Research on Carbon Futures Forecast and Related Asset Impact Analysis Based on ARIMA-GARCH and RBF Contribution Analysis

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Abstract: To studies the trend of carbon futures price and influencing factors. In this paper, the EU carbon financial emission market carbon trading settlement price EUA is selected as the research object. Based on the carbon futures price data from 2008 to 2021, this paper constructs an Autoregressive Integrated Moving Average-generalized autoregressive conditional heteroscedasticity model to Forecast the price of carbon futures in the next three months. On this basis, the RBF (Radial Basis Function) neural network is constructed, and seven indexes such as stock index and crude oil price were selected from the aspects of energy and finance to analyze the contribution of the carbon price. The results are as follows: The ARIMA-GARCH model predicts that EUA prices will increase significantly in the next three months. The stock market is the most influential economic factor, followed by energy. Finally, this paper puts forward corresponding policy suggestions according to the results.

1 INTRODUCTION

Under the severe form of global warming, carbon emission has attracted increasing attention from the international community. The European Emissions Trading System, established by the European Union in 2005, is the world's most extensive carbon emissions trading system, in which carbon futures have proved to be not only an essential tool for people to cope with climate change but also an effective method for producers and consumers to manage and hedge risks. (Tang, Wang, Li, Yang & Mi 2020) In 2020, China will strive to achieve the goal of carbon peak by 2030, achieve carbon neutrality by 2060, and start constructing a national carbon trading market. The experience and lessons of the European Union in carbon finance are of great reference significance for China to build a tough carbon finance market.

There is a wide range of studies on carbon finance, and this paper considers EUA carbon futures. The main research direction of EUA literature is the price of EUA spot futures, including price prediction, market arbitrage, energy prices, and the impact of economic factors. In terms of price prediction, Yah Architects et al. (Yahşi, Çanakoğlu & Ağralı 2019) used an artificial neural network and decision tree algorithm to predict carbon prices using Brent crude oil futures, coal, electricity, and natural gas prices, as well as DAX and Standard & Poor's indexes as explanatory variables. In the aspect of market arbitrage, researchers hope to find a pricing model of the carbon price and explain the underlying mechanism of the carbon price. Stefan (Trück & Weron 2016) found that participants were willing to pay an additional risk premium in the futures market to hedge against the increasing volatility of EUA prices. In terms of energy price factors, Dutta (Dutta & Anupam 2017) assessed the impact of the oil market on carbon prices and concluded a strong correlation between implied fluctuations in the oil market and carbon prices. Qiang et al. (Ji, Zhang & Jiang-bo, et al. 2018) proved that Brent crude oil price plays an important role in influencing carbon price changes and risks. For example, in terms of economic factors, Yuan (Yuan & Yang 2020), using generalized autoregressive - dynamic copulas, connects the model to study financial market uncertainty and asymmetric risk spillover between the carbon market. It is concluded that systemic event occurs, the uncertainty of the stock market than the uncertainty of the crude oil market in risk transfer to the carbon market showed a more significant impact.

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To forecast and study the EU carbon futures EUA, this paper establishes the ARIMA-GARCH model based on the EUA price data of January 7, 2008, solstice, and May 18, 2021, and carries out the forecast for the next 12 weeks. The RBF neural network model is established based on the EUA price data of March 22, 2010, solstice, and June 3, 2021, to explore the influence mechanism of economic and energy factors on carbon futures price and the degree price change.

2 PRICE ANALYSIS OF CARBON FUTURES

2.1 Policy Analysis

The fourth phase of the EU's EUETS program begins in 2021. This phase will bring stricter rules, with a new target of cutting emissions by 40% by 2030. To meet the target, the industries covered by the EU's Emissions Trading Scheme would have to cut their emissions by 43% from 2005 levels. The total quota would have to fall by 2.2% a year from 2021 and by 1.74% in the third phase. Industries under the EU's Emissions Trading Scheme will reduce emissions by an additional 556m tonnes over the next decade. Therefore, it is essential to study the factors of carbon price fluctuation and the degree of change. The study on the EU carbon futures price in this paper can enrich the methods of studying the carbon financial market and provide a good reference for investors to avoid risks and policymakers to stabilize the carbon financial market.

2.2 Analysis of Influencing Factors

2.2.1 Energy Price Factors

Energy supply and demand will affect companies' production behaviour, which will affect the carbon price. From a supply point of view, market participants can obtain the amount of carbon dioxide allotted annually from the National Distribution Plans (NAPS). From the perspective of demand, enterprises and facilities can choose to pay for the carbon emission right according to their energy consumption level and buy and sell the quota according to their actual emissions. When the price of energy changes, the price of related products will also change, and enterprises will adjust their production level accordingly, affecting carbon emissions. Actual emissions depend on the type of energy. The schematic diagram is shown in Figure 1.

Among them, the crude oil price is the continuous price of Brent crude oil futures. At present, more than 65% of the world's physical crude oil is priced by the Brent system. Brent, whose main customers include refineries in northwest Europe, is a good proxy for the cost of oil for European energy inputs.

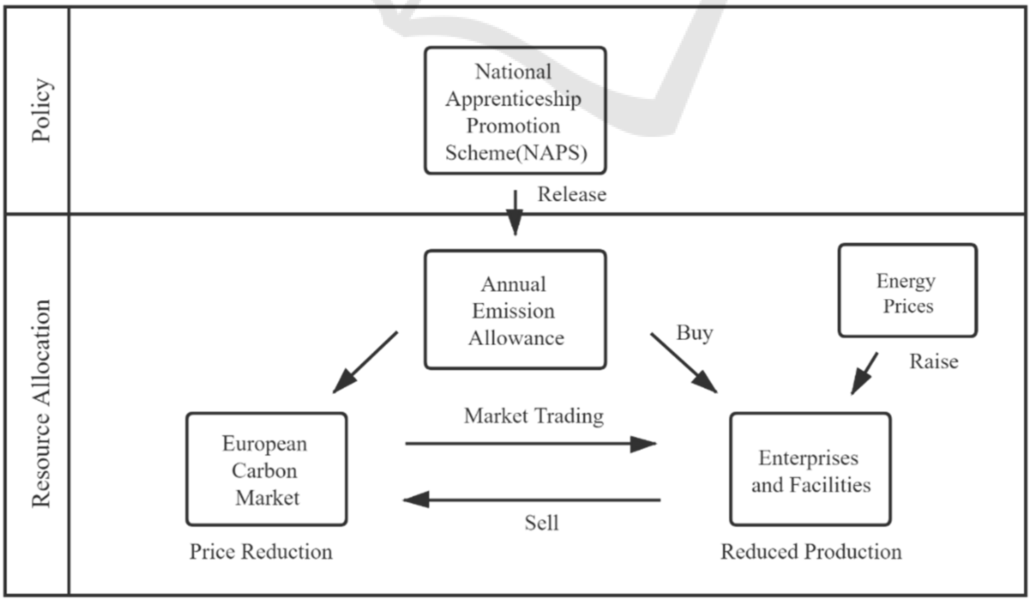


Figure 1: Schematic diagram of price impact.

Natural gas price is the natural gas futures price at the National Equilibrium Point (NBP) in the UK. The prices of various trading markets in the EU are correlated and interactive. Among them, NBP is the most representative market, which can be used to represent the natural gas cost of energy input in Europe.

The coal price is based on the spot price of coal for the next month's delivery in Antwerp/Rotterdam/Amstor (ARA) at various European ports. The coal trading price index is published weekly, representing the cost of imported coal in northwest Europe.

As the primary source of carbon emissions and the main entity to purchase carbon emission quotas, power enterprises will greatly impact the carbon market. However, the power price factor is not correlated with carbon emissions as other energy variables, and the power conversion variable can be given by Equation (1). P is the cost of carbon emissions of the balance. P_c and P_G are the corresponding price of coal and natural gas at the corresponding time point. M_c and M_G are the carbon emissions for each 10^5 units of electricity generated by two different power generation methods. K_C and K_G are conversion variables, which are related to the type of settlement currency, unit commodity quantity, and power generation efficiency. The P of the equilibrium point is the target power conversion.

$$P\times M_C + {P_C}/{k_C} = P\times M_G + {P_G}/{k_G} \tag{1}$$

2.2.2 Economic Factors

Economic factors will lead to the fluctuation of carbon futures prices. Carbon emission permits are the production costs of enterprises with high energy consumption. The rise and fall of the price of carbon emission permits may affect a particular industry, and the prosperity degree of the industry will also affect the carbon price. For example, the stock market index mainly reflects the profit expectation of enterprises and investors' optimism about the prospect of economic development, which will affect the production of enterprises and thus affect carbon emissions. However, different markets have different paths and degrees of influence.

The economic factors used in this paper include the CRB index price that reflects the bulk commodity market. The CRB index includes the price fluctuation of the core commodity, which is widely used to observe and analyze the price fluctuation of the commodity market and the macro-economic fluctuation and reveal the future trend of the macro-economy to a certain extent.

The *Stoxx* 50 Index, which reflects the stock market, is a weighted average index composed of 50 super blue-chip stocks listed in the capital markets of 12 countries such as France and Germany, which are members of the European Union. The financial securities circles regard the index as an indicator of the overall situation of the share prices of large listed companies in the eurozone.

The *Traxx* Europe International Credit Derivatives Index, which reflects the bond market, comprises one hundred and twenty-five (125) liquid European entities with investment-grade credit ratings. It can be regarded as a benchmark index for the continental bond market, and investors can use it to obtain the latest developments in the European bond market.

3 EUA FORECAST BASED ON ARIMA-GARCH

$ARIMA(p, d, q)$ (summation autoregressive moving average model) is a method with high short-term prediction accuracy. It is composed of difference order, autoregressive model, and moving average model. The non-stationary time series of the ARIMA model is transformed into the ARMA model by d-order difference. The form of the model is:

$$\Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t \tag{2}$$

$$\varepsilon_t \sim WN(0,\sigma^2) \tag{3}$$

Meanwhile, the data stationarity should be tested before using the $\boldsymbol{ARIMA(p,d,q)}$ model.

The generalized autoregressive conditional heteroscedasticity model (GARCH) is mainly aimed at autocorrelation, which can effectively fit the current conditional variance with long-term correlation. $\boldsymbol{GARCH(p,q)}$ model satisfies:

$$u_t = \sigma_t \varepsilon_t \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i u_{t-i}^2 + \sum_{i=1}^{p}\beta_i \sigma_{t-i}^2 \tag{5}$$

$$\varepsilon_t \overset{iid}{\sim} N(0,1) \tag{6}$$

This paper uses the EU carbon futures settlement price (EUA) to establish an ARIMA-GARCH model and uses this model to forecast the EUA price in the next three months.

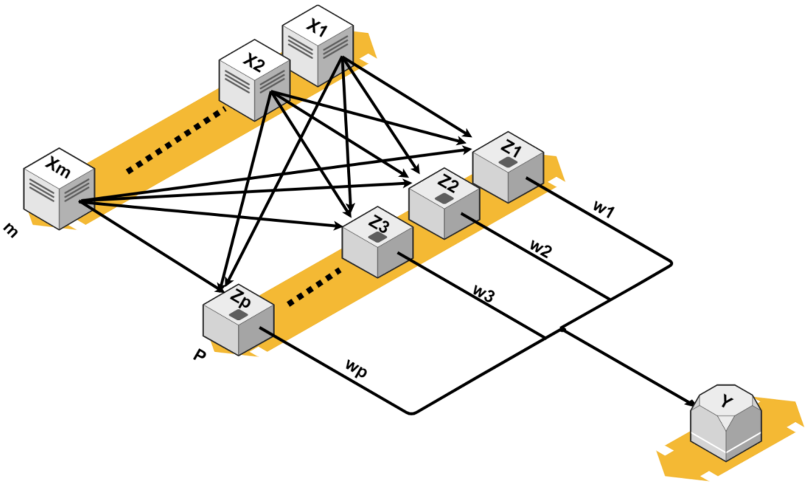


Figure 2: RBF Philosophy diagram.

4 RBF NEURAL NETWORK

RBF neural network is a kind of local approximation neural network, which usually has only one hidden layer. The process of mapping the data of the input layer to the hidden layer applies the idea of the kernel function, which is nonlinear. The transformation of the hidden space pointing to the output layer is linear. It is nonlinear for the data itself, but for the corresponding parameters, it is linear, which will significantly simplify the solution of the parameters, so it has a great advantage in the learning speed compared with the traditional BP neural network.

The hidden node of the RBF neural network uses the distance between the input mode and the centre vector as the independent variable of the function and uses the radial basis function as the activation function. In most cases, the Gaussian function is used as the radial basis function. The corresponding activation functions are as follows:

$$R(x_m - c_i) = \exp(-\frac{1}{2\sigma^2}\left\|x_m - c_i\right\|^2) \tag{7}$$

$\boldsymbol{x_i}$ is the vector corresponding to the original explanatory variable, while $\boldsymbol{\sigma^2}$ is the variance of the Gaussian function. The expression from the input layer to the hidden layer is as follows:

$$z_j = \exp(-\left\|\frac{X - c_j}{D_j}\right\|) \tag{8}$$

In the above formula, $\boldsymbol{C_j}$ can be regarded as the centre vector corresponding to the $\boldsymbol{j}$ th hidden layer neuron, which is composed of the central components of all $\boldsymbol{x}$ in the input layer connected by the $\boldsymbol{j}$ th neuron in the hidden layer. $\boldsymbol{D_j}$ is the width vector of the j th neuron in the hidden layer. The linear expression from the hidden layer to the output layer is:

$$y_i = \sum_{i=1}^{p} \omega_{ij} z_j \tag{9}$$

$$\sigma = \frac{1}{P}\sum_{j}^{m}\left\|d_j - y_j c_i\right\|^2 \tag{10}$$

RBF neural network has a considerable performance on dealing with the details of related variables, with a good effect on various financial data with large time series fluctuations. In this paper, based on the RBF model, through the contribution analysis of European economic indicators and energy prices related to EUA, the influence of seven explanatory variables on EUA price fluctuation is obtained.

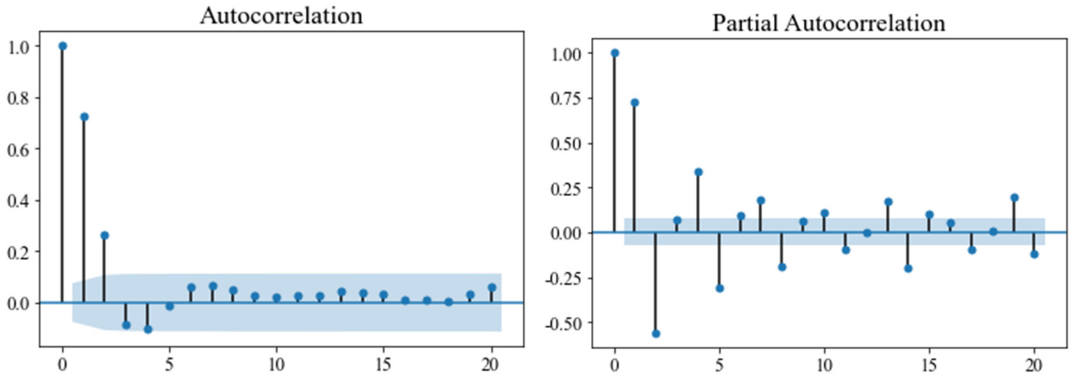
5 RESEARCH ON CARBON FUTURES FORECAST AND RELATED ASSETS IMPACT ANALYSIS BASED ON ARIMA-GARCH AND RBF NEURAL NETWORK

5.1 Carbon Futures Forecast Based on ARIMA-GARCH

Daily EUA carbon futures settlement price is all from the WIND database, from January 7, 2008, to May 18, 2021, with 3440 samples. The calculated average value of every five days is taken as weekly data, and.

Table 1: Stationarity test results.

ADF test	Critical value 0.01	Critical value 0.05	Critical value 0.10	P-value	Lag order
-18.11	-3.44	-2.87	-2.57	$2.54e^{-30}$	3



(a)ACF **(b)PACF**

Figure 3: ACF PACF Schematic Diagram.

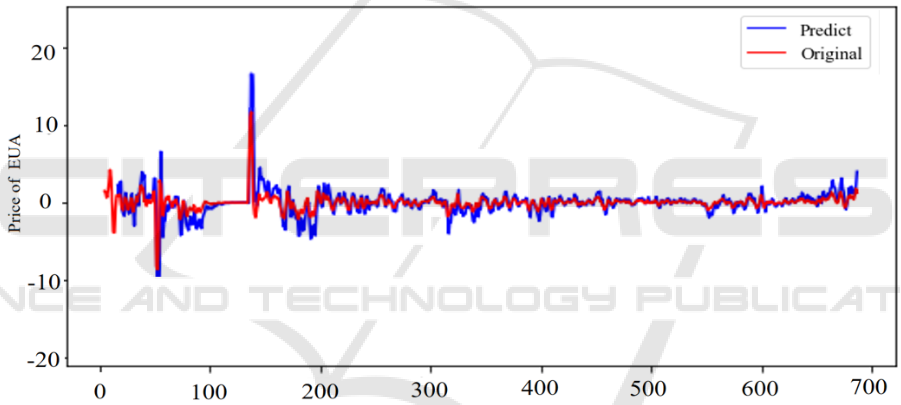


Figure 4: Fitting renderings.

the carbon futures price data are processed for 688 sets of data. Before establishing the ARIMA model, the ADF test method is used to carry on the stationarity test to the weekly data. See Table 1.

The results show that after the third-order difference of the weekly average EUA price data, the ADF test value of the EUA price sequence is less than the critical value of 1% confidence interval under the confidence of 1%, 5%, and 10%. The p-value is much less than 0.1, showing that the EUA price data is stable. Autocorrelation diagram (ACF) and partial autocorrelation (PACF) diagram are used to determine the Model parameters of the ARIMA model, which can be seen in Figure 3.

By observing chart (a), it is found that the AR part of the weekly average EUA price is a trailing order of order 5, that is, AR (5). By observing graph (b), it is found that the MA part of the sequence shows a typical uncensored property. On this basis, this paper uses the BIC criterion to determine the order of the ARIMA model accurately. By comparing the BIC values of ARIMA(4,3,1), ARIMA(4,3,2), ARIMA(5,3,1), ARIMA(5,3,2), the final model is ARIMA(5,3,1). Confirm the corresponding parameters and determine the model for forecasting futures as follows. Meanwhile, the relevant results can be found in Figure 4.

$$\begin{aligned} x_t - 1.1974x_{t-1} + 0.5213x_{t-2} + 0.5213x_{t-3} \\ + 1.2979x_{t-4} + 1.2979x_{t-5} \\ = \varepsilon_t - 7.7025\varepsilon_{t-1} \end{aligned} \quad (11)$$

The white noise test was carried out on the residual data, and the result showed that the residual sequence was not white noise, indicating that the information in the data was not fully extracted. On this basis, GARCH (1,1) model was established for the residual sequence in this paper. The model is as follows:

$$\sigma_t^2 = 0.4738 + 0.3491\mu_{t-1}^2 + 0.4971\sigma_{t-1}^2 \quad (12)$$

On this basis, the model is used to predict the carbon futures EUA price in the next 12 weeks, and the results are shown in Table2.

Table 2: Forecast data for the next 12 weeks.

Week1	Week2	Week3	Week4
20.37	22.81	22.67	22.51
Week5	Week6	Week7	Week8
24.97	24.84	24.69	27.14
Week9	Week10	Week11	Week12
27.02	26.87	26.88	29.33

The RMSE value of the residual sequence of the relevant data is calculated, and the fitting effect of the model is judged. The calculated result was RMSE=2.89, indicating that the fitting effect of the model was good and the reliability of the prediction results was extensive. From the forecast results, the EU carbon futures price is on an upward trend in a short period, which may be affected by a series of factors, such as the European political situation, good EU policy guidance, financial market fluctuations, etc. Therefore, carbon futures investors and related enterprises need to make an optimal decision by considering all aspects of factors when investing.

5.2 Contribution Analysis of Related Assets Based on RBF Neural Network

The prices of crude oil, natural gas, coal, and CRB of commodities, *iDraxx* of bonds, and STOXX 50 index of stocks used for contribution analysis are all derived from the Wind database. There are 2876 observation time points based on the settlement price and closing index corresponding to the trading day from March 22, 2010, to June 3, 2021, in which bond-related data show a tiny proportion of breakpoints and outliers. Numerous interpolations are carried out by using multiple interpolation methods and the K-means clustering method. The SWITCH power conversion variables are obtained by solving the formula (1). Descriptive statistics of 7 types of variables can be found in Table 3.

A relatively optimal RBF network model is constructed, in which the number of nodes in the input layer is the number of the input layer is 7 of the input variables, corresponding to the corresponding index of the normalized influencing factors, the output is the EUA price, and the number of nodes in the output layer is 1. In the model construction, 69.6% of the data points were selected as the training set. 30.4% of the data points were selected as the test set. The best performance was achieved when the Softmax function was selected as RBF, and the hidden layer had 99 neurons.

The training error and test error corresponding to the RBF carbon futures price model are less than 0.1%, and the model shows good robustness. The fitting effect between the measured price and the predicted price can be seen in Figure5. The scattered points are concentrated on both sides of the straight line with a As can be seen from the figure, the slope of the predicted results are close to 1, indicating the constructed model can accurately predict the carbon futures price.

Table 3: Descriptive statistics of explanatory variables.

Variations	Symbol	Mean	Std	Min	Max	Median	Skew	Kurt
EUA	EUA	12.90	0.17	2.7	56.49	8.07	1.50	2.32
Stoxx50	STOCK	3104.1	7.92	1995.01	4088.5	3137.1	-0.31	-0.52
Oil Price	OIL	76.20	0.50	19.33	126.65	69.02	0.21	-1.30
Gas Price	GAS	50.05	0.28	8.74	77.86	51.13	-0.38	-0.61
COAL Price	COAL	78.51	0.40	38.55	131.50	78.55	0.36	-0.44
CRB	COMM	232.48	1.15	106.28	370.56	200.87	0.30	-1.28
iTraxx	BOND	82.46	0.64	41.26	207.96	71.73	1.14	1.34
Balance P	ESWITCH	91.50	0.83	-6.38	185.70	86.05	0.34	-0.5

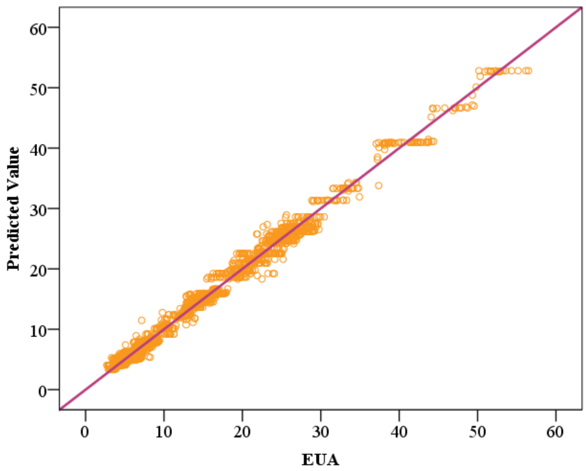


Figure 5: The fitting price corresponds to the EUA scatter diagram.

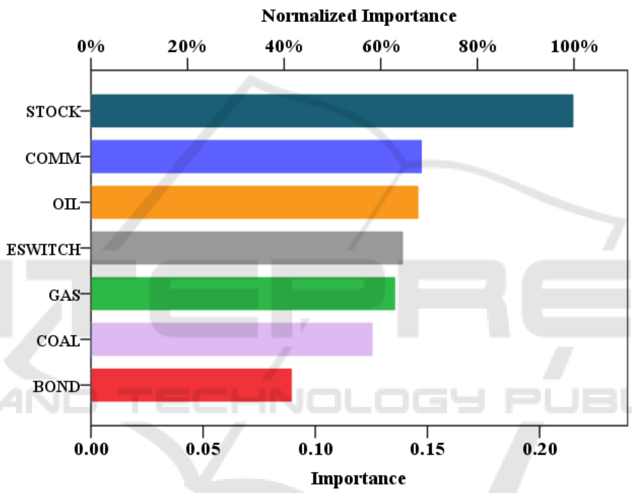


Figure 6: Contributions of explanatory variables.

The contribution of seven types of related assets can be vividly analyzed by Figure 6.

(1) from the perspective of various indicators at the economic level, the stock index has the most significant impact on the trend of carbon futures prices, and the rise of the stock index often indicates that the overall economic trend is developing for the better, which effectively promotes enterprises to participate in quota market trading, so carbon futures price will also be higher. The fluctuation of the commodity index will also affect the trend of carbon futures because there is always a direct correlation between the flow speed of commodities and the carbon emissions produced by enterprises.

(2) Three different energy prices are of the same importance to the final carbon futures price in the energy market. The crude oil price has a significant positive impact on the carbon futures price. The fluctuation of this price will often prompt large chemical enterprises to adjust their quota demand. Electrical switching variable importance degree on natural gas and coal, the influence of the lower than the price of crude oil, but in fact, power conversion variable is affected by many factors, such as the maximum power limit of power plant units, the government's macro-control of national electricity price and many other factors. It can not carry all the information about the raw material adjustment of the power plant according to the carbon futures price under the ideal condition. The power conversion variable is directly linked to the overall supply and demand of carbon emission rights, and its contribution to EUA price will be more obvious.

6 CONCLUSION

This paper aims at the trend of European carbon futures price, and its influencing factors take the EUA price trend from 2008 to 2021 as the research object, extracts the information from the residual term of time series model by constructing ARIMA-GARCH model, and obtains the prediction result with good fitting effect. RBF neural network is used to contribute quantitative analysis. The specific conclusions are as follows :

(1) This paper uses EUA price data of 2008 and 2021 to forecast the carbon futures price in the next 12 weeks. According to the forecast results, the settlement price of carbon futures is still in the rising stage in the short term, which may be affected by a series of factors such as the supply relationship of carbon quotas, market arbitrage speculation, and relevant policies.

(2) The stock market has the most considerable influence among economic factors, and its contribution reaches 0.215. Among other factors, commodity market has a more significant impact on economic factors, while bond has a minor impact on economic factors. As for energy, different energy sources have similar effects on prices, with crude oil having the most considerable impact. The actual contribution of the power conversion variable switch to carbon futures prices is likely to be underestimated due to many factors.

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