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CO2 Emission Forecasting in Indonesia Until 2030: Evaluation of ETS Smoothing Prediction Models and Their Implications for Global Climate Change Mitigation

Saepul Aripiyanto[1,*], Dewi Khairani[2], Ambran Hartono[3]

[1,2,3] *State Islamic University Syarif Hidayatullah, Jakarta, Indonesia*

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Abstract

The objective of this study is to predict CO2 emissions in Indonesia until 2030 utilizing the ETS smoothing prediction model in line with the pressing demand for viable climate change mitigation approaches. Through an assessment of the model's efficacy, several fundamental evaluation metrics have been identified. The research findings reveal that the Mean Absolute Error (MAE) stands at 146,154.40, presenting an overview of the average absolute disparity between the projected and actual CO2 emission values. The Mean Squared Error (MSE) of 21,838,251,772.37 characterizes the mean of the squared variances between projections and actual values, gauging the variability of predictive errors. The Root Mean Squared Error (RMSE) at 147,777.71, derived from the square root of MSE, reflects the degree of uncertainty in CO2 emission predictions. Simultaneously, the Mean Absolute Percentage Error (MAPE) of 7.24% provides an overview of the average percentage of absolute discrepancies between projections and actual values. Projections suggest that CO2 emissions could potentially reach 1 million tons in 2030. This evaluation furnishes an in-depth comprehension of the precision of the ETS smoothing model in the context of substantial emission escalation. The implications on the challenges of climate change mitigation become increasingly crucial, underscoring the immediacy of preemptive measures and sustainable policies. While the model delineates emission trends, it is imperative to acknowledge that these forecasts are subject to various influences, such as policy and technological shifts. Consequently, this study underscores the necessity for heightened awareness and the formulation of more efficacious policies to address the potential surge in CO2 emissions in the forthcoming years.

Keywords: Climate Change, CO2 Emissions, Forecasting Until 2030, ETS Smoothing Prediction Model.

1. Introduction

Global climate change poses profound challenges to environmental sustainability and human well-being. The rise in global temperatures, changes in extreme weather patterns, and adverse impacts on ecosystems are not merely symptoms but also warnings of the serious consequences that can result from our actions towards the environment [1]. In addressing this climate crisis, the need for collective efforts to mitigate its impacts is becoming increasingly urgent. Extensive global research has been mobilized to deepen our understanding of the contributions of greenhouse gas emissions, particularly carbon dioxide (CO2), to the dynamics of global climate change [2].

Given that CO2 is a major factor causing climate change, research focused on predicting CO2 emissions is becoming increasingly crucial as an integral step in global efforts to address this crisis. By understanding emission trends and developing effective strategies to reduce them, we can engage the global community in efforts to achieve established mitigation targets. Therefore, this research is not only a scientific obligation but also a key to designing policies and concrete actions that can bring about positive change and preserve environmental sustainability for future generations.

Indonesia, as a country with extraordinary natural wealth and a large population, plays a significant role in global emission mitigation efforts. Factors such as deforestation, urbanization, and industrialization complicate the understanding of CO2 emission dynamics at the national level [3]. Hence, this research is aimed at filling knowledge gaps related to the prediction of CO2 emissions in Indonesia up to the year 2030. By capturing and forecasting these

*Corresponding author: Saepul Aripiyanto (saepul.aripiyanto@uinjkt.ac.id)
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emission patterns, this research is expected to make a valuable contribution to designing mitigation policies that are contextually relevant.

The ETS smoothing approach, used as the main foundation in this research, has been a crucial focus for predicting future trends in CO2 emissions. Previous studies have shown that this model is highly effective in various global contexts [4]. Through the application of the ETS smoothing method, the main objective of this research is not only to provide a more accurate overview of emission dynamics but also to delve deeply into the factors that significantly contribute to emission patterns at the national level. Thus, this research is not merely descriptive but also analytical, making a meaningful contribution to our understanding of the sources and key variables shaping CO2 emission trends at the national level.

The urgency of this research is further strengthened by the pressing need for a clearer understanding of the direction of CO2 emissions in Indonesia. The results of this research are expected to provide deeper insights for policymakers in addressing the challenges of climate change and also make a significant contribution to the scientific literature in the context of CO2 emission prediction. By understanding trends and influencing factors, we can design policies that are not only responsive to current challenges but also sustainable in the long term.

2. Literature Review

2.1. Global Climate Change and Greenhouse Gas Emissions

The rise in emissions of greenhouse gases, particularly carbon dioxide (CO2), has garnered significant attention concerning the issue of worldwide climate change. Over the past few decades, the effects of global warming have become more apparent, leading to collaborative efforts on a global scale to curb greenhouse gas emissions. Indonesia, being a populous country with a diverse ecosystem, bears the responsibility of comprehending and controlling its role in contributing to CO2 emissions as part of the broader initiative to alleviate the impact of global climate change [1][2].

2.2. CO2 Emission Prediction Modeling

Various modeling methods have been developed to predict CO2 emissions. In addressing this challenge, smoothing models have emerged as an effective approach. Smoothing models, particularly the Error-Trend-Seasonality (ETS) model, enable the capture of long-term trends, seasonal variations, and adjustments for errors in time series data. The advantage of this model lies in its ability to adapt to the changing complexity of CO2 emission data over time [4].

2.3. Literature Related to CO2 Emission Prediction in Indonesia

Several studies have been conducted to understand and forecast CO2 emissions in Indonesia. Rahmawati [3] extensively explores the impact of energy policies on emission patterns at the national level. These findings provide valuable insights into the effectiveness of current policies and potential directions for future policy. On the other hand, Tambunan [5] employs a statistical approach to predict future trends based on historical data. Integrating time series data with statistical methods provides a strong foundation for understanding the dynamics of CO2 emissions in Indonesia.

2.4. Relationship Between Economic Factors and CO2 Emissions

It is important to consider economic factors that can influence CO2 emissions. Sugiharto [6] specifically highlights the link between economic growth and greenhouse gas emissions. This analysis not only identifies the cause-and-effect relationship between economic factors and emissions but also measures the significant impacts that may arise. On the other hand, Nurcahyani [7] focuses on evaluating the impact of technology on emission patterns. Investigating how technological advancements can alter emission patterns provides critical insights for the development of sustainable policies.

2.5. Challenges and Opportunities in Predicting CO2 Emissions

Despite the development of various models, predicting CO2 emissions remains a complex challenge. Arifin [8] notes the uncertainty in forecasting the impacts of climate change, especially due to the unpredictable nature of natural variability. In this context, recognizing the limitations of models becomes key to improving forecast precision. On the flip side, Li [9] highlights the potential mitigation opportunities. Identifying opportunities to reduce emissions lays the groundwork for the development of effective and sustainable mitigation strategies, paving the way for policies that are more responsive to the challenges of global climate change.

3. Method

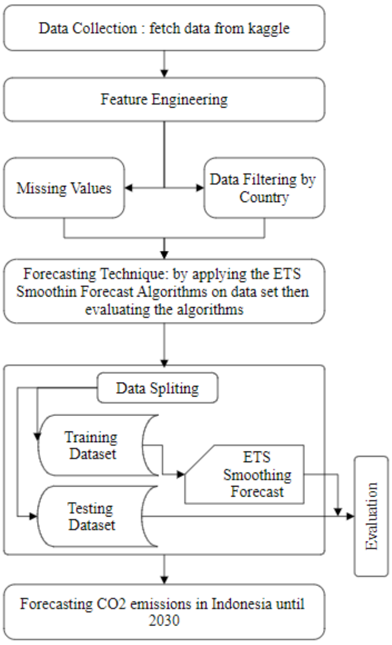

Figure 1. Research Workflow

3.1. Data Collection

In order to predict CO2 emissions in Indonesia, this research adopts a comprehensive and informative methodological approach. The CO2 emission data serving as the basis for analysis is derived from Kaggle, a leading online resource in the field of scientific data. The dataset utilized in this study encapsulates CO2 emissions worldwide from the year 1960 to 2019. The primary data sources are reputable institutions in the context of climate change, such as the United Nations Framework Convention on Climate Change (UNFCCC) and the International Energy Agency (IEA).

This dataset includes detailed information on CO2 emissions from all countries, providing a robust global overview of emission trends and patterns over a significant period. The sustainability and accuracy of this dataset are reinforced by the fact that its sources originate from credible institutions involved in monitoring and assessing the impacts of climate change. The table presented below provides a concise summary of the dataset used, offering a better understanding of the data framework that forms the basis for predictive analysis of CO2 emissions in Indonesia within a global context.

Table 1. Global CO2 Emission Dataset Summary

country_name	Value (CO2 Emissions in kiloton (kt))
World	1.317557e+09
High income	6.672858e+08
IDA & IBRD total	6.667335e+08
OECD members	6.537873e+08
IBRD only	6.398760e+08
...	...
Sao Tome and Principe	3.257741e+03
Turks and Caicos Islands	3.036276e+03
Sint Maarten (Dutch part)	2.145195e+03

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Kiribati	2.120060e+03
Tuvalu	3.000000e+02

3.2. Feature Engineering

The obtained data is subsequently cleaned and processed to eliminate outliers and incomplete entries. Additionally, the data is filtered based on the country's name for utilization in the predictive model. In this research, the data employed pertains to CO2 emissions in Indonesia. The CO2 emission data for Indonesia utilized in this study encompasses aggregate CO2 emissions per country and year. These emissions originate from various economic sectors in Indonesia, including the industrial, transportation, and residential sectors. Information regarding the economic sectors contributing to CO2 emissions was obtained from a survey conducted by the Central Statistics Agency (Badan Pusat Statistik - BPS) in 2019.

Although Indonesia still exhibits a lower rate of emission increase compared to other countries, such as India, it does not imply that Indonesia has a low CO2 emission increase. Based on the data we acquired, the increase in CO2 emissions in Indonesia from 1990 to 2019 indicates a quite significant figure, rising from 148 million tons in 1990 to 619 million tons in 2019. These figures consistently show high growth. Figure 2 below illustrates a graph comparing the increase in CO2 emission levels in Indonesia with that of India.

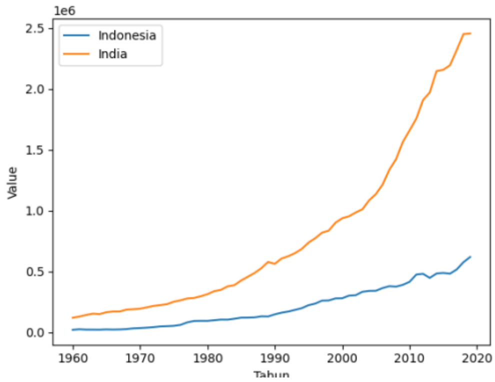

Figure 2. Comparison of CO2 Emissions between Indonesia and India

3.3. Forecasting Technique

The study utilizes the Error-Trend-Seasonal (ETS) Smoothing Method as its predictive model. The ETS smoothing method is a technique for smoothing data that integrates three elements: error, trend, and seasonality [10]. This selection was made due to its ability to effectively capture the trends and seasonal variations present in Indonesia's CO2 emissions data.

During the component identification phase, the researchers utilized run charts and seasonal decomposition graphs to identify the presence and characteristics of the error, trend, and seasonal components in the time series of CO2 emissions in Indonesia.

In determining the smoothing parameter values, the researchers employed a trial-and-error approach to ascertain the optimal values. The selected smoothing parameter values are α = 0.2 and β = 0.3. For updating predictions, the researchers utilized the mathematical equation for ETS smoothing with a simple exponential smoothing (SES) model [11]. The mathematical equation employed is as follows:

$$Ft = \alpha \times Yt - 1 + (1 - \alpha) \times Ft - 1 \tag{1}$$

Explanation:

Ft is the predicted value at time period t.

Yt is the actual value at time period t.

α is the smoothing coefficient.

3.4. Model Evaluation

In this section, four evaluation metrics are employed to assess the effectiveness of the created model. This model is utilized to analyze CO_2 emissions in Indonesia and make predictions up to the year 2030, addressing a regression-type problem. Before employing these metrics, understanding of residual errors, namely (y - ŷ), is necessary. Here, y and ŷ represent the actual and predicted values, respectively. The performance metrics used to evaluate the model are as follows.

3.4.1. Mean Absolute Error (MAE)

MAE serves as a measure of the average discrepancy between predicted and actual values. A lower MAE signifies superior model performance [12]. MAE offers a more equitable consideration of all observations, making it less susceptible to outliers in comparison to MSE. The computation formula for MAE is outlined as follows:

$$MAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n} \tag{2}$$

Where:

y is the actual value

ŷ is the predicted value

n is the number of data points

3.4.2. Mean Squared Error (MSE)

The Mean Squared Error (MSE) is employed to assess the magnitude of squared variances between predicted and actual values, with a particular emphasis on larger discrepancies. It offers a summary of the overall significance of prediction errors [13]. A diminished MSE value signifies improved model performance. The calculation formula for MSE is outlined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

Where:

y is the actual value,

ŷ is the predicted value,

n is the number of data points.

3.4.3. Root Mean Squared Error (RMSE)

The assessment of the model's effectiveness involves the utilization of Root Mean Squared Error (RMSE), a measurement that assesses the mean deviation between predicted and actual values. The computation of RMSE involves obtaining the square root of the mean of the squared variances between predictions and observations [11]. A reduced RMSE value suggests an enhanced model fit, indicating a more precise alignment between predictions and real-world outcomes.

Mathematically, RMSE is expressed as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}} \tag{4}$$

Where:

y is the actual value

ŷ is the predicted value

n is the number of data points

In this research, Root Mean Squared Error (RMSE) serves as the primary indicator of model accuracy, providing a quantitative measure of how well the model captures the underlying relationships in the data. Furthermore, comparing the RMSE values obtained from different models enables the selection of the most optimal model for further analysis and interpretation.

3.4.4. Mean Absolute Percentage Error (MAPE)

In this study, MAPE provides an overview of how well our model can estimate actual values by considering relative errors as a percentage of the actual value. The lower the MAPE value, the better the model performance [14]. The formula for calculating MAPE is as follows:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (6)$$

Where:

n represents the number of observations or data points.

y_i denotes the actual value.

$\hat{y}_i$ signifies the estimated or predicted value

4. Result and Discussion

4.1. CO2 Emissions in Indonesia (1990-2019)

This research meticulously details the changes in CO2 emission levels in Indonesia from 1990 to 2019, providing a comprehensive overview of the dynamic changes during this period. As reflected in the accompanying graph, there is a consistent upward trend in emissions, indicating a substantial increase from 148 million tons in 1990 to 619 million tons in 2019. This significant increase can be closely linked to several driving factors, including rapid economic growth, a swift population expansion, and an escalation in the use of fossil fuels. The depicted graph vividly visualizes the annual rise in CO2 emissions, showcasing the tangible impact of growth dynamics in Indonesia over the last two decades. A thorough analysis of this data can offer further insights into the relationship between these factors and their implications for greenhouse gas emissions in the country.

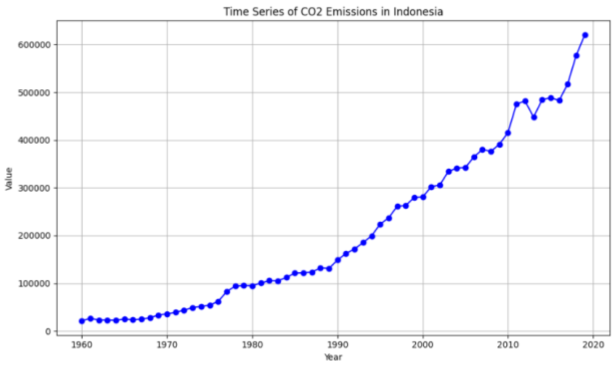

Figure 3. Carbon Dioxide Emission Graph in Indonesia Over the Years.

Economic growth reaching 5.2% per year during this period not only serves as a supporter of societal well-being but also has serious implications for the environment. The increase in economic growth figures acts as a primary driver of CO2 emissions, attributable to the heightened industrial, transportation, and housing development activities. The high energy demand from these sectors not only reflects sustained economic impetus but also exposes challenges in achieving environmental sustainability.

Furthermore, the rapid population growth plays a significant role in increasing energy demand, particularly in the transportation and housing sectors. The expanding population signifies increased mobility and the need for housing infrastructure, subsequently escalating energy consumption. Thus, the challenge for policymakers is to strike a balance between sustainable economic growth, meeting energy needs, and environmental protection to create a sustainable future for future generations.

Indonesia's high dependency on fossil fuels, especially coal, accounting for approximately 58% of total energy consumption in 2019, has had serious environmental consequences. The substantial contribution of coal as the primary energy source has led to increased greenhouse gas emissions, significantly contributing to global climate change. Therefore, to address the pressing environmental challenges, concrete and sustainable steps need to be taken to reduce dependence on fossil fuels and transition to more sustainable and environmentally friendly energy sources. Diversifying the energy portfolio, improving energy efficiency, and promoting clean technologies are key responses to these issues, ensuring that Indonesia can achieve economic sustainability without compromising environmental balance.

4.2. Projection of Indonesia's CO2 Emissions until 2030

This research meticulously describes the changes in CO2 emission levels in Indonesia from 1960 to 2019, providing a comprehensive overview of the dynamics during that period. Table 1 presents the accuracy test results of the CO2 emission prediction model using the ETS smoothing forecast method, with testing conducted using Indonesia's CO2 emission data from 1996 to 2019.

Table 2. Accuracy of the CO2 Emission Prediction Model in Indonesia

Metric	Value
MAE	146154.39849593994
MSE	21838251772.3729
RMSE	147777.71067509774
MAPE	7.24%

The model's performance evaluation metrics, including the Mean Absolute Error (MAE), suggest an average deviation of around 146,154.39 tons between the model predictions and actual values. Additionally, the Mean Squared Error (MSE) reflects notable disparities between predictions and actual values, as indicated by an MSE value of 2,183,825,1772.37. The Root Mean Squared Error (RMSE) of 147,777.71 signals the presence of outliers in predictions, affecting both MSE and RMSE values. Simultaneously, the Mean Absolute Percentage Error (MAPE) of 7.24% provides insight into the absolute percentage distinction between CO2 emission predictions and actual values.

Subsequently, a comprehensive analysis of the changes in Indonesia's CO2 emissions from 1960 to 2019 reveals that high economic growth, population expansion, and increased fossil fuel usage are the main drivers of emission increases. The annual CO2 emission graph reflects the tangible impact of growth dynamics in Indonesia over the past two decades. The analysis results indicate that the time series of Indonesia's CO2 emissions exhibits a higher trend compared to the seasonal pattern. The obtained trend value reaches 1.00, while the seasonal value ranges around 0.54. The trend value suggests that CO2 emission increases in Indonesia are likely to continue to rise, whereas the seasonal value indicates that CO2 emissions tend to increase during the dry season and decrease during the rainy season. This is influenced by weather factors such as air temperature and rainfall. The figure below illustrates the graph of the decomposition of CO2 emissions in Indonesia.

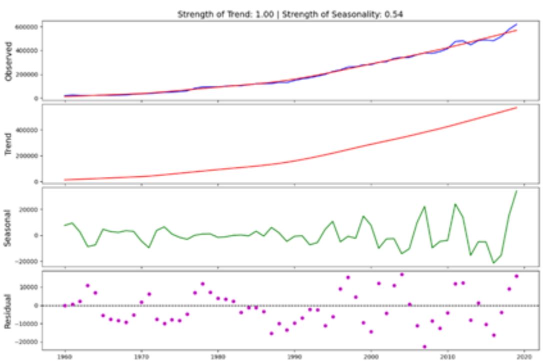

Figure 5. Decomposition of CO2 Emissions in Indonesia

In the context of economic growth reaching 5.2% per year, the increase in economic growth figures becomes a primary driver of CO2 emissions. The high energy demand from the industrial, transportation, and housing sectors reflects sustainable economic impetus but also exposes challenges in achieving environmental sustainability.

It is important to note that Indonesia's high dependence on fossil fuels, especially coal, has had serious environmental implications and a significant contribution to global climate change. Therefore, concrete measures such as energy portfolio diversification, enhanced energy efficiency, and the promotion of clean technologies are crucial in responding to these environmental challenges.

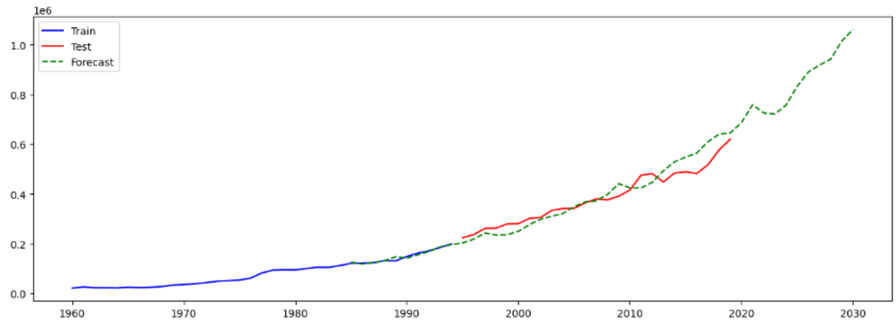

Figure 6. Forecasting Results

The projections of CO2 emissions until the year 2030 reveal a concerning trend, with predictions indicating that Indonesia will generate more than 1 billion tons of CO2 emissions during that period. Although the forecasting results show a somewhat insignificant decrease in the upcoming years, concerted efforts and stricter policy changes are necessary to mitigate the negative environmental impacts and achieve global emission reduction targets. The increase in CO2 emissions has become an urgent global issue, and a holistic solution involving changes in energy consumption patterns and investments in environmentally friendly technologies is increasingly imperative to address the escalating challenges of global warming.

5. Conclusion

This research outlines the results of an analysis on the dynamics of CO2 emissions in Indonesia until 2030, utilizing the ETS smoothing approach to forecast future trends. The application of this model has provided a deeper understanding of emission patterns, yielding several crucial findings that can serve as a foundation for the development of more effective mitigation policies. Through time series analysis, this research successfully identified key factors influencing CO2 emission patterns at the national level. These findings encompass the impact of energy policies, their interconnection with economic growth, and the role of technology in shaping emission trends. In-depth knowledge of these factors is essential in designing policies that not only reduce emissions but also support sustainable growth.

The applied ETS smoothing model in this study proved to be effective and relevant in the context of predicting CO2 emissions. Its ability to capture trends, seasonality, and error fluctuations provides a robust foundation for long-term policy planning. Consequently, this research offers a valuable tool for policymakers to make informed and effective decisions. In addition to contributing to the understanding of CO2 emission dynamics in Indonesia, this research also highlights future challenges and opportunities. Recognizing the complexity of predicting emissions with high precision serves as a basis for further research. These challenges can be addressed through the development of more sophisticated models and improvements in the quality of the data used. Thus, this research not only provides profound insights for policymakers, researchers, and practitioners but also lays the groundwork for future studies. In the context of the global urgency to reduce greenhouse gas emissions, the results of this research are expected to make a significant contribution to climate change mitigation efforts.

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6. Declarations

6.1. Author Contributions

Conceptualization: S.A. and D.K.; Methodology: D.K.; Software: S.A.; Validation: S.A. and D.K.; Formal Analysis: S.A. and D.K.; Investigation: A.H.; Resources: A.H.; Data Curation: A.H.; Writing Original Draft Preparation: A.H. and S.A.; Writing Review and Editing: A.H. and S.A.; Visualization: S.A.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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