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TECHNOLOGY FOR OBTAINING INFORMATION ON CO2 EMISSIONS CAUSED BY NATURAL AND MAN-MADE FACTORS USING THE ARIMA MODEL

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ABSTRACT

The study aims to test a hypothesis on the applicability of the ARIMA model for forecasting time series that reflect the dynamics of carbon dioxide emissions into the atmosphere caused by natural (the Mauna Loa volcano) and anthropogenic (CO2 emissions in Germany, France, and Italy) factors. Stationarity of the time series is tested using the augmented Dickey-Fuller test; autocorrelation of the time series is tested using the Ljung-Box test. The study identifies forecasted values of CO2 emissions for stationary and non-stationary time series. In the first case, the obtained forecasted values of the time series are more precise. The authors conclude that additional adjustments are needed to increase the predictive capabilities of ARIMA models for non-stationary time series.

Keywords: *CO2, Climate Change, ARIMA, Stationary and Non-Stationary Time Series, Forecasting.*

1. INTRODUCTION

The combustion of fossil fuels and the resulting emissions of carbon dioxide have a devastating effect on the climate, causing its warming.

Despite the increased influence of geopolitical factors on the economy of Russia, the country's government is not giving up on the climate agenda, including the transition to carbon neutrality. This is evidenced by the recent steps made by the Government of the Russian Federation in this regard [1]. However, internal decarbonization cannot be accomplished without economic and technological support. The urgency of the transition from fossil fuels to a low-carbon economy remains, and the risks are particularly great for the Arctic and Russia. Against the backdrop of sanctions pressure, some Russian exporters will still have to deal with the EU's carbon border adjustment mechanism (CBAM). Several characteristics of the modern decarbonization process can be distinguished. Firstly, decarbonization has become an integral feature of scientific and technological progress. Secondly, the competitiveness of products in the world market began to be evaluated in terms of their carbon intensity. In addition, the decarbonization policy becomes a national obligation.

The global practice of fulfilling the need for decarbonization and plans to achieve carbon neutrality offers two solutions: carbon credits or tax regulation of greenhouse gas emissions. Each tool on its own has both positive and negative sides. The example of Kazakhstan shows that the current regulated carbon market there has proven ineffective, as excessive free emission allowances are easily handed out at the request of businesses. The danger with carbon taxes is that the government would not put a price on carbon that would encourage businesses to reduce emissions, which would be of little help in actually reducing emissions. The example of a regulated carbon market in California shows that such a price covers only 10% of companies' expenses to reduce emissions. On the other hand, the trading of emission credits is more effective than a carbon tax in terms of limiting the negative effects on the end consumer and stimulating the growth of efficiency and the development of high-tech industries. For this reason, for Russia to achieve carbon neutrality, both mechanisms need to be used in combination, blending subsidies for technological development with fees for emissions.

Previous studies have shown that in connection with the problems of climate change on the Earth, which in turn are associated with natural [2] and

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man-made factors of influence [3], it is necessary to solve the problem of regulating emissions of various pollutants in general [4], and hydrocarbons [5], in particular.

The research question that authors are trying to answer in this article is "How can the application of a mathematical model help improve the efficiency of environmental and economic policy development in Russia and other countries?"

In the article, authors propose the use of the ARIMA economic and mathematical model, which allows modeling and predicting carbon dioxide emissions into the atmosphere.

The general hypothesis of the study is that the ARIMA model shows the best results in forecasts for stationary time series, and additional adjustments are needed for non-stationary time series.

The null hypothesis is the presence of the unit root; if the time series has one unit root ($\alpha = 1$), then the first differences are stationary by definition.

The novelty of using the ARIMA model to predict CO2 emissions caused by natural and man-made factors lies in its ability to handle the complexity of such data. Natural and man-made factors can have both short-term and long-term effects on CO2 emissions, and these effects can interact in complex and nonlinear ways. The ARIMA model can capture such complexity by incorporating multiple autoregressive and moving average terms, as well as differencing to account for non-stationarity in the data.

2. LITERATURE REVIEW

The findings of the UN climate report are of concern to governments, scientists, and the public alike. Since the publication of the Club of Rome's work in the 1970s, there have been far more tragic natural disasters than those predicted in it [6]. After the Club of Rome report, the parallels between the 1970s and 2022 are becoming ever more apparent [7-9]. The team of authors of the Club of Rome, using the system dynamics computer modeling method at the global level, has formed scenarios of general development from 1900 to 2100. The authors express concern about the coming critical situation related to the physical limitations of resources over the growing production and consumption, propose various scenarios of possible development, and point out the limits of growth. J.W. Forrester [10] predicted the depletion of resources and the collapse of the global economic system by the end of the 20th and beginning of the 21st centuries. Later on, the results and conclusions of modeling have been confirmed by Forrester's followers [11-13]. Over 30 years, the Club of Rome team evaluated the results of the World3 scenario model, changing the parameters of technological development, natural resources, and social priorities. The variety of scenarios has led to a so-called stabilized world in which predictable collapse can be avoided and prosperity can be increased. An important conclusion of the growth limits model is the assumption that on the time horizon under study, the limits of economic growth will be exceeded, economic systems will not survive, and the population will begin to decline. As a positive conclusion, the authors promise that the 21st century will bring technological, behavioral, and political changes that will avert this collapse [14]. In 2008 and 2014, G.M. Turner conducted a growth limits analysis for the period of 1970-2000, 30 years later, expanding the number of variables analyzed. The study was conducted to compare the World3 model's forecasts and the state of the variables of the new period and to identify the key drivers of economic growth [15]. G. Herrington [16], using the method of the Club of Rome, conducted a macro-level country analysis in addition to the existing Club of Rome forecasts and tested for consistency between the Club of Rome's third World3 model forecast and the current state of the global economy.

As evidenced by years of experience in the development of effective climate policy [17], its primary tools are direct methods of regulating emissions: emissions trading system (ETS), the carbon tax, and hybrid methods [18]. It is also noted that in the short term, the carbon tax brings five times the benefit of the ETS [19,20].

The behavior of people and the political will of national governments have only exacerbated and amplified the effects of economic growth. However, rapid advances in technology and the Coronavirus crisis have also made a difference. In particular, empirical findings suggest that most innovative environmental measures in China are effective at reducing carbon emissions [21,22]. A viable approach to curbing the impact of such emissions is the introduction of advanced carbon capture and storage (CCS) technology, which can capture more than 90% of the CO2 produced by power plants. T. Wilberforce et al. [23] present an assessment of contemporary technologies used in CO2 capture, including post-combustion, pre-combustion, and oxygen combustion, as well as the storage and transportation of CO2. K.T. Raimi [24] considers the opportunity of using geoengineering – removing CO2 and managing solar radiation to control the Earth's climate. At the current stage, these factors need to be considered in the new forecasts. Many policies in limiting greenhouse gas emissions focus on setting a price on carbon emissions. The problem of the impact of carbon pricing on households due to both an increase in the cost of carbon-intensive products and changes in factor prices was analyzed by S. Rausch et al. [25].

The methodological foundation for our analysis and time series forecasting is formed by the major works of G.E.P. Box et al. [26], P.J. Brockwell and R.A Davis [27], and R.J. Hyndman and G. Athanasopoulos [28]. S.J. Taylor and B. Letham [29] consider the problem of forecasting as a curve-fitting task that is inherently different from time series models, which explicitly take into account the structure of the time dependence in the data. This formulation of the problem of forecasting, according to the authors named, provides several practical advantages, including flexibility: it is possible to easily adjust the seasonality of multiple periods, which will allow the analyst to make various assumptions about trends; measurements do not have to be distributed regularly, and it is not necessary to interpolate missing values, e.g., from the removal of outliers; the forecast model has easily interpretable parameters that can be changed by the analyst to make assumptions. In addition, analysts usually have experience with regression and are readily able to extend the model to include new components.

H. Castro [30] performed a similar task for CO2 emissions caused by natural sources for a smaller data set. We are expanding on his analysis and applying the appropriate methods to analyze and forecast CO2 emissions due to anthropogenic factors in three European countries.

3. MATERIALS AND METHODS

3.1 Data

We analyzed two data sets, one for natural CO2 emissions, and the other for anthropogenic ones.

For the first case, we used information on CO2 emissions by the Mauna Loa volcano. Data on CO2 emissions at Mauna Loa Observatory, known as the Keeling Curve, are the world's longest uninterrupted data on atmospheric CO2 concentrations. Scientists conduct atmospheric measurements at remote locations to sample air that is representative of a large volume of Earth's atmosphere and relatively free of local influences. The data on CO2 have been collected and published by the Scripps Institute of Oceanography at the University of California, led by C.D. Keeling and supported by the U.S. Department of Energy, the Earth Networks, and the National Science Foundation [31].

This data set includes monthly observations of atmospheric CO2 concentrations from the Mauna Loa Observatory (Hawaii) at 3,397 meters above sea level. The dataset contains the monthly CO2 concentrations measured at 24:00 hours on the fifteenth of each month.

CO2 data from 1958 to 2018 were used to train the model, and data for 2019-2021 are those predicted based on the proposed forecast model. Next, we compared the data obtained with the actual data available for the period from 2019 to 2021.

To analyze anthropogenic CO2 emissions, we used data on CO2 emissions in metric tons per capita in countries around the world for 1990-2018, provided by the World Data Bank [32].

Data on CO2 from 1990 to 2016 were used to train the proposed model, which enabled us to make a forecast for 2017-2018. In our analysis and forecast, we limited our analysis to CO2 emission data for three European countries: Germany, France, and Italy.

3.2 Methods

ARIMA models offer one approach to forecasting time series. Exponential smoothing and ARIMA are the two most common approaches to time series forecasting and provide additional approaches to the problem. While exponential smoothing models rely on the description of the trend and seasonality in the data, ARIMA models focus on describing autocorrelations in the data.

The basis of forecasting with the ARIMA model is Wold's theorem, which stipulates that each time series can be represented in the form of an infinite-order moving average. Note that automatic ARIMA forecasts are susceptible to large trend errors when there is a change in trend near the cutoff period, and they do not capture seasonality. ARIMA models can include seasonal covariates, but adding these covariates causes very long debugging periods. Exponential smoothing and seasonal naïve forecasts can determine weekly seasonality but overlook long-term seasonality.

The ARIMA model gets its name from the acronym Auto Regressive Integrated Moving Average, which indicates that the ARIMA model has three components: AR – autoregressive term, I – differentiating member, and MA – moving average.

ARIMA models can be expressed in two forms:

1) Non-seasonal models, in which the model has an order in the form (p, d, q), where:
- p – the order of the automatic regression model;
- d – the order of differentiation;
- q – the order of the moving average.

Automatic regression models are similar to regression models, but the regressor in this case is the same dependent variable with a specific lag.

For ARIMA to work, the time series must be stationary at best. This means that the mean and variance are constant over the entire set. Differentiation is used to transform the data to make it stationary. It is assumed that if a time series is stationary, there is a high probability of it repeating the same patterns in the future.

Moving averages are widely used in time series analysis and are a well-known concept. This involves obtaining the average number of points in a series for a particular lag and can be expressed as:

$$\hat{T}_t = \frac{1}{m} \sum_{j=-k}^{k} y_{t+j} \quad (1)$$

where m = 2k +1,
k – the number of values used on average before and after the point used,
t – the time in which the trend cycle is calculated.

With the naïve method, all predictions for the future are equal to the last observed value of the series:

$$\hat{y}_{T+h|T} = y_T \quad (2)$$

where h = 1, 2 …. The naïve method thus assumes that the most recent observation is the only one that matters and that all previous observations give no insight into the future. This can be thought of as a weighted average, in which all the weight corresponds to the last observation.

With the averaging method, all future forecasts are equal to the simple mean value of the observed data:

$$\hat{y}_{T+h|T} = \frac{1}{T} \sum_{t=1}^{T} y_t \quad (3)$$

where h = 1, 2 …. The averaging method thereby presumes that all observations have the same value, and gives them equal weight when producing forecasts.

Therefore, it may be appropriate to give more weight to more recent observations than to those from the distant past. This very concept lies at the heart of simple exponential smoothing. Predictions are calculated using weighted averages, where weights exponentially decrease as observations come from the more distant past, so the lowest weights are attributed to the oldest observations:

$$\hat{y}_{T+h|T} = \alpha y_T + \alpha(1-\alpha) y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots \quad (4)$$

where $0 \le \alpha \le 1$ – the smoothing parameter. A one-step-ahead time forecast T + 1 is the weighted average of all observations in the series $y_1, \ldots, y_t$. The rate at which the weight decreases is controlled by the parameter α.

2) Seasonal ARIMA (SARIMA) models account for seasonality in the data and perform the same steps as ARIMA but on a seasonal model. Thus, if the data have a seasonal pattern each quarter, then SARIMA will get an order for (p, d, q) for all points and (P, D, Q) for each quarter.

Stationary time series are those whose properties do not depend on the time of observation of the dynamics series. A series of white noise, on the other hand, is stationary – the time of its observation is irrelevant, it has to look almost the same at each moment in time

Some cases can be misleading – time series with cyclical behavior (but no trend or seasonality) – are unchanging. This comes from the fact that cycles have no fixed length, so before making observations of a series, one cannot be sure where the peaks and valleys of the cycles will be.

In general, stationary time series will not have a predictable structure in the long run. Time plots show that these series are roughly horizontal (although some cyclical processes are possible), with constant variance.

An autoregressive model uses lagged target values as predictors in the regression. An autoregressive model of order p can be written as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \quad (5)$$

Instead of using past values of the forecast variable in the regression, the moving average model uses past forecast errors in the regression model.

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (6)$$

where ε_t – white noise.

These two approaches can be combined into one system, which has been subsequently extended to cover seasonality and additional regressors. It should be noted that the time series should be stationary to satisfy the underlying assumptions of the model. As a rule, if the first difference in the time series is taken, it becomes stationary.

The stationarity of the time series was tested using the Augmented Dickey-Fuller test examining the value of the coefficient α in the first-order autoregressive equation:

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$$y_t = \alpha * y_{t-1} + \varepsilon_t \quad (7)$$

where y_t – the time series, ε_t – error.

If $\alpha = 1$, the process has a unit root, in which case the y_t series is non-stationary.

If $|\alpha| < 1$, the series is stationary.

Since the process can be a higher order autoregression, we add lags of the first differences and obtain the following test model:

$$\Delta y_t = (a_1 + a_2 - 1)y_{t-1} - a_2 \Delta y_{t-1} + \varepsilon_t \quad (8)$$

If the resulting time series has one unit root, then the first differences are stationary by definition.

Before the Augmented Dickey-Fuller test, we condense our data by removing the trend from it and then re-center the time series by giving it an average value of zero. The test delivers a p-value: if $p < 0.05$, the time series probably returns to the mean (i.e., it is stationary), whereas $p > 0.05$ gives no such indication since the null hypothesis cannot be rejected. When a time series returns to the mean, it tends to return to its long-term average. In turn, if the time series does not return to its mean value, it can shift and never come back to its average. In the latter case, the considered time series is non-stationary.

Testing of the time series for autocorrelations is performed using the Ljung-Box test, which is well suited for time series of short length (as in our case) and also provides a p-value.

$$\tilde{Q} = n(n+2)\sum_{k=1}^{m} \frac{\hat{p}_k^2}{n-k} \quad (9)$$

where n – the number of observations, $\hat{p}_k$ – autocorrelation of the *k-th* order, and m – the number of lags tested.

The Ljung-Box test was applied to the residuals of the resulting ARIMA model.

4. RESULTS

4.1 Analysis of Mauna-Loa CO2 Emissions in 1958-2018

First, we analyze data on CO2 emissions by the Mauna Loa volcano for observation from 1958 to 2018, which are used to train the model. For this purpose, we present the available data, selected over equal time intervals, in our case – a month, which will be the frequency of the argument. The results are given in Figure 1.

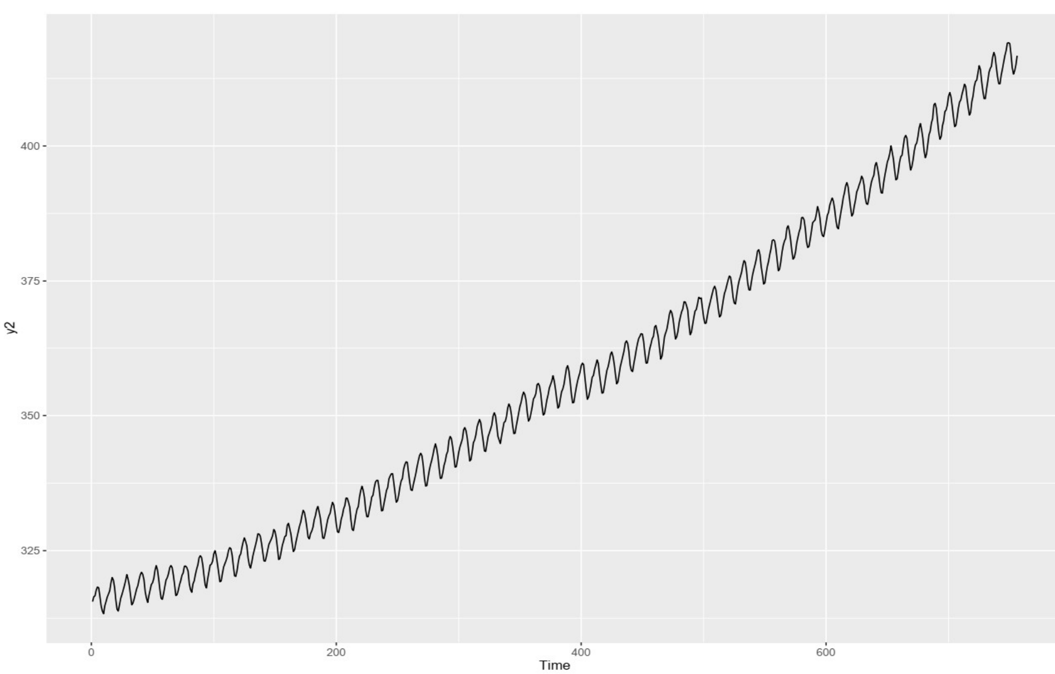

Figure 1: Data on CO2 Emissions for 1958-2018 as a Time Series
The x-axis is time periods, the y-axis is CO2 emissions.

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The obtained time series demonstrates an upward trend and is stationary.

4.2 Forecast of Mauna-Loa CO2 Emissions in 2019-2021

Now we shall make forecasts using the ARIMA model, which is applied to the training period of 1958-2018. From the results obtained, we select the version of the model with the lowest Akaike Information Criterion (AIC). In our case, this is the model ARIMA (2,1,1), AIC = 1500.625. This model is used to make forecasts for 36 months ahead, i.e., 2019-2021. The results are presented in Figure 2.

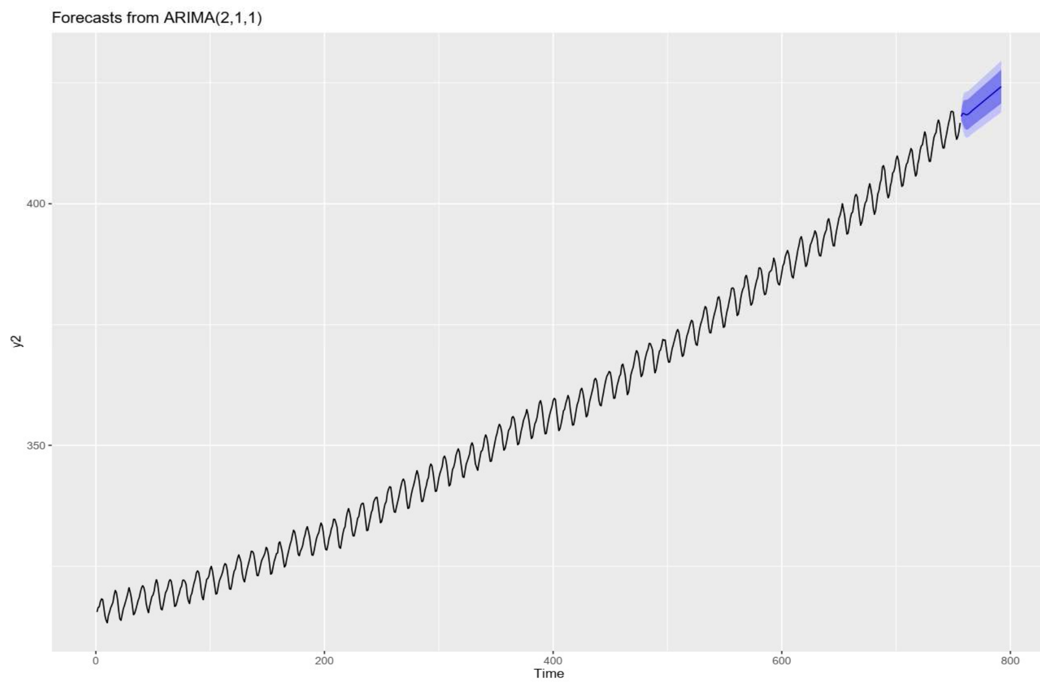

Figure 2: CO2 Emissions Forecast for 2019-2021, Mauna Loa
Dark blue indicates projected data, and light blue indicates the confidence interval.

Judging by the visualization of the model given in Figure 3, the forecast data are quite consistent with those of the training period and do not fall outside the confidence interval.

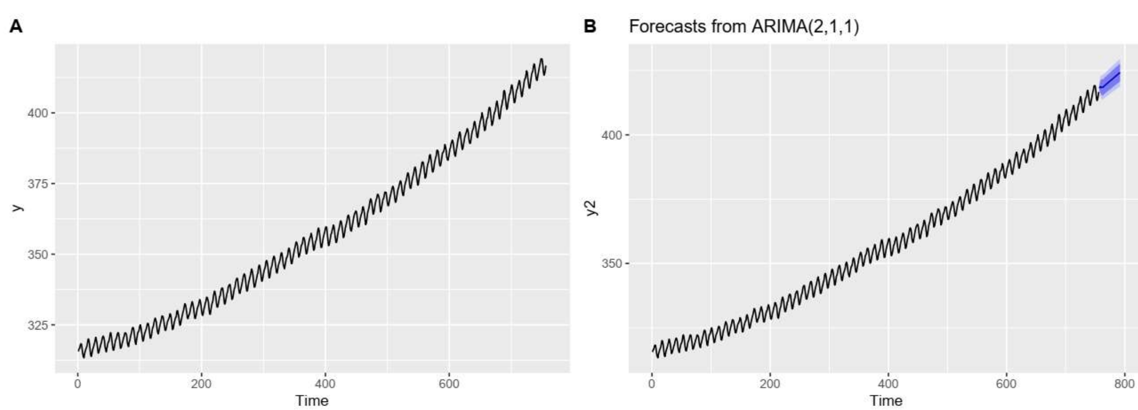

Figure 3: Actual (A) and Predicted (B) CO2 Emissions from the Mauna Loa Volcano in 1958-2021

The Liung-Box test (179.73) and p-value (2.2e-16 in scientific notation) give reason to reject the null hypothesis and confirm the hypothesis that the model chosen for forecasting is correct.

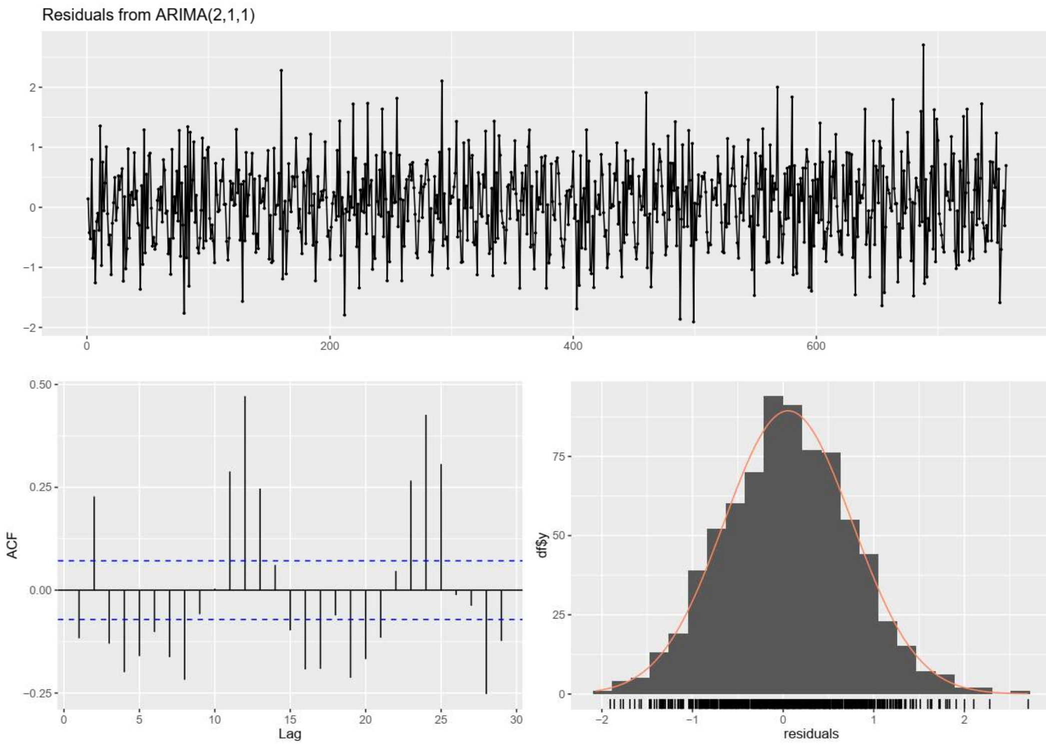

Figure 4: Analysis of Residuals in the Forecast Model of CO2 Emission by the Mauna Loa Volcano, 2019-2021

Data in Figure 4 indicate that the residuals of the proposed time series forecast model are close to the normal distribution and are seasonal, although much of them fall outside of the confidence interval. No volatility clusters are detected. The residuals are rather symmetrical. The P-value in the Ljung-Box test is low, which means that the inconsistencies have patterns, i.e. not all of the information is extracted by the model. The autocorrelation function shows significant autocorrelations between the residuals.

4.3 Analysis of CO2 Emissions in Germany, France, and Italy in 1990-2016

Below we shall analyze and predict anthropogenically generated CO2 emissions in European countries. For this purpose, we employ the methods described above. To do this, data on CO2 emissions are converted into time series (Figures 5-7). The period between 1990 and 2016 is used for model training and the forecast is made for 2017-2018.

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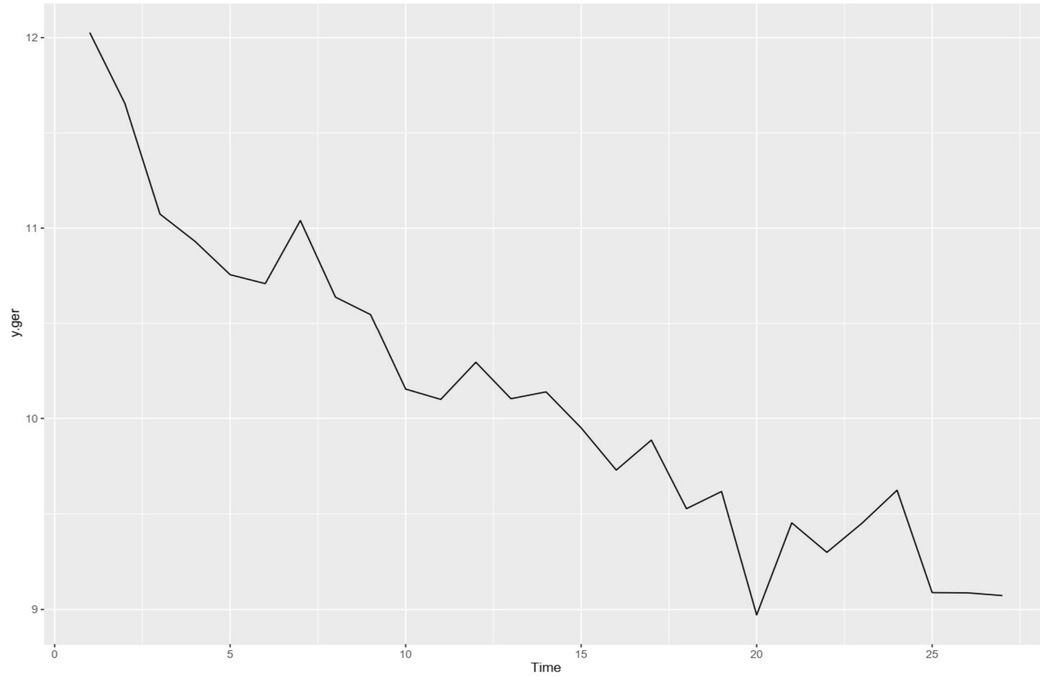

Figure 5: Time Series Data on CO2 Emissions from 1990 to 2016 in Germany

Augmented Dickey-Fuller Test for Germany:
Dickey-Fuller = -3.0497, Lag order = 2
p-value = 0.1717
Alternative hypothesis: stationary

Since the p-value is above 0.05, the null hypothesis cannot be rejected, which means that the time series is non-stationary (has some time-dependent structure and does not have a constant variance over time).

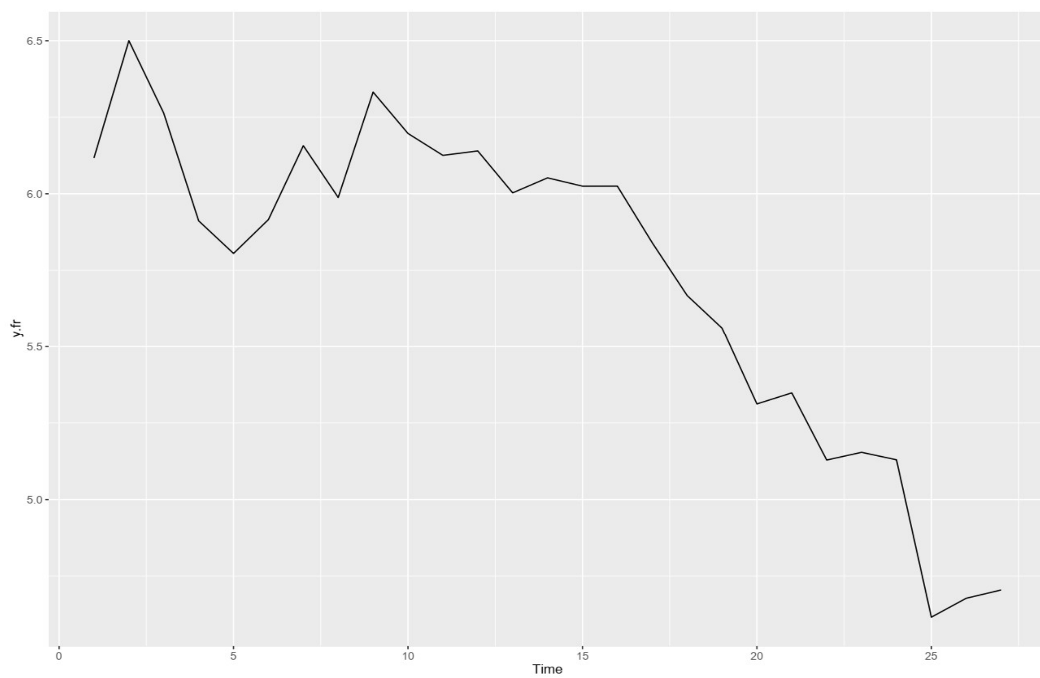

Figure 6: Time Series Data on CO2 Emissions from 1990 to 2016 in France

Augmented Dickey-Fuller Test for France:
Dickey-Fuller = -0.86131, Lag order = 2
p-value = 0.9414
Alternative hypothesis: stationary

Since the p-value is above 0.05, the null hypothesis cannot be rejected, which means that the time series is non-stationary (has some time-dependent structure and does not have a constant variance over time).

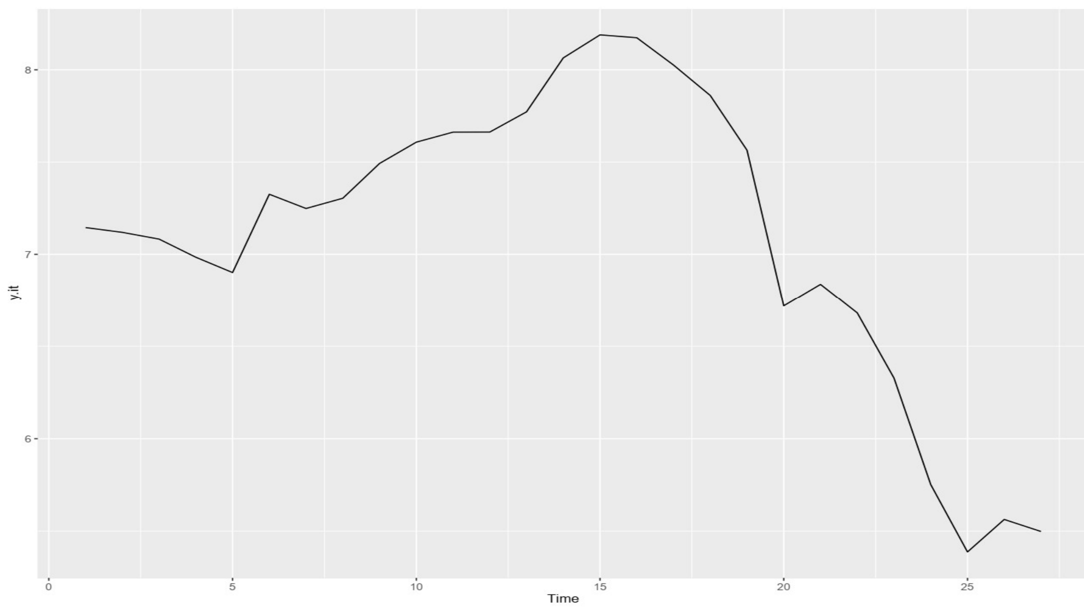

Figure 7: Time Series Data on CO2 Emissions from 1990 to 2016 in Italy

Augmented Dickey-Fuller Test for Italy:
Dickey-Fuller = -0.72133, Lag order = 2
p-value = 0.9568
Alternative hypothesis: stationary

Since the p-value is above 0.05, the null hypothesis cannot be rejected, which means that the time series is non-stationary (has some time-dependent structure and does not have a constant variance over time).

The curves characterizing CO2 emissions in the three European countries in 1990-2016 give evidence that the time series models for them do not have a seasonal pattern and that the series themselves are not stationary. To bring the obtained time series to the stationary version, we differentiate the original series twice using the autoregression process, i.e. the moving average orders p, d, q – ARIMA.

A preliminary analysis of the data on CO2 emissions is conducted to build a forecasting model based on ARIMA.

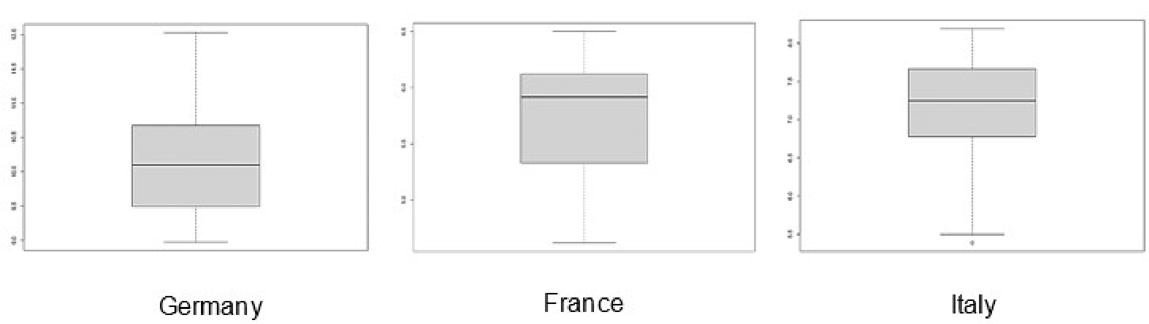

Figure 8: Box Plots for CO2 Emissions in Germany, France, and Italy in 1990-2016

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Figure 8 gives box plots for total CO2 emissions in the considered countries in the testing period. The values of outliers are quite diverse (the value of CO2 emissions in Italy has statistical outliers that fall outside the rest of the data, while analysis on Germany and France reveals no outliers), which allows testing the model on heterogeneous material.

4.4 Forecast of CO2 Emissions in Germany, France, and Italy for 2017-2018

Below we provide forecasts of CO2 emissions based on the ARIMA model for Germany, France, and Italy for 2017-2018.

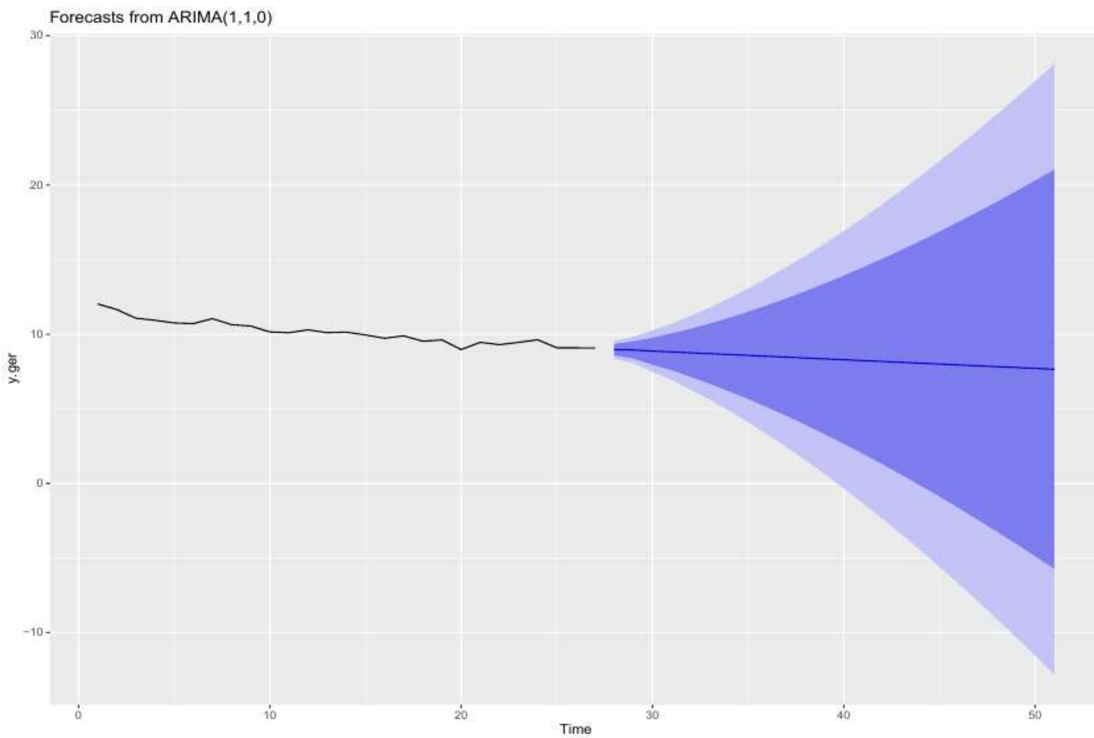

Figure 9: CO2 Emissions Forecast for 2017-2018, Germany.
Dark blue indicates projected data, and light blue indicates the confidence interval.

The Liung-Box test for the forecast of CO2 emissions in Germany in 2017-2018 (10.489) and p-value (0.03295) disprove the null hypothesis and confirm the hypothesis that the model chosen for forecasting is correct.

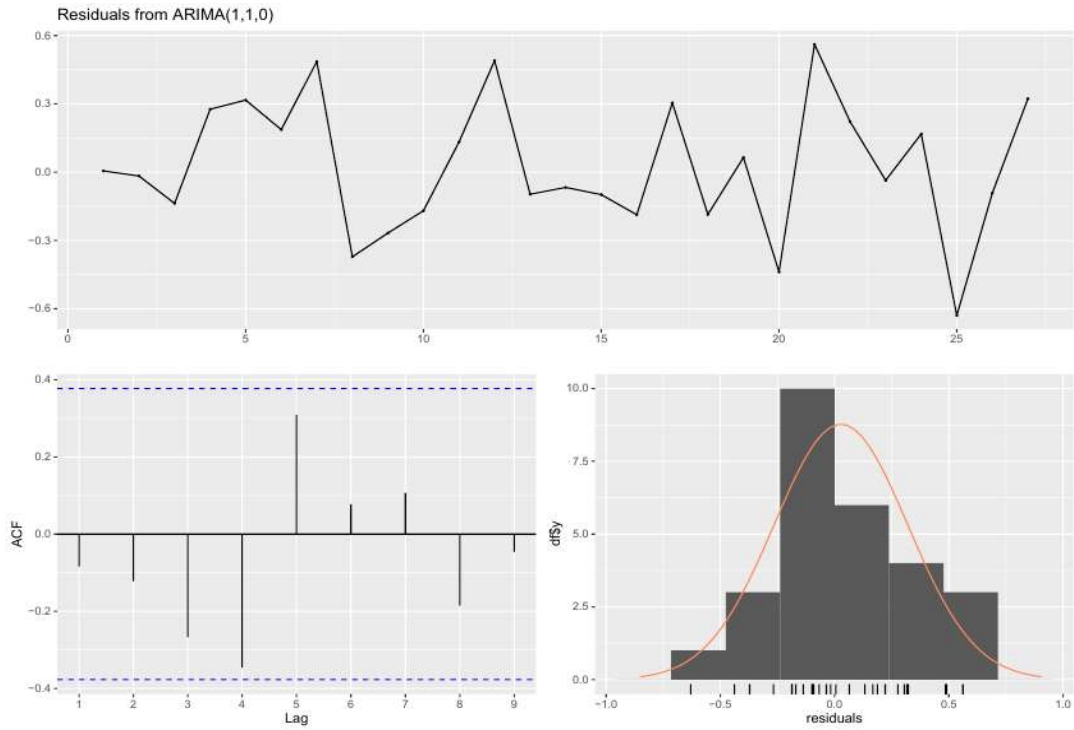

Figure 10: Analysis of Residuals in the CO2 Emission Forecast Model, Germany, 2017-2018

Figure 10 demonstrates that the residuals of the proposed ARIMA time series model for Germany in 2017-2018 show a seasonal pattern, lie within the normal distribution, and have no autocorrelation. Standardized residuals do not reveal volatility clusters.

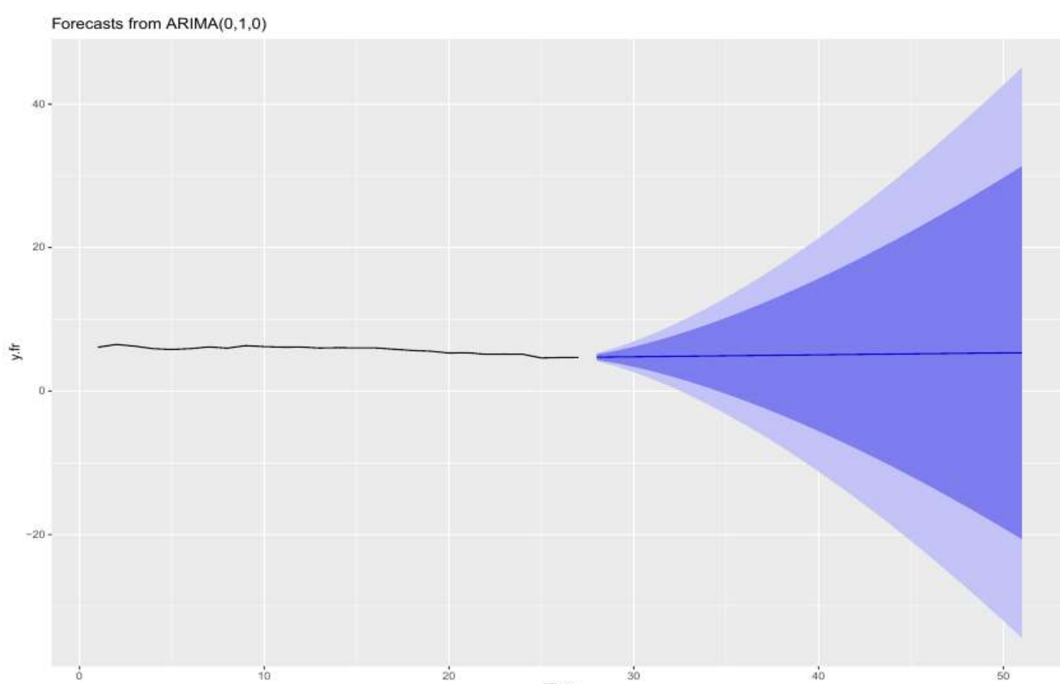

Figure 11: CO2 Emissions Forecast for 2017-2018, France
Dark blue indicates projected data, and light blue indicates the confidence interval.

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The Liung-Box test for the forecast of CO2 emissions in France in 2017-2018 (11.208) and p-value (0.0474) indicate that the null hypothesis is incorrect and prove the hypothesis that the model chosen for forecasting is correct.

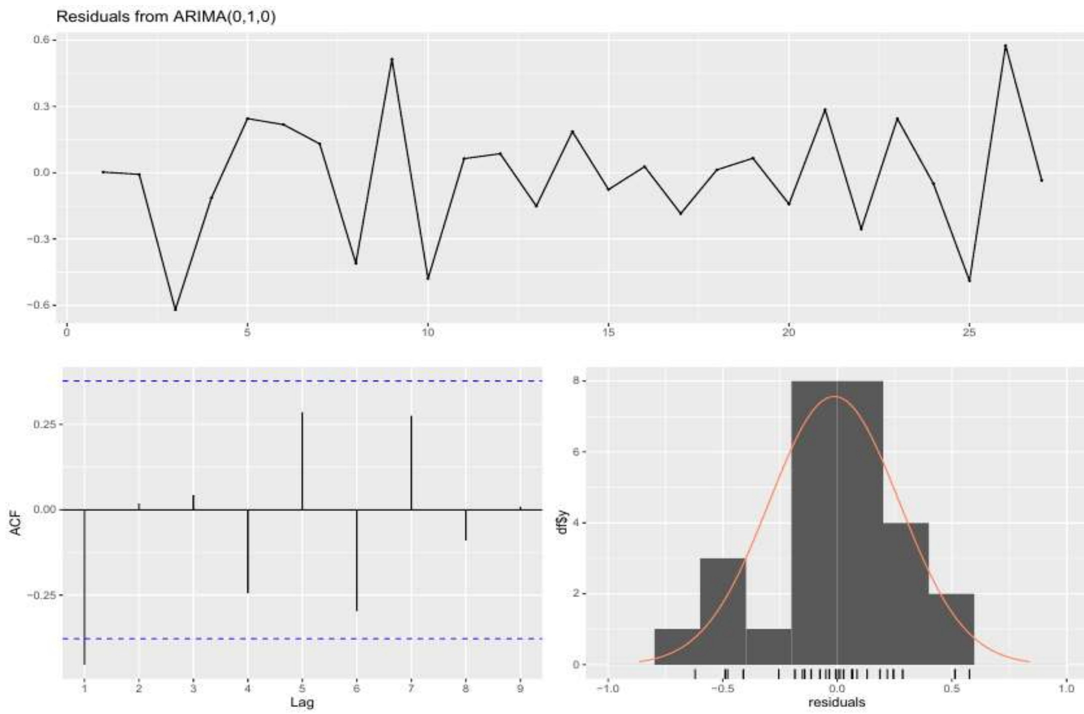

Figure 12: Analysis of Residuals in the CO2 Emission Forecast Model, France, 2017-2018

The data presented in Figure 12 indicate that the residuals of the proposed ARIMA time series forecast model for France in 2017-2018 are close to the normal distribution and have a seasonal pattern, but some of them are outside the confidence interval and there is no autocorrelation between them.

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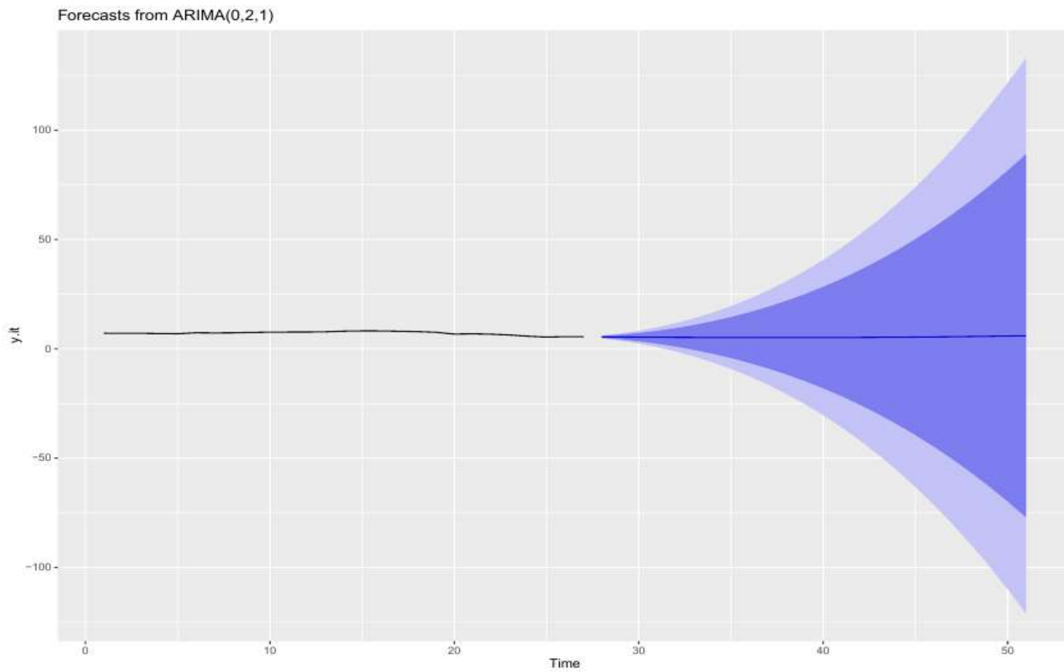

Figure 13: CO2 Emissions Forecast for 2017-2018, Italy
Dark blue indicates projected data, and light blue indicates the confidence interval.

The Liung-Box test for the forecast of CO2 emissions in Italy in 2017-2018 amounts to 7.096. However, the p-value for the period of the forecast (0.1309) prevents us from rejecting the null hypothesis and confirming the proposed hypothesis stating that the selected forecast model is correct.

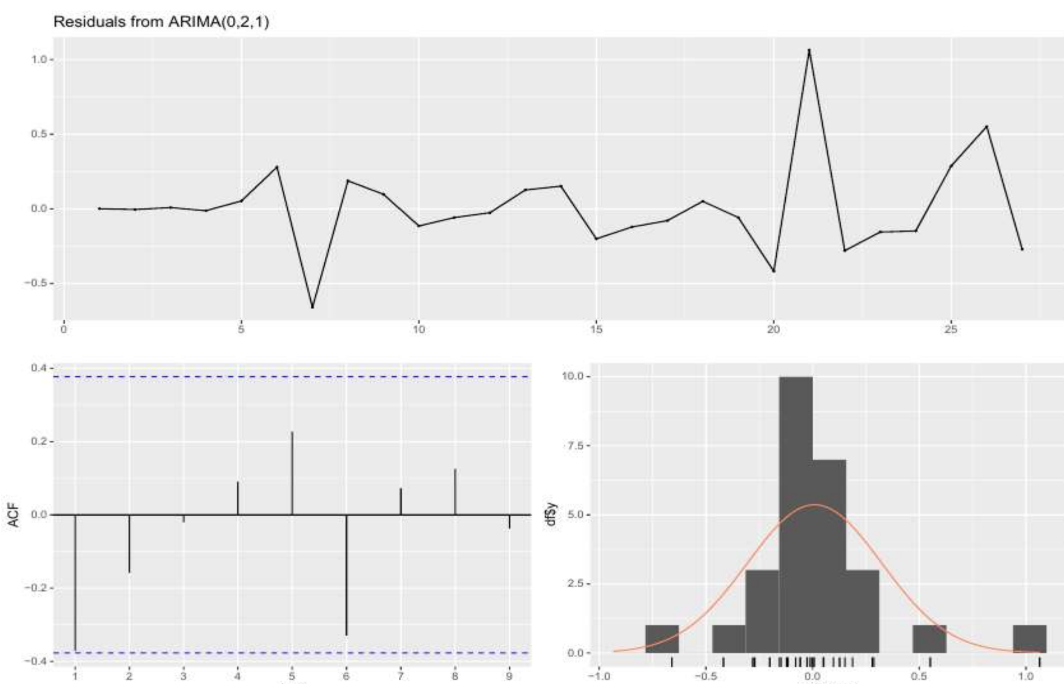

Figure 14: Analysis of Residuals in the CO2 Emission Forecast Model, Italy, 2017-2018

The data reported in Figure 14 demonstrate that the residuals of the proposed ARIMA time series prediction model for Italy in 2017-2018 are far from the normal distribution, have a seasonal pattern, and stay within the confidence interval in the specified period. There are no autocorrelations between model residuals, and the p-value in the Ljung-Box test for Italy has a larger value than in similar tests for Germany and France, which makes it more likely that all information has been extracted by the model leaving only noise.

5. DISCUSSION

The ARIMA methodology is a statistical method for analyzing and building a forecasting model that best represents a time series by modeling correlations in the data [33].

According to the researchers [34], the main advantage of the ARIMA model for forecasting emissions of CO2 is its ability to capture both short-term and long-term patterns in the data, including seasonal fluctuations, trend, and irregular fluctuations, in particular, volcanic eruptions. This is achieved by incorporating autoregressive and moving average components, as well as differencing to account for non-stationarity [35].

As in the study [36], the authors conclude that another advantage of the ARIMA model is its flexibility in handling data with missing values or irregular time intervals. It can also be used to model non-linear relationships between CO2 emissions and other factors, such as economic activity or energy consumption [37].

Compared to other models, such as exponential smoothing [35] or state-space models [38], the ARIMA model has the advantage of being well-established and widely used in time series analysis [39]. According to research [40] it also provides a straightforward and interpretable framework for understanding the underlying patterns in the data.

The study investigated the hypothesis of the applicability of the ARIMA model for time series analysis and forecasting. We used data on monthly average CO2 emissions from the Mauna Loa volcano for 1958-2018 (natural factors) and on annual CO2 emissions in Germany, France, and Italy for 1990-2016 (anthropogenic/technogenic factors).

The authors of the article believe that in order to improve the ARMA model, it can be extended to include exogenous variables, such as economic indicators, weather data, or policy changes, that may influence the behavior of the variable being analyzed. The inclusion of exogenous variables can affect the predictive power of the model and its ability to capture the complex relationships between variables.

The Augmented Dickey-Fuller test indicates that the time series of the Mauna Loa volcano emissions are stationary, while the anthropogenic emissions in the considered European countries are non-stationary.

Using the Mauna Loa volcano's CO2 emissions data from 1959-2018 as the training period for the model, we plotted a forecast of CO2 emissions for 2019-2021. The forecast suggests that CO2 emissions into the atmosphere will increase. The p-value for this prediction is less than 0.05, which gives reason to reject the null hypothesis and confirms sufficient reliability of the capabilities of our model. The model residuals show patterns, meaning that not all the information has been extracted by our model; there are significant autocorrelations between the model residuals.

Based on data on CO2 emissions in Germany, France, and Italy in 1990-2016 (the model's training period), we built a forecast of CO2 emissions in these countries for 2017-2018. Testing of the obtained forecast data proves the proposed model to be usable for Germany and France, while for Italy the null hypothesis could not be rejected. This can be explained by the fact that the residuals of the ARIMA model for Italy are the least symmetrical, and the data on CO2 emissions in this country for the analyzed period have statistical outliers.

The study's limitations relate primarily to the fact that the ARIMA model is better suited for capturing short-term patterns in the data, such as seasonality or cyclicality, rather than long-term trends. For this reason, further research may need to consider alternative models, such as trend models or structural time series models, if they are interested in modeling long-term trends in CO2 emissions.

6. CONCLUSION

CO2 emissions generated by natural sources are expected to increase. The resulting model provides us with the corresponding prediction. However, this model (like any other model) is powerless to predict the explosive growth of CO2 emissions resulting from volcanic eruptions, as happened with the Mauna Loa volcano in mid-December 2022.

The use of ARIMA models has become more relevant in the context of climate change and the need for accurate and reliable emissions forecasts. ARIMA models could help to anticipate future emissions in the energy sector and develop strategies to mitigate the negative impacts of climate change.

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Considering technogenic emissions, all three time series describing the dynamics of CO2 emissions in Germany, France, and Italy show a trend of decreasing CO2 emissions, both in the test period and in the forecast period. It appears expedient to conduct a further study of the dynamics of CO2 emissions in European countries. This suggestion is based on our expectations that emissions will decrease in 2022 owing not to the EU's effective environmental policy, but to the high prices of hydrocarbon raw materials for the industry due to the sanctions policy against Russia. Another reason for the decrease in CO2 emissions in the near future will be the relocation of industrial production from European countries to the United States. We believe that research into the reduction of CO2 emissions in some countries should be tied in with the study of the increase in such emissions in other countries of the world. Otherwise, it will be impossible to formulate credible arguments in defense of declarations about the effectiveness of proposed environmental measures in a single state or region.

We also argue that our results support the hypothesis that ARIMA models give the best results in forecasts for stationary time series. Non-stationary time series require additional model adjustments, for instance, elimination of seasonality, removal of the trend and insignificant coefficients from the ARIMA, change of the confidence interval, etc., which will increase the predictive capabilities of the proposed model. By providing a robust and flexible framework for time series analysis, the ARIMA model can enable researchers and policymakers to better understand the dynamics of CO2 emissions and make more informed decisions.

Overall, the novelty of using the ARIMA model lies in its ability to capture the complexity of CO2 emissions data caused by natural and man-made factors, and to provide accurate and reliable forecasts that can inform policy decisions

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