IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(3), 239-244.

EJ EconJournals

Optimizing Energy Consumption Efficiency in Global Industrial Systems Using the Random Forest Algorithm

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Received: 29 November 2024 **Accepted:** 15 March 2025 **DOI:** https://doi.org/10.32479/ijeep.18796

ABSTRACT

This study employs the Random Forest method, a type of machine learning, to investigate strategies for improving industrial energy use. The algorithm accurately estimated energy consumption efficiency in this industry, with results indicating (MSE: 0.001, MAPE: 0.049, R^2: 96.4). The findings highlight that industrial value added significantly impacts energy consumption efficiency, representing 60.2%, while industrial CO_2 emissions account for 39.8%. The study uncovered a significant negative correlation between Energy consumption efficiency in the industrial sector and all industrial value added, including industrial CO_2 emissions. Energy consumption efficiency in the industrial sector diminishes as industrial growth accelerates, resulting in higher emissions. Economic growth frequently leads to increased energy consumption and environmental damage. The conclusion is that the industrial sector does not use energy efficiently; the expansion of this sector will lead to inefficiency in energy use on the one hand and, on the other, an increase in emissions, which negatively affects energy use efficiency.

Keywords: Machine Learning, Random Forest, Energy Efficiency, Industrial CO_2 Emissions, Industrial Energy Consumption
JEL Classifications: C63, C80, C81, C87

1. INTRODUCTION

Energy consumption efficiency in the industrial sector is a top concern in global initiatives for sustainability. With businesses consuming significant global energy, monitoring and reducing energy consumption has economic and environmental implications. Optimizing resource management and sustainability is crucial for addressing global industrial energy use, which contributes significantly to greenhouse gas emissions. This study encourages sustainable practices by investigating the relationship between industrial energy consumption efficiency, economic output, and environmental impact to improve energy consumption efficiency. Energy efficiency is the ability of an industrial system to turn input energy into usable output while reducing waste. The notion includes technology, operational procedures, and managerial strategies. Industries that improve energy efficiency can lower operational costs and environmental implications while retaining productivity. Manufacturing systems utilize a substantial amount of energy, making up about 37% of the world's total final energy consumption. Optimizing energy use in manufacturing processes has become a top goal as worries about environmental sustainability and growing energy costs. Efficient energy use minimizes greenhouse gas emissions and operating costs, consistent with international climate change commitments like the Paris Agreement (International Energy Agency, 2023).

The complexity of modern manufacturing systems, characterized by diverse machinery, varying production schedules, and fluctuating energy demands, poses significant challenges for energy optimization. Lean manufacturing and Six Sigma are two examples of traditional energy management approaches that have significantly progressed. However, they frequently lack the flexibility to adjust to quickly shifting operational situations. Furthermore, these methods usually rely on historical data and static rules, which may not be sufficient to handle energy usage's dynamic and linked nature in manufacturing ecosystems.

These problems can be successfully resolved by machine learning techniques, which enable the analysis of massive datasets to identify trends and generate predictions. The Random Forest algorithm has shown the most promise among these techniques due to its ability to handle high-dimensional, non-linear, and heterogeneous data. An ensemble learning method called Random Forest (RF) constructs many decision trees during training and aggregates their output to increase prediction accuracy and robustness. The RF is a valuable tool for determining the primary reasons for energy use because it provides interpretability through feature importance analysis that distinguishes it from other machine learning algorithms (Breiman, 2001).

Energy consumption efficiency in the industrial sector is a complex issue driven by the energy consumed, the economic value generated, and the emissions generated from energy consumption. Efficient use of energy reduces operational costs and reduces the environmental impact of industrial activity, thus increasing the added value of the sector. The growing demand for energy efficiency solutions underscores the importance of developing frameworks to link energy consumption with industrial efficiency and environmental sustainability. Aligning industrial practices with global climate goals, such as reducing carbon dioxide emissions, is critical to ensuring sustainable economic growth worldwide. This study explores the complex relationship between industrial energy use, economic value, and industrial CO_2 emissions to identify the factors affecting energy efficiency. To achieve this, advanced machine learning was used to explore how these factors affect energy efficiency. We hope the results will help policymakers and industry stakeholders achieve a balance between economic growth, environmental responsibility, and energy efficiency.

2. LITERATURE REVIEW

Previous studies always set the tone for future studies. However, unfortunately, previous studies on energy efficiency were engineering and physical studies and considering energy efficiency as a dependent variable is not shared. Therefore, we have tried hard to cite studies on energy consumption efficiency in the industrial sector, which can be listed in the following paragraphs:

Thollander and Palm (2012). This article investigates the barriers to improving energy consumption efficiency in industrial energy systems, focusing on the challenges preventing adopting energy-efficient practices and technology. It seeks to examine the impact of energy audits, energy management methods, and associated laws and programs in improving industrial energy consumption efficiency, offering an interdisciplinary view of how these elements might help reduce global warming. The research underscores the significance of industrial energy efficiency in tackling the risks linked to global warming and positions it as a vital strategy for environmental sustainability. It examines the challenges and barriers to adopting energy-efficient practices in industrial settings, indicating that their broad implementation is constrained despite the availability of various technical solutions for energy consumption efficiency.

According to Opoku et al. (2022), the fundamental goal of the study is to discover and enhance independent variables that influence electricity usage and costs in industrial contexts. This endeavor aims to improve sustainable energy management and reduce waste. Furthermore, the study demonstrates the usefulness of the suggested strategy by analyzing historical power consumption data from an oil distribution company, demonstrating significant potential savings in electricity usage and expenses when operating under optimal conditions. According to Montalbano and Nenci's (2019) analysis, EE has a beneficial effect on productivity regarding the economic performance of businesses in Latin American nations. Brown et al. (2017) examine EE as a carbon emission reduction method using a model for the US. They evaluate the impact of emission reductions and mitigation costs but ignore value-added and employment. Although they do not specifically focus on the industrial sector, Cantore et al. (2019) examine the effects of different scenarios for renewable energy adoption and energy efficiency on generating jobs in Africa. According to their findings, jobs are created by greener scenarios and the gradual phase-out of fossil fuels.

Gopalakrishnan et al. (2007) investigate the effects of industrial energy efficiency on reducing emissions and preserving the environment, highlighting the significance of energy efficiency enhancements for sustainable manufacturing. The paper also addresses the economic advantages of energy efficiency within the manufacturing industry, which include reduced operating costs, greater global competitiveness, increased profitability, and growth, alongside impacts on societal fossil fuel use and energy pricing. It underscores that although U.S. industries use more energy than those in other developed countries, this does not automatically imply inefficiency. Various factors, including industrial composition, relative input costs, and energy consumption efficiency, play a role in the variations in energy intensity across nations. Similarly, neelis et al. (2008) Develop a scheduling methodology to minimize energy costs and CO_2 emissions in manufacturing, and the paperOptimized energy consumption while ensuring cost efficiency in production systems.

3. EMPIRICAL FRAMEWORK, DATA AND METHODOLOGY

This research explores the relationship between energy consumption efficiency in the industrial sector and each of the industrial sector's added value and industrial sector carbon dioxide emissions, which the following equation can clearly illustrate:

EE= IN CO2 + IVA

Where,

EE= Energy Efficiency

CO_2= Industrial CO_2 Emissions

IVA= Industrial Value Added (% GDP)

3.1. Data

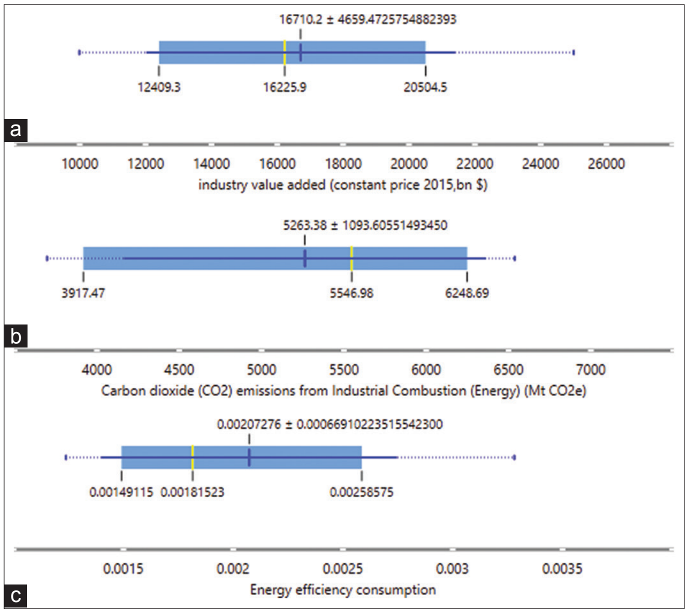
The paper depends on its data analysis from the World Bank dataset and International Energy Analysis (IEA), covering 1994

Table 1: Data statistics and descriptions

Variables	Abbreviation	Source of data	Mean	Mode	Median	Dispersion	Minimum	Maximum
Energy efficiency	EE	IEA	0.0020	0.0012	0.0018	0.322	0.00123	0.0032
Industrial CO_2 emissions	CO_2	World bank	5263.38	3697.12	5546.9	0.207	3697.12	6537.54
Industrial value added	IVA	World bank	16710.2	9989.2	16225.9	0.27884	9989.23	25003.8

Source: Made by the author (using Python language)

Figure 1: Box plot score for all variables



Source: Made by the author

to 2023. The paper presents a descriptive analysis of the variables in Table 1, and Figure 1a-c show data stability:

Figure 1 shows that the data is stable, and most variables do not have outliers. However, the independent variables, like industrial value-added and industrial CO2 emissions, tend to have high values. In contrast, the dependent variable, Energy efficiency consumption in industrial sectors, tends to have low values.

3.2. Methodology

3.2.1. The ML algorithms

Random Forest (RF) is an ensemble learning method that creates a "forest" of decision trees by picking random attributes and using bootstrap sampling. In contrast to Gradient Boosting, which builds trees sequentially, training all trees independently decreases computing costs and overfitting dangers (Breiman, 2001).

Using random feature subsets at each split, the technique generates distinct decision trees and datasets through sampling and replacement. The final forecast is created by aggregating results (for example, a majority vote for classification or an average for regression) (El-Aal et al., 2024). Random Forest specializes in handling high-dimensional data, detecting fraud, and modeling the environment. It is well-known for its capacity to handle overfitting while coping with outliers and missing data, making it suitable for various applications (Hastie et al., 2009).

The Random Forest (RF) model includes the following fundamental steps:

Step 1: Tree Construction for Each Bootstrap Sample

For m=1 to M (number of trees in the forest):

1. Bootstrap Sampling:
Create a bootstrapped sample set, Z, of size N from the training data.

2. Tree Growth:
For each terminal node in the tree:

- Randomly select X variables from the P total variables.
- Determine the best split point among specified variables to minimize Mean Squared Error (MSE):

$$F_0(x) = \frac{1}{n}\sum_{i=1}^{n}(Y-\hat{Y})^2 \tag{1}$$

Where Y is the actual value, $\hat{Y}$ and is the predicted value.

- Split the node based on the best variable to produce new nodes.
- Continue splitting until a predefined minimum node size (n_{min}) is reached.

4. RANDOMIZATION AND ROBUSTNESS

The random selection of variables for splitting at each node adds diversity, which reduces dependence between trees. This randomization improves the model's resistance to overfitting, which occurs when trees become incredibly complicated and customized to training data. Overfitting reduces a model's capacity to generalize to fresh data. Some trees or nodes can be trimmed to reduce this, El-Aal and Mohamed (2024).

Step 2: Forest Output

The RF model combines the outputs of M individual trees. The collective prediction of the forest is given by:

$$\hat{F}_{rf}^{M}(x) = \frac{1}{M}\sum_{m=1}^{M}T_m(x) \tag{2}$$

Here:

- $T_m(x)$ is the prediction from the m-th tree.
- $\hat{F}_{rf}^{M}(x)$ represents the final output of the RF model, obtained by averaging the predictions from all trees.

Averaging predictions stabilizes the model's overall performance while reducing variance. This ensemble approach ensures accurate predictions, even with noisy data or complex interactions.

5. EMPIRICAL RESULTS

5.1. Model Evaluation

To determine the model's accuracy in prediction, each of the following must be calculated: RMSE, MSE, MAE, and R^2, as shown in Table 2.

Table 2 shows how well the model predicts the dependent variable. The MSE and RMSE values are 0.001. The R^2 is 96.4%, indicating the RF algorithm's high accuracy.

5.2. The RF Algorithm Prediction Performance

To determine the accuracy of using Random Forest in the future, the actual values must be compared with the predicted values during the study period, as shown in Table 3.

By converting the previous table to Figure 2, we find that the model is highly effective in predicting the dependent variable.

5.3. RF Algorithms Feature Importance

Acknowledging the importance of features can only open the dark box of ML models. paper evaluates the model's classifications or predictions, measuring the influence of each feature or input variable. Data scientists can better understand their models' performance by prioritizing these attributes using significance ratings (El-Aal et al., 2024). Users may advance, enhance their models, and make more accurate and precise decisions using this information. This information allows users to improve their models, drive progress, and make more precise and accurate decisions. Table 4 demonstrates how important the RF algorithm's feature is.

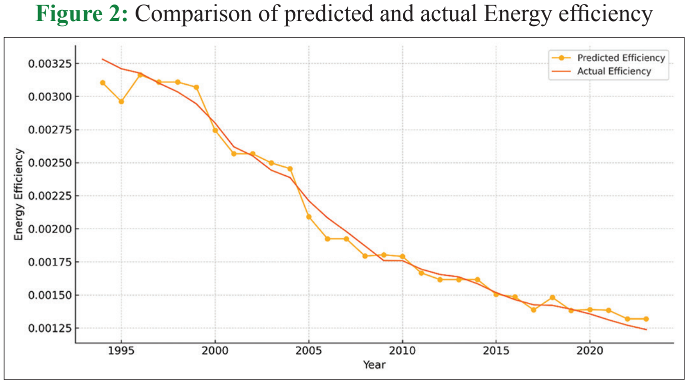
Table 4 shows that the variables most influencing energy efficiency are industrial value added by 60.2% and Industrial CO_2 Emissions by 38.8%. To clarify this further and determine the type of relationship between the variables, we can refer to Table 5, which shows the Pearson coefficient.

Table 5 shows a strong inverse relationship between Energy Efficiency, industrial Value Added, and Industrial CO_2 Emissions. Figure 3 illustrates this more clearly.

A 3D scatter plot in Figure 3 shows the relationship between Industry Value Added, CO_2 Emissions, and Energy Efficiency Consumption. Here is a thorough interpretation:

- Energy efficiency declines with time.

Figure 2: Comparison of predicted and actual Energy efficiency



Source: Made by author

The plot indicates that when Industry Value Added increases, Energy Efficiency Consumption decreases. The color gradient shows that older years had higher energy efficiency (lighter colors), but subsequent years had lesser efficiency (darker hues).

- CO_2 Emissions and Industrial Growth.

Higher Industry Value Added is linked to higher CO_2 Emissions, indicating that industrial expansion contributes to rising emissions.

Table 2: The RF accuracy

Model	MSE	RMSE	MAPE	R^2
Random forest	0.001	0.001	0.049	0.964

Table 3: The RF prediction performance

Year	Random forest energy efficiency consumption prediction	Energy efficiency consumption (actual data)
1994	0.00310344	0.00328
1995	0.00296144	0.00321
1996	0.00316337	0.00318
1997	0.00310902	0.00310
1998	0.00310902	0.00304
1999	0.00306999	0.00294
2000	0.00274432	0.00280
2001	0.00256724	0.00262
2002	0.00256724	0.00255
2003	0.00249781	0.00244
2004	0.00245492	0.00239
2005	0.00209138	0.00221
2006	0.0019246	0.00208
2007	0.0019246	0.00198
2008	0.00179428	0.00187
2009	0.00180331	0.00176
2010	0.00179114	0.00176
2011	0.00166669	0.00169
2012	0.00161649	0.00165
2013	0.00161649	0.00164
2014	0.00161649	0.00159
2015	0.00150468	0.00152
2016	0.00148597	0.00146
2017	0.00138709	0.00143
2018	0.00148139	0.00142
2019	0.00138269	0.00139
2020	0.00138962	0.00136
2021	0.00138428	0.00131
2022	0.00131948	0.00127
2023	0.00131948	0.00124

Source: Made by author

Table 4: The RF algorithms feature important indicators

Variables	RF feature importance
Industrial Value Added	60.2
Industrial CO_2 Emissions	39.8

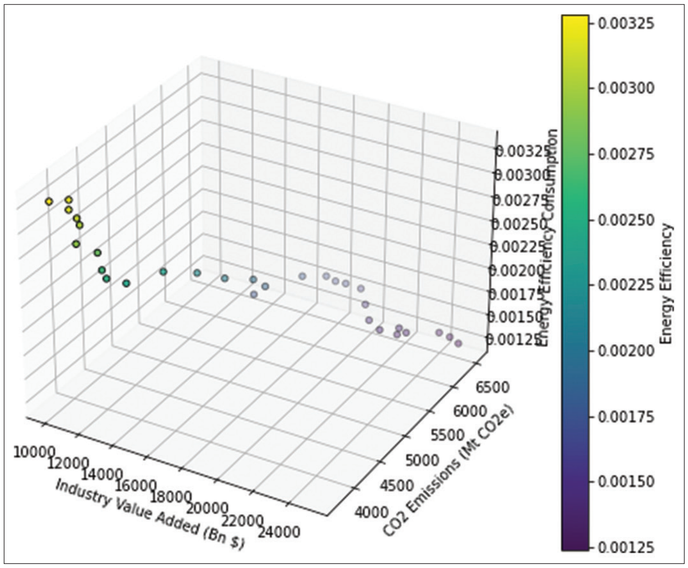
Source: Made by author

Table 5: Pearson correlation

Independent variables	Dependent variable	Pearson correlation
Industrial value added	Energy efficiency	−0.953
Industrial CO_2 emissions	Energy efficiency	−0.962

Source: Made by the author

Figure 3: 3D scatter plot shows the relationship between variables and energy efficiency



Source: Made by the author

This is consistent with patterns in which economic expansion is frequently connected to increased energy usage and emissions.

• Trade-off Between Industrialization and Sustainability
While economic output has increased, energy efficiency has not kept pace, leading to higher energy consumption per output unit. This could be due to outdated infrastructure, reliance on fossil fuels, or inefficient energy policies.

6. CONCLUSION

This study examines the complex relationships between global industrial systems, energy efficiency, and broader economic and environmental implications. The findings suggest that increasing energy efficiency in business is critical to driving economic growth, sustainability, and environmental protection. Analyzing several industrial sectors demonstrates that implementing energy efficiency methods reduces costs, increases productivity, and reduces carbon emissions, all of which contribute to the worldwide shift toward sustainable development.

In conclusion, improving industrial energy efficiency is essential for attaining global economic resilience and environmental sustainability. By implementing data-driven policies and technological innovations, industries can significantly reduce climate change effects while ensuring long-term financial stability and competitiveness. Ongoing research and strategic policy implementation will advance the next phase of industrial transformation toward a future that is more energy-efficient and sustainable.

The findings emphasize the importance of technological advances and regulatory measures in improving energy efficiency in the industrial sector. Combining renewable and nonrenewable choices while diversifying energy sources can boost the industrial sector's value-added and reduce dependence on fossil fuels. In addition, no country can achieve this independently, but international cooperation is required to address energy use issues, especially in the industrial sector. Improving energy efficiency requires coordinated efforts between different economies. Despite these optimistic expectations, there are existing problems, such as economic problems facing countries. On the other hand, some countries have an abundance of oil reserves and, therefore, do not currently need to address such issues, as their goal is always to achieve maximum economic growth rates regardless of inefficiency. To solve these issues, a comprehensive strategy must be developed that supports collaboration between governments and businesses.

7. FUNDING

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2503)

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