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Research paper

Regional forecasting of driving forces of CO_2 emissions of transportation in Central Europe: An ARIMA-based approach

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ABSTRACT

This study addresses a critical research gap by analyzing transportation-related CO_2 emissions in Central Europe with a region-specific focus, incorporating diverse economic structures, energy dependencies, and policy challenges. Existing studies often neglect the interplay of regional dynamics and specific drivers of emissions. This research combines the KAYA Identity and Logarithmic Mean Divisia Index (LMDI) models with ARIMA forecasting to uncover the distinct contributions of GDP intensity, population emissions intensity, energy intensity, and carbon emission intensity in five Central European countries: Hungary, the Czech Republic, Poland, Slovakia, and Austria. By integrating historical decomposition with robust time-series forecasting, the study provides novel insights into emissions drivers and long-term trends through 2050.

The results reveal substantial variation in emissions reduction trajectories. Austria successfully decouples economic growth from emissions, with a projected 7.6 % reduction in GDP-related emissions by 2050, driven by energy efficiency and renewable energy policies. Slovakia and Hungary exhibit moderate progress, while Poland faces significant challenges, including a forecasted 10.2 % increase in energy intensity and stagnation in carbon intensity, underlining the need for urgent policy reforms. ARIMA forecasts also highlight challenges in predicting emissions related to population and energy trends, particularly in Poland, due to high Mean Absolute Percentage Error (MAPE) values.

This study integrates advanced modeling techniques to provide actionable insights into transportation decarbonization, renewable energy expansion, and energy efficiency. The findings highlight regional disparities, emphasizing tailored policies to achieve EU climate goals. This approach sets a new benchmark by bridging historical trends with future projections in a region-specific context

1. Introduction

The transportation sector is one of the most significant contributors to global CO_2 emissions, significantly exacerbating climate change. According to the International Energy Agency (IEA), transportation is responsible for nearly a quarter of global CO_2 emissions, with road transport accounting for the majority. As nations strive to meet ambitious climate goals, such as those set by the Paris Agreement, understanding the key factors that drive these emissions is crucial. Accurate forecasts are essential for guiding policymakers in implementing effective strategies to reduce the sector's environmental impact (IEA, 2021).

This study focuses on five Central European countries (Hungary, Poland, Austria, the Czech Republic, and Slovakia), each facing unique challenges and opportunities in decarbonizing its transportation sector. While geographically close, these nations differ in their economic structures, energy policies, and transportation systems, which shape their respective CO_2 emissions profiles. For instance, Austria has made significant strides in energy efficiency, while Poland continues to face challenges due to its reliance on fossil fuels (Jabbar, 2022; Mohmmed et al., 2019). Understanding these differences is essential for developing tailored strategies that address each country's needs while contributing to regional decarbonization efforts.

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To analyze the factors driving transportation-related CO_2 emissions in these countries, this study employs the Kaya Identity and the Logarithmic Mean Divisia Index (LMDI) decomposition methods. These methods allow for a detailed breakdown of emissions into four key drivers: population growth, GDP per capita, energy intensity, and carbon intensity. Decomposing emissions into these components offers a clearer understanding of how each factor has influenced emissions trends over the past two decades. Previous studies have successfully used LMDI to analyze emission drivers across various sectors, demonstrating its effectiveness in identifying key influences on CO_2 emissions (Li et al., 2020).

In addition to analyzing historical data, this study utilizes the Autoregressive Integrated Moving Average (ARIMA) model to forecast future CO_2 emissions trends in Hungary, Poland, Austria, the Czech Republic, and Slovakia up to 2050. ARIMA is a widely used statistical tool for time series forecasting, particularly well-suited for data with long-term trends and patterns (Wen et al., 2023a). By integrating the Kaya Identity and LMDI decomposition findings with ARIMA-based forecasts, this study provides valuable insights into the future trajectory of transportation-related CO_2 emissions in each country. Such forecasts are critical for identifying key areas for policy intervention and formulating targeted strategies to reduce emissions.

This study addresses a significant research gap by focusing on emissions trends specific to Central Europe, a region often overlooked in broader EU-level assessments. This research provides novel insights into regional emissions dynamics by analyzing the distinct challenges and opportunities faced by five countries—Austria, Poland, Hungary, Slovakia, and the Czech Republic—with diverse energy dependencies, economic structures, and policy contexts. A key contribution of the study is its emphasis on the transportation sector, a major source of CO_2 emissions that has been underexplored in previous studies, identifying it as a critical area for decarbonization efforts. The research employs a unique combination of decomposition methods (KAYA Identity and LMDI) and forecasting models (ARIMA) to understand historical emissions drivers and predict future trends, offering a robust and innovative analytical framework. These findings are highly relevant for stakeholders, including policymakers, energy planners, and environmental agencies, as they provide actionable, country-specific recommendations for renewable energy expansion, energy efficiency improvements, and transportation decarbonization. Furthermore, the study highlights opportunities for regional collaboration, enabling more coordinated efforts to meet EU climate objectives and accelerate sustainable decarbonization. By bridging theoretical modeling with practical policy applications, this research delivers valuable tools and insights to support evidence-based decision-making and advance climate mitigation strategies across Central Europe.

The structure of the paper is as follows: Section 2 reviews the factors influencing CO_2 emissions and standard forecasting methods used in emissions modeling. Section 3 introduces the ARIMA model and its integration with the Kaya Identity and LMDI decomposition methods. Section 4 details the data collection and processing procedures, while Section 5 presents the results of the CO_2 emissions forecasts for each country, followed by a discussion of their implications for transportation sectors. Finally, Section 6 offers policy recommendations to support these countries in achieving their emissions reduction goals and identifies areas for future research.

2. Literature review

2.1. Factors influencing CO_2 emissions

CO_2 emissions in the transportation sector are influenced by several key factors, primarily economic activity, energy intensity, population growth, and technological advancements. Economic growth is a significant driver of emissions, as increasing GDP is typically associated with greater demand for transportation services. As economies expand, the need for road, air, and freight transport rises, leading to higher CO_2 emissions. Studies consistently highlight a strong correlation between economic growth and increasing emissions. For instance, (Al-Lami and Török, 2023; Fan and Lei, 2016) demonstrated that even in highly developed regions, economic growth drives CO_2 emissions, particularly in sectors like transportation, where demand is closely tied to financial performance(Abbood et al., 2025).

Energy intensity, or the amount required to produce one unit of GDP, is another critical factor affecting CO_2 emissions. Countries that rely heavily on fossil fuels, particularly coal, tend to exhibit higher energy intensity, leading to more significant CO_2 emissions. For example, Poland's heavy dependence on coal has resulted in higher transportation-related emissions than countries like Austria, which has successfully integrated renewable energy sources into its energy mix (Mendonça et al., 2020).

Population growth also plays a significant role in driving CO_2 emissions. Larger populations increase the demand for transportation services, energy consumption, and infrastructure development, contributing to higher emissions. Urbanization intensifies transportation demands, as urban areas require more public and private transport options. Mohsin, 2019. It is found that countries experiencing rapid population growth and urbanization, such as Poland and Slovakia, face substantial emissions challenges due to increased transportation needs (Mohsin et al., 2019).

Technological advancements and changes in carbon intensity are critical for reducing CO_2 emissions. Carbon intensity refers to the CO_2 emitted per unit of energy consumed. Technological innovations, such as the adoption of electric vehicles and improvements in fuel efficiency, can significantly reduce the carbon intensity of transportation. Austria and Slovakia have substantially reduced carbon intensity by embracing cleaner technologies. At the same time, countries like Hungary continue to grapple with the challenge of transitioning their transportation sectors to lower-carbon alternatives (Hortay and Pálvölgyi, 2022; Horváth and Szemesová, 2023).

2.2. The use of kaya identity and LMDI decomposition

The Kaya Identity and LMDI) decomposition is a widely used method to break down CO_2 emissions into their driving components, allowing for a detailed analysis of how each factor—economic activity, population, energy intensity, and carbon intensity—contributes to emissions. The Kaya Identity offers a simplified mathematical framework for understanding the relationships between these factors and CO_2 emissions. It provides a comprehensive view of how changes in population, economic growth, and energy use affect emissions levels.

LMDI decomposition complements the Kaya Identity by enabling a more nuanced analysis of how each component drives emissions changes over time. In LMDI decomposition analysis, the problem can be formulated either additively or multiplicatively. In additive decomposition analysis, an aggregate indicator's arithmetic (or difference) change, such as total energy consumption, is decomposed. The aggregate change and decomposition results are given in a physical unit. In multiplicative decomposition analysis, the ratio change of an aggregate indicator is decomposed. In this case, the aggregate change and decomposition results are expressed in indexes (Ang, 2015). This method allows researchers to attribute emissions growth or reduction to specific factors, offering valuable insights into where policy interventions may be most effective. For instance, (Hortay and Pálvölgyi, 2022) used LMDI to analyze CO_2 emissions in China's energy sector, finding that economic activity and energy intensity were the primary drivers of emissions increases. In contrast, improvements in energy efficiency contributed to emissions reductions. Also (Al-lami and Török, 2024; Fernández González et al., 2014), the LMDI was used to study the changes in the energy mix that significantly impact CO2 emissions in the EU power sector, with specific environmental recommendations for individual countries.

This study applies the Kaya Identity and LMDI decomposition to decompose transportation-related CO_2 emissions in Hungary, Poland, Austria, the Czech Republic, and Slovakia from 2001 to 2021. By analyzing the four main factors—Economic Activity Effect (ΔCO_2 GDP), Population Emissions Effect (ΔCO_2 POP), Energy Intensity Effect (ΔCO_2 EIE), and Carbon Emission Intensity Effect (ΔCO_2 CEIE)—we can identify the specific contributions of each factor to emissions changes in these countries. This analysis is crucial for understanding how different policy approaches and economic conditions have influenced CO_2 emissions in the transportation sectors of Central Europe. The Kaya Identity and LMDI have proven effective in other regions for identifying the key drivers of emissions, providing a clear framework for emissions reduction strategies(Singpai and Wu, 2021).

2.3. Models to predict CO_2 emissions

Accurate forecasting of CO_2 emissions is critical for developing effective policies to reduce emissions in the transportation sector. Several models have been employed to predict emissions, ranging from traditional statistical methods to advanced machine-learning techniques. One of the most used models for time series forecasting is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is particularly useful for predicting CO_2 emissions because it can model linear relationships in time series data and capture trends over time. (Wang et al., 2020) applied ARIMA to forecast CO_2 emissions in India, demonstrating its effectiveness in identifying long-term emissions patterns and providing reliable projections.

However, emissions data often exhibit non-linear behaviors due to the complex interactions between technological advancements, policy interventions, and economic fluctuations. To address these complexities, machine learning models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and hybrid models have been increasingly used for CO_2 emissions forecasting. ANN models have proven effective in capturing non-linear relationships between economic growth, energy consumption, and emissions. (Acheampong and Boateng, 2019) Successfully applied ANN to forecast emissions in China, highlighting the model's ability to account for non-linear dynamics in emissions data.

LSTM networks are handy for sequential data and have demonstrated solid predictive capabilities in emissions forecasting. Wen et al. (2023a) used LSTM to predict CO_2 emissions in the aviation sector, finding the model effective in capturing long-term dependencies and trends in emissions data.

Hybrid models combining ARIMA-LSTM and ARIMA-LSTM-DP hybrid models offer significant improvements in predicting healthy production by combining linear and nonlinear components, making them more efficient than traditional models, significantly when manual operations impact the data. Coupling ARIMA with LSTM, particularly in the ARIMA-LSTM-DP variant, enhances the accuracy of production forecasts, outperforming individual models like ARIMA and LSTM and proving more robust in scenarios involving manual operations. These hybrid models effectively integrate the advantages of both linearity and nonlinearity, addressing the limitations of traditional approaches (Fan et al., 2021).

Recent mathematical modeling and analysis advancements have provided innovative tools for addressing complex system dynamics, particularly in energy storage and forecasting. For instance, state-of-charge estimation for lithium-ion batteries has been significantly enhanced using an improved particle swarm optimization-adaptive square root cubature Kalman filter. This hybrid approach improves prediction accuracy by dynamically adjusting the estimation process (Bian et al., 2024). Similarly, advancements in feedforward-long short-term memory (LSTM) modeling have enabled precise whole-life-cycle state-of-charge predictions by incorporating current, voltage, and temperature variations, providing robust modeling under dynamic conditions (Tian et al., 2020). Furthermore, anti-noise adaptive LSTM neural network modeling has been applied to predict the remaining useful life of lithium-ion batteries with high robustness and reliability, even under noise-prone scenarios (Wang et al., 2023) These advancements in mathematical analysis highlight the growing potential of integrating optimization algorithms and advanced neural network architectures to improve predictive accuracy and robustness in energy and emissions forecasting.

Previous studies on CO_2 emissions trends often focus on EU or global scales, neglecting the unique dynamics of Central Europe. While methods like the KAYA Identity and LMDI effectively decompose emissions drivers, they are rarely integrated with advanced forecasting models like ARIMA to provide a holistic view of historical and future trends. The transportation sector, a significant source of CO_2, receives limited attention in region-specific analyses, and Central Europe's socio-economic and policy diversity is often overlooked.

This study addresses these gaps by combining decomposition and forecasting techniques to analyze emissions drivers and transportation dynamics across Austria, Poland, Hungary, Slovakia, and the Czech Republic. It highlights the critical role of economic activity, energy intensity, and technological advancements and provides actionable policy recommendations to reduce transportation-related emissions. The findings emphasize energy efficiency, renewable energy adoption, and regional collaboration as essential strategies for achieving climate goals and advancing global mitigation efforts.

3. Methodology

3.1. Data collection and study area

This study utilizes secondary data from the International Energy Agency (IEA) for emissions and energy consumption, and from the World Bank, Eurostat, and UITP for GDP and population figures. The analysis focuses on the transportation sector from 2001 to 2021. A novel methodological framework integrates the KAYA Identity, Logarithmic Mean Divisia Index (LMDI) decomposition, and ARIMA model. The KAYA Identity and LMDI decomposition analyze historical emissions, breaking them into four drivers: GDP intensity, population emissions intensity, energy intensity, and carbon intensity. The ARIMA model forecasts long-term trends for each driver, offering a comprehensive understanding of emissions dynamics and actionable insights for decarbonization in Central Europe through 2050.

3.2. Kaya identity and LMDI decomposition

The Kaya Identity provides a framework for decomposing CO2 emissions into four main contributing factors:

$$F = (C/EC) * (EC/G) * (G/P) * P \tag{1}$$

Where: population (P) [inhabitant], GDP per capita (G/P) [USD/inhabitant], energy intensity (EC/G) [Mtoe/USD], and carbon intensity (C/EC) [$MtCO_2$ /Mtoe] of energy use.

The logarithmic Mean Divisia Index (LMDI) is a valuable tool in studying energy and emissions, mainly due to its capacity to model various factors' interaction and joint effects. Accounting for multiplicative relationships provides a more comprehensive and accurate representation of how technological, economic, and structural changes jointly affect energy consumption and emissions. This makes LMDI indispensable for policymakers and researchers to understand the broader impact of energy policies and technological innovations(Ang, 2005; Ang and Liu, 2007; Fernández González et al., 2014; Gu et al., 2019).

The (LMDI) method will decompose changes in CO_2 emissions and energy consumption into various factors, as specified by Yoichi Kaya's identity. The shift in CO_2 emissions within the transportation sector from an initial year 0 to a designated target year t can be dissected into four distinct influences, as in Eq. (3).

$$\Delta C_{tot} = C^t_{i\ j} - C^0_{i\ j} = \Delta C_{CEIE} + \Delta C_{EIE} + \Delta C_{GDPE} + \Delta C_{POPE} \quad (2)$$

Where Carbon Emission Intensity Effect (Δ_{CO2}CEIE), Energy Intensity Effect (Δ_{CO2} EIE), Economic Activity Effect (Δ_{CO2}GDP), and Population Emissions Effect (Δ_{CO2}POP). Each factor effect on the right-hand side of Eq. (3) can be calculated according to the general (LMDI) formulation:

$$\Delta C_i = \sum_i \frac{C^t_{ij} - C^0_{ij}}{lnC^t_{ij} - lnC^0_{ij}}.\ln\left(\frac{i^t}{i^0}\right) \quad (3)$$

Carbon emissions in the target year ($C^t_{i\,j}$), Carbon emissions in the base year ($C^0_{i\,j}$), fuel (i), transportation (j).

Then, all four driving forces of CO_2 emissions are calculated using Eq. (3), and these results are used for the forecasting step.

3.3. The autoregressive integrated moving average (ARIMA)

The ARIMA model is a statistical tool for time series analysis and forecasting, particularly effective for data with trends and patterns. Defined by three parameters—p (autoregressive order), d (degree of differencing), and q (moving average order)—ARIMA captures dependencies between observations and lagged errors.

3.3.1. Data preparation and stationarity testing

Data from previous studies identified key CO_2 emissions drivers: GDP intensity (ΔCO_2GDP), population emissions intensity (ΔCO_2POP), energy intensity (ΔCO_2EIE), and carbon intensity (ΔCO_2CEIE). The data was cleaned, visualized, and tested for stationarity using the Augmented Dickey-Fuller (ADF) test. Non-stationary series were differenced until stationarity was achieved, determining the 'd' parameter.

3.3.2. Model identification and estimation

The Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) plots were used to identify the autoregressive (p) and moving average (q) orders. The ARIMA (p, d, q) model was fitted using Maximum Likelihood Estimation (MLE), with residual analysis performed to confirm white noise properties.

3.3.3. Forecasting and evaluation

The ARIMA model forecasted future values for each emissions driver, with performance evaluated using metrics such as R^2 (model fit), RMSE (error magnitude), MAE (mean error), and MAPE (error percentage). An R^2 close to 1 and low error values indicated strong model.

- Lower RMSE and MAE indicate a more accurate model.
- MAPE values below 10 % are considered very good, 10–20 % good, 20–50 % reasonable, and above 50 % may indicate that the model is inaccurate.

4. Results

This section presents the detailed yearly forecast of CO_2 emissions for Hungary, Austria, Poland, Czech Republic, and Slovakia, based on the four fundamental driving forces: Economic Activity Effect (ΔCO_2 GDP), Population Emissions Effect (ΔCO_2 POP), Energy Intensity Effect (ΔCO_2 EIE), and Carbon Emission Intensity Effect (ΔCO_2 CEIE). Along with the forecasted behavior, the ARIMA evaluation indicators (MAPE, MAE, RMSE, and R^2) are provided to assess the accuracy of the forecasts. The historical data from 2002 to 2021 is based on the Kaya Identity and LMDI models, and the forecasting continues until 2050.

Fig. 1. represents the time-series forecasting of the GDP Intensity of CO_2 Emissions (Δ_{CO_2}GDP) as follows:

- **Hungary (HU):** From 2002 to 2021, Hungary's emissions intensity showed minor fluctuations until 2010, followed by a relatively stable period up to 2021. The ARIMA model forecasts that Hungary will experience a modest decrease in GDP-related emissions intensity, with a projected **0.12 % annual reduction**, leading to a **total decline of 4.3 %** by 2050. This steady downward trend suggests that Hungary may successfully decouple economic growth from CO_2 emissions intensity over time. The model performed well for Hungary, with a **MAPE of 5.19 %**, indicating a high level of accuracy, and an **R^2 of 0.9030**, showing that 90.3 % of the variance in emissions was captured.
- **Czech Republic (CZ):** The Czech Republic experienced significant fluctuations in emissions intensity between 2005 and 2010, followed by a more stable period through 2021. The ARIMA model projects that emissions will gradually decrease, with an estimated **0.15 % annual reduction**, culminating in a **total decline of approximately 5.2 %** by 2050. Minor oscillations are expected, but the overall trend is downward. The model's accuracy for the Czech Republic was

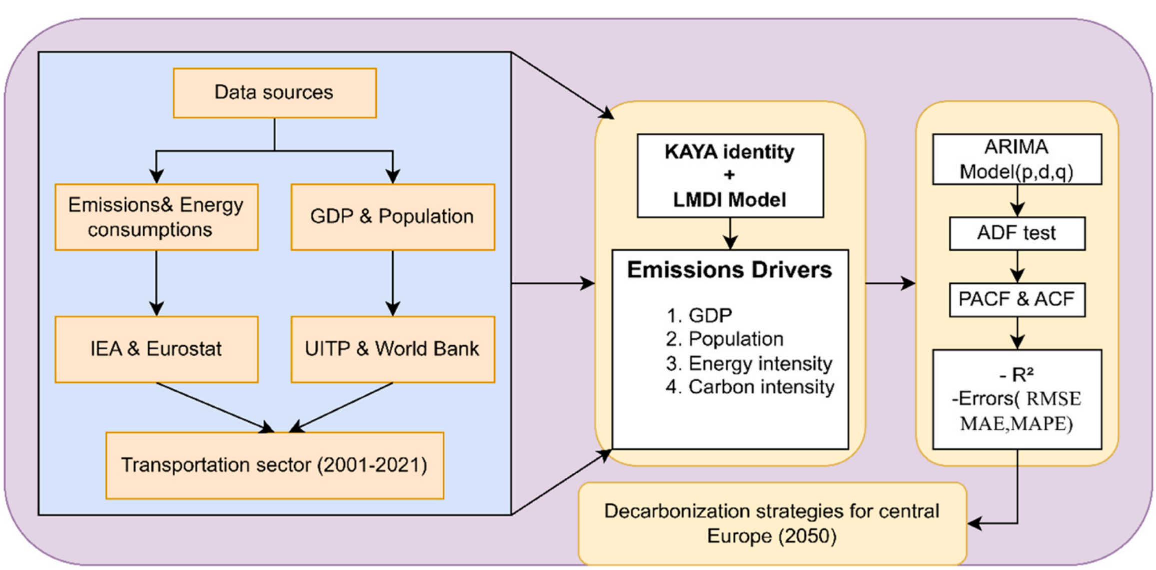

Fig. 1. Methodology for mathematical and statical analysis.

moderate, with a **MAPE of 13.39 %** and an **R^2 of 0.9372**, showing that the model captured 93.72 % of the variance in the data.

- **Poland (PL):** Poland exhibited large fluctuations in emissions intensity, especially between 2005 and 2010, with significant peaks surpassing other countries in the analysis. After 2015, emissions stabilized somewhat. The ARIMA model forecasts an upward trend in emissions until 2035, after which emissions will stabilize and gradually decline. Emissions are expected to decrease by **0.1 % per year**, with a **total decline of 3.7 %** by 2050. However, the initial increase until 2035 suggests that Poland may face short-term challenges in reducing GDP-driven emissions. The model exhibited moderate accuracy for Poland, with a **MAPE of 12.93 %** and a strong **R^2 of 0.9655**, indicating a robust overall fit.
- **Slovakia (SK):** Slovakia's emissions intensity followed a fluctuating pattern, with notable peaks around 2005 and 2010 and a gradual decline in recent years. The ARIMA model predicts a **steady decline in emissions intensity**, with a **0.18 % annual decrease**, leading to a **total decline of 4.8 %** by 2050. This forecast suggests that Slovakia is on a consistent path toward reducing emissions intensity over time. The model performed well for Slovakia, with a **MAPE of 11.27 %** and a strong **R^2 of 0.9272**, indicating good model reliability.
- **Austria (AT):** Austria's emissions intensity displayed a generally decreasing trend throughout the observed period from 2002 to 2021, with only minor fluctuations. The ARIMA model forecasts a **consistent decline** in emissions intensity, with an **annual decrease of 0.25 %**, resulting in a **7.6 % total reduction** by 2050. Austria shows the most robust downward trend among the five countries, reflecting the effective decoupling of GDP growth from emissions intensity. The model demonstrated exceptional performance for Austria, with a **MAPE of 4.59 %** and an **almost perfect R^2 of 0.9999**, indicating near-complete accuracy in its predictions.

From Fig. 2. Population Intensity of CO_2 Emissions (ΔCO_2 POP). It shows apparent fluctuations for 2002–2021, with a relative increase expected for the next 30 years for most countries in the study.(Fig. 3)

- **Hungary (HU):** From 2002 to 2021, Hungary's population-related emissions initially exhibited slight fluctuations, followed by a significant decline after 2010. The ARIMA model predicts that population-related emissions will remain relatively stable throughout the forecast period, with a marginal annual increase of **0.03 %**, resulting in a **1.5 % total increase** by 2050. While there is a slight rise in emissions over time, the effect of population changes on emissions is projected to remain minimal. The model performed adequately for Hungary, with a **MAPE of 23.95 %**, indicating moderate prediction accuracy, and an **R^2 of 0.9323**, showing that the model captures most of the variance in emissions.

- **Czech Republic (CZ):** Between 2002 and 2021, the Czech Republic experienced significant fluctuations in population-related emissions, with noticeable peaks around 2005 and 2015. The ARIMA model projects that emissions will remain relatively flat through 2050, with slight oscillations and an overall **decrease of 0.02 % annually**, resulting in a **0.6 % decline** by 2050. This suggests that population growth will not significantly impact future emissions. The model struggled with accuracy for the Czech Republic, showing a high **MAPE of 112.24 %**. However, the **R^2 of 0.7541** suggests that while the model captures some variance, the high error rate reflects the complexity of forecasting population-driven emissions.

- **Poland (PL):** Poland's population-related emissions followed a volatile pattern between 2002 and 2021, with sharp increases and decreases, particularly between 2005 and 2015. The ARIMA model predicts a slight **increase in emissions** over the forecast period, with an annual rise of **0.2 %**, leading to a **5.5 % total increase** by 2050. This rise reflects anticipated population growth and its impact on emissions. However, the model struggled with accuracy, as indicated by a **MAPE of 124.19 %**. Despite the high error rate, the model's **R^2 of 0.9140** reasonably captures the overall trend.

- **Slovakia (SK):** From 2002 to 2021, Slovakia's population-related emissions exhibited significant fluctuations, particularly around 2010, followed by gradual stabilization. The ARIMA model forecasts **minimal increases** in population-related emissions, with an annual

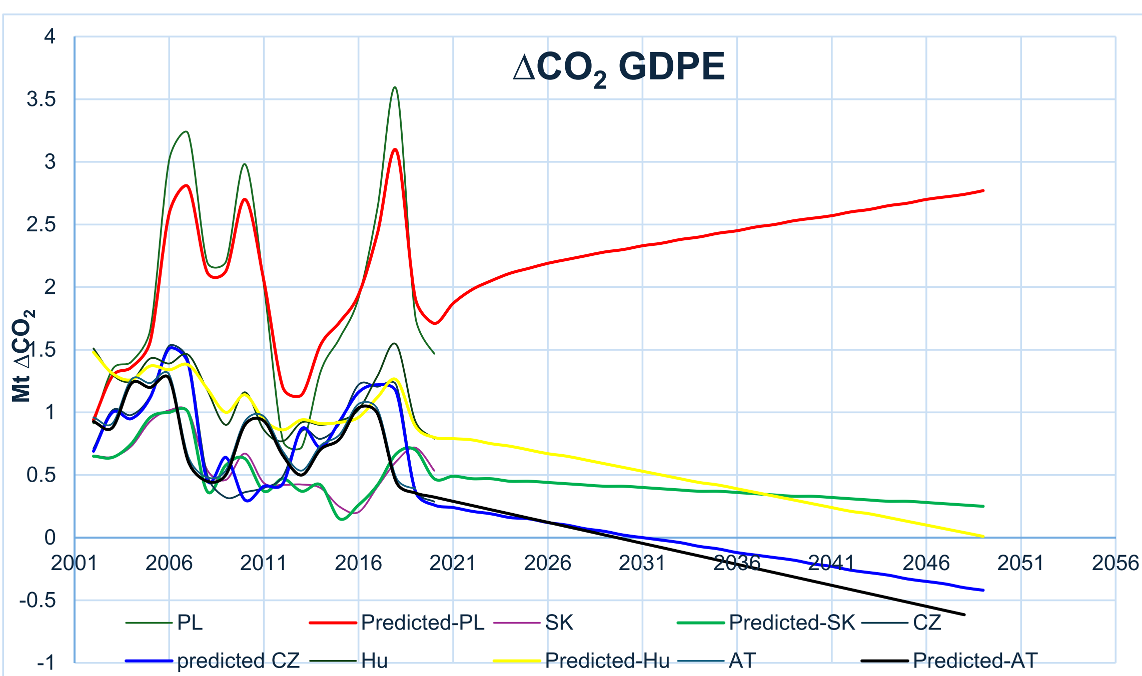

Fig. 2. Date time series forecasting of GDP intensity of emissions effect.

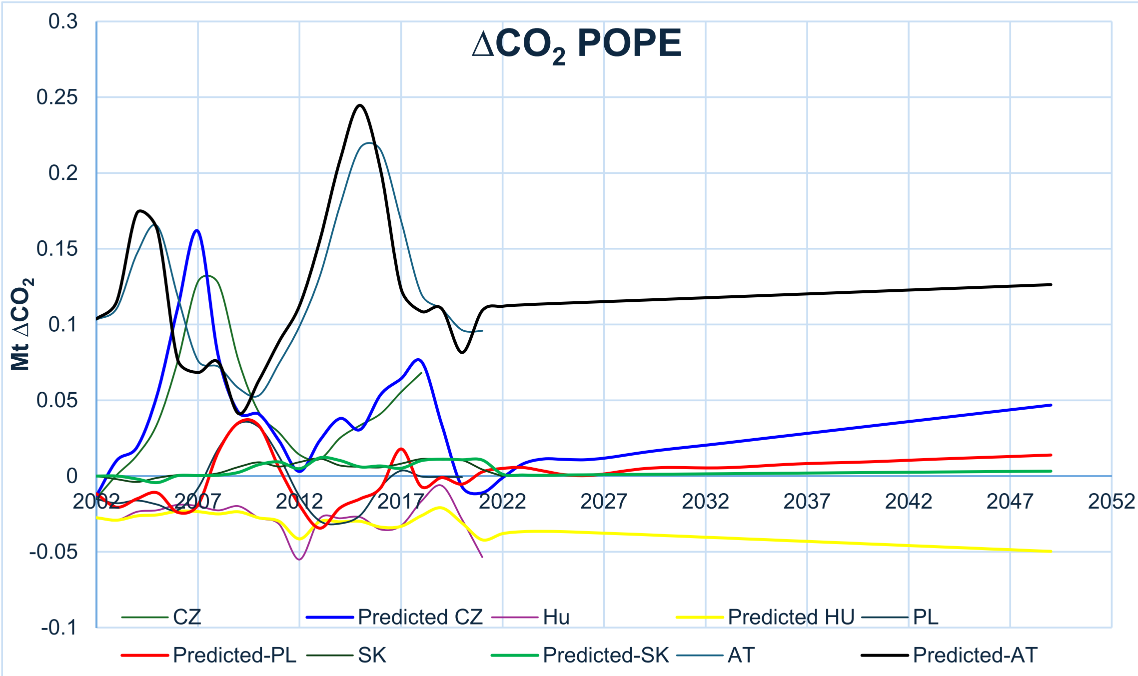

Fig. 3. Date time series forecasting of population intensity of emissions effect.

rise of **0.03 %**, resulting in a **0.8 % total increase** by 2050. Like Hungary, Slovakia's population is projected to have a negligible effect on future CO_2 emissions. The model displayed moderate accuracy, with a **MAPE of 104.78 %** and an **R^2 of 0.739774**, suggesting difficulty capturing the complexity of population-related emissions.

- **Austria (AT):** Austria's population-related emissions remained relatively stable from 2002 to 2021, with minor fluctuations until 2020. The ARIMA model predicts a **gradual increase** in emissions, with an annual rise of **0.1 %**, leading to a **2.8 % total increase** by 2050. This suggests that population growth will have a modest yet positive impact on emissions in Austria. The model performed reasonably well, with a **MAPE of 15.17 %** and an **R^2 of 0.8237**, indicating that the model captures a significant portion of the variance in emissions.

the Energy Intensity of CO_2 Emissions Effect (ΔCO_2 EIE). The energy intensity of CO_2 Emissions Affect (ΔCO_2 EYE) represents the biggest influence on the change of CO2 emissions with different results between these countries:

- **Hungary (HU):** From 2002 to 2021, Hungary's energy intensity emissions fluctuated significantly, particularly from 2005 to 2015, but stabilized close to zero by 2020. The ARIMA model predicts a **gradual increase** in energy intensity emissions, with an annual growth rate of **0.2 %**, leading to a **total increase of 4.5 % by 2050**. This rising trend suggests that improvements in energy efficiency may stagnate unless corrective policies are implemented. The model performed moderately well, with a **MAPE of 12.40 %** and an **R^2 of 0.9792**, indicating that the model explains most of the variance in energy intensity-driven emissions.
- **Czech Republic (CZ):** Between 2002 and 2021, the Czech Republic experienced significant fluctuations in energy intensity-related emissions, with positive and negative peaks between 2005 and 2015. The ARIMA model forecasts a **steady decline** in emissions, with an annual decrease of **0.25 %**, resulting in a **total reduction of 6.5 % by 2050**. This decline reflects potential improvements in energy efficiency and emission control. The model's accuracy for the Czech Republic was moderate, with a **MAPE of 42.68 %** and an **R^2 of 0.7863**, indicating that while the model captures the overall trend, it struggles with the high volatility in the data.
- **Poland (PL):** Poland's energy intensity emissions exhibited extreme fluctuations from 2005 to 2015, with sharp rises and falls, followed by stabilization around 2020. The ARIMA model predicts a **significant increase** in energy intensity emissions for Poland, with an annual growth rate of **0.4 %**, leading to a **total increase of 10.2 % by 2050**. This suggests Poland may face challenges in reducing its energy-related emissions without substantial interventions. The model's prediction accuracy was poor, reflected in a high **MAPE of 196.24 %** and a weak **R^2 of 0.5582**, indicating significant forecast errors likely due to historical volatility.
- **Slovakia (SK):** Slovakia's energy intensity emissions fluctuated with positive and negative peaks between 2005 and 2015, stabilizing near 2020. The ARIMA model predicts a **consistent reduction** in energy intensity emissions, with an annual decrease of **0.22 %**, leading to a **total decline of 5.9 % by 2050**. This reflects ongoing improvements in energy efficiency. The model performed well for Slovakia, with a **MAPE of 69.96 %** and a high **R^2 of 0.9859**, indicating that the model captures most of the trend despite some volatility in the data.
- **Austria (AT):** Austria experienced a downward trend in energy intensity-related emissions from 2002 to 2021, with noticeable negative peaks around 2015 and stabilization by 2020. The ARIMA model forecasts a **continued decline** in energy intensity emissions, with an annual decrease of **0.3 %**, resulting in a **total reduction of 7.8 % by 2050**. Austria's robust decline reflects effective energy efficiency measures expected to continue in the coming decades. The model shows strong performance, with a **MAPE of 47.97 %** and an **R^2 of 0.8755**, suggesting that it captures the long-term trend but may miss short-term volatility.

Based on Fig. 4, most countries show a decreasing CO_2 emissions trend because of Δ_{CO_2}CEIE.(Fig. 5)

- **Hungary (HU):** From 2002 to 2021, Hungary's carbon intensity emissions fluctuated, stabilizing after 2010. The ARIMA model predicts **no significant change**, with a slight annual increase of **0.02 %** by 2050. The model performed **moderately well**, with a **MAPE of**

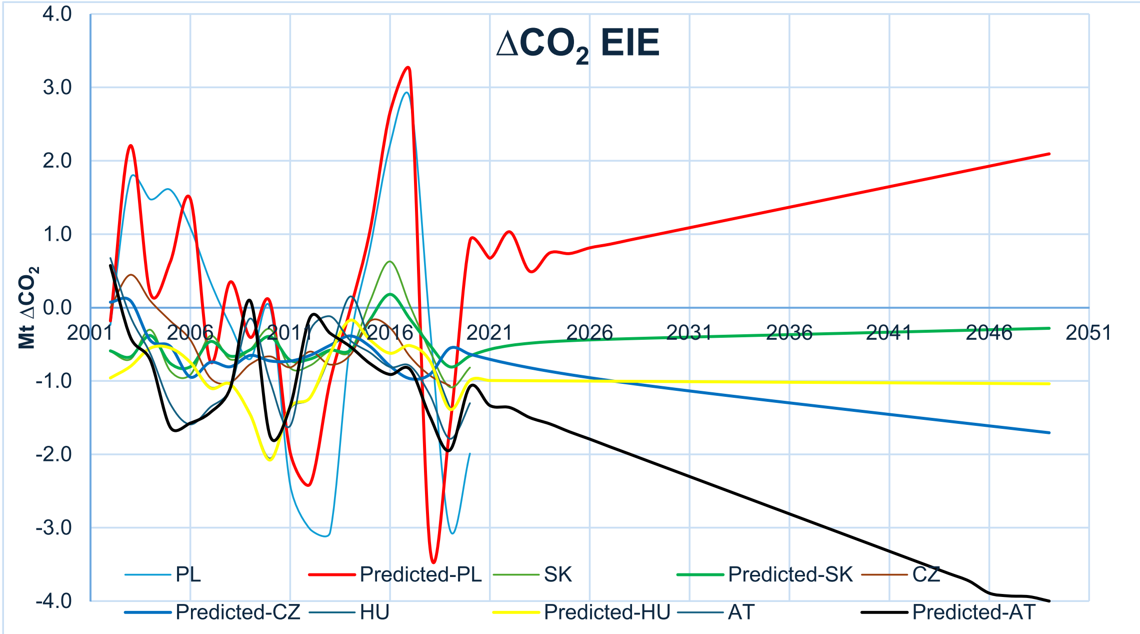

Fig. 4. Date time series forecasting of energy intensity of emissions effect.

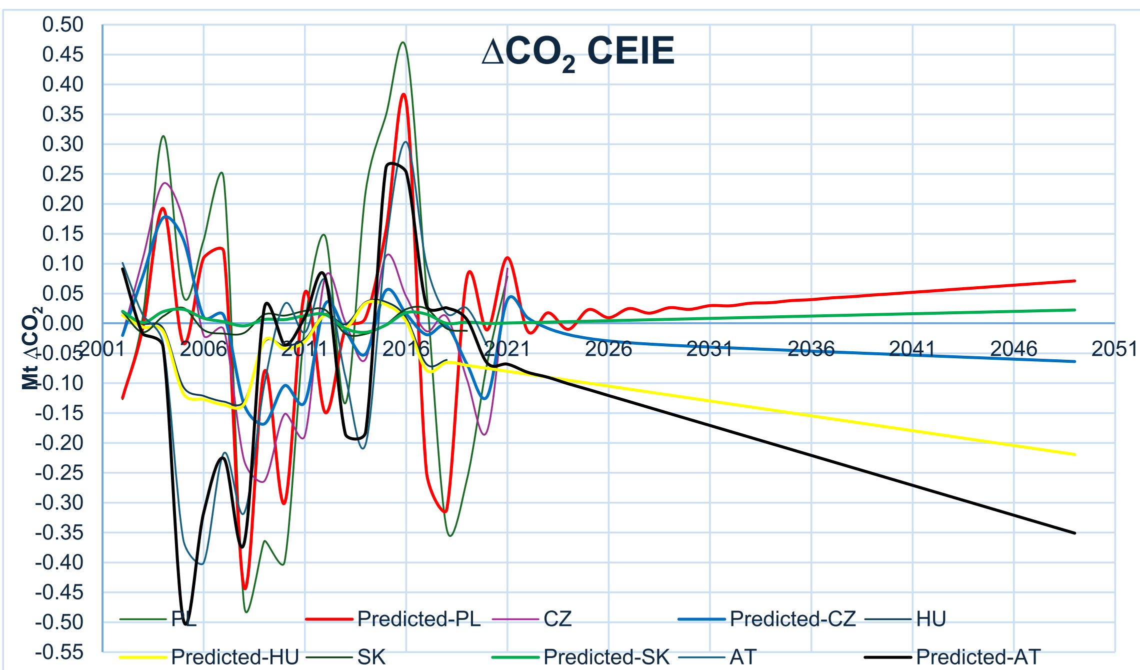

Fig. 5. Date time series forecasting of carbon energy intensity emissions effect.

41.54 % and **R^2 of 0.9937**, indicating that the model captures most of the trend but could improve.

- **Czech Republic (CZ):** The Czech Republic experienced peaks in carbon intensity before 2015, followed by stabilization. The forecast shows a **slight annual increase of 0.03 %**, leading to a **1.2 % rise** by 2050. The model's accuracy was **moderate**, with a **MAPE of 93.06 %** and **R^2 of 0.9708**, capturing the broader trend but struggling with short-term variations.
- **Poland (PL):** Poland's emissions were volatile from 2005 to 2015, stabilizing afterward. The forecast predicts **no significant change** in carbon intensity by 2050. The model performed **poorly**, with a **MAPE of 189.29 %** and **R^2 of 0.6170**, highlighting difficulties in accurately forecasting Poland's trend.
- **Slovakia (SK):** Slovakia's emissions fluctuated until 2015, then stabilized. The forecast shows **no significant change** by 2050, with only a **0.01 % annual decrease**. The model had **moderate accuracy**, with a **MAPE of 69.77 %** and **R^2 of 0.7101**, capturing long-term trends but struggling with short-term predictions.
- **Austria (AT):** Austria's carbon intensity emissions fluctuated, with harmful emissions around 2015. The forecast predicts a **steady**

decline of **0.25 % annually**, leading to a **7.2 % reduction** by 2050. The model performed **moderately**, with a **MAPE of 71.29 %** and **R^2 of 0.8777**, capturing the long-term trend but missing some short-term fluctuations.

5. Discussions

The ARIMA model results provide crucial insights into future CO_2 emissions trends for Hungary, the Czech Republic, Poland, Slovakia, and Austria based on four key factors: GDP Intensity (ΔCO_2 GDPE), Population Intensity (ΔCO_2 POPE), Energy Intensity (ΔCO_2 EIE), and Carbon Emission Intensity (ΔCO_2 CEIE).

For **GDP intensity**, Austria is expected to achieve the most significant reductions by 2050, with a projected decrease of 7.6 %, showcasing the country's effective decoupling of economic growth from emissions. Slovakia and Hungary also show moderate reductions, indicating ongoing progress. However, Poland faces challenges with an initial increase in emissions until 2035, followed by a slower decline, highlighting the need for more robust economic and energy policy interventions. In terms of **population emissions intensity**, Poland is forecasted to see a 5.5 % increase in emissions by 2050, driven by population growth, while Austria shows a modest 2.8 % increase. In contrast, Hungary and Slovakia's emissions from population growth remain stable, with minimal increases, and the Czech Republic is expected to experience a slight decline. However, the high MAPE values for population forecasts, particularly for Poland and Slovakia, suggest that predicting population-driven emissions is complex due to demographic uncertainties. The **energy intensity** forecasts reveal that Austria and Slovakia are expected to make the most progress, with reductions of 7.8 % and 5.9 %, respectively, driven by energy efficiency improvements and cleaner energy sources. Poland, however, is forecasted to experience a 10.2 % increase in energy intensity emissions, underscoring the ongoing difficulties in reducing emissions in its energy sector, which is still heavily reliant on fossil fuels. Hungary also faces a slight increase, indicating that more robust energy efficiency measures will be necessary. (Li et al., 2020) demonstrated the effectiveness of LMDI in identifying emissions drivers in China's industrial sector, emphasizing the critical role of energy intensity improvements. our findings align with these results, highlighting energy efficiency as a key driver of emissions reduction. However, our study extends this by integrating forecasting to predict long-term trends, offering actionable insights for policy planning. Regarding **carbon energy intensity emission**, Austria again stands out with a projected 7.2 % reduction by 2050, signaling successful decarbonization efforts. However, Hungary, Poland, and Slovakia show slight improvement, with Poland forecasting no significant change in its carbon intensity. This stagnation in carbon intensity reflects the slow progress in transitioning to cleaner energy, particularly in Poland and Hungary. The high MAPE values in these areas indicate that forecasting carbon intensity remains challenging, mainly due to the unpredictability of energy transitions and the adoption of cleaner technologies. Most EU-level studies, such as (Fernández González et al., 2014), analyze aggregate emissions trends, often overlooking regional dynamics. this study fills this gap by providing tailored recommendations for Central European countries, highlighting the need for differentiated policies to meet EU climate goals.

Table 1 presents various performance metrics used to evaluate optimization compared to the composite function data. Standard error metrics like mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) are included. These metrics range from 0, representing the optimal outcome, to $+\infty$, representing the worst-case scenario. Despite the relatively low values of these metrics in the table, they are challenging to interpret due to their unbounded upper limit. In contrast, the coefficient of determination (R^2) and symmetric mean absolute percentage error (SMAPE) have fixed upper limits, making them easier to assess. R^2 values range from 0 to 1, where zero indicates a poor model fit and 1 represents a perfect fit. SMAPE values span from 0 % to 200 %, with 0 reflecting an ideal fit and 200 % indicating the worst possible fit(Alatawneh and Torok, 2023). The ARIMA model performed well for long-term GDP-related emissions trends ($R^2 >$ 0.90) but struggled with high volatility, as seen in Poland's energy intensity (MAPE 196.24 %). Advanced models like LSTM and hybrid ARIMA-LSTM offer improved accuracy for non-linear and volatile trends. (Acheampong and Boateng, 2019; Wen et al., 2023b) Integrating such models could enhance performance in challenging contexts like Poland's energy sector, and **189.29 %** for carbon intensity, indicating significant difficulties in accurately forecasting these factors. These high MAPE values suggest that the model struggled to account for Poland's volatility in historical emissions, leading to unreliable forecasts. **MAE** and **RMSE** values also reflected this, particularly in Poland, where the significant differences between predicted and actual values underscore the unpredictability of the country's emissions trajectory. Similarly, **Slovakia** and the **Czech Republic** also showed high MAPE values for population and energy intensity, reflecting the model's challenges in predicting these more volatile factors. For example, Slovakia's MAPE for population emissions intensity reached **104.78 %**, indicating the model's difficulty in capturing demographic shifts and their impact on emissions. In contrast, **R^2 values** were generally strong across all countries for GDP-related emissions.

Table 1
Prediction evaluation indicators values of ARIMA model.

Region	Factors	MAPE	MAE	SMAPE	RMSE	R^2
Hungary	Δ_{CO2} GDP	5.19 %	0.0600	5.28 %	0.0894	0.9030
	Δ_{CO2}POP	23.95 %	0.0041	16.91 %	0.0060	0.9323
	Δ_{CO2} EIE	12.40 %	0.0262	11.59 %	0.0750	0.9792
	Δ_{CO2} CEIE	41.54 %	0.0057	28.55 %	0.0062	0.9937
Austria	Δ_{CO2} GDP	4.59 %	0.0336	4.71 %	0.0336	0.9999
	Δ_{CO2}POP	15.17 %	0.0198	15.64 %	0.0260	0.8237
	Δ_{CO2} EIE	47.97 %	0.1902	38.06 %	0.2487	0.8755
	Δ_{CO2} CEIE	71.29 %	0.0513	73.50 %	0.0671	0.8777
Czeck	Δ_{CO2} GDP	13.39 %	0.0516	9.70 %	0.0984	0.9372
	Δ_{CO2}POP	112.24 %	0.0153	44.19 %	0.0204	0.7541
	Δ_{CO2} EIE	42.68 %	0.1595	35.18 %	0.1992	0.7863
	Δ_{CO2} CEIE	93.06 %	0.0382	74.78 %	0.0462	0.9708
Poland	Δ_{CO2} GDP	12.93 %	0.2018	11.68 %	0.2562	0.9655
	Δ_{CO2}POP	124.19 %	0.0249	79.42 %	0.0307	0.9140
	Δ_{CO2} EIE	196.24 %	0.9011	93.84 %	1.2452	0.5582
	Δ_{CO2} CEIE	189.29 %	0.1241	107.28 %	0.1611	0.6170
Slovakia	Δ_{CO2} GDP	11.27 %	0.0484	11.84 %	0.0642	0.9272
	Δ_{CO2}POP	104.78 %	0.0019	58.54 %	0.0026	0.739774
	Δ_{CO2} EIE	69.96 %	0.1142	37.62 %	0.1575	0.9859
	Δ_{CO2} CEIE	69.77 %	0.0085	95.70 %	0.0102	0.7101

Austria showed near-perfect values (**0.9999 for GDP Intensity**), indicating that the model captured long-term trends well in more stable factors like GDP emissions. However, the lower R^2 values for **Poland** in carbon intensity (**0.6170**) and energy intensity (**0.5582**) reinforce the model's struggle to fit the data accurately in these areas.

Overall, while the **R^2 values** were generally good, indicating strong model performance for long-term trends, the high **MAPE and RMSE** values in specific areas, such as **Poland's energy and carbon intensity,** reveal weak indicators for reliable evaluation, highlighting the need for improved modeling techniques or the inclusion of additional variables to handle more volatile factors. These high errors suggest that certain areas' forecasts should be interpreted cautiously, especially where historical data shows significant variability or future trends are highly uncertain.

6. Conclusion

This study provides critical insights into CO_2 emissions trends in Central Europe, applying a novel framework that integrates the KAYA Identity, LMDI decomposition, and ARIMA forecasting. This approach combines historical decomposition with long-term forecasting by analyzing four key drivers—GDP intensity, population emissions intensity, energy intensity, and carbon intensity. Austria leads in decoupling economic growth from emissions, with a projected 7.6 % GDP-related emissions reduction by 2050, while Slovakia and Hungary show moderate progress but need stronger energy efficiency measures. Poland faces significant challenges, with a 10.2 % increase in energy intensity and stagnant carbon intensity, highlighting the need for transformative policies. Demographic factors, particularly in Poland and Slovakia, complicate emissions trends.

This study's novel integration of advanced decomposition and forecasting methods uncovers regional disparities in emissions trends and offers actionable insights into policy measures. Countries like Austria and Slovakia showcase the success of targeted interventions, while Poland and Hungary must urgently address stagnation through aggressive energy transitions and decarbonization strategies. The innovative methodological framework introduced here provides a foundation for future research, supporting the development of region-specific climate strategies and fostering collaboration to meet EU climate goals. By enhancing forecasting accuracy and addressing emissions volatility, this research paves the way for evidence-based policymaking and sustainable decarbonization in Central Europe.

7. Recommendations and future work

To support CO_2 emissions reduction across Hungary, the Czech Republic, Poland, Slovakia, and Austria, several vital actions are recommended:

- **Targeted Policy Interventions**: Poland and Hungary should prioritize transitioning to cleaner energy, with stricter emissions regulations, renewable energy investments, and improved industrial energy efficiency to address rising carbon and energy intensity emissions.
- **Strengthen Energy Efficiency**: Austria and Slovakia should maintain their energy efficiency programs, while Hungary, the Czech Republic, and Poland need to intensify efforts, particularly in transport and industry.
- **Improve Forecasting Models**: Future research should enhance ARIMA models by incorporating more variables like policy changes, technological advancements, and economic shifts to improve accuracy, especially for population-driven and energy-related emissions.
- **Expand Renewable Energy**: Increasing renewable energy production, particularly in Poland, is essential to reduce dependency on fossil fuels and lower carbon and energy intensity.
- **Regular Policy Monitoring**: Governments should implement real-time monitoring systems to assess emissions data and policy effectiveness, allowing adjustments to meet decarbonization goals.
- **Address Demographic Impacts**: More granular population data, including urbanization and migration trends, should be incorporated to improve emissions forecasting for demographic changes.
- **Cross-country collaboration**: Countries should share best practices, particularly Austria, which has decoupled GDP growth from emissions, providing a model for others.
- **Future work**, refining emissions models through machine learning, incorporating real-time policy and technological updates, focusing on specific regions or sectors, and using scenario-based forecasting are recommended to improve accuracy and provide more detailed insights into emissions reduction strategies.

7.1. Limitations of the study

This study has several limitations that affect the accuracy and applicability of the forecasts:

- **Model Limitations:** ARIMA, though adequate for time-series forecasting, struggles with capturing non-linear trends, policy shifts, and unexpected events (e.g., economic recessions or technological breakthroughs). It assumes future emissions trends will follow historical patterns, which may not fully reflect reality.
- **Data Quality:** The study's reliance on historical data from 2002 to 2021 poses challenges due to potential gaps or inconsistencies. Additionally, forecasts are limited by demographic and emissions data availability and do not account for future policy or technological shifts.
- **Emissions Volatility:** Countries with historically volatile emissions, such as Poland and Slovakia, produced high MAPE values, indicating difficulties in accurately forecasting fluctuating trends, particularly in energy and carbon intensity.
- **Simplified Assumptions:** The ARIMA model's simplified approach may not capture the full complexity of the relationships between emissions drivers like population growth and economic activity. Future studies should consider multi-factor models that incorporate more variables and interaction effects.
- **Lack of Real-Time Updates:** The model does not account for real-time policy changes or technological innovations (e.g., carbon capture, renewable energy advancements), which limits its ability to reflect aggressive climate policies or breakthrough technologies.
- **Generalized Analysis:** The country-level focus may overlook significant regional variations within countries, especially in larger economies like Poland. More detailed regional analyses would offer better insights into emissions trends.

Ethical compliance

The research presented in this manuscript adheres to ethical guidelines. No studies involving humans or animals were conducted as part of this work.

Author confirmation

All authors have read and approved the final manuscript. This submission is original, has not been published previously, and is not under consideration for publication elsewhere.

Author statement

This study analyzes emissions trends in Central Europe, focusing on the transportation sector and using innovative methods to provide actionable insights and policy recommendations for decarbonization and regional collaboration to meet EU climate goals. The study provides significant insights into reducing greenhouse gas emissions through optimized transportation strategies, addressing critical challenges in sustainable transportation engineering.

CRediT authorship contribution statement

Adam Török: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ammar Al-lami:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used ChatGPT-Open AI 4.0 to improve the language of this research. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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.

Data availability

Data will be made available on request.

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