431 | 0.408 | 0.260 | 0.510 | 6.351 | 0.401 | 0.248 | 0.498 |
| 12 | 6.780 | 0.430 | 0.289 | 0.538 | 6.657 | 0.419 | 0.273 | 0.522 |
| 13 | 7.138 | 0.453 | 0.317 | 0.563 | 6.985 | 0.439 | 0.298 | 0.546 |
| 14 | 7.452 | 0.472 | 0.342 | 0.585 | 7.207 | 0.453 | 0.320 | 0.566 |
| 15 | 7.768 | 0.492 | 0.371 | 0.609 | 7.482 | 0.470 | 0.344 | 0.586 |
| 16 | 8.031 | 0.509 | 0.396 | 0.629 | 7.760 | 0.487 | 0.367 | 0.606 |
| 17 | 8.371 | 0.529 | 0.423 | 0.650 | 8.111 | 0.508 | 0.393 | 0.627 |
| 18 | 8.690 | 0.548 | 0.452 | 0.672 | 8.453 | 0.529 | 0.422 | 0.649 |
| 19 | 8.995 | 0.566 | 0.479 | 0.692 | 8.775 | 0.548 | 0.448 | 0.670 |
| 20 | 9.302 | 0.584 | 0.507 | 0.712 | 9.071 | 0.566 | 0.476 | 0.690 |
| Average | 6.135 | 0.388 | 0.258 | 0.484 | 6.037 | 0.380 | 0.244 | 0.473 |

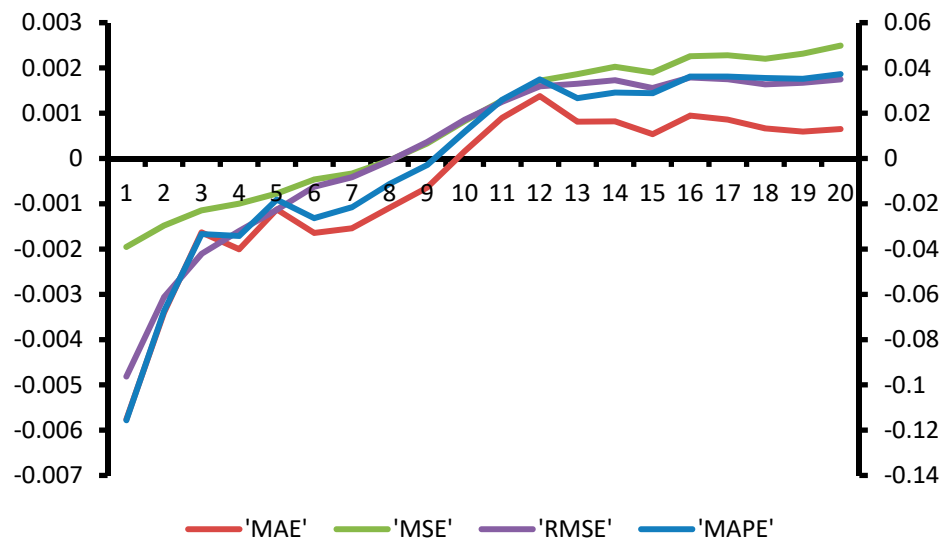


Figure 3. Differential errors between predictions when using only prices of CO₂ emission allowances and when electricity prices are added.

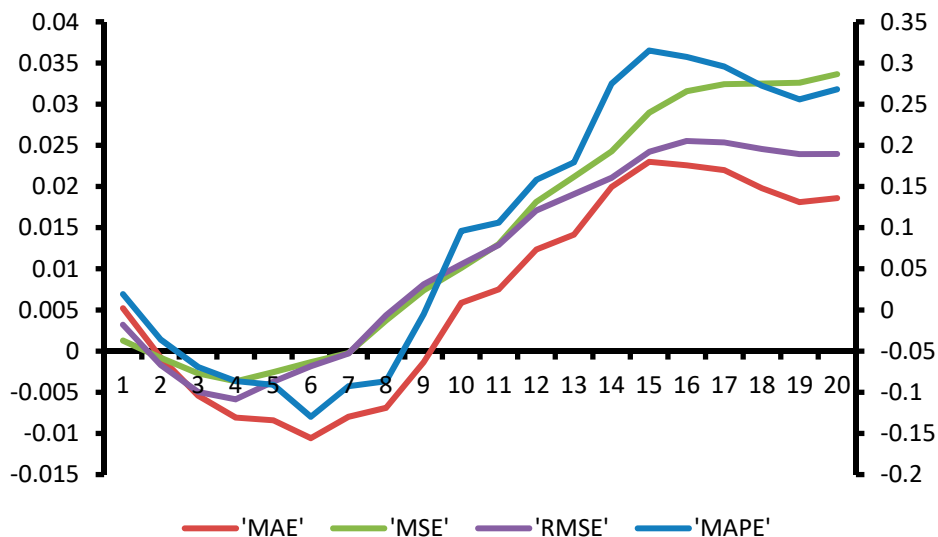


Figure 4. Differential errors between predictions when using only prices of CO₂ emission allowances and when iron and steel prices are added.

These results are very interesting, since they indicate that changes in the polluting sectors independently added to the forecasting model do affect the predictions of CO₂ emission allowance prices for time horizons greater than 10 days ahead; that is to say, they appear to suggest that “fundamentals” do affect the price of CO₂ if we account for long-term forecasting horizons. This could be an indication that the market is working properly, as it appears to reflect that polluting companies react to variations in the “fundamentals” by either decisions aimed at buying and selling emission rights, changes in their production processes, or decisions on investments in decarbonization.

One structure that was able to provide a global improvement in prediction accuracy was the inclusion of fluctuations of both electricity prices and iron and steel prices (Table 6). When only one of them was added to prices of CO₂ emission allowances, predictions were noticeably worse. This improvement needs a detailed analysis to find out how it behaves from the point of view of the time horizon (Figure 5). There is a clear improvement in the short run, which gradually decreases as the time horizon increases. Therefore, the forecasting errors become equal in both models in the last five days (last week). This effect is clearly opposite to what was observed when electricity prices or iron

and steel prices were individually added to the network input. The difference is that the improvement in prediction accuracy now lasts for more days, providing an overall average improvement of model performance. Note that not only did the inclusion of only one variable not improve accuracy, it actually detracted from it. This could mean that the neural model is able to identify both fluctuations (when input together to the network) as a kind of perturbation of the time evolution of prices of CO₂ emission allowance generated by economic or social factors and to provide a sort of correction to its evolution in the short time horizon. It is reasonable to assume that the long-term estimation of such factors is not accurate enough, whereby not only did the prediction of prices of CO₂ emission allowances not improve but it actually worsened for the long time horizon. On the other hand, it is also noticeable that only the combined use of electricity and of iron and steel price fluctuations contributes to the aforementioned improvement. Accordingly, it appears that social or political factors influencing the price of CO₂ emission allowances could be estimated based on only the joint, rather than the individual, analysis of electricity and of iron and steel price fluctuations.

The models that separately included the electricity and the iron and steel price trends as network inputs along with prices of CO₂ emission allowances provided the most significant improvements in forecasting accuracy. Table 7 shows the results of both models, where there is a clear improvement in average errors. Figures 6 and 7 show a comparison with the results for the prices of CO₂ emission allowances only (differential errors). We find that, although the overall improvement in both models is clear, particular improvements related to time horizon show significant differences. When power prices are used, we can see a significant improvement in the short-term prediction accuracy, which slowly decreases as the time horizon increases, becoming almost negligible (or a little worse) for the last forecasted data. Nevertheless, when iron and steel prices are used, there is a clear improvement for all time horizons, which is more significant for medium-term predictions.

Table 6. Prediction errors of prices of CO₂ emission allowances when fluctuations of electricity prices and iron and steel prices are also used simultaneously as input variables.

| Days Ahead | MAPE | MAE | MSE | RMSE |
|------------|-------|-------|-------|-------|
| 1 | 1.890 | 0.117 | 0.025 | 0.159 |
| 2 | 2.445 | 0.151 | 0.040 | 0.201 |
| 3 | 3.004 | 0.185 | 0.058 | 0.241 |
| 4 | 3.494 | 0.216 | 0.081 | 0.285 |
| 5 | 3.959 | 0.246 | 0.103 | 0.321 |
| 6 | 4.402 | 0.275 | 0.127 | 0.356 |
| 7 | 4.825 | 0.301 | 0.149 | 0.386 |
| 8 | 5.219 | 0.325 | 0.173 | 0.416 |
| 9 | 5.606 | 0.349 | 0.198 | 0.445 |
| 10 | 6.010 | 0.374 | 0.223 | 0.472 |
| 11 | 6.342 | 0.396 | 0.251 | 0.501 |
| 12 | 6.757 | 0.421 | 0.280 | 0.529 |
| 13 | 7.133 | 0.444 | 0.309 | 0.556 |
| 14 | 7.518 | 0.467 | 0.339 | 0.582 |
| 15 | 7.829 | 0.487 | 0.365 | 0.604 |
| 16 | 8.172 | 0.508 | 0.393 | 0.627 |
| 17 | 8.541 | 0.530 | 0.424 | 0.651 |
| 18 | 8.879 | 0.551 | 0.451 | 0.672 |
| 19 | 9.187 | 0.570 | 0.480 | 0.693 |
| 20 | 9.551 | 0.592 | 0.514 | 0.717 |
| Average | 6.038 | 0.375 | 0.249 | 0.470 |

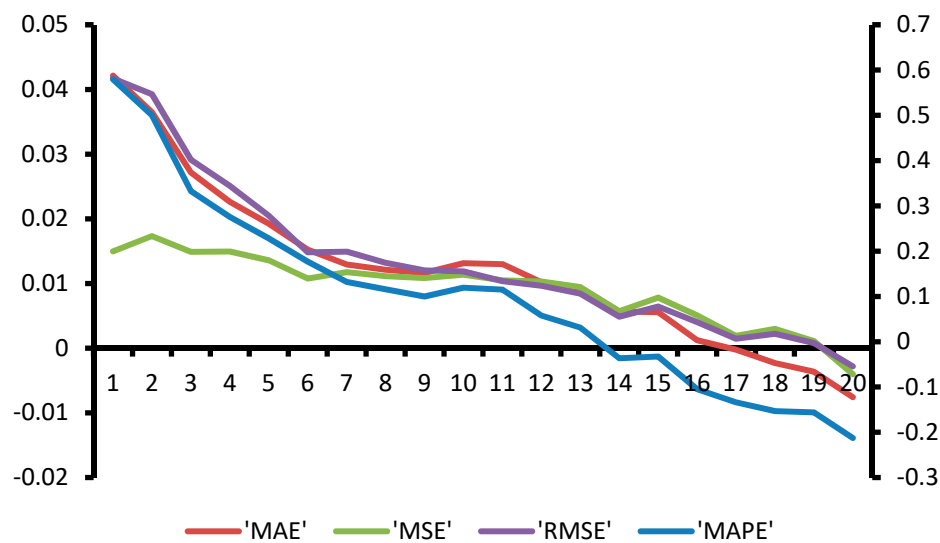


Figure 5. Differential errors between predictions when using prices of CO₂ emission allowances only and when fluctuations of electricity and of iron and steel prices are also used as input variables.

Table 7. Prediction errors of CO₂ emission allowance prices when electricity trends or iron and steel trends are also used as input variables.

| Days Ahead | EUA Prices and Electricity Trend | | | | EUA Prices and Iron & Steel Trend | | | |
|------------|----------------------------------|-------|-------|-------|-----------------------------------|-------|-------|-------|
| | MAPE | MAE | MSE | RMSE | MAPE | MAE | MSE | RMSE |
| 1 | 1.766 | 0.109 | 0.022 | 0.149 | 2.358 | 0.151 | 0.037 | 0.193 |
| 2 | 2.446 | 0.150 | 0.041 | 0.202 | 2.726 | 0.169 | 0.052 | 0.228 |
| 3 | 2.957 | 0.182 | 0.057 | 0.240 | 3.097 | 0.191 | 0.066 | 0.257 |
| 4 | 3.481 | 0.215 | 0.081 | 0.284 | 3.532 | 0.218 | 0.086 | 0.294 |
| 5 | 3.944 | 0.245 | 0.103 | 0.320 | 3.952 | 0.245 | 0.107 | 0.327 |
| 6 | 4.382 | 0.273 | 0.125 | 0.353 | 4.404 | 0.272 | 0.128 | 0.358 |
| 7 | 4.826 | 0.301 | 0.149 | 0.385 | 4.771 | 0.295 | 0.149 | 0.386 |
| 8 | 5.215 | 0.324 | 0.173 | 0.416 | 5.101 | 0.314 | 0.171 | 0.413 |
| 9 | 5.601 | 0.349 | 0.198 | 0.445 | 5.426 | 0.334 | 0.194 | 0.440 |
| 10 | 6.023 | 0.375 | 0.224 | 0.473 | 5.738 | 0.352 | 0.218 | 0.467 |
| 11 | 6.368 | 0.396 | 0.251 | 0.501 | 6.044 | 0.371 | 0.243 | 0.493 |
| 12 | 6.746 | 0.420 | 0.280 | 0.529 | 6.470 | 0.398 | 0.272 | 0.522 |
| 13 | 7.113 | 0.444 | 0.309 | 0.555 | 6.866 | 0.424 | 0.302 | 0.549 |
| 14 | 7.466 | 0.465 | 0.335 | 0.579 | 7.178 | 0.443 | 0.327 | 0.572 |
| 15 | 7.815 | 0.487 | 0.363 | 0.603 | 7.485 | 0.462 | 0.355 | 0.596 |
| 16 | 8.149 | 0.508 | 0.391 | 0.625 | 7.890 | 0.489 | 0.385 | 0.621 |
| 17 | 8.506 | 0.530 | 0.420 | 0.648 | 8.367 | 0.520 | 0.420 | 0.648 |
| 18 | 8.868 | 0.553 | 0.451 | 0.671 | 8.711 | 0.542 | 0.450 | 0.671 |
| 19 | 9.212 | 0.573 | 0.480 | 0.693 | 8.990 | 0.558 | 0.476 | 0.690 |
| 20 | 9.550 | 0.594 | 0.510 | 0.714 | 9.324 | 0.579 | 0.508 | 0.713 |
| Average | 6.022 | 0.375 | 0.248 | 0.469 | 5.921 | 0.366 | 0.247 | 0.472 |

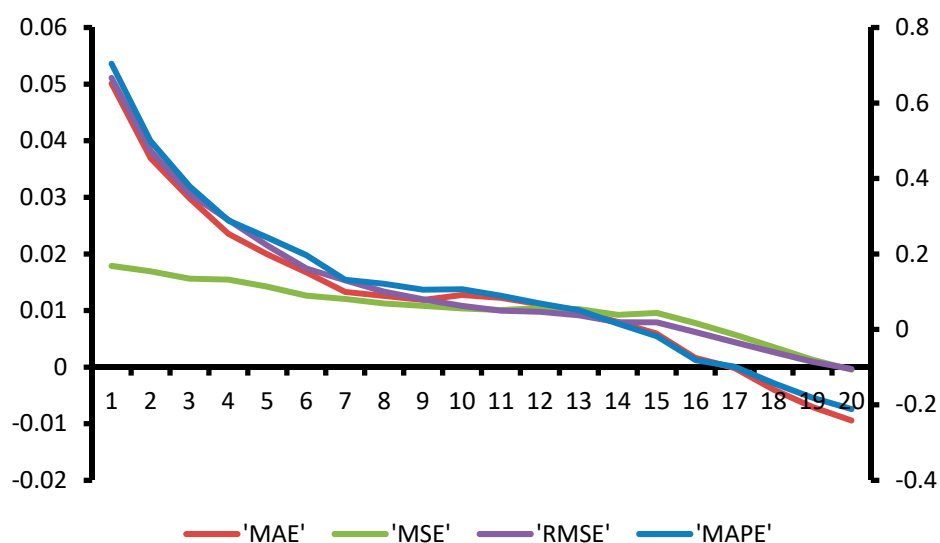


Figure 6. Differential errors between predictions when using prices of CO₂ emission allowances only and when the electricity price trend is also used as an input variable.

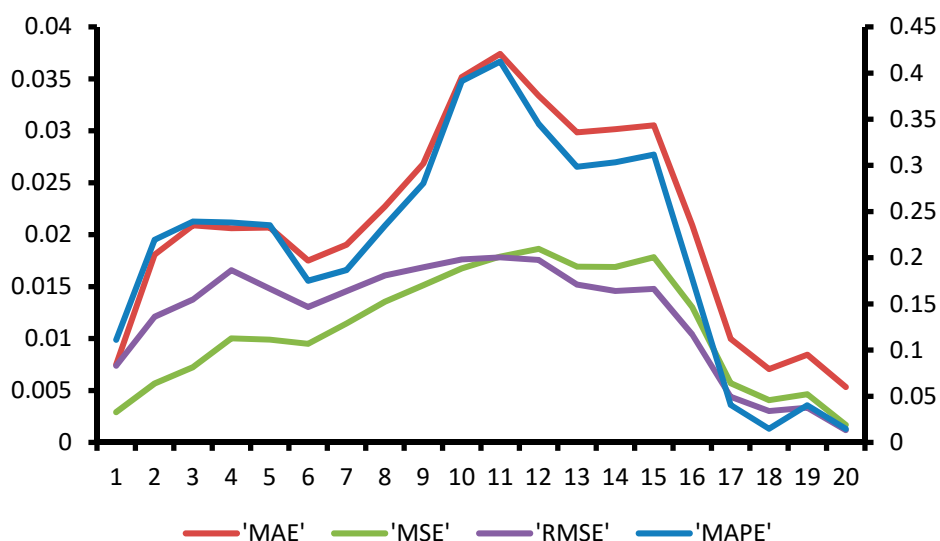


Figure 7. Differential errors between predictions when using prices of CO₂ emission allowances only and when the iron and steel price trend is also used as an input variable.

These results may be construed as meaning that the trend of electricity prices directly influences short-term variations of CO₂ emission allowance prices; that is to say, electricity prices slightly drive CO₂ emission allowances in the short run. On the other hand, it may also be assumed that the iron and steel trend evolution has a delayed influence on CO₂ emission allowance price behavior.

This result suggests that changes in the polluting sectors affect the forecasts of future CO₂ prices and that “fundamentals” do affect the carbon price for time horizons greater than 10 days ahead.

Note that the one-day prediction provided by the model using the electricity price trend was able to match the accuracy provided by a neural network forecasting a single future data item (an error of 1.75%, as mentioned above).

In view of the results, it can be said that EUA prices work like a kind of financial asset, which can be traded. This result has strong policy implications, since enterprises can use predictions of future EUA prices to make decisions regarding buying or selling them.

In future research, it could be worth analyzing the EU ETS effects within a broader theoretical framework, in which enterprise performance is considered beyond the traditional profit making by including environmental, social, and governance dimensions [43].

4. Conclusions

In this paper, we have forecasted the prices of CO₂ emission allowances using a multilayer perceptron, a kind of neural network, which was able to reproduce their nonlinear behavior providing accurate predictions. We forecasted a set of future data rather than a single data item, as is usual when forecasting time series. A time horizon of 20 predictions was used, as this was the highest number that returned an error of less than 10%. Although short-term forecasting produced greater error values (2.469%) than for predictions of a single future data item (1.75%), the large number of future predictions provided at once offset that loss of accuracy. As expected, prediction errors increase as the time horizon increases. Contrary to expectations, adding exogenous variables closely related to CO₂ emission allowance prices (electricity prices and iron and steel prices) to the forecasting model did not significantly improve prediction accuracy, despite the fact that those variables had been found to be highly correlated with CO₂ emission allowance prices. Accuracy was almost equal to the network using only past data of CO₂ emission allowance prices. There was only a slight improvement in long-term prediction accuracy, mainly when iron and steel prices were added, an effect that has the negative impact of worsening short-term accuracy. Therefore, we can conclude that there is no point in including those exogenous variables in the model, as they do not lead to any significant improvement in forecasting accuracy, and the network structure becomes more complex.

Nevertheless, we also made predictions by splitting time series into trend and fluctuations. These new series were used separately as network inputs to investigate possible improvements in forecasting accuracy. The inclusion of fluctuations of both electricity prices and iron and steel prices in the network inputs improved short-term forecasting accuracy, although the improvement faded as the time horizon increased. In addition, when the electricity and iron and steel price trends were added separately to the network input, an overall improvement of accuracy was achieved. It was again greater for short-term predictions when electricity prices were used but was more significant for medium-term predictions when iron and steel trends were taken into account.

From these results, we can say that using exogenous variables along with CO₂ emission allowance prices only provides slight improvements in forecasting accuracy. Only when those variables are electricity price and iron and steel price trends is their use worth the added complication of the forecasting model.

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