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The Impact of Energy Consumption on Global Energy Intensity Based on K-Nearest Neighbor Algorithm

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ABSTRACT

The primary objective of this study is to utilize the K-Nearest Neighbor Algorithm (KNN) to investigate the relationship between energy intensity and energy consumption across the Residential, Commercial, Industrial, Transportation, and electric power sectors. The paper approved the KNN Algorithm as more accurate than the remaining algorithms. The most influential factors affecting energy intensity are the Power Sector (61.89%), the Industrial Sector (24.62%), the Transportation Sector (8.5%), the Residential Sector (3.6%), and the Commercial Sector (1.3%). Consequently, the Industrial, Electric Power, and industrial Sectors have the most significant influence on energy intensity. Thus, enhancing the energy performance of these sectors can reduce energy intensity and maximize efficiency, leading to improved environmental sustainability.

Keywords: K-Nearest Neighbor Algorithm, Energy Intensity, Industrial Sector, Electricity Sector, Energy Efficiency

INTRODUCTION

Energy consumption is a key component of economic expansion and industrial development. It plays a critical role in shaping national and global economies, influencing productivity, technological advancements, and the overall well-being of society. Energy efficiency, particularly in terms of sustainability and environmental preservation, remains a significant challenge. One of the primary indicators for assessing energy efficiency at the macroeconomic level is energy intensity, defined as the amount of energy used per unit of economic output. It is usually expressed as energy use per unit of GDP (IEA, 2023) [i]. A lower energy intensity value indicates greater efficiency and less energy waste, while a higher value indicates greater energy consumption relative to economic productivity, as stated by [ii]. Therefore, a thorough understanding of the key factors influencing global energy intensity is crucial for promoting sustainable energy use and enhancing economic resilience.

Economists and policymakers have focused on the relationship between energy intensity and consumption in many sectors. Energy use varies across different sectors, including transportation, electricity, industry, commerce, and residential areas, and each sector affects the overall energy intensity. The electrical industry is one of the largest energy consumers among all sectors, as it generates power primarily from fossil fuels and renewable energy sources [i]. Similarly, the transportation industry consumes a significant amount of energy, particularly petroleum-related fuels [iii]. Energy intensity is significantly affected by the industrial sector, which encompasses manufacturing, heavy industries, and material processing [iv]. The commercial and residential sectors also contribute to energy intensity through the use of appliances, heating, and cooling, reflecting variations in energy consumption patterns that are specific to regional and economic systems [v].

Examining sectoral contributions to global energy intensity is vital for several reasons. First, it helps identify the primary factors driving energy inefficiency across industries and regions, enabling targeted interventions to improve energy usage. Second, understanding these relationships facilitates the development of effective policies that balance economic growth with environmental sustainability. Governments and international organizations are increasingly focusing on reducing energy intensity as part of their commitments to climate change mitigation and the achievement of Sustainable Development Goals (SDGs). The Paris Agreement (2015) and subsequent climate action frameworks emphasize the need to decouple economic growth from energy consumption and promote cleaner and more efficient energy technologies [vi].

According to research, global energy intensity can be significantly reduced by enhancing energy efficiency in critical industries. Fuel-efficient vehicles, automated manufacturing, and renewable energy innovations are transforming consumption patterns to use less energy per unit of economic output [vii] . Global trends toward reducing energy intensity play a significant role through several policies, the most important of which include implementing carbon taxes, adjusting energy prices, and policies that stimulate clean energy, such as incentives for energy-efficient infrastructure [viii]. Continued global reductions in energy intensity face challenges due to disparities in industrialization rates among countries, varying levels of economic development (even within countries on the same continent), and unequal access to energy.

This study examines the impact of total primary energy consumption across key economic sectors on global energy intensity. Studying the effect of sectoral energy consumption on energy intensity will clarify how various industries influence changes in global energy efficiency. The findings are expected to have a significant impact on government policies aimed at enhancing energy efficiency and promoting environmental sustainability.

In summary, energy intensity is a crucial metric for evaluating the effectiveness of energy use in driving economic growth. Considering the global energy transitions and environmental challenges, a thorough analysis of the relationships between sectoral energy consumption and overall energy intensity is essential. By examining trends in energy consumption, this study will enhance the broader discussion on sustainable energy management and economic efficiency.

LITERATURE REVIEW

Many research investigations have focused on energy use and its impact on global energy intensity. Various subjects have been studied, including sectoral disparities, the effects of structure and technology, trends in energy efficiency, and the consequences of policies. This section highlights significant contributions to the field.

Several studies have examined global trends in energy intensity. [ix] investigated changes in energy intensity across 40 major economies. They discovered that while structural changes had a minimal impact on reducing energy intensity, technological advancements were the main drivers. [x] offered a historical perspective on advancements in energy efficiency, demonstrating that energy intensity has gradually converged across various regions. Building on this analysis, [xi] anticipated shifts in energy intensity and predicted that developed nations would continue to lead in breakthroughs related to energy efficiency. [xii] examined global trends in the relationship between energy and the economy, highlighting the necessity for enhanced energy demand models. [xiii] evaluated the energy intensity of the EU and global economies, noting that four countries accounted for 51% of the world's energy consumption.

The impact of technology developments and digitization on energy intensity has been the subject of numerous studies. In their 2024 study, [xiv]. examined how digitalization maximizes energy use in EU nations, emphasizing its contribution to a more efficient energy structure by integrating renewable energy. [xv] analyzed energy intensity trends over the last thirty years and discovered that advancements in technology and capital investment have played a significant role in its decrease. [xvi] argue that technological innovations, rather than structural transformations, were the primary drivers of energy efficiency in 40 countries from 1995 to 2007. In his analysis of whether energy intensity is a more valuable metric than the carbon factor in climate change studies, [xvii] concluded that the differences in energy intensity among nations are more significant. Regional and cross-country analyses have also revealed variations in energy intensity. According to [xviii], energy-saving technologies were the primary factor affecting the differences in industrial energy intensity between nations.

[xix] analyzed electrification and energy intensity, concluding that technological innovation contributes to a reduction in energy intensity. [xx] focused on OECD nations, demonstrating that countries relying on zero-carbon-

emission energy sources achieved optimal energy efficiency. In their 2015 study [xxi], performed a scenario analysis of China's energy intensity using input-output theory, forecasting a 16% decrease in energy intensity. Meanwhile, [xxii] examined newly industrialized nations and found that while industrialization increased energy intensity, trade openness helped mitigate this trend over the long term.

Several researchers have assessed the sectoral impact of energy intensity. [xxiii] studied the Iranian transportation sector, revealing that high energy consumption was mainly driven by net intensity effects rather than structural changes. [xxiv] explored the agricultural sector's potential for reducing energy intensity, estimating that improvements could mitigate up to 500 million tons of CO_2 emissions annually. [xxv] compared Romania's energy intensity with that of the European Union, revealing a disparity between energy consumption and economic growth. [xxvi] investigated the impact of renewable energy on energy intensity across European Union (EU) nations, demonstrating that the use of clean energy and higher income levels are associated with lower energy intensity.

The relationship between energy intensity and economic growth has garnered significant interest. [xxvii] discovered that although economic growth influences energy consumption, this relationship exhibits low elasticity. [xxviii] examined capital-energy substitution and concluded that enhancing energy efficiency is vital for sustainable economic development. [xxix] examined Africa's energy intensity and found that renewable energy reduces CO_2 emissions, while economic growth had mixed effects. [27] also compared energy efficiency between the UAE and Saudi Arabia, showing that the UAE uses energy more efficiently. Energy costs and the industrial structure were shown to be the main determinants of changes in energy intensity by [xxx].

Studies have also examined the impact of energy structure and policy on energy intensity. [xxxi] demonstrated that upgrading the energy structure reduces energy consumption per unit of GDP. However, changes in the primary industry structure may lead to an increase in energy intensity. [xxxii] examined the rebound effect of reducing energy intensity, presenting empirical findings for 40 regions. [xxxiii] examined the convergence of energy consumption intensity across various regions and found that absolute beta-convergence is lacking in areas with high energy consumption intensity.

There are still significant gaps in the vast body of knowledge about energy intensity. Much research has focused on historical trends and regional comparisons, but few have employed machine-learning approaches, such as the K-nearest Neighbor (KNN) algorithm, to analyze patterns of energy intensity. Predictive analytics remains only partially integrated into energy intensity estimates, as much of the existing research concentrates on structural and technical enhancements. This study presents an innovative methodological framework for analyzing energy efficiency to fill these voids. It utilizes the K-nearest Neighbor algorithm to examine the connection between energy consumption and global energy intensity.

Empirical Framework

The primary objective of this study is to investigate the relationship between energy intensity and energy consumption across the Residential, Commercial, Industrial, Transportation, and Electric Power sectors, utilizing the K-nearest Neighbor algorithm, as outlined in Equation 1.

$$EI = ECR + ECC + ECI + ECT + ECE$$

Where,

EI = Energy Intensity
ECR = Energy Consumed by the Residential Sector
ECC = Energy Consumed by the Commercial Sector
ECI = Energy Consumed by the Industrial Sector
ECT = Energy Consumed by the Transportation Sector
ECE = Energy Consumed by the Electric Power Sector

Data

Data collected from the [1] and [xxxiv] datasets encompasses all variables. The dependent variables represent Energy Intensity, while the independent variables represent Energy Consumption by the Residential, Commercial, Industrial, Transportation, and electric power sectors. Data covers the period from 2000 to 2023, to avoid missing data in other years. The data statistics are described in Table 1, and the data stability and limitations are illustrated in the violin plot in Figure 1.

Table 1: Data statistics description

Variables	Source of data	mean	mode	median	dispersion	min	Max
Energy Intensity	**World Bank**	5.18	4.52	5.23	0.1	4.52	6.02
Energy Consumed by the Residential Sector	**EIA**	19806.5	18381	19933.2	0.038	18381	20986.5

Energy Consumed by the Commercial Sector	**EIA**	16780.6	15312.3	16862.3	0.029	15312.3	17650.7
Energy Consumed by the Industrial Sector	**EIA**	31160.8	27782.1	31021.8	0.036	27782.1	33944.7
Energy Consumed by the Transportation Sector	**EIA**	27278.6	24452.7	27161.2	0.036	24452.7	28810.9
Primary Energy Consumed by the Electric Power Sector	**EIA**	35360.6	31727.7	35668.5	0.051	31727.7	38457.8

Source: Made by author

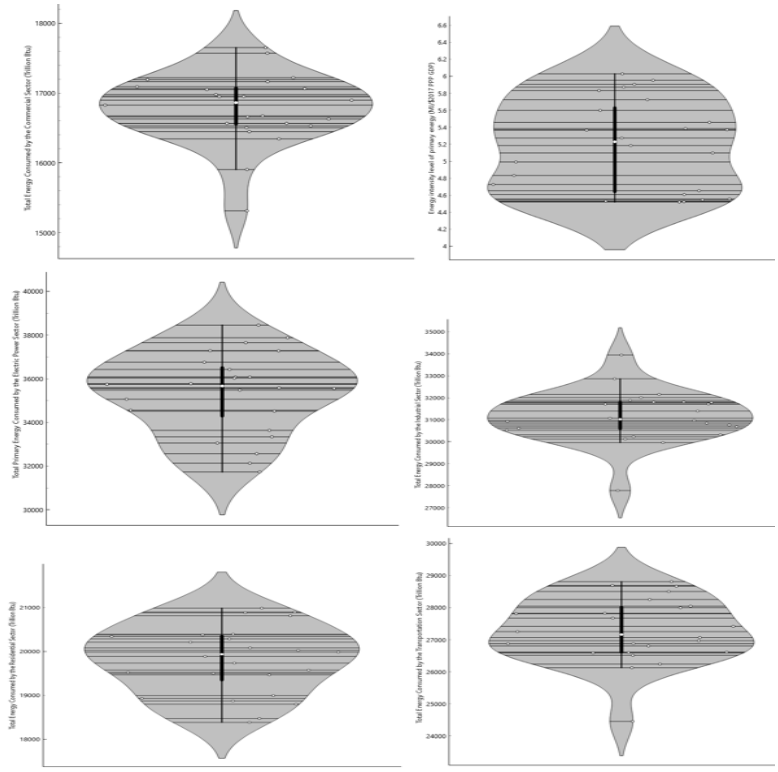

Figure 1: Violin plot
Source: Made by author

METHODOLOGY

K-Nearest Neighbors (KNN) is a reputable instance-based, non-parametric machine learning technique for classification and regression applications. In regression problems, KNN uses the average values of the K closest data points in the feature space to predict a continuous target variable. This approach is convenient for managing complex and nonlinear datasets, operating on the principle that similar data points exhibit comparable behaviors [xxxv].

Distance Metrics

KNN regression uses a Chosen distance measure to assess similar data points. The following are the distance functions that are most frequently used:

Euclidean Distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}$$

Manhattan Distance:

$$d(x_i, x_j) = \sum_{k=1}^{n} |x_{ik} - x_{jk}|$$

Minkowski Distance (Generalized Form):

$$d(x_i, x_j) = \left(\sum_{k=1}^{n} |x_{ik} - x_{jk}|^p\right)^{\frac{1}{p}}$$

Depending on the type of data, the choice of distance metric has a significant impact on model performance.

Prediction Function in KNN Regression

Once the K-nearest neighbors are identified, the predicted value $\hat{y}$ for a new data point is calculated using the following formula:

Following the identification of the K-nearest neighbors, the following formula is used to determine the predicted value $\hat{y}$ for a new data point:

$$\hat{y} = \frac{1}{K}\sum_{i=1}^{K} y_i$$

Where y_i refers to the K-nearest neighbors' target values.

As an alternative, closer neighbors are given more weight in distance-weighted KNN regression:

$$\hat{y} = \frac{\sum_{i=1}^{K} w_i y_i}{\sum_{i=1}^{K} w_i}$$

Where the weight w_i is commonly understood to be the inverse of distance:

This method increases prediction accuracy, particularly when data points have different densities. To determine the accuracy, compare the actual energy intensity values with the KNN prediction values, as shown in Table 2 and Figure 2.

Table 2: Comparison between Energy intensity actual values and KNN prediction values

Year	Energy intensity (MJ/$2017 PPP GDP)	KNN prediction values
2000	6.02934	5.91811
2001	5.95235	5.56393
2002	5.90579	5.56393
2003	5.87189	5.56393
2004	5.83119	5.78604
2005	5.72338	5.59609
2006	5.59797	5.59609
2007	5.45776	5.59609
2008	5.38436	5.22347
2009	5.37015	5.44178
2010	5.36524	5.26131
2011	5.27324	5.11614
2012	5.18554	5.07638
2013	5.09818	5.21365
2014	4.99144	5.21365
2015	4.83349	4.96726
2016	4.72763	4.67066
2017	4.65275	4.59502
2018	4.6094	4.64905
2019	4.55622	4.66301

2020	4.54472	4.57137
2021	4.53	4.55415
2022	4.52327	4.55415
2023	4.52	4.55415

Source: Made by author

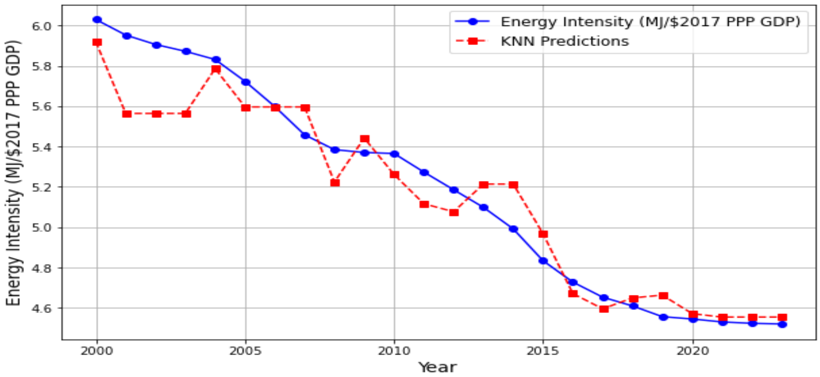

Figure 2: Actual values vs. prediction values
Source: Made by author

Figure 2 illustrates the performance of KNN algorithms for prediction, where the distance between the predicted and actual values is minimal. Therefore, policymakers must rely on KNN for energy intensity estimates based on energy consumption in the residential, commercial, industrial, transportation, and electric power sectors.

Model Evaluation Metrics

Several error measures are used to evaluate KNN regression's performance:

- **Mean Squared Error (MSE):**

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

- **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{MSE}$$

- **Mean Absolute Error (MAE):**

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

- **R-squared (R^2):**

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

A lower MSE or RMSE and a higher R2 imply improved model performance, as shown in Table 3.

Table 3: The ML algorithms' prediction

Model	MSE	RMSE	MAE	R2
KNN	0.043	0.208	0.167	0.839
SVM	0.049	0.221	0.171	0.818
RF	0.062	0.249	0.186	0.77
GB	0.066	0.256	0.15	0.757
DT	0.071	0.266	0.176	0.738

Source: Made by author

Table 3 shows that KNN is more accurate than the remaining algorithms, as evidenced by the lowest MSE value and the highest R^2 value. So, the paper depends on it to determine the coefficient regression, as clearly shown in Table 4.

Table 4: KNN Feature Importance

KNN Feature selection	Score
Energy Consumed by the Residential Sector	3.642326
Energy Consumed by the Commercial Sector	1.309931
Energy Consumed by the Industrial Sector	24.62908
Energy Consumed by the Transportation Sector	8.518995
Energy Consumed by the Electric Power Sector	61.89967

Source: Made by author

Table 4 illustrates the relationship between energy intensity and all variables. The most influential factors affecting energy intensity are the Power Sector (61.89%), the Industrial Sector (24.62%), the Transportation Sector (8.5%), the Residential Sector (3.6%), and the Commercial Sector (1.3%), as depicted in Figure 3. Consequently, the Industrial, Electric Power, and Transportation Sectors have the Greatest influence on energy intensity. Thus, enhancing the energy performance of these sectors can reduce energy intensity and maximize efficiency, leading to improved environmental sustainability.

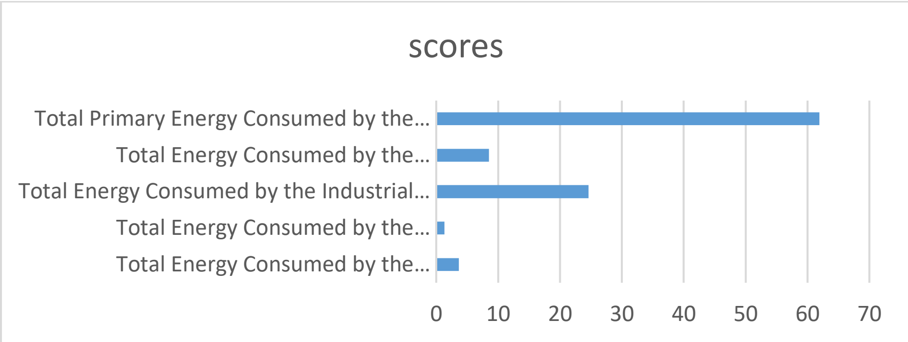

Figure 3: KNN feature scores
Source: Made by author

CONCLUSION

This study employs the k-nearest neighbor (KNN) technique to investigate the relationship between global energy intensity and consumption across major economic sectors, including industry, residential areas, electricity, commercial, and transportation. The results indicate that energy consumption in the industrial and electricity sectors has a significant impact on energy intensity. The results showed that improving energy performance in these sectors could lead to increased energy efficiency and decreased energy intensity. The study also demonstrates how KNN regression outperforms other machine learning models in predicting trends in energy intensity. KNN is, therefore, a helpful tool for policymakers in energy planning and control.

The findings underscore the necessity for tailored energy efficiency regulations across various sectors. As the largest energy consumer, the industrial sector must invest significantly in cleaner technologies and energy conservation initiatives to mitigate its environmental impact. Similarly, the electric power sector, which heavily relies on fossil fuels, must shift towards renewable energy sources to minimize energy waste and reduce carbon emissions. Given its critical role in facilitating trade and mobility, the Transportation Sector must adopt innovative fuel-efficient technologies and improved logistical practices to reduce its overall energy demand and emissions. Transitioning to cleaner transportation alternatives—such as electric or hybrid vehicles—and optimizing supply chain operations can significantly reduce energy consumption, thereby contributing to overall improvements in energy efficiency and a decrease in environmental impacts.

Furthermore, merging traditional econometric methods with advanced data analytics provides policymakers with a potent tool. Besides enhancing prediction accuracy, the KNN algorithm elucidates how sector-specific energy consumption trends impact global energy intensity. This combination enables the development of targeted interventions that modernize outdated industrial practices and promote cleaner, more efficient technologies. These tactics are therefore necessary to achieve sustainable economic growth and lessen the environmental impact of critical economic sectors. In conclusion, the study provides a strong empirical basis for advancing energy efficiency policies through a data-driven approach. The insights derived from the KNN regression model advocate for focused investments in technology upgrades and energy management practices across critical sectors. Moving forward, it is recommended that policymakers utilize these findings to develop targeted, actionable strategies that strike a balance between economic growth and environmental responsibility.

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