A Comparative Study and Forecast of Carbon Dioxide Emissions in EU Countries over the Next Decade Using SARIMAX and GRU Models

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Keywords: CO2 Emission, GRU Model, SARIMAX Model.

Abstract: Recently, the world has faced major challenges in addressing climate change. One of the primary contributors to global warming is carbon dioxide (CO2), and as one of the major CO2 emission regions in the world, the effectiveness of the emission reduction measures taken by the European Union has attracted much attention. Therefore, based on the global CO2 emission data set from 1980 to 2022, this study uses a linear regression model to test whether the gross domestic product (GDP), energy consumption, and population of each country are driving factors of CO2 emissions, and uses them as exogenous variables of the Seasonal Autoregressive Integrated Moving Average and exogenous variables (SARIMAX) model and Characteristic variables of the Gated recurrent units (GRU) model to participate in the prediction. Secondly, the SARIMAX model and the GRU model are trained using a rolling test set, and the trend of EU countries' carbon dioxide emissions in the next 10 years is predicted. According to the study, the GRU model has higher average MAE and MSE values than the SARIMAX model. CO2 emissions in most EU countries will continue to decline in the future. Therefore, in small sample situations, the SARIMAX prediction model is better than the GRU model. The emission reduction measures taken by EU countries are effective.

1 INTRODUCTION

CO2 is one of the main components of greenhouse gases, and its increased emissions will trigger a series of serious environmental, ecological, economic and social problems, including the intensification of global warming. Although in 2015, countries signed the Paris Agreement in Paris, France, pledging to limit the increase in global average temperature to well below 2 degrees Celsius compared to the pre-industrial period and strive to limit the temperature rise to 1.5 degrees Celsius. However, the United Nations Environment Program noted in the 2023 Environmental Gap Report that global greenhouse gas emissions rose by 1.2% in 2022 and carbon dioxide emissions hit a new high of 57.4 billion tons. Therefore, although many countries have actively taken measures to reduce CO2 emissions in recent years, they have failed to effectively reduce emissions, resulting in a significant gap between the projected emissions in 2030 and the emission levels required to achieve the Paris Agreement targets.

The EU is one of the world's major CO2 emitting regions, accounting for about 7% of global emissions. In 2022, the EU's greenhouse gas emissions fell by 0.8% compared to 2021 (United Nations Environment Programme, 2023). The EU's goal is to reduce greenhouse gas emissions by 55% by 2030 compared to 1990 levels. In order to do this, the EU has implemented a series of emission reduction policies, including expanding the Emissions Trading System (EU ETS), the biggest carbon market in the world (Cifuentes-Faura, 2022). However, due to the large size of the EU system, covering 27 countries, achieving effective emission reductions requires coordinating the policies of various countries to ensure consistency of goals. Therefore, it is of great significance to monitor the implementation progress of each country's emission reduction targets through forecasting and analyzing CO2, evaluating existing policies, providing reasonable references for policy

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Zhang, J.
A Comparative Study and Forecast of Carbon Dioxide Emissions in EU Countries over the Next Decade Using SARIMAX and GRU Models.
DOI: 10.5220/0013689600004670

In *Proceedings of the 2nd International Conference on Data Science and Engineering (ICDSE 2025)*, pages 332-339
ISBN: 978-989-758-765-8

adjustments, and assessing whether the goals promised in the Paris Agreement can be achieved.

In recent years, a large number of scholars have conducted research on CO2 emission prediction methods, and the models are mainly divided into three categories. The first group consists of statistical models, including the autoregressive integrated moving average model (ARIMA) and its variations (SARIMA and SARIMAX), as well as the popular grey model (GM). The second group is machine learning models, such as support vector machines (SVM) and neural network models. Among neural network models, long short-term memory networks (LSTM) are also widely used in CO2 emission prediction due to their powerful nonlinear fitting capabilities and advantages in processing time series data (Wen, Liu, Bai, et al, 2023). The third category is the hybrid model, which usually combines the statistical model with the machine learning model to take advantage of different models (Zhao & Li, 2021). Compared to LSTM model, GRU model demonstrates simpler architecture and greater effectiveness in mitigating gradient explosion issues. However, there has been limited research on its application for performance evaluation in CO2 emission forecasting across EU countries, and with few studies comparing its predictive capabilities with statistical approaches like the SARIMAX model.

Therefore, this study investigates the forecast of EU CO2 emissions based on the SARIMAX and GRU models and compares the performance of the two models. The data for this study comes from the global CO2 emissions dataset from 1980 to 2022 on the Kaggle website. A linear regression model is used to analyze whether the economy, energy consumption, and population of each country are significant driving factors of CO2 emissions ($P<0.05$), and these are used as exogenous variables of the country's SARIMAX model and characteristic variables of the GRU model for prediction. In the SARIMAX model, the SARIMA model is used to generate the forecast value of the exogenous variable for the next ten years, and the GRU model is used to generate the feature vector value for the next ten years through linear extrapolation, and they are respectively involved in the forecast. Both models use a rolling test set, then finally assess the forecast model's performance using the average MSE and average MAE values (Hodson, 2022). It aims to verify the effectiveness of the EU's current emission reduction policy and provide empirical evidence for other countries to formulate relevant emission reduction policies.

2 METHOD

2.1 Linear Regression

In 2021, Riza Radmehr and other scholars analyzed the data of EU22 member states from 1995 to 2014 when studying the driving factors of CO_2 emissions in EU countries. They concluded that GDP and energy consumption have a significant impact on CO_2 emissions, while population is usually included as an exogenous variable in CO_2 forecasts (Radmehr & Henneberry & Shayanmehr, 2021). In 2024, Yukai Jin and other scholars conducted a review of carbon emission prediction models and further proved that the gross domestic product, population, and energy consumption have an impact on CO_2 emissions (Jin et al., 2024). Therefore, a highly transparent linear regression model is used to characterize the impact of population, economy, and energy consumption on CO_2 emissions in the 27 EU member states. Linear regression model is established for the three independent variables of population, GDP, and energy consumption in EU countries, and a significance test is performed. The P value is used to determine whether the independent variable has a significant effect on CO_2 emissions. The driving factors that pass the p-value test for each country are used as exogenous variables of the SARIMAX model and characteristic variables of the GRU model are input into the model.

Its equation is:

$$\mathrm{CO_2} = \beta_0 + \beta_1 \cdot \mathrm{P} + \epsilon \tag{1}$$

Where β_0 is the intercept term, β_1 is the independent variable coefficient, ϵ is the error term, and P is GDP or population or energy consumption.

2.2 SARIMAX Model

The SARIMAX model is distinctive among many forecasting models because it can make forecasts based on the trend of time data while capturing seasonal changes in data, and to increase forecast accuracy, it includes exogenous variables in the study.

The foundation of the SARIMAX model is the ARIMA model, a traditional statistical model for time series modeling and forecasting that is composed of three components: integration (I), moving average (MA), and autoregression (AR) (Li & Zhang, 2023). AR (p) autoregressive term order, which represents the linear relationship between the current value and the past p values, I (d) difference term order, which can transform the non-stationary series into a stationary series through difference, and MA (q) moving average term order, which represents the linear relationship between the current error and the past q errors. The SARIMAX model retains the three basic components of the ARIMA model while adding seasonal factors and exogenous variables. The parameters of the SARIMAX model also introduce the seasonal autoregressive order SAR (P), with a period of S, the seasonal difference order SI (D), and the seasonal moving average order SMA (Q), in addition to the autoregressive order AR (p), the difference order I (d), and the moving average order (q).

The expression is:

$$\varphi_p(B)\phi_P(B^S)(1-B)^d(1-B^S)^D y_t = c + \sum_{i=1}^{k} \beta_i x_{i,t} + \theta_q(B)\Theta_Q(B^s)\epsilon_t \tag{2}$$

Among them, c is a constant term, $\beta_i x_{i,t}$ is an exogenous variable, i.e., a linear combination of the factors affecting CO_2 emissions at time t (k=1, 2, 3), ϵ_t is an error term, $(1-B)^d$ is a non-seasonal difference with a difference number of d, and $(1-B^S)^D$ is a seasonal difference with a difference number of D.

$\varphi_p(B)$ is the non-seasonal autoregressive polynomial:

$$\varphi_p(B) = 1 - \varphi_1(B) - \ldots - \varphi_p(B^p) \tag{3}$$

$\phi_P(B^S)$ is the seasonal autoregressive polynomial:

$$\phi_P(B^S) = 1 - \phi_1 B^S - \ldots - \phi_P B^{PS} \tag{4}$$

$\theta_q(B)$ is the non-seasonal moving average polynomial:

$$\theta_q(B) = 1 + \theta_1 B + \ldots + \theta_q B^q \tag{5}$$

$\Theta_Q(B^S)$ is the seasonal moving average polynomial:

$$\Theta_Q(B^S) = 1 + \Theta_Q B^S + \ldots + \Theta_Q B^{QS} \tag{6}$$

The modeling and prediction of the SARIMAX model includes six steps, as depicted in Figure 1:

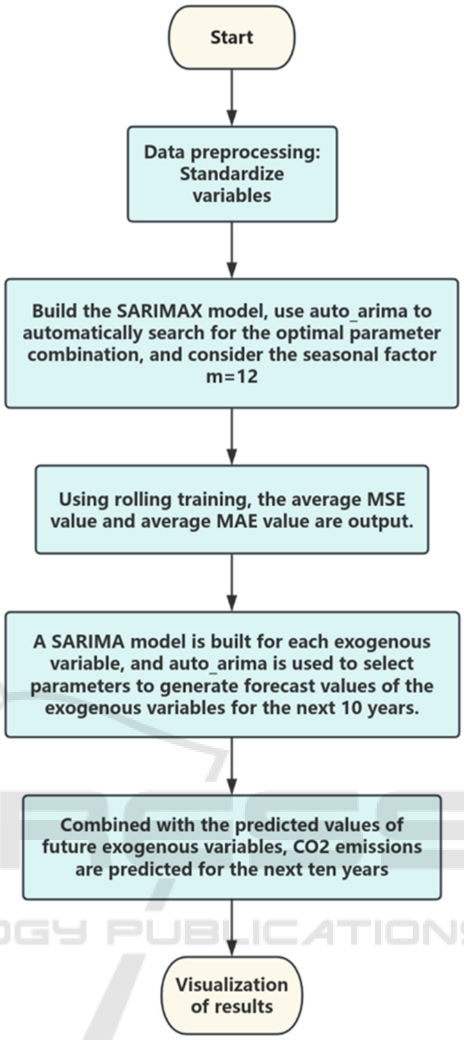

Figure 1: SARIMAX prediction model flow chart (Picture credit: original).

2.3 GRU Model

The GRU model is a variant model based on the LSTM model architecture. It updates and resets the hidden state through a gating mechanism to balance historical information and new information currently input, thereby dynamically controlling the flow of information. Compared with the complex gating mechanism of the LSTM model, GRU optimizes the association between the input gate and the forget gate in the LSTM into an update gate (Mahjoub, Chrifi-Alaoui, Marhic, et al, 2022). Therefore, the gated recurrent unit of GRU has only two gates, namely the reset gate and the update gate. The update gate (Z_t) determines the extent to which the new hidden state is updated to the current hidden state, that is, how much new information is updated. The reset gate (R_t) determines the degree of forgetting historical information, that is, it determines the degree to which the hidden state at the previous moment can affect the current hidden state. A candidate hidden state ($\widetilde{H}_t$) is a temporarily generated hidden state that combines the current input information with some historical information. Finally, the candidate hidden state and the previous hidden state are combined via the update gate to calculate the hidden state, and this resultant hidden state is then fed as input to the next gated unit in the sequence.

The expression of the gate unit is：

$$Z_t = \sigma(W_z \cdot [H_{t-1}, x_t] + a_Z) \tag{7}$$

$$R_t = \sigma(W_R \cdot [H_{t-1}, x_t] + a_R) \tag{8}$$

$$\widetilde{H}_t = \tanh(W_H \cdot [R_t \odot H_{t-1},\ x_t] + a_H) \tag{9}$$

$$H_t = (1 - Z_t) \odot \widetilde{H}_t + Z_t \odot H_{t-1} \tag{10}$$

Where x_t is the current input, H_{t-1} is the hidden state at the previous moment, W_R, W_H, W_Z are weight parameters, a_Z, a_R, a_H is the bias parameter, σ is the sigmoid function, the symbol $\odot$ represents the Hadamard product, and tanh is the nonlinear activation function.

One of the gate unit processes is shown in Figure 2:

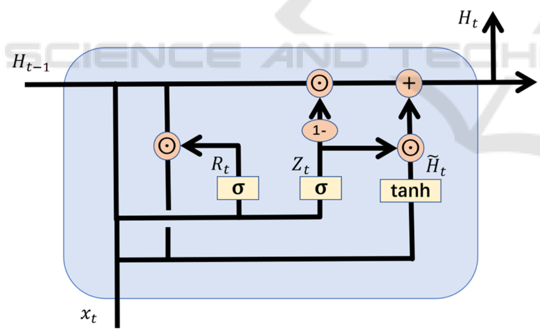

Figure 2: GRU model gate unit flow chart (Picture credit: original).

According to studies, the GRU model performs similarly to the LSTM model in many situations. However, GRU speeds up training by reducing the LSTM's input, forget, and output gates to an update gate and a reset gate. More importantly, the direct transmission of the GRU hidden state makes the gradient propagation path more direct, which can effectively alleviate problems such as gradient disappearance or explosion (Shiri, Perumal, Mustapha, et al, 2024). In addition, the LSTM model is better at processing very long sequences, and the GRU model requires relatively less summarized data, so it is more suitable for predicting CO_2 emissions based on annual data.

The modeling and prediction of the GRU model mainly includes 7 steps, as shown in Figure 3:

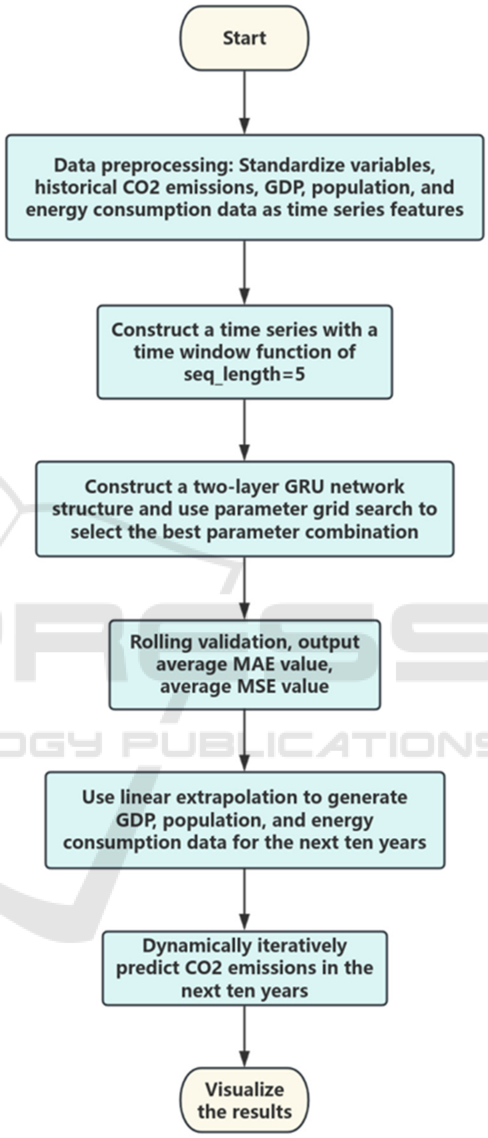

Figure 3: GRU prediction model flow chart (Picture credit: original).

3 RESULTS

3.1 Driving Factors

Among the 27 EU member states, the three driving factors of most member states passed the p-value test based on the linear regression model, indicating that they have a significant impact on CO_2 emissions.

All three factors of Malta failed the p-value test, so the SARIMA model was used to model it without adding exogenous variables. When predicting with the GRU model, only CO_2 historical data was used as the characteristic variable, and no other variables were added.

The population and GDP factors of Croatia, Finland, Italy, Luxembourg, and the Netherlands did not pass the p-value test, so only energy consumption was used as an exogenous variable and eigenvector in the prediction.

The GDP factors of Estonia, Latvia, Lithuania, and Slovenia did not pass the p-value test, so energy consumption and population size were used as exogenous variables and eigenvectors to participate in the prediction.

3.2 Average MAE and Average MSE

As shown in the results in Table 1 and Table 2, for most EU countries, the average MSE and average MAE indicators of the SARIMAX model and the GRU model are close to 0, which indicates that both the average absolute error and the average square error between the two models' actual values and their predictions are minor. The performance of both models is relatively good, and the prediction of CO_2 emissions is relatively reliable. The SARIMAX model's average MSE and average MAE values are less than the GRU model's, suggesting that there are fewer outliers in the training results of the SARIMAX model, and the average prediction deviation under the stationarity assumption is also smaller than that of the GRU model. Compared with the GRU model, it shows good time series processing capabilities and is better suited for forecasting CO_2 emissions in EU member states.

Table 1: Average MAE value of the two models.

Average MAE	SARIMAX	GRU
Austria	0.08463	0.14220
Belgium	0.09486	0.14692
Bulgaria	0.02233	0.08012
Croatia	0.11287	0.09653
Cyprus	0.04145	0.08090
Czechia	0.02292	0.05710
Denmark	0.02962	0.07477
Estonia	0.03359	0.07863
Finland	0.03627	0.15370
France	0.04181	0.04479
Germany	0.02376	0.05496
Greece	0.04687	0.06994
Hungary	0.01781	0.04249
Ireland	0.02324	0.11046
Italy	0.02834	0.10906
Latvia	0.03057	0.01763
Lithuania	0.02621	0.01054
Luxembourg	0.03029	0.10679
Malta	0.13111	0.08099
Netherlands	0.05900	0.18846
Poland	0.01478	0.10907
Portugal	0.06811	0.14421
Romania	0.03057	0.01830
Slovakia	0.01816	0.07619
Slovenia	0.05058	0.08561
Spain	0.04226	0.10774
Sweden	0.02416	0.04887

Table 2: Average MSE value of the two models.

Average MSE	SARIMAX	GRU
Austria	0.01153	0.02467
Belgium	0.01190	0.02612
Bulgaria	0.00087	0.00853
Croatia	0.02142	0.01159
Cyprus	0.00274	0.01191
Czechia	0.00069	0.00382
Denmark	0.00116	0.00680
Estonia	0.00126	0.01123
Finland	0.00208	0.02906
France	0.00211	0.00301
Germany	0.00085	0.00638
Greece	0.00281	0.00862
Hungary	0.00043	0.00205
Ireland	0.00118	0.02289
Italy	0.00106	0.01598
Latvia	0.00197	0.00049
Lithuania	0.00083	0.00026
Luxembourg	0.00207	0.01582
Malta	0.03242	0.01279
Netherlands	0.00499	0.05676
Poland	0.00049	0.01407
Portugal	0.00632	0.03379
Romania	0.00115	0.00049
Slovakia	0.00052	0.00660
Slovenia	0.00411	0.00887
Spain	0.00273	0.02126
Sweden	0.00086	0.00459

3.3 Forecast Results of Carbon Dioxide Emissions in the Next Ten Years

The prediction results are shown by taking Germany, France and Poland, three countries with high emissions in 2022, as examples. The results show that the SRIMAX and GRU models forecast similar trends for the majority of countries. The SARIMAX model can better fit the fluctuations in historical data. In contrast, the GRU model fits the training history data less well than the SARIMAX model and performs poorly when dealing with outliers in historical data.

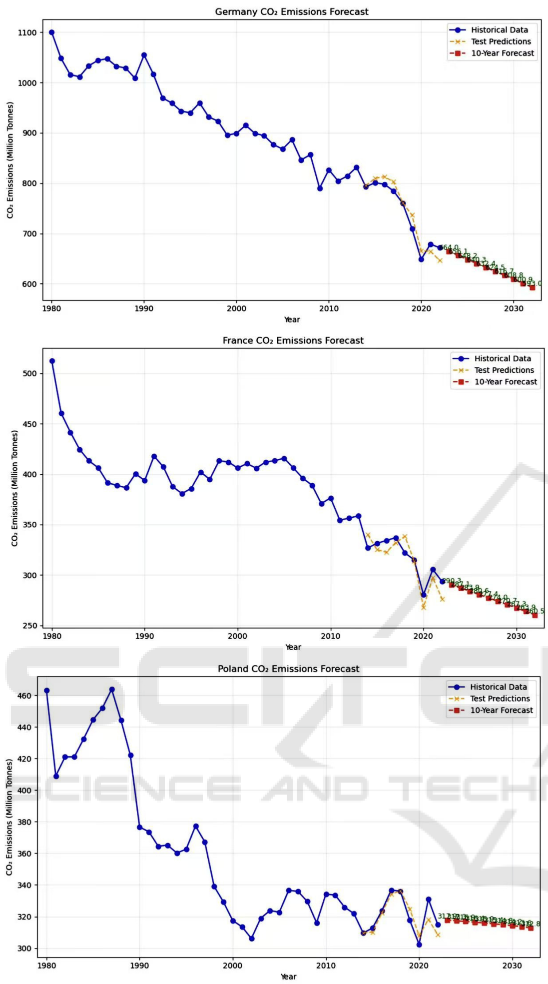

Figure 4: SARIMAX model prediction results (Picture credit: original).

It is speculated that the possible reason for the error between the training data and the real data is that the model cannot capture the intervention of policy factors and there are fewer driving factors. In addition, it is speculated that the possible reason why the SARIMAX model has a higher fitting accuracy for historical data with large fluctuations than the GRU model is that the SARIMAX model, as a traditional statistical model, is more suitable for small sample time series, while GRU, as a neural network model, requires more data to capture complex patterns. The SARIMAX model captures cyclical changes through seasonal_order, which may have a more significant advantage in long-term trend forecasting. The SARIMAX model explicitly quantifies the impact of exogenous variables on CO2 through differentials, which is highly interpretable, while the GRU model inputs feature variables into a black box network, which may result in the inability to effectively separate the independent impact of driving factors.

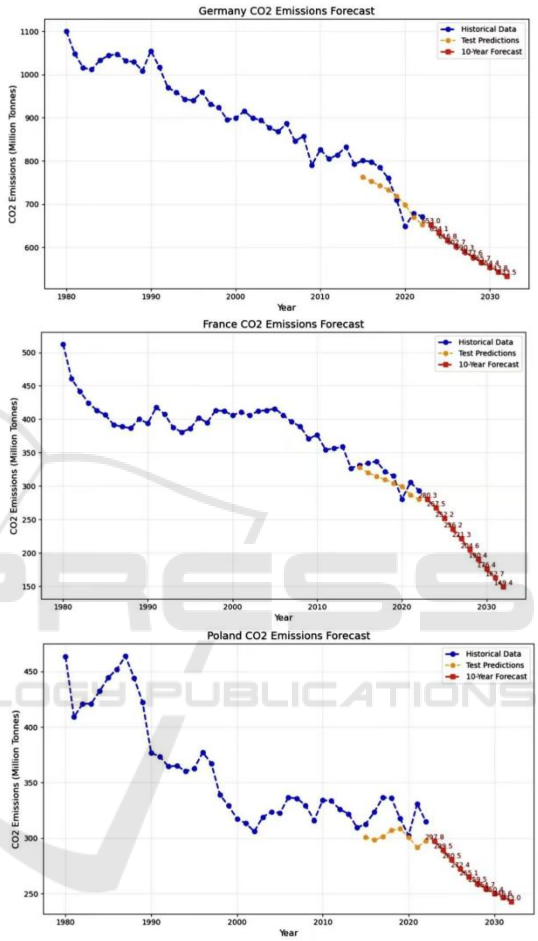

Figure 5: GRU model prediction results (Picture credit: original).

Although the prediction trends of CO_2 emissions for most EU countries based on the SARIMAX model and the GRU model are the same, there are some countries with opposite prediction trends. It is speculated that the possible reason is that the SARIMAX model predicts a downward trend when CO_2 emissions show a non-monotonic trend of first increasing and then decreasing due to the fixed difference order, while the GRU model may have captured the recovery signal after the inflection point. The GRU model generates future features through linear extrapolation and has poor adaptability to changes in nonlinear feature vectors (such as sudden population growth). Figure 4 and Figure 5 show that the SARIMAX model and the GRU model differ in predicting the rate of decline in CO_2 emissions. It is speculated that the possible reason is that some countries have quickly turned to renewable energy, resulting in a CO_2 decline rate that is higher than the historical law. At the same time, the SARIMAX model relies on historical data and may underestimate the speed of emission reduction. If the GRU model captures recent mutation signals, it may predict a more radical decline.

4 DISCUSSIONS

This study shows that the CO_2 emissions of 17 of the 27 EU member states are declining in the trends predicted by both models, indicating that the measures and policies taken by the EU have effectively reduced CO_2 emissions. The rate of decline in CO_2 emissions in most countries has increased significantly since 2005, presumably because the EU carbon emissions trading system established in 2005 has been effective in reducing greenhouse gas emissions. At the same time, CO_2 emissions in EU countries also dropped significantly after 2018. It is speculated that the possible reason is that the revision of the Renewable Energy Directive in 2018 effectively improved energy efficiency, resulting in a significant drop in CO_2 emissions. The series of measures taken by the EU have achieved remarkable results in reducing CO_2 emissions. Therefore, other countries should actively learn from its successful experience and strengthen international cooperation. The EU should actively provide corresponding assistance and support, give full play to its leading role, and help advance the global climate governance process to achieve the goals set out in the Paris Agreement.

Although the average MAE and average MSE values of the SARIMAX model and the GRU model are close to 0, they can still be further improved. The SARIMAX model is more reliable in predicting countries with relatively stable historical trends, while GRU is good at capturing mutation signals to make predictions, so a GRU-SARIMAX hybrid model can be constructed to predict CO_2 emissions. At the same time, this study uses monthly data. If high-precision predictions of CO_2 emissions for a specific country are required, it is recommended to use monthly and quarterly data on CO_2 emissions to better capture historical trends and mutation nodes. It is difficult to find the same driving factors for CO_2 emissions for the entire EU countries. Therefore, this study only uses three driving factors to make predictions for the countries. If a specific country is studied, additional driving factors can be added based on the country's national conditions to better fit the historical data curve and improve model performance.

5 CONCLUSIONS

Through the study and prediction of CO_2 emissions in EU countries in the next 10 years, the SARIMAX model's average MAE and average MSE values are found to be lower than the GRU model's. Consequently, the SARIMAX model is more suited for forecasting CO_2 emissions in EU countries in this study. The possible reason is that the SARIMAX model's superiority for small sample time series prediction. At the same time, the study found that CO_2 emissions in most EU countries will continue to decline in the next 10 years. Therefore, it is anticipated that the European Climate Law's target of reducing greenhouse gas emissions by at least 55% by 2030 in comparison to 1990 will be met. The main contribution of this study is the prediction of carbon emissions of 27 EU countries in the next 10 years, proving that the policies formulated by the EU have achieved significant results in emission reduction, and contrasting the GRU prediction model's performance in a small sample scenario with that of the SARIMAX prediction model. This study provides a reference for other scholars when selecting a small sample CO_2 emission prediction model. In addition, other major CO_2 emitting countries can learn from the EU's economic transformation approach and measures and policies such as improving energy efficiency to promote the realization of the goals of the Paris Agreement, thereby alleviating major problems facing society today, such as climate change, environmental degradation and resource depletion. As described in this study, the SARIMAX model and the GRU model each have their own advantages. In future studies, a hybrid model GRU-SARIMAX can be proposed to improve prediction accuracy and model performance.

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