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Recurrent neural network strategies for decoupling energy consumption and greenhouse gas emissions in Hungary's industrial sector

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ABSTRACT

This study addresses the critical challenge facing Hungary's industrial sector by focusing on the need to decouple economic growth from greenhouse gas (GHG) emissions to meet EU climate targets while maintaining industrial productivity. Although Hungary has achieved significant emission reductions, its industrial sector remains heavily reliant on carbon-intensive energy sources, underscoring the need for advanced analytical approaches to identify effective decoupling strategies. To address this gap, the study utilizes a Recurrent Neural Network (RNN), which is effective for modeling complex, non-linear, and temporal relationships, to analyze the interactions among industrial energy consumption, economic performance, and GHG emissions from 1995 to 2020. The results indicate that reducing coal and heat consumption by 2.5 petajoules yields significant GHG emission decreases of 4.4 percent and 4.3 percent, respectively, while a similar reduction in renewables and waste leads to a 3.5 percent drop in emissions. A 2.5 petajoule reduction in natural gas consumption results in just over a 1 percent decrease in GHG emissions, highlighting its lower emissions intensity and role as a viable transitional fuel. These findings provide critical insights for designing targeted policy interventions prioritizing coal and heat reduction and scaling up low-emission renewables to meet Hungary's climate commitments. The methodological contribution of using RNN offers a scalable and replicable framework for other countries aiming to balance industrial productivity with sustainable development objectives.

1. Introduction

The intrinsic coupling between economic growth and greenhouse gas (GHG) emissions in the field of environmental economics has gained substantial attention from academics, practitioners, industry professionals, and policymakers in the ongoing efforts to tackle climate change. However, effective decoupling of economic growth trajectories from rising carbon emissions is a fundamental requirement for reducing the negative effects of climate change and encouraging sustainable development paths [1].

This necessity underscores the importance of transitioning economies away from entrenched reliance on carbon-intensive fossil fuel sources, which remains central to developing and implementing a comprehensive global climate policy framework [2]. Decoupling economic growth from GHG emissions has gained widespread endorsement as a pivotal strategy in addressing climate governance challenges. Global climate policy frameworks, such as the Clean Energy Act in the United States, the European Climate Act instituted by the European Union, and Japan's Climate Change Adaptation Act, explicitly highlight this approach [3 4].

The effectiveness of these frameworks is evidenced by measurable outcomes: the United States reduced its carbon dioxide (CO2) emissions by approximately 3 % in 2022 compared to 1990 levels, the European Union achieved a significant reduction of 27.47 % from 1990 levels, and Japan reduced its CO2 emissions by approximately 2 % over the same period [5]. These reductions signify the global recognition of the need to decouple industrial and economic activities from their carbon footprints, reflecting the tangible progress made in mitigating climate change through policy-driven decoupling efforts.

A substantial body of research has demonstrated that energy decarbonization and the decoupling of economic growth from emissions are principal strategies for mitigating the destructive impacts of GHG emissions. Decarbonization entails the critical process of reducing or eliminating CO2 emissions associated with human activities,

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particularly from the combustion of fossil fuels, by transitioning to low-carbon or carbon-free energy sources such as renewables, nuclear power, and carbon capture technologies [6]. Meanwhile, decoupling focuses on breaking the long-standing link between economic growth and environmental degradation caused by GHG emissions, with absolute decoupling, where gross domestic product (GDP) rises while absolute emissions decline, being the most desirable outcome [7,8].

Building on global strategies for decarbonization and the decoupling of economic growth from emissions, many countries have implemented robust climate policies to mitigate the impacts of GHG emissions. The European Union (EU), for instance, has adopted the European Climate Act, a comprehensive framework inspired by the Clean Energy Act in the United States and Japan's Climate Change Adaptation Act. This framework sets ambitious climate and energy legislation for 2030, requiring member states, including Hungary, to develop National Energy and Climate Plans (NECPs) for the 2021–2030 period [9].

Hungary has made significant progress in reducing its GHG emissions, achieving a 43.2 % reduction by 2020 compared to its base year (1985–1987 average). While this performance exceeds the EU average reduction of 34.3 %, Hungary's pace of reduction has lagged behind regional peers like Romania (64.2 %) and Estonia (71.2 %) [10]. Moving forward, Hungary faces more stringent EU-mandated targets for the 2021–2030 period, requiring a 7 % reduction below 2005 levels in non-trading sector emissions. Meeting these targets will necessitate innovative approaches to address the intricate dynamics between energy consumption, economic performance, and environmental sustainability.

Hungary represents a strategically significant case for examining the decoupling of economic growth from GHG emissions due to its distinct industrial structure and carbon-intensive energy profile in comparison with both EU and non-EU countries. In 2022, the industrial sector accounted for 37.7 percent of Hungary's gross domestic product (GDP), a higher share than in Germany at 30.7 percent, Poland at 27.3 percent, the Czech Republic at 26.3 percent, and France at 19.1 percent, reflecting Hungary's continued reliance on energy-intensive production [11]. Concurrently, Hungary's energy supply remains dominated by fossil fuels, with oil and natural gas accounting for 32 percent and 31 percent, respectively [12]. In contrast, several EU economies have made substantial progress in transitioning to cleaner energy sources. Sweden derives approximately 68.5 percent of its gross final energy consumption from renewables, Austria around 33.6 percent, and Germany more than 45 percent, supported by long-term national energy strategies [13,14]. In comparison, non-EU countries such as Serbia, Ukraine, and Turkey remain more fossil-fuel dependent. Serbia's primary energy mix consists of more than 70 percent fossil fuels [15], Ukraine's 2021 energy mix included 67.8 percent fossil fuels and only 6.8 percent renewables [16], and Turkey in 2018 reported 47.7 percent renewables and 51.6 percent fossil fuels [17]. This intermediate position, being more industrialized and fossil-dependent than many EU peers while operating under more robust climate policy frameworks than its non-EU neighbors, renders Hungary a representative and policy-relevant context for modeling decoupling trajectories.

To support Hungary's transition toward a low-carbon, resource-efficient industrial sector, this study investigates the potential for effectively decoupling energy-related GHG emissions in the industrial sector using recurrent neural networks (RNNs). RNNs are uniquely suited for modeling complex temporal patterns and non-linear relationships, offering policymakers data-driven insights into the interdependencies among energy use, economic growth, and environmental impact. By leveraging these advanced analytical tools, this research aims to inform strategic policy interventions that harmonize economic development with environmental sustainability. Ultimately, the findings seek to guide Hungary in aligning its industrial practices with the goals of the European Climate Act and its NECP for 2021–2030, ensuring the country's competitive edge while advancing its climate commitments.

This study presents a novel approach to addressing the persistent challenge of decoupling economic growth from GHG emissions in Hungary's industrial sector by leveraging RNNs. Unlike prior research that primarily relied on linear modeling techniques, this study integrates advanced machine learning to capture complex temporal patterns and non-linear relationships among energy consumption, economic performance, and environmental impact. The key objectives are to provide data-driven insights into the dynamics governing energy consumption and emissions, identify the energy sources with the greatest potential for emissions reductions, and offer actionable recommendations to policymakers for meeting Hungary's 2021–2030 EU-mandated climate targets. By analyzing energy consumption data across multiple sources such as coal, heat, natural gas, and renewables, and their associated emissions from 1995 to 2020, the scope of this study extends beyond traditional decarbonization analyses to propose tailored strategies that harmonize Hungary's industrial productivity with its climate commitments, offering a replicable framework for other countries.

The manuscript is structured into seven main sections. Section 1 introduces the research context, objectives, and the relevance of applying AI-based modeling to explore decoupling in Hungary's industrial sector. Section 2 provides a thematically organized review of relevant studies, including the theoretical foundations of economic and environmental decoupling, applications of machine learning in energy and emissions modeling, and Hungary-specific research. Section 3 describes the data sources and methodological framework, including the development and implementation of the RNN model. Section 4 presents the empirical results, highlighting non-linear and asymmetric relationships between energy use and GHG emissions. Section 5 offers a discussion of the findings and the findings in comparison to existing studies and links them to relevant policy frameworks. Section 6 concludes the study by summarizing its key findings and methodological contributions as well as the study's limitations and proposes directions for future research. Section 7 outlines specific policy implications derived from the analysis.

2. Literature review

Economic growth is often linked to substantial energy consumption [18]. However, this energy consumption is also the primary source of carbon emissions [19]. Countries committed to global climate governance emphasize the coordination between energy consumption, economic development, and carbon emissions [20]. Thus, decoupling carbon emissions from economic growth has become a critical issue in the pursuit of carbon peaking and carbon neutrality [21]. Notably, efforts to decouple carbon emissions from economic growth exhibit strong geographical variations [22]. Non-renewable energy consumption, while environmentally harmful, supports economic stability. Conversely, renewable energy consumption is environmentally beneficial but can destabilize economic growth due to current technological limitations [23 24].

The type of energy consumed is closely tied to carbon emissions. Coal, in particular, has the most pronounced impact on carbon emission growth, making its reduction crucial for achieving carbon neutrality [25]. In contrast, natural gas can reduce CO2 emissions compared to oil and coal [26]. Renewable energy sources, such as hydropower, wind, and solar, are seen as effective for achieving carbon neutrality goals [27].

The decoupling of energy sources from GDP growth is facilitated by the increasing adoption of renewable energy technologies, such as solar, wind, and hydroelectric power. Advancements in energy storage solutions and smart grid technologies have played a crucial role in enabling greater integration of intermittent renewable sources into the energy mix [28]. Additionally, improvements in energy efficiency across various sectors, including transportation, manufacturing, and buildings, have contributed to reducing the overall energy intensity of economic output [29].

Studies on decoupling based on the (Organization for Economic Co-

Operation and Development (OECD) methodology [30] can be broadly categorized into two groups. The first group focuses on analyzing decoupling patterns of large groupings of nations or examining a small number of pollutants on a worldwide scale. The second category performs comparative evaluations among developed and developing nations [31].

In 2014 Muangthai et al. conducted a study to analyze the factors influencing CO2 emissions from between 2000 and 2011 in Thailand [32]. The researchers used decoupling analysis and Divisia index decomposition to assess this relationship. The findings revealed that economic growth was the critical factor driving the increase in CO2 emissions. Despite this, certain periods, notably 2000–2001 and 2008–2009, showed a decline in CO2 emissions due to slower economic growth influenced by financial crises.

In 2018, Chen et al. developed a study to analyze the factors influencing CO_2 emissions in OECD countries from 2001 to 2015 [33]. Using the Logarithmic Mean Divisia Index (LMDI) decomposition method combined with decoupling analysis, they explored these relationships across four distinct periods and conducted a year-by-year analysis for consistency. The findings revealed that energy intensity and per capita GDP were the primary drivers of changes in CO_2 emissions, with technological progress leading to lower energy intensity and economic growth generally increasing emissions. The study underscored the complex interplay of factors affecting CO_2 emissions and highlighted the need for targeted policies to address these drivers effectively. Also, the article demonstrated that CO_2 emissions reduction goals can be achieved without sacrificing economic growth.

In 2020, Chovancová and Tej conducted a study to assess the relationship between the economic growth of the energy sector and GHG emissions produced by the energy sector in Visegrad Group (V4) countries (Czech Republic, Hungary, Poland, and Slovakia) from 1995 to 2016 [7]. The authors applied the decoupling method to quantitatively assess the link between the economic growth of the energy sector and GHG emissions produced by the industry. They found that strong decoupling prevails in the majority of the examined cases, which can be considered a positive trend. However, the extent of decoupling varies among the V4 countries and across different periods. Despite the positive findings and reforms implemented in the energy sector, V4 countries still have higher energy intensity compared to the EU average, mostly due to historical context, economic structure, and the state of development.

Hungary, an EU member state with 9.8 million people accounting for 2.2 % of the EU-27 population in 2019 [34], has been working to reduce its GHG emissions in line with EU climate and energy legislation. The country submitted its National Energy and Climate Plan (NECP) outlining strategies for 2021–2030 [35]. While Hungary's emissions reduction has been slower than the EU average since 2005 [36], it has made progress in several areas. In 2019, Hungary's total emissions constituted 1.7 % of the EU total, decreasing by 16.2 % since 2005 compared to the 19 % EU-wide reduction [37].

For 2021–2030, Hungary faces the critical challenge of reducing its GHG emissions by 7 % compared to 2005 levels [37]. Achieving this target will require significant shifts in energy policy. However, existing efforts have been criticized for lacking ambition, highlighting the need for a more focused and data-driven approach to decarbonization [38].

Achieving this balance requires a deeper understanding of the complex relationships between energy consumption, economic output, and emissions. Addressing this problem necessitates robust methods and comprehensive data to capture the intricate dynamics and interdependencies across these domains. Hence, this study tackles these challenges by employing RNN models to analyze the temporal and non-linear relationships among Hungary's energy consumption, economic performance, and GHG emissions. To support this analysis, data from multiple reputable sources, including the International Energy Agency (IEA), World Bank, and Climate Watch, are integrated to form a cohesive framework. The datasets encompass various energy sources, economic indicators, and emissions data, providing a holistic view of the industrial sector's dynamics. The findings identify critical thresholds for decoupling emissions from economic growth and propose actionable strategies for transitioning to a more sustainable energy mix. Beyond Hungary, this integrative methodology offers a scalable framework for other regions navigating the complexities of energy transition and industrial decarbonization.

A rich body of empirical research has examined decoupling theory, machine learning (ML) application in energy and emissions modeling, and region-specific assessments, including Hungary. Decoupling investigations by [32] and [33] have utilized sophisticated decomposition techniques, notably the Divisia Index and Logarithmic Mean Divisia Index (LMDI), to understand relationships between economic growth and carbon emissions, consistently finding that energy intensity and per capita GDP predominantly influence emission trajectories. When studying Visegrad Group nations, [7] discovered significant but variable decoupling patterns, which they linked to underlying structural differences and historical development contexts. Alongside these developments, ML approaches have increasingly permeated energy forecasting and emissions modeling. Researchers have deployed various neural network architectures, including Recurrent Neural Network, Convolutional Neural Network, and hybrid models, to capture temporal relationships and non-linear patterns in energy use and carbon emissions data [39]. Despite these advances, few existing models comprehensively address decoupling dynamics across multiple sectors or geographical regions. For Hungary specifically, most current research remains either policy-focused or reliant on traditional econometric methods [40,13], with minimal integration of artificial intelligence or machine learning to investigate sector-specific pathways for emissions reduction, a gap our work seeks to address.

Concerning Hungary's industrial sector specifically, an obvious research gap persists despite the country's progressive climate commitments under the EU 2030 framework and its distinctive economic structure, where industry contributes nearly 38 % of GDP [11]. Existing studies have either taken a broad national-economic perspective or narrowly focused on energy policy compliance, often without employing advanced modeling techniques capable of capturing the complex interdependencies among energy consumption, economic output, and greenhouse gas emissions [14,36]. This study addresses that gap by applying Recurrent Neural Networks to examine temporal patterns and interaction effects among industrial energy use, emissions, and productivity indicators. The approach introduces a novel analytical contribution to the decoupling literature and offers practical insights for aligning Hungary's industrial development with its climate objectives.

3. Methodology

This study positions itself within the framework of empirical energy economics, seeking to quantify the sensitivity of industrial sector GHG emissions to energy input mixes. While deep learning models such as RNNs are used for high dimensional temporal pattern recognition, their use here is structured to serve a functional equivalent of marginal analysis. Specifically, after model training, energy variables are perturbed in isolation to evaluate their impact on emissions, thereby constructing a partial response surface analogous to elasticity analysis. This approach aligns with applied economic modeling practices where counterfactual scenarios are tested while holding other factors constant.

The research methodology adopted in this study, as shown in Fig. 1, was systematically executed. Initially, 'Data Preparation' was undertaken, entailing the compilation of datasets that detailed the energy consumption within the industrial sector, the economic contribution of the industrial sector of Hungary, and its environmental impact through GHGs. Subsequently, 'Model Training and Testing' was conducted, where RNN models were trained. The final phase of the methodology, 'Results and Analysis,' encompassed the application of the refined model to assess the impact of each energy consumption source on GHGs.

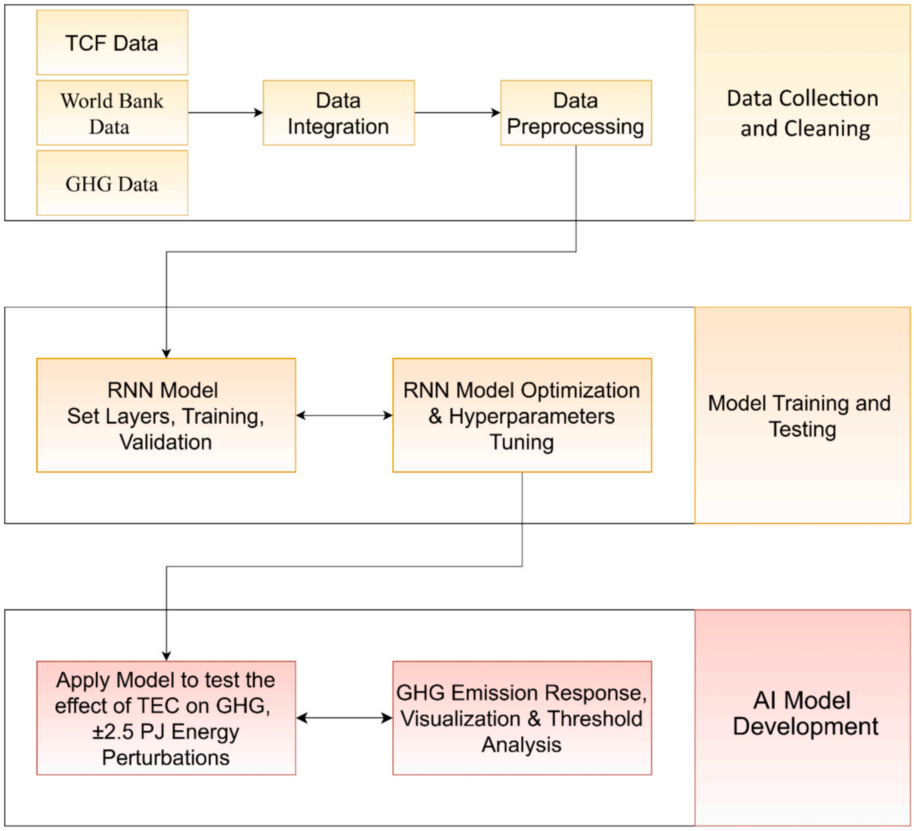

Fig. 1. Sequential methodology flowchart for RNN-based analysis.

3.1. Data

This study leverages three datasets. The first dataset, detailing Industry Total Final Consumption (TFC) in petajoule (PJ) by source, provides a record of the industry's energy annual usage by source categories such as coal, oil products, natural gas, nuclear, renewables and waste, electricity, and heat. The data is sourced from the IEA's World Energy Balances and is available at the IEA World Energy Statistics and Balances. The second dataset derives from the World Bank's national accounts data, augmented by OECD National Accounts data files, and encapsulates the annual Industry's value added as a percentage of GDP. This dataset unveils the financial magnitude of the industry, cataloging its economic vitality and how it underpins Hungary's GDP.

The final dataset focuses on environmental responsibility, capturing the annual GHG emissions attributed to the industrial sector, articulated in tonnes. This dataset was proffered by Climate Watch and refined by Our World in Data for the year 2023.

Table 1 summarizes the key variables used, along with their descriptions, measurement units, and corresponding sources. Note that the delineation of industry consumption within this study adheres to the International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4 (Rev. 4) classification framework [41]. Under this schema, 'Industry' aggregates the data from various sub-sectors as compiled by the IEA Secretariat, encompassing Iron and steel; Chemical and petrochemical; Non-ferrous metals; Non-metallic minerals; Transport equipment; Machinery; Mining and quarrying; Food and tobacco;

Table 1
Summary of variables utilized in this study.

Dataset	Variable	Description	Unit	Source
TFC	Coal, peat, and oil shale	Includes all coal types and derived fuels, peat, and oil shale.	PJ	IEA World Energy Balances
TFC	Crude, NGL, and feedstocks	Comprises crude oil, natural gas liquids, and other related hydrocarbons.	PJ	IEA World Energy Balances
TFC	Oil products	A variety of refined oil products including gases, fuels, and waxes.	PJ	IEA World Energy Balances
TFC	Natural gas	Encompasses both associated and non-associated gas, excluding liquids.	PJ	IEA World Energy Balances
TFC	Nuclear	Represents the heat equivalent of electricity from nuclear plants with an average efficiency.	PJ	IEA World Energy Balances
TFC	Renewables and waste	Includes renewable energy forms and waste used for electricity and heat generation.	PJ	IEA World Energy Balances
TFC	Electricity	Indicates final consumption and trade in electricity.	PJ	IEA World Energy Balances
TFC	Heat	Shows the disposition of heat produced for sale, including heat from fuel combustion and heat pumps.	PJ	IEA World Energy Balances
World Bank national accounts	Industry Value Added	Measures the economic output of the industrial sector.	% of GDP	World Bank national accounts data, OECD National Accounts data files
GHG	GHG Emissions – Industry	Tracks greenhouse gas emissions attributable to the industrial sector.	Tonnes	Climate Watch (2023) – processed by Our World in Data

Paper, pulp, and print; Wood and wood products; Construction; Textile and leather; along with industries not otherwise specified. Please note that the energy consumption attributed to industrial transportation is not included within these categories.

In this study, “heat” is included as a distinct category in the energy consumption dataset, consistent with the classification adopted by the IEA. Although heat is a form of energy rather than a primary source, it is reported separately in TFC statistics due to its direct end-use (such as district heating and industrial process heat) and measurable contribution to GHG emissions. Therefore, it is treated as a standalone energy carrier in both statistical reporting and emissions modeling.

As the integrated datasets consist of multiple variables with various scales and units, standardization is an essential preprocessing step that transforms each feature of the dataset to have a mean (μ) of 0 and a standard deviation (σ) of 1. The formula for standardizing a feature x_j for a given sample i is given by *1*:

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{1}$$

Where x_{ij} is the original value of feature j for sample i. μ_j is the mean of feature j across all samples N. σ_j is the standard deviation of feature j across all samples N. x'_{ij} is the standardized value.

3.2. RNN model

Upon standardizing the dataset, an RNN is employed to model the complex relationships between various energy consumption sources and GHG emissions. The selection of RNNs is driven by several factors related to the dataset and the modeling challenge. Firstly, the dataset comprises annual observations, resulting in a relatively small sample size. Traditional machine learning models often struggle with such limited temporal data; however, RNNs are particularly well-suited for this scenario. Their architecture allows for the efficient capture of temporal dependencies by maintaining an internal memory of past inputs, making them ideal for time series modeling even when data points are sparse [42]. Secondly, energy consumption data is inherently noisy due to fluctuations driven by economic activities, weather variations, policy changes, and energy market volatility. This stochastic nature of the data introduces significant uncertainty in modeling GHG emissions. RNNs, particularly variants like Long Short-Term Memory (LSTM) networks, are robust in managing noisy sequences, as they can learn long-term dependencies while filtering out short-term irregularities [42]. Finally, the dataset displays complex, non-linear interdependencies among variables. Different energy sources (such as coal, natural gas, renewables, and nuclear) contribute to GHG emissions through distinct pathways, and their effects are not simply additive. These interactions can exhibit delayed effects and feedback mechanisms. RNNs are capable of learning such non-linear patterns and time-dependent relationships, thanks to their recurrent structure and internal state mechanisms, which help capture both sequential patterns and variable interrelationships [43]. Therefore, the application of RNNs in this context is justified not only by their ability to handle time series data but also by their strength in managing noise and capturing complex, non-linear dynamics inherent in energy systems and emissions data.

The RNN model is built by stacking layers, including Simple RNN layers for capturing temporal dynamics and a dense layer for output prediction. The basic unit of computation in an RNN, as shown in Fig. 2, is the hidden state h_t, which is updated at each time step t. The update takes into account the current input x_t and the previous hidden state h_{t-1}. For a simple RNN layer, this update is performed using the formula:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h) \tag{2}$$

And for subsequent layers:

$$h_t^l = \sigma\left(W_h^l h_{t-1}^l + W_x^l h_t^{l-1} + b_h^l\right) \tag{3}$$

Where:

h_t is the hidden state at time t. x_t is the input at time t. W_h and W_x are the weight matrices for the hidden state and input, respectively. b_h is the bias vector. σ represents the ReLU activation function, l indexes the layer in the network.

The output of the network is given by the dense layer, calculated as:

$$y_t = W_\circ h_T + b_\circ \tag{4}$$

Where:

$W_\circ$ is the weight matrix from the final hidden state to the output, $b_\circ$ is the output bias, y_t is the predicted value. T denotes the final time step in the sequence.

The model’s performance is measured using a loss function, with Mean Squared Error (MSE) being a common choice for regression:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

In addition to the primary loss, L2 regularization is often applied to the weights to combat overfitting, adding a penalty term to the loss function:

$$L_{reg} = L + \lambda \Sigma_K W_k^2 \tag{6}$$

Where L is the original loss (MSE in this case article). λ is the regularization strength, and W_k represents the weight matrices.

The Adam optimizer is used to minimize the loss function. It updates each weight W in the network based on first moments (the mean of the gradients) and second moments (the uncentered variance of the gradients):

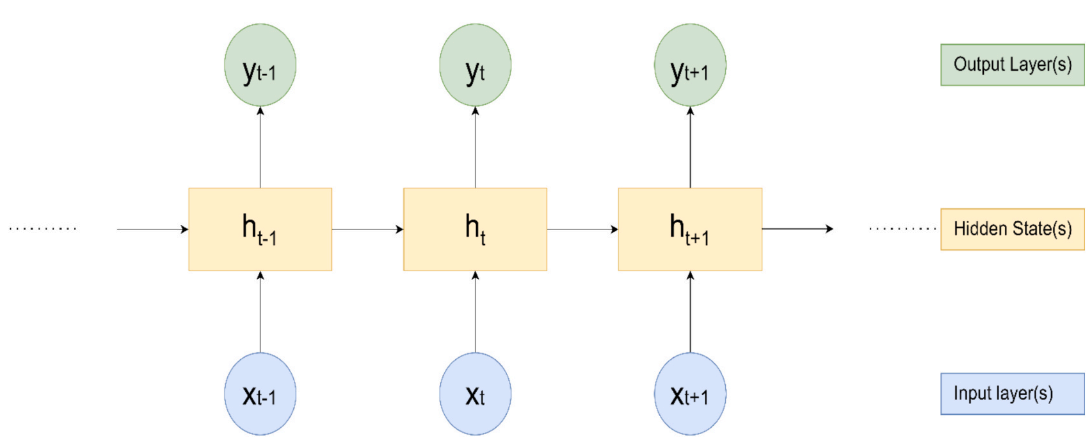

Fig. 2. Recurrent Neural Network (RNN) architecture.

$$W_{t+1} = W_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t \quad (7)$$

Where W_t and W_{t+1} are the weights at times t and $t+1$, respectively. η is the learning rate. $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected estimates of the first and second moments. ϵ is a small scalar added to improve numerical stability.

The model's performance is evaluated on a separate test dataset using the mean squared error (MSE), Root-mean-square deviation (RMSE), and coefficient of determination (R^2).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (10)$$

Where $\bar{y}$ is the mean of the actual values y_i.

The approach for optimizing the RNN model involves a comprehensive strategy using the Randomized Search CV, which effectively explores the vast parameter space to find the optimal model settings. This method contrasts traditional grid search by random sampling from predefined hyperparameters, significantly reducing the computational expense while still covering a broad range of possibilities. The RNN model is tailored through varying parameters such as the number of layers, neurons per layer, learning rate, and regularization strength, aiming to minimize the MSE on the test set. The optimization process is supported by the Early Stopping callback, which monitors validation loss and halts training when improvements cease, preventing overfitting and ensuring computational efficiency. The final model parameters are determined after evaluating several configurations over multiple training cycles, each using a subset of training data. This method ensures that the model is not only tuned to the training data but also validated against a portion of unseen data to assess its generalization capabilities. Table 2 illustrates the RNN model's hyperparameters that were adjusted during the optimization process, providing insights into the range of values explored and their impact on model performance.

The dataset is partitioned into training and test subsets, with 70 % of the data allocated for training and the remaining 30 % reserved for testing. Furthermore, within the Randomized Search CV framework, a 3-fold cross-validation is employed on the training data. This method involves dividing the training set into three smaller subsets. The model is trained on two of these subsets while the third serves as a validation set. This process is repeated three times, with each subset serving as the validation set once. This cross-validation approach allows for a more robust estimation of model performance by averaging the results from multiple training and validation cycles. It reduces the potential variability that could arise from the random selection of the train-test split, providing a more stable and reliable assessment of the model's true predictive power.

The trained RNN model was then used to project the impacts of variations in individual energy sources on GHG emissions. Each source was independently adjusted by ±2.5 PJ in 0.025 PJ increments while maintaining others at their most recent values. This approach ensured that observed effects were attributable solely to changes in the target source. This approach emulates a ceteris paribus economic experiment and allows the derivation of response gradients i.e., the estimated marginal effect of each energy type on GHG emissions. These gradients can be interpreted as empirical proxies for the emissions intensity and substitution elasticity of different energy sources within Hungary's industrial sector.

4. Results

Aligned with the three-stage methodology employed in this study, the forthcoming sections present the results derived from the data preparation, model training and testing, and subsequent analysis phases.

4.1. Dataset overview

For the key variables are presented in Table 3. The dataset spans 26 annual observations from 1995 to 2020 and captures energy consumption by source, industrial value added, and total GHG emissions. The variability in GHG emissions (mean: 3.20 million tons CO_2-eq; std. dev.: 659365) reflects both structural and policy driven changes over the period. Some sources, such as nuclear energy and crude oil derivatives, show zero values, indicating no recorded final consumption within the industrial sector during the studied years.

Fig. 3 provides a three pronged overview of Hungary's industrial performance and its environmental cost between 1995 and 2020. At the outset of the series, the sector accounted for roughly a quarter of

Table 3
Key descriptive statistics of energy use, economic output, and GHG emissions (1995–2020).[1]

Variable	Mean	Min	Max	Range	Std. Dev.
Coal, peat and oil shale	11.72	5.14	18.20	13.06	4.13
Crude, NGL and feedstocks	0.00	0.00	0.00	0.00	0.00
Oil products	16.79	5.79	30.47	24.68	8.16
Natural gas	56.19	34.22	79.41	45.19	10.88
Nuclear	0.00	0.00	0.00	0.00	0.00
Renewables and waste	5.63	1.86	14.97	13.11	3.89
Electricity	41.71	29.83	63.90	34.07	12.45
Heat	15.21	4.57	21.65	17.08	3.75
Industry value added (% of GDP)	26.08	24.39	28.10	3.71	1.06
GHG emissions	3,202,308	2,360,000	4,390,000	2,030,000	659,365

[1] Energy in ktoe; GHG in metric tons CO_2-equivalent; Industry as % of GDP.

Table 2
Hyperparameters of the RNN and their ranges for optimization.

Parameter	Explanation	Tested values
Number of layers	The number of recurrent layers in the RNN. This affects the depth of the network, influencing its ability to process and remember information over time.	1 to 5 layers
Neurons per layer	The number of neurons in each RNN layer. More neurons can increase the model's capacity to learn complex patterns but may lead to overfitting.	2 to 20 neurons
Learning rate	The step size at each iteration while moving toward a minimum of a loss function. Proper tuning ensures efficient convergence.	0.001 to 0.01
L2 Regularization	Regularization strength to prevent overfitting by penalizing large weights.	0.001 to 0.1
Batch size	The number of samples per batch to be used for training the network. Smaller batch sizes often lead to better generalization.	8 to 64
Epochs	The number of times the learning algorithm will work through the entire training dataset.	100 (fixed, with early stopping)

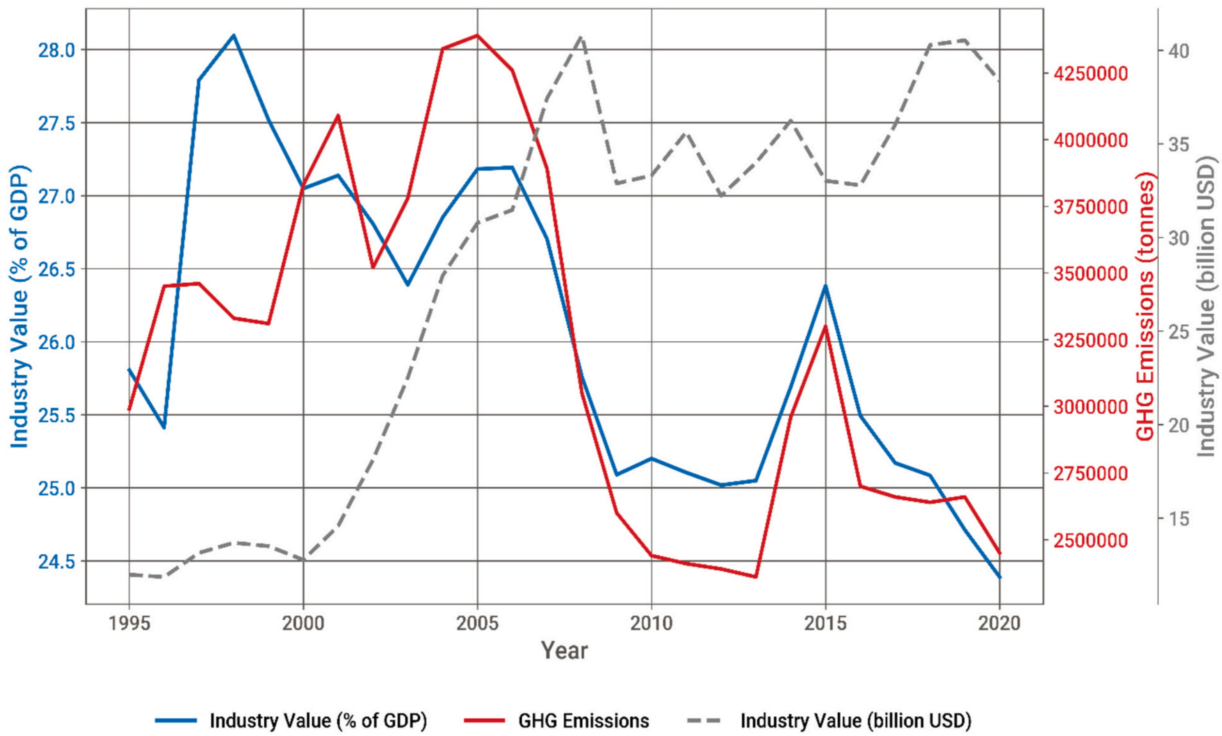

Fig. 3. Comparison of industrial value added (relative and absolute) and GHG emissions in Hungary (1995–2020) (Industrial value added in billion USD was calculated by multiplying the percentage of GDP by Hungary's annual GDP (current USD).).

national output (≈25.8 % of GDP), generated only about 12–13 billion constant price USD in gross value added, yet already produced nearly 3 million tonnes of GHG emissions. Through the late-1990 s these three measures rose in unison. By 2001 the industrial share of GDP had climbed above 27 %, emissions approached 4 million tonnes, and absolute value added breached 15 billion USD. Early post transition growth, therefore, was expansionary but still strongly carbon intensive.

A more pronounced surge followed from 2002 to 2006. All three curves accelerated, real GVA leaped towards 30 billion USD, the sector's weight in GDP hovered around 27 %, and emissions reached their historical high of just over 4.25 million tonnes. This synchronized expansion illustrates the phase in which industrial output, economic relevance, and carbon releases were tightly coupled, suggesting reliance on energy and material heavy activities to fuel growth.

The global financial crisis then triggered a broad contraction. Between 2007 and 2013 emissions slid first, dipping below 3 million tonnes by 2008, while value added and GDP share both sagged in the wake of falling external demand. By 2010 the sector's GDP contribution had fallen to roughly 25 % and real output stagnated near the upper 20 billion USD range, marking the only multi year spell in which economic and environmental indicators declined together.

A short lived rebound occurred in 2014–2016. Industrial GVA climbed back to 34–36 billion USD, the GDP share returned to about 26.5–27 %, and emissions ticked up past 3.2 million tonnes. Yet even at this third peak, the carbon footprint remained a full million tonnes lower than in 2005, hinting at efficiency gains or a gradual tilt towards less emission-intensive subsectors. From 2017 onwards, the picture changes markedly. Real value added grows steadily, surpassing 40 billion USD by

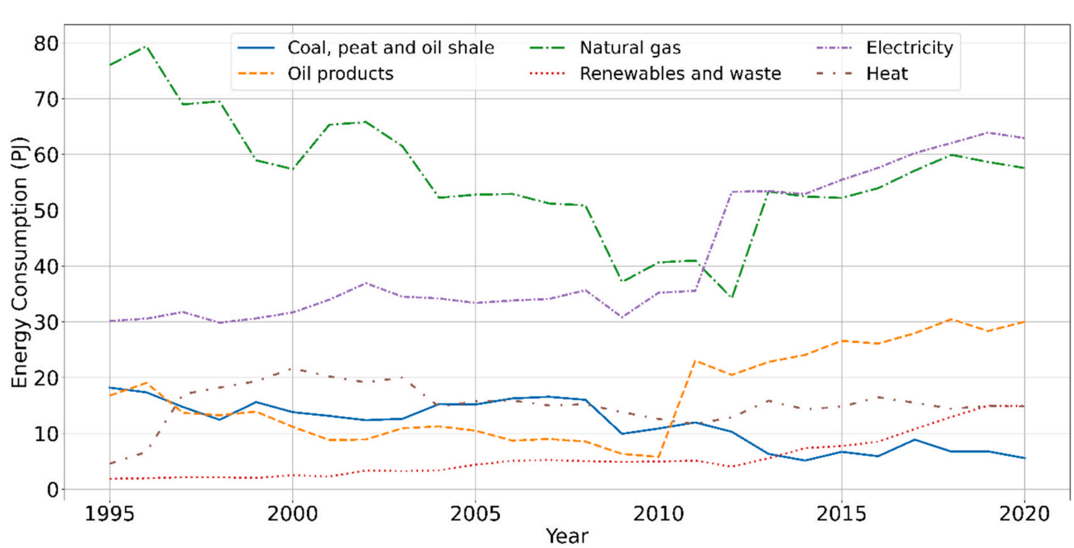

Fig. 4. Trends in energy consumption by source in Hungary (1995–2020).

2019, even as the sector's GDP share drifts below 25 % and emissions retreat to around 2.5 million tonnes.

The temporal evolution of Hungary's energy landscape from 1995 to 2020 is shown in Fig. 4. A diverse energy mix comprising coal, peat, and oil shale, crude, natural gas liquids and feedstocks, oil products, natural gas, nuclear, renewables, waste, electricity, and heat fueled Hungary's industrial activities throughout the studied period. Natural gas emerged as the predominant energy source, consistently exhibiting the highest consumption levels across most years, peaking at around 80 PJ in 1996. The contribution of coal, peat, and oil shale displayed fluctuations, ranging from 18.1 PJ in 1995 to as low as 5.5 PJ in 2020. Oil products experienced a substantial decline from 16.7 PJ in 1995 to around 8–11 PJ in the early 2000s, before increasing gradually and averaging around 26–30 PJ in subsequent years. Electricity consumption remained significant throughout, ranging from 30.1 PJ in 1995 to 63.9 PJ in 2019. Heat consumption exhibited a generally stable trend, reaching 14.8 PJ by 2020. A notable surge in renewables and waste is observed, particularly from 2013 onward, rising from 5.5 PJ in 2013 to 14.9 PJ by 2020, signaling a gradual transition towards cleaner energy sources. Conversely, the role of nuclear energy, crude, NGL, and feedstocks remained negligible throughout the studied timeframe.

4.2. RNN results

Using Randomized Search CV, it was found that the most effective configuration for the RNN model consisted of four layers, each with twenty neurons. The model operated with a learning rate of 0.0025, an L2 regularization parameter of 0.005, and was trained over 100 epochs with a batch size of 64. This setup was shown to minimize the RMSE during the validation and testing phases, achieving an RMSE of 401,060 on the test set. Further insight into the model's efficacy is provided by the test R2 value of 0.64. The complementary nature of these two metrics, when interpreted in the context of the target variable's scale, supports the conclusion that the model, equipped with the identified optimal parameters, is effective in capturing the underlying patterns and trends in the GHG emissions data for Hungary's industrial sector.

Fig. 5 presents the predicted percentage change in GHG emissions in response to marginal adjustments in coal energy consumption within Hungary's industrial sector. The results are derived from the trained RNN model, which simulates isolated changes in coal consumption while holding all other inputs constant at their most recent values. The graph demonstrates an asymmetric, non-linear relationship. A reduction of 2.5 PJ in coal consumption leads to a projected GHG emission decrease of approximately 4.4 %, whereas an increase of 2.5 PJ results in a more modest rise of about 1.8 %. This asymmetry suggests that reductions in coal use yield disproportionately greater emission savings compared to the emission increases associated with equivalent consumption growth. Such behavior may reflect non-linear interactions within the trained model, as well as historical energy substitution patterns where reductions in coal consumption were often replaced with lower-emission sources. A notable inflection point is observed around a decrease of −0.25 PJ, beyond which the emissions-reduction effect becomes significantly steeper. This threshold effect suggests that marginal coal reductions past this point contribute more effectively to emission mitigation, potentially due to the modeled displacement of particularly carbon-intensive coal applications in the historical data.

Fig. 6 shows the predicted marginal effect of electricity consumption changes on GHG emissions in the industrial sector. The model simulates isolated, incremental changes in electricity consumption in PJ while holding all other energy inputs constant at their most recent levels. The results reveal a weak inverse relationship, increases in electricity consumption are associated with modest decreases in GHG emissions, whereas reductions in electricity use result in slight emission increases. Specifically, a 2.5 PJ increase in electricity consumption is projected to lower emissions by approximately 0.8 %, while a 2.5 PJ decrease leads to a rise of similar magnitude. This near-linear and symmetric response pattern suggests a relatively stable emissions elasticity with respect to electricity consumption. The underlying explanation for this trend lies in the carbon intensity of electricity generation in Hungary, which based on historical data is lower than that of direct fossil fuel use in industrial processes. The model likely captures patterns where shifts from on-site combustion (e.g., coal or gas) toward electrified processes corresponded with reduced emissions, due to Hungary's increasingly decarbonized power mix. However, it is important to emphasize that these

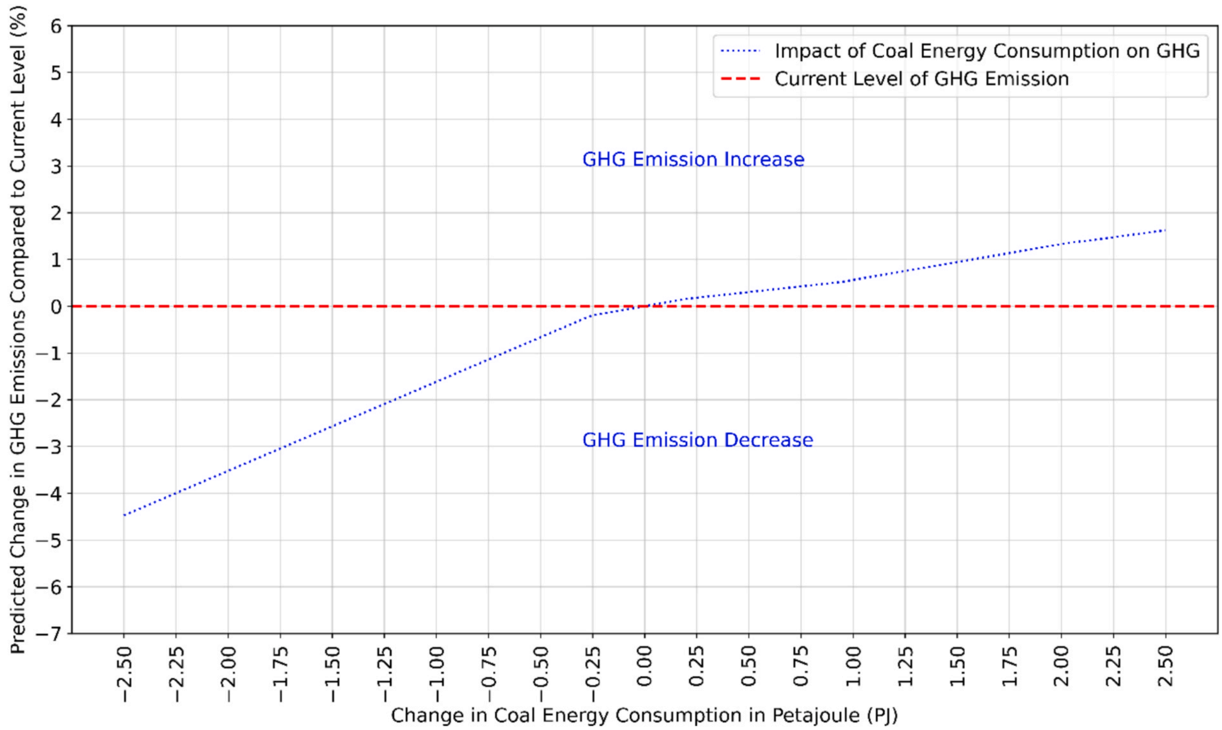

Fig. 5. Impact of coal consumption changes on GHG emissions in Hungary's industrial sector.

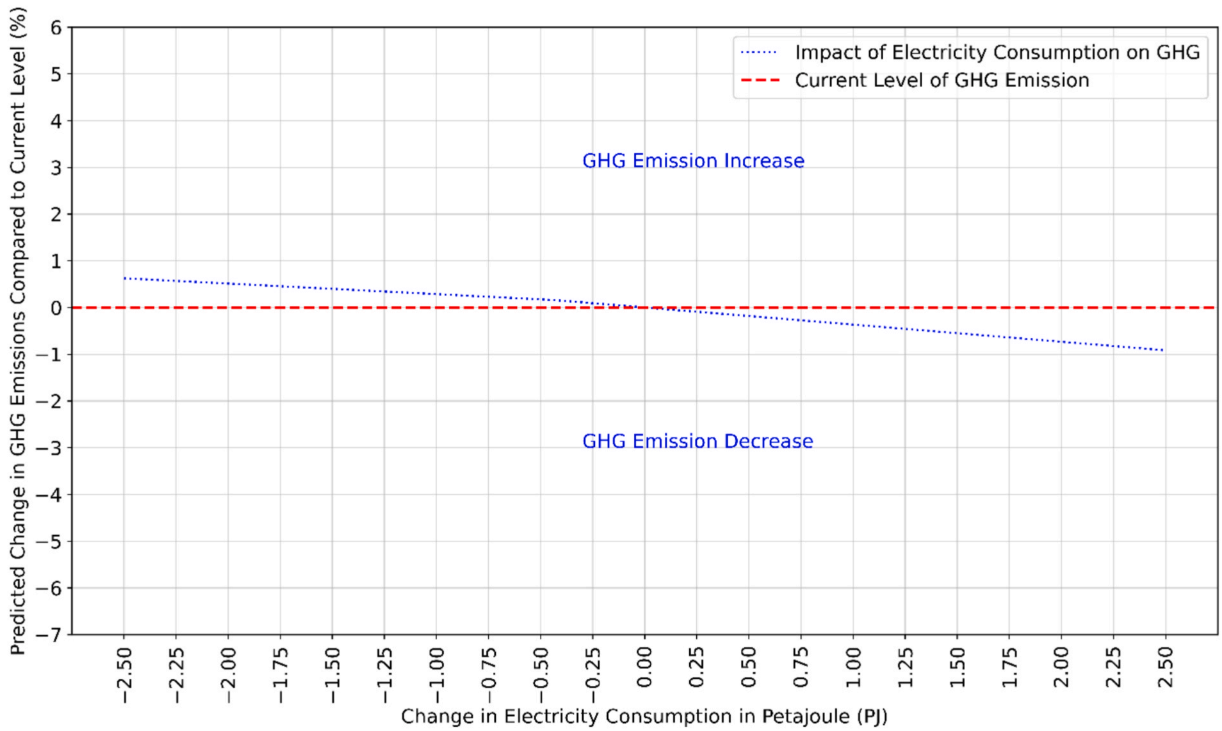

Fig. 6. Impact of electricity consumption changes on GHG emissions in Hungary's industrial sector.

results reflect marginal predictions within the bounds of past system behavior. They do not account for the source of additional electricity (e.g., domestic vs imported) or broader grid dynamics. Thus, while electricity appears to offer emissions advantages at the margin, energy security and system-level carbon accounting must be considered.

Fig. 7 presents the predicted marginal changes in industrial GHG emissions in response to isolated variations in natural gas consumption. The results show a mild but consistent inverse relationship: a 2.5 PJ decrease in natural gas consumption leads to an approximate 1.2 % reduction in GHG emissions. Interestingly, the model predicts that increases in natural gas consumption produce negligible changes in emissions, resulting in a slightly negative or near-zero slope. This asymmetric response suggests that emission reductions from curbing gas use are more pronounced than emissions added from increasing it. This behavior may stem from the historical role of natural gas as a transitional fuel in Hungary's industrial sector. When gas consumption

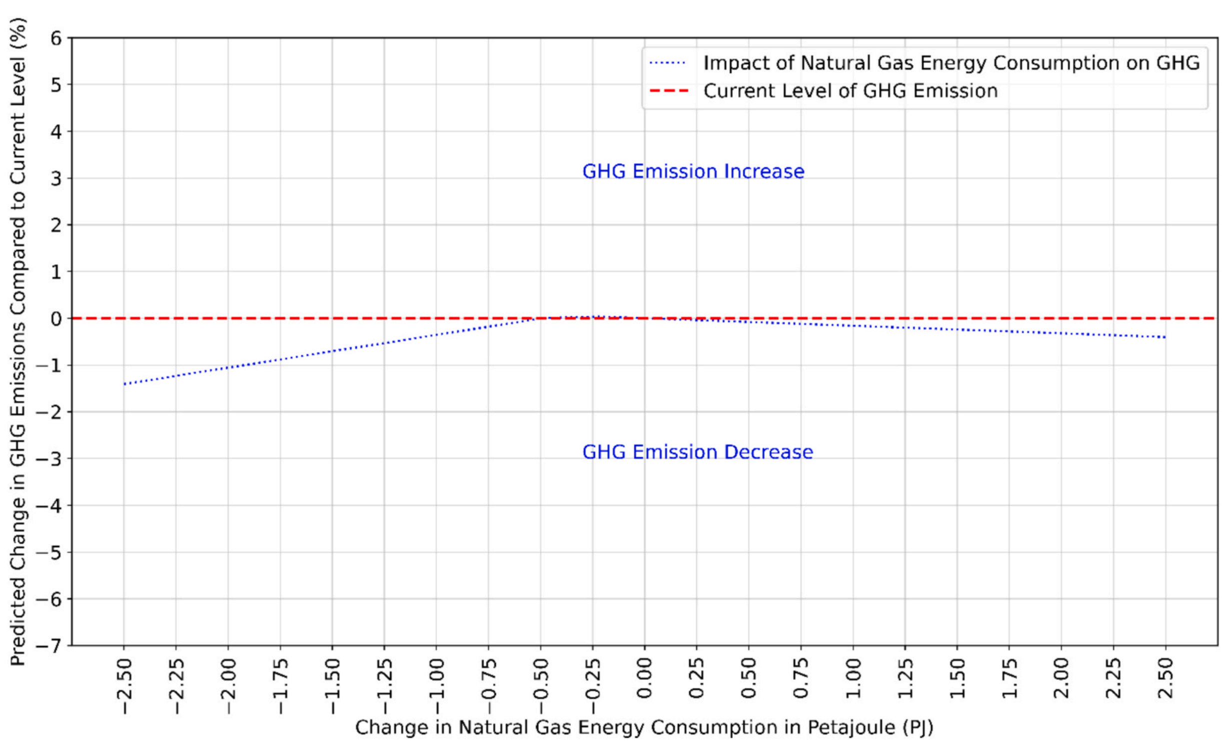

Fig. 7. Impact of natural gas consumption changes on GHG emissions in Hungary's industrial sector.

declined in the past, it may have been replaced by cleaner alternatives such as renewables. Conversely, increased gas use might have substituted for more carbon-intensive fuels like coal, resulting in no net emission rise or even slight reductions. Importantly, while natural gas is not a zero-emission source, it is significantly cleaner than coal or oil on a per-unit basis. The relatively flat and near-linear shape of the response curve beyond ±1.0 PJ suggests a limited marginal impact at larger deviations, with no strong threshold effect evident. This implies that natural gas, although not entirely benign, offers relatively low emissions sensitivity within the observed range.

Fig. 8 depicts the predicted percentage change in GHG emissions in response to variations in industrial heat energy consumption. The results reveal an asymmetric and non-linear relationship. A 2.5 PJ decrease in heat consumption is associated with a reduction of more than 4.3 % in GHG emissions, while a corresponding increase results in just over a 2 % rise. This asymmetry indicates that reducing heat consumption has a stronger effect on emissions mitigation than increasing it has on emissions growth. The shape of the curve suggests that the emissions associated with heat energy are particularly sensitive to reductions, possibly due to high baseline emission intensity. Two threshold effects can be observed. The first is near a reduction of –1.5 PJ, beyond which further reductions lead to disproportionately larger decreases in emissions. This may indicate that historical reductions in heat usage were often accompanied by shifts away from highly carbon-intensive heat generation sources. The second threshold appears near a +1.65 PJ increase, beyond which further increases in heat usage produce a diminishing marginal effect on emissions, suggesting possible saturation or efficiency effects in the modeled response. Between these thresholds, the relationship appears approximately linear, though the slope remains steeper on the reduction side. This behavior highlights the potential emission reduction leverage associated with scaling down industrial heat demand, particularly in sectors where heat is generated from fossil fuels or district heating systems with high carbon intensity. It should be noted that these findings reflect localized model behavior rather than holistic energy system dynamics. Other implications would depend on the fuel mix used for heat generation, end-use technologies, and the feasibility of substitution with lower emission alternatives.

Fig. 9 illustrates the predicted marginal effect of changes in industrial oil energy consumption on greenhouse gas emissions. The model exhibits a stable and nearly linear relationship between oil consumption and emissions. Both increases and decreases in oil use yield changes in GHG emissions of less than 1 %, with the slope appearing symmetric and modest in magnitude. A 2.5 PJ increase in oil consumption leads to a projected emission rise of approximately 0.8 %, while an equivalent reduction results in a comparable decline. This low sensitivity suggests that oil based processes in Hungary's industrial sector contribute moderately to total emissions and that marginal shifts in oil consumption exert a relatively small influence. The linearity and symmetry observed in the response curve indicate that the model captures no strong non-linearities or threshold effects within the tested range. This is likely a reflection of oil's limited share in the total industrial energy mix and its relatively consistent emission factor per unit of energy. Although oil combustion is generally more carbon intensive than natural gas or electricity, its overall role in the industrial sector may be context specific, concentrated in applications where alternatives are limited, or in small-scale usage. Consequently, changes in oil consumption do not dominate the emissions profile, especially when compared to sources like coal or industrial heat. These results should be interpreted as local sensitivities, not system-wide forecasts. Broader energy planning must consider substitution pathways, sectoral constraints, and the strategic importance of oil in specific industrial sub-processes.

Fig. 10 presents the predicted marginal effects of changes in renewables and waste energy consumption on GHG emissions in Hungary's industrial sector. The results reveal a strongly asymmetric and non-linear relationship. A 2.5 PJ decrease in consumption of renewables and waste leads to an estimated reduction of nearly 3.5 % in industrial GHG emissions, while an equivalent increase results in a modest reduction of less than 0.5 %. This response pattern indicates that historical reductions in high-emission components of this energy category (particularly waste incineration) contributed more substantially to emissions mitigation than marginal increases, which may have included cleaner forms of renewables. Two inflection points are evident in the response curve. The first occurs near –0.25 PJ, beyond which further reductions in consumption are associated with increasingly sharp

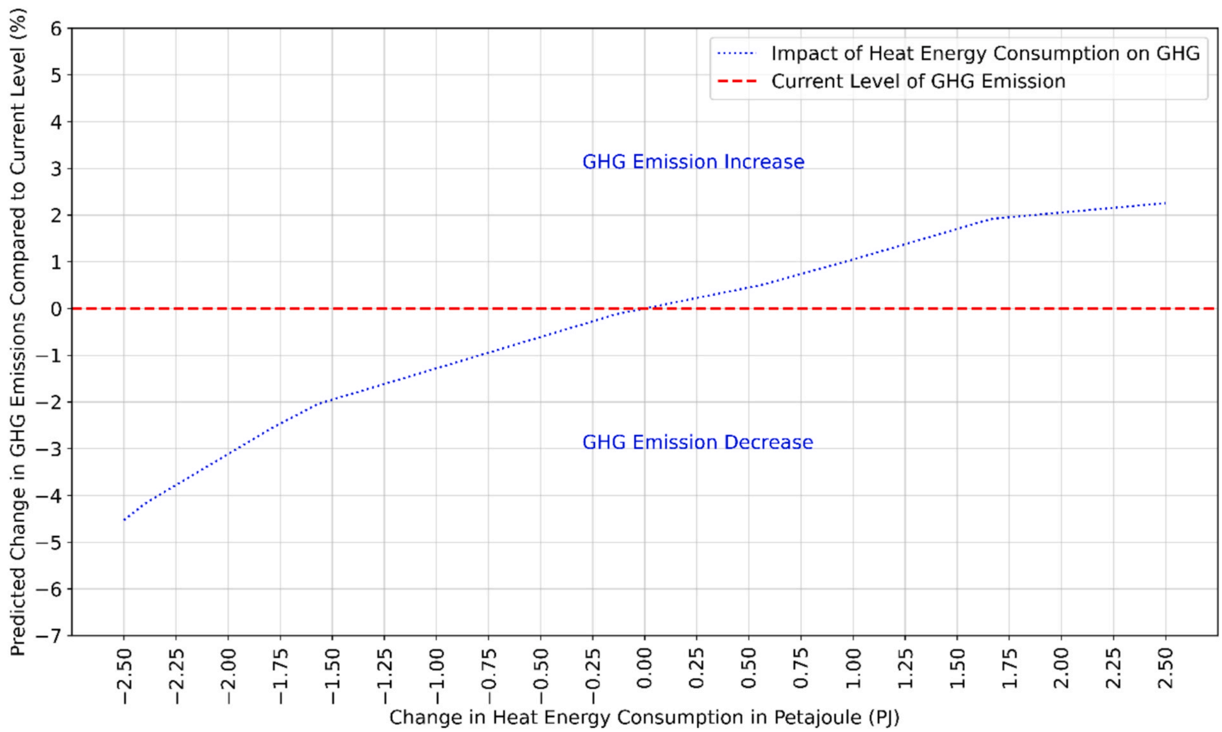

Fig. 8. Impact of heat consumption changes on GHG emissions in Hungary's industrial sector.

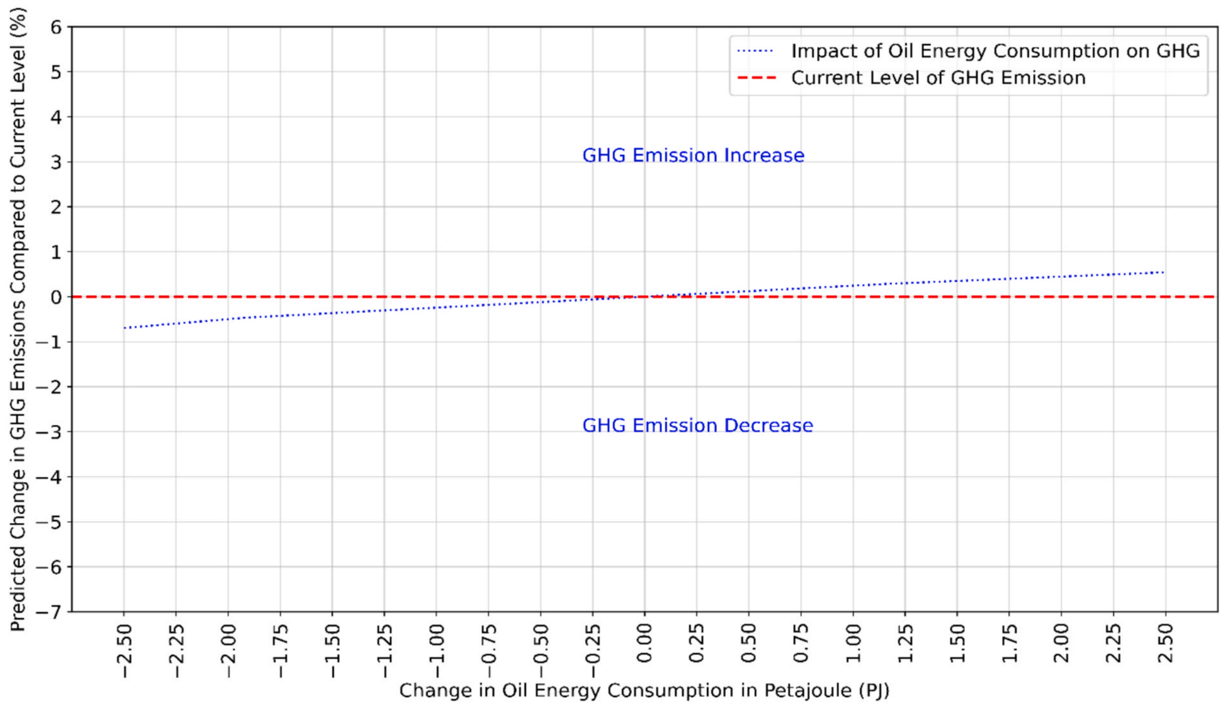

Fig. 9. Impact of oil consumption changes on GHG emissions in Hungary's industrial sector.

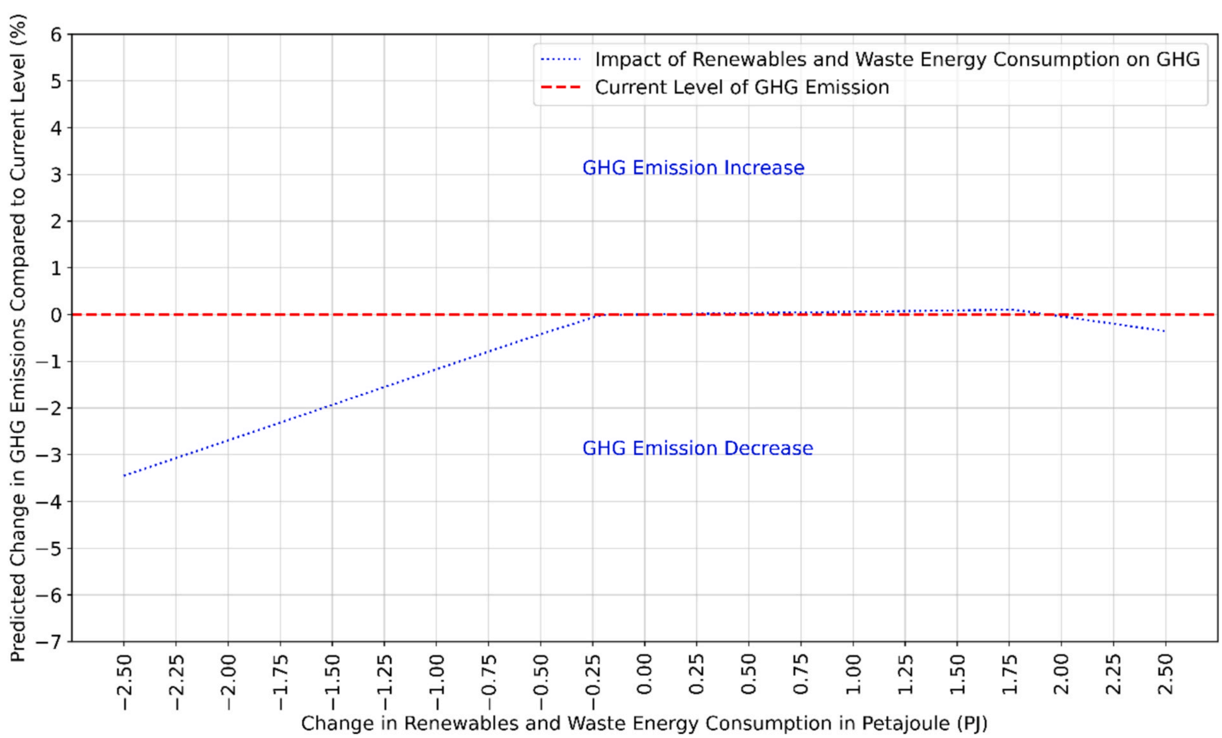

Fig. 10. Impact of renewable and waste consumption changes on GHG emissions in Hungary's industrial sector.

decreases in emissions. The second lies above +1.75 PJ, where the emissions-reducing effect of increased renewables and waste consumption becomes slightly more pronounced. Between these thresholds, the response remains relatively flat, suggesting limited sensitivity to small changes in this category.

These results highlight the importance of considering the internal heterogeneity of aggregated energy categories. While the label "renewables and waste" suggests an overall environmentally beneficial profile, certain subcomponents (such as municipal or industrial waste) can have relatively high emissions per unit of energy. Consequently, the modeled emission benefits of reducing this energy source may reflect reductions in waste combustion rather than clean renewable sources. It is important to interpret these findings as localized, model-derived marginal. The RNN model estimates emissions changes based on historical correlations, assuming ceteris paribus conditions. Broader system level dynamics (such as the substitution effects between domestic electricity generation and imports or between waste-derived fuels and biomass) are not captured in this framework. Nevertheless, the results underscore the value of disaggregating energy data and suggest that targeted reductions in high-emission waste energy could yield meaningful environmental benefits without compromising the broader trajectory of renewable energy development.

5. Discussion

The findings of this study reveal critical insights into the relationship between energy consumption, economic performance, and environmental impact within Hungary's industrial sector. The industry's contribution to GDP remained relatively stable, fluctuating nearly between 24 % and 28 %, despite significant shifts in energy consumption patterns. This indicates that the industrial sector has managed to maintain its economic output while undergoing substantial changes in its energy mix.

A notable finding of this study is the persistent coupling between industrial activity and GHG emissions. This strong linkage underscores that economic growth in Hungary's industrial sector has historically been reliant on energy-intensive and high-emission processes. Although there has been a decline in GHG emissions since 2005, this reduction coincides with a parallel decline in the industrial sector's GDP contribution, further emphasizing the strong coupling between economic activity and environmental impact in Hungary's industrial sector.

The temporal analysis of Hungary's energy consumption patterns provides a comprehensive view of the transition towards cleaner energy sources. The decline in the use of coal, peat, and oil shale reflects a strategic move away from high-carbon energy sources. This shift aligns with global trends and national policies aimed at reducing carbon emissions. Conversely, the consumption of renewables and waste energy saw a substantial increase. However, the inclusion of waste energy, which often has higher GHG emissions compared to other renewables, complicates the overall environmental benefit.

The detailed analysis of individual energy sources' impacts on GHG emissions offers valuable insights for policy-making. Reducing coal consumption was found to have a significant effect on lowering GHG emissions. The non-linear relationship, particularly beyond a reduction threshold of −0.25 PJ, highlights the efficacy of targeted coal reduction policies. Setting clear goals to reduce coal consumption by specific amounts, especially targeting reductions beyond the −0.25 PJ threshold, can significantly enhance the effectiveness of emission reduction strategies. Policymakers should focus on creating targeted coal reduction initiatives that emphasize crossing these critical reduction points to maximize environmental benefits. Establishing incremental reduction milestones and monitoring their impact can ensure that coal reduction efforts are both measurable and effective, thereby contributing to substantial GHG emissions reductions.

Changes in electricity consumption had a relatively stable linear impact on GHG emissions. Interestingly, an increase in electricity consumption resulted in a slight decrease in GHG emissions, whereas a decrease in electricity consumption led to a minor increase in emissions. This counterintuitive impact is likely due to Hungary's electricity generation mix. In 2020, according to the IEA Hungary 2022 Energy Policy Review, low-carbon sources contributed significantly to total electricity generation, with nuclear energy accounting for 46 %, solar for 7 %, wind for 2 %, and biofuels for 7 % [44]. Compared to other energy sources, this mix has a lower carbon footprint, thereby contributing to the observed effect where increased electricity usage displaces more carbon-intensive fuels, leading to an overall reduction in GHG emissions. This suggests that while managing electricity consumption is crucial, it alone cannot drive significant GHG reductions, and a comprehensive approach targeting higher-emission sources is necessary to achieve substantial emissions cuts.

Changes in natural gas consumption exhibited an asymmetric impact on GHG emissions. Increasing natural gas consumption did not significantly raise GHG emissions, while reductions led to substantial decreases. This finding indicates that natural gas has a lower GHG intensity compared to other fossil fuels. Our results suggest that natural gas can be effectively used to replace more carbon-intensive energy sources, thereby achieving immediate environmental benefits. Supporting this finding, a study by Howarth et al. highlights that natural gas, when used in place of coal and oil, results in lower GHG emissions due to its higher efficiency and lower carbon content [45]. Therefore, by promoting natural gas as a transitional fuel, policymakers can leverage its cleaner profile to displace higher-emission fuels, contributing to overall GHG reductions. Strategic policies that encourage the use of natural gas in place of more polluting fuels are essential for Hungary's energy transition and emission reduction goals.

The consumption of heat energy showed a significant potential for GHG reduction, with a critical threshold at −1.6 PJ, beyond which further reductions result in sharply higher decreases in emissions. This highlights the importance of targeting heat energy consumption reductions in policy frameworks. By recognizing the critical threshold, policies can be designed to prioritize and achieve these specific reductions in heat energy use, leading to substantial decreases in GHG emissions.

Oil energy consumption changes had a minimal impact on GHG emissions, demonstrating a near-linear response. Both increases and decreases of 2.5 PJ resulted in less than a 1 % change in emissions. This limited impact is likely due to its use in applications that are less variable in energy efficiency. Studies, such as those by McGlade and Ekins, have shown that oil's role in energy consumption is often less flexible compared to other energy sources, resulting in minor changes in emissions when consumption levels are adjusted [46]. This suggests that oil consumption adjustments alone are insufficient for substantial emissions reductions. Therefore, policy strategies should recognize that focusing solely on oil consumption will not yield significant emission reductions and should instead adopt a comprehensive approach that includes multiple energy sources to achieve more substantial GHG reductions.

The response of GHG emissions to changes in renewables and waste energy consumption was particularly revealing. An increase of 2.5 PJ in these sources led to a modest decrease in emissions, while a decrease of the same magnitude resulted in a sharper reduction. This asymmetry underscores the complexity introduced by waste energy's higher baseline emissions compared to other renewables. Studies, such as those by Panepinto et al., have highlighted that while waste energy processes are considered renewable, they often emit more GHGs compared to other renewable sources like wind or solar [47]. Therefore, the higher baseline emissions from waste energy result in a more significant impact when consumption is reduced. These findings suggest that policies should focus on increasing the capacities of low-emission renewables, such as solar and wind, while carefully managing and potentially reducing reliance on waste energy to optimize GHG reductions.

The findings of this study emphasize the critical importance of implementing targeted policies to achieve effective decoupling of economic growth from GHG emissions in Hungary's industrial sector. This research highlights how specific reduction thresholds and the strategic use of less GHG-intensive fuels can contribute to balancing economic performance with environmental sustainability. The proposed utilization of transitional fuels and careful management of renewable energy sources present viable pathways for optimizing GHG reductions while maintaining industrial productivity. These strategies not only address the immediate need for emissions reduction but also lay the groundwork for long-term sustainable industrial practices. However, it's important to note a limitation in our approach: the treatment of waste energy as a homogeneous category, despite its higher baseline emissions compared to other renewable sources. This oversimplification may obscure the nuanced impacts of different renewable energy sources on GHG emissions. Future research should address this by utilizing more detailed datasets that differentiate between various types of renewable energy, allowing for a more granular analysis of their individual and combined effects on GHG emissions. By demonstrating the potential for significant GHG reductions without compromising economic output, this study provides valuable insights for policymakers and industry leaders, while also highlighting areas for refinement in future analyses. The implications extend beyond Hungary, offering a potential model for other emerging economies grappling with the challenge of decoupling economic growth from environmental impact.

The findings of this study align with and advance earlier research on decoupling. While Tapio-style elasticity indices and decomposition methods such as the Divisia Index [32] and Logarithmic Mean Divisia Index [33] capture linear relationships between economic growth and CO_2 emissions, they fail to detect threshold effects and non-linear behaviors. The current RNN-based analysis reveals asymmetric responses. For example, a 2.5 PJ reduction in coal results in a 4.4 % decrease in emissions, while a similar increase leads to only a 1.8 % rise. This observation complements the findings of [7], who identified decoupling patterns in Visegrad countries but did not address temporal asymmetries. Furthermore, although previous studies by [39] and apply machine learning for energy forecasting and emissions modeling, few integrate these tools within a decoupling framework. The RNN model utilized in this study captures complex, time-lagged interactions and provides simulated outcomes for targeted energy policy actions, offering a methodological contribution that extends beyond conventional modeling.

The results hold significant value in forming Hungary's climate policy and its alignment with European directives. Key decoupling thresholds such as the marked reduction in emissions following a 2.5 PJ decrease in coal or industrial heat consumption offer actionable insights for implementing the National Energy and Climate Plan (NECP) for 2021–2030 [48] and fulfilling the European Green Deal [36]. Hungary's industrial sector remains dependent on fossil fuels, especially coal and natural gas, despite progress in overall emissions reduction. The study confirms the transitional role of natural gas, supporting its short-term substitution for more carbon-intensive sources. Additionally, the asymmetry observed in emissions linked to renewables and waste highlights the importance of distinguishing between low-emission renewables like solar and wind, and higher-emitting waste-to-energy. These findings reinforce the strategic need for precise, data-driven policies and demonstrate the usefulness of AI-based models in supporting Hungary's path toward industrial decarbonization and compliance with EU climate frameworks.

6. Conclusion and limitations

This study investigated the decoupling of economic growth from greenhouse gas (GHG) emissions in Hungary's industrial sector using Recurrent Neural Networks (RNNs), a machine learning technique capable of capturing non-linear and temporal relationships. The analysis was based on time-series data from 1995 to 2020, including industrial energy consumption, sectoral GDP contribution, and GHG emissions. The results identified significant non-linear and asymmetric emission responses to changes in different energy sources. Specifically, a 2.5 PJ reduction in coal and industrial heat use led to the most substantial GHG reductions of 4.4 percent and 4.3 percent, respectively, followed by renewables and waste at 3.5 percent. Natural gas showed a relatively modest but consistent impact, reinforcing its role as a cleaner transitional fuel. In contrast to conventional linear models or decomposition techniques, the RNN model enabled the detection of threshold effects and dynamic interactions between variables, offering more precise insight into how policy changes might influence emissions outcomes. This methodological contribution fills a critical research gap in Hungary-specific decoupling analysis and demonstrates how AI-based tools can offer greater interpretability and predictive power. The approach is not only applicable to Hungary but also scalable to other carbon-intensive economies seeking to reconcile industrial growth with climate targets. The study provides a foundation for more detailed sectoral modeling, real-time policy evaluation, and adaptive mitigation strategies in future research.

While this study provides important insights into the decoupling of economic growth from GHG emissions in Hungary's industrial sector, several limitations must be acknowledged. First, the analysis relies on annual data, which limits the granularity of temporal dynamics that could be captured with higher-frequency datasets. Second, the RNN model operates under the assumption that past energy-emissions relationships will continue into the future, which may not fully account for unexpected policy shifts, technological breakthroughs, or economic disruptions. Additionally, the categorization of energy types, particularly within the "renewables and waste" group, is treated homogeneously due to data constraints, potentially obscuring differences in emission intensity across subcategories. Future research should consider incorporating hybrid modeling approaches, combining machine learning techniques with econometric or optimization models to improve explanatory power and policy simulation capabilities. Cross-country validation, especially among other Central and Eastern European nations with similar industrial structures and energy dependencies, could enhance the generalizability of the findings. Furthermore, future studies could explore disaggregated sector-level modeling, apply real-time data sources, and test the integration of AI-based forecasting into national monitoring and reporting systems. These extensions would further strengthen the robustness and practical utility of AI-supported decoupling analysis.

7. Policy implications

The results highlight the need for targeted, data-driven climate action in Hungary's industrial sector, where GHG emissions remain closely linked to fossil fuel consumption. Policymakers should focus on differentiated strategies that prioritize the reduction of coal and industrial heat usage, particularly beyond identified thresholds that yield disproportionate environmental benefits. These findings support the phased substitution of coal with lower emission alternatives and promote demand-side measures such as process heat recovery and thermal efficiency improvements. The analysis also demonstrates the viability of natural gas as a transitional fuel, offering lower emissions intensity compared to coal and oil. Policy frameworks could therefore support short to medium-term investments in cleaner combustion technologies and infrastructure that facilitate the gradual phase-out of more polluting energy sources. At the same time, increased reliance on natural gas should be managed with a view toward eventual replacement by renewables to ensure long-term alignment with the EU's net-zero targets. However, to enable more responsive climate governance, Hungary's National Energy and Climate Plan and EU climate frameworks could integrate AI-aided monitoring and forecasting systems. These tools can track energy consumption and emissions in near real time, helping to identify deviations from targets and optimize interventions dynamically. In particular, AI models such as RNNs offer valuable predictive capabilities that could be integrated into regulatory mechanisms, carbon pricing models, and industrial energy audits. The findings also emphasize the need for sector-specific decarbonization incentives. These may include subsidies for retrofitting industrial processes, tax incentives for adopting low-emission technologies, or performance-based grants linked to energy efficiency improvements. Effective differentiation within the renewables category is also critical. Since waste-to-energy processes, while technically renewable, tend to exhibit higher GHG emissions than solar or wind, their role should be reassessed. Expanding the share of low-emission renewables while regulating higher-emission subtypes can enhance the net climate benefits of the green energy transition. Taken together, these policy implications extend beyond the Hungarian context and offer a replicable approach for other carbon-intensive economies facing similar industrial and regulatory challenges.

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

During the preparation of this work, the authors used ChatGPT and Bing to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Mohamad Ali Saleh Saleh: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mutaz AlShafeey:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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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