



SCIENTIFIC OASIS

## Spectrum of Mechanical Engineering and Operational Research

Journal homepage: [www.smeor-journal.org](http://www.smeor-journal.org)  
eISSN: 3042-0288

SMEOR

ISSN: 3042-0288

Spectrum of  
Mechanical  
Engineering and  
Operational  
Research

Scientific Oasis

JG10

<https://doi.org/10.31181/smeor.2025.01>

# Utilizing Artificial Neural Networks to Correlate Energy Consumption and Intensity in Metal Industries for the Midwest States

Mohamed I. Youssef<sup>1</sup>, Kada Kada<sup>1</sup>, Yazeed Abushanab<sup>1</sup>, Qais Alnawafah<sup>1</sup>, Ryoichi S. Amano<sup>2</sup>, Asma Khasawneh<sup>1,\*</sup>

<sup>1</sup> University of Wisconsin Milwaukee, Milwaukee, WI, 53211, USA

<sup>2</sup> University of Wisconsin Milwaukee, ASME Life Fellow Richard & Joanne Grigg Fellow Professor, Milwaukee, WI, 53211, USA

### ARTICLE INFO

#### Article history:

Received 29 January 2025

Received in revised form 19 March 2025

Accepted 18 April 2025

Available online 2 May 2025

#### Keywords:

Energy Audits; Energy Optimization; Energy Efficiency; Machine Learning; Artificial Intelligence; ANN.

### ABSTRACT

Energy optimization and analysis are significant in mapping energy consumption and savings for various industries. This study sheds light on utilizing two main energy evaluation parameters: Energy Intensity Utilization (EIU) and Specific energy consumption (SEC). This research paper is founded on an extensive 10-year study, from 2013 to 2023, on more than 196 on-site energy assessments performed on various manufacturing companies in Wisconsin and Northern Illinois. This research is considered a comparative study, which aims to explore the correlation between those two parameters using linear regression analysis using SPSS (Statistical Package for Social Sciences) and validate the outcomes using Artificial Neural Networks (ANN). Besides, it is also employed to assess the most updated methods, procedures, and technological applications that are meant to increase energy efficiency. This study demonstrates the relationship between energy consumption, energy savings, and the effects of energy assessment across several industrial sectors. The results have shown a linear correlation between the EIU and SEC as two of the most significant parameters in measuring energy footprint in the energy-auditing sector. Also, the results have shown that the Annual Energy Savings Percentage (AES%) could have interdependence with both the SEC and EIU energy evaluation parameters, which could provide an energy footprint baseline for any stakeholder interested in penetrating the fabricated metal products industry. The ANN results have shown that underfitting occurs when the data model cannot accurately capture the relationship between the input and output variables. The reasons for the underfitting are that the data points are small (95 data points) for a neural network, and the complexity of the model is simplistic for a machine learning application.

## 1. Introduction

Climate change, driven by fossil fuel combustion, threatens human health through air pollution and global warming, with anthropogenic emissions raising Earth's temperature by about 1.1 °C over the past century. Limiting the temperature rise to 1.5 °C, as recommended by the IPCC, is crucial to

\* Corresponding author: [iyoussef@uwm.edu](mailto:iyoussef@uwm.edu)

<https://doi.org/10.31181/smeor21202541>

© The Author(s) 2025 | [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

avoid severe consequences. Fossil fuels release fine particulate matter and hazardous gases, worsening air pollution and harming health [1]. Renewable energy sources, such as biomass, offer sustainable alternatives. Biomass energy, derived from organic materials, is both efficient and environmentally friendly, making it essential for meeting future energy demands while reducing carbon footprints [2] and [3].

Total energy consumption among the top five countries. Fig. 1 illustrates the significant disparity in global energy consumption, with China leading at 8,392 terawatt-hours, followed by the United States (4,065 TWh), India (1,407 TWh), Russia (997 TWh), and Japan (909 TWh) (Statista Research Department 2024). These figures highlight the varying energy landscapes of major economies, with China's dominant share underscoring its role as a global energy demand leader.

Fig. 2 depicts the U.S. energy mix in net electricity generation: 60.3% from fossil fuels, 21.2% from renewables, 18.2% from nuclear, and 0.3% from other sources. This mix reflects a shift toward sustainable energy solutions, with the industrial sector remaining the largest energy consumer, using 33% of total energy in 2021, largely from natural gas, electricity, and petroleum [4]. The U.S. also ranks as the second-largest electricity producer, contributing 15% of global supply, half of China's output [5].

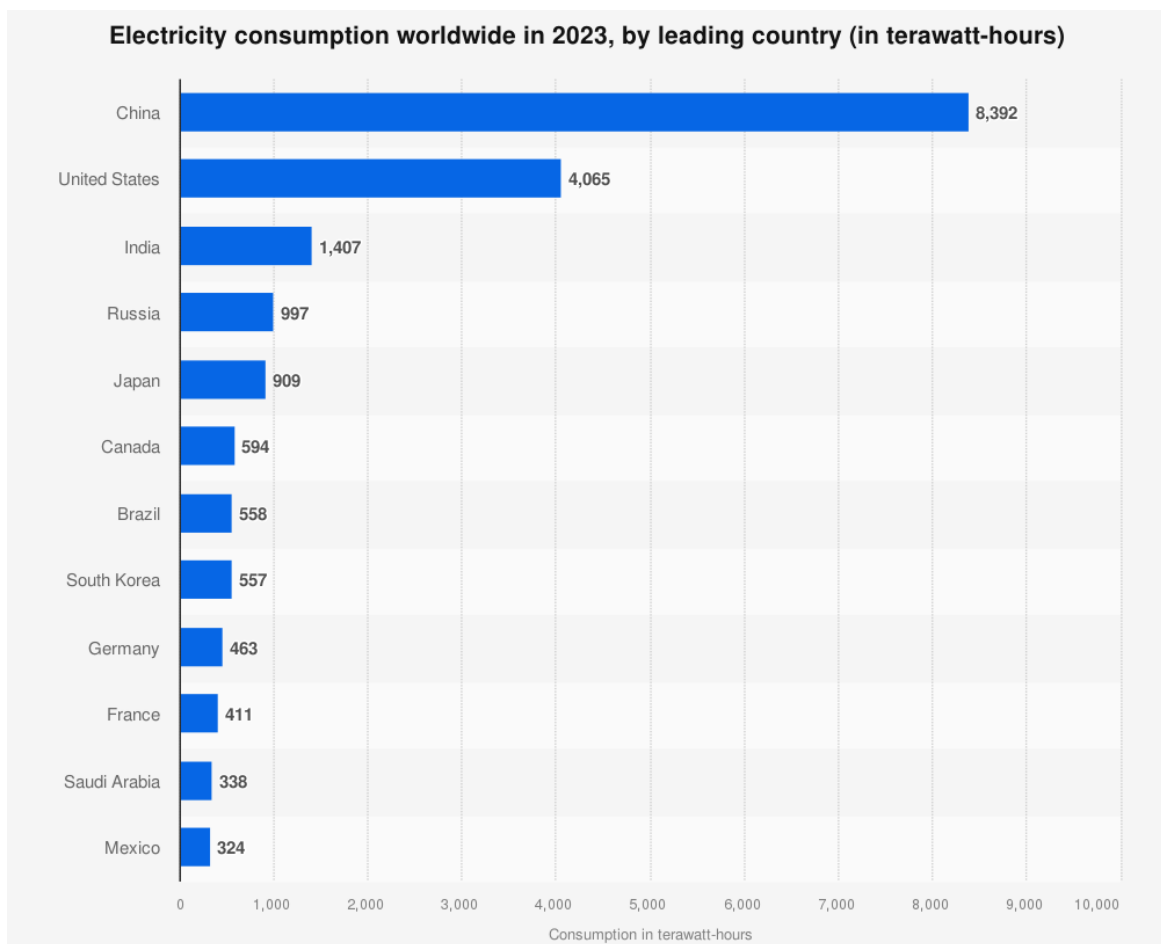
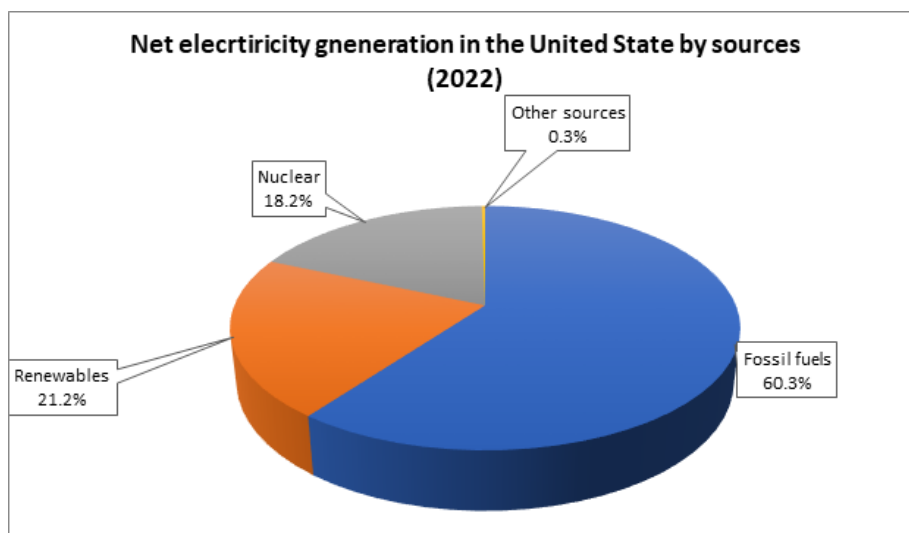


Fig. 1. Global energy disparities among top five nations [6]



**Fig. 2.** Net generation in the state by sources

The Department of Energy (DOE) promotes energy efficiency through initiatives like the Industrial Training and Assessment Centers (ITAC) program. ITACs offer free energy assessments to manufacturers, identifying over \$130,000 in annual savings per assessment, with nearly \$50,000 implemented in the first year. Since 1976, more than 20,000 ITAC assessments have been conducted, enhancing energy efficiency and competitiveness across the industrial sector.

Energy audits are critical for assessing energy consumption and identifying reduction opportunities. They are divided into four stages: initial review, brief on-site examination, comprehensive analysis, and in-depth assessment requiring major investment [7]. Audits are also classified as walk-through, mini, and max, offering varying detail levels [8] [9]. Industrial process audits have proven effective in significantly reducing energy use [10], while building audits identify conservation opportunities across services, supporting energy management [11]. In SMEs, audits address information gaps and promote energy efficiency investments [12]. Residential and commercial audits enhance efficiency by recommending improvements for high-energy-consuming devices [13]. Overall, audits guide energy efficiency investments and highlight financial and environmental impacts [1]. For instance, optimizing processes and adopting renewable energy in the U.S. iron and steel industry can significantly reduce energy use and CO<sub>2</sub> emissions [14], such as renewable energy solutions [15].

In recent years, advanced technologies such as Artificial Neural Networks (ANNs) and deep learning have demonstrated significant potential for optimizing energy consumption in the industrial sector by analyzing complex datasets and uncovering patterns often missed by traditional methods. Specially for quantification methods in various applications. [16] For example, cyber-physical systems in smart manufacturing have enabled real-time monitoring and simulation, leading to notable energy savings [17]. Innovations like active photovoltaic cooling systems [18] and IoT-based smart cold storage solutions further illustrate how advanced energy management can reduce consumption and enhance efficiency [19]. Similarly, detailed numerical and experimental investigations, such as the study on serpentine channel cooling for turbine blades in both stationary and rotational modes, demonstrate the critical role that advanced thermal management techniques play in improving the efficiency and safety of high-temperature systems [20]. Studies on biomass energy potential using adaptive clustering methods and the influence of metal particles on nanofluids underscore the role of emerging technologies in improving energy efficiency [21]. Reliable hybrid systems for nuclear facility power supply [22] and optimized flow paths in air-cooled heat exchangers highlight

engineering advancements in critical industrial applications [23]. In the Midwest, efficiency improvements across metal-based durable manufacturing industries, particularly in basic iron and steel production [24], could significantly reduce operational costs, CO<sub>2</sub> emissions, and environmental impact [25].

Integrating renewable energy with intelligent control systems has proven effective in optimizing real time energy management while lowering costs. For example, smart control algorithms have been shown to enhance the integration of renewable sources in industrial settings [26]. Dynamic sun tracking techniques, which adjust photovoltaic panels to the sun's position, further improve energy capture [27]. Additionally, employing GIS-based approaches has enabled optimal siting of renewable installations to match local energy demand, thereby enhancing overall operational efficiency [28].

Addressing operational challenges is equally crucial for system resilience. Detailed analyses reveal that adaptive monitoring and control can significantly reduce energy losses and extend equipment lifespan in industrial circuits [29]. Furthermore, innovative models for renewable energy allocation in microgrids help balance generation and consumption more effectively [30], while research on wind energy integration offers strategies to overcome local barriers [31]. Advanced computational frameworks that optimize data dissemination in sensor networks demonstrate the potential of digital technologies to further enhance energy efficiency and competitiveness in industrial operations [32].

The study aimed to diagnose the energy efficiency of the metal casting industry reveals significant energy losses through fuel gases as the main source. Proposals to reduce these losses include heat recovery from fuel gases to heat combustion air, which could make industrial processes more efficient and competitive, benefiting the environment by reducing GHG emissions [33].

The industrial sector is the second-largest end-use sector in the U.S., accounting for  $27.7 \times 10^{15}$  kJ (26.3 quadrillion BTUs) in 2018, which is 35% of the total energy consumption (Independent Statistics and Analysis). Regular energy audits help identify inefficiencies and potential areas for improvement. Continuous energy monitoring systems can pinpoint exactly where energy is being used and wasted, allowing for targeted interventions [34]. Building energy efficiency measures in the industrial sector, benchmarking serves as a strategic tool to further enhance performance. It involves measuring key business metrics and practices, comparing them within business areas or against competitors, industry peers, or other global companies. This process helps organizations understand where they need to change to enhance performance. There are four primary types of benchmarking: internal, external, performance, and practice. Thus, benchmarking, in conjunction with regular energy audits and continuous monitoring, can significantly contribute to energy optimization in the industrial sector [35].

Moving on, the Energy Use Intensity (EUI) evaluates a "building's energy efficiency". It's calculated by dividing the total annual energy consumption of the building by its gross floor area. The result is expressed in kilowatt-hours per square foot (kWh/ft<sup>2</sup>). It provides insight into how much energy a building uses relative to its size, with lower values indicating better energy performance [36]. Additionally, the Energy Cost Index (ECI) allows comparison of expected energy costs across various aspects, such as commercial office spaces, lighting, or industrial air filtration. ECI considers the impact on energy costs from individual devices up to complex systems. 'It's calculated by dividing the contributory annual energy consumption cost by the number of affected units, expressed in dollars per square foot (\$/ft<sup>2</sup>) [37]. To lower demand charges, several manufacturers in the industrial sector are searching for creative solutions. Industrial facilities' expenses while utilizing power are known as demand charges [38]. Lastly, Specific Energy Consumption (SEC) is crucial in manufacturing. It reveals how efficient energy resources are used to produce goods. By calculating

SEC, companies can identify areas for improvement and optimize energy usage, reducing environmental impact and operational costs. Using sensor and physical system data, several technologies, such as Equipment Energy Usage Management (EECM), have greatly aided in monitoring, analyzing, optimizing, and forecasting energy usage [39].

## 2. Materials and Methods

### 2.1 Study Limitations

This study focuses on facilities within the Fabricated Metal Products industry and is geographically limited to the Midwest, excluding other regions. It primarily assesses facilities with limited knowledge of energy optimization methods, often lacking internal energy management specialists and relying on benchmarking to share experiences. Many decision-makers are unaware of state-specific incentives provided by the DOE and its national partners. The study emphasizes the last decade to reflect recent technological advancements in manufacturing, though this limits the number of assessments analyzed compared to those conducted since ITAC's founding in the 1980s. Additionally, inconsistent production measurement units across facilities—such as pounds, feet, tons, and units—pose challenges. Despite these constraints, artificial intelligence validation tools confirmed the statistical outcomes, supporting the study's predictive methodology [40]. Also, this can serve as a springboard for further research into estimating and forecasting energy use in the food and beverage industry, using its findings and conclusions in a multi-criteria decision-making process, like the PROMETHEE, OAT and COMSAM models, to predict how that industry will behave [41] [42]. In addition to fuzzy approach that might prove useful with that prediction as the one used in [43] [44].

### 2.2 Study Limitations

This study investigates the possibility of using energy optimization evaluation parameters to guide energy auditors and consultants in the fabricated metal products industry. Not only do we need to understand how certain variables, like energy consumption (SEC) and energy intensity utilization (EIU), may correlate with the Annual Energy Savings (AES) percentage, but we also need to understand how these variables might serve as a benchmark for any parties involved in entering this market, particularly in the early stages of design. That said, the descriptive and analytical approach must be appropriate for the facts, observations, and information gathered from many sources and in various methods according to the nature of the study. Those parameters (SEC, EIU, AES, and AES%) are defined respectively. The Specific Energy Consumption (SEC) represents the amount of energy consumed by the facility per production unit [kWh/unit]. It is calculated using Eq. (1):

$$SEC = \frac{\text{Annual Electricity Consumption [kWh]}}{\text{Annual Total Production [unit]}} \quad (1)$$

Meanwhile, the energy intensity usage (EIU) measures the amount of energy consumed per unit of floor area [kWh/ft<sup>2</sup>]. It is calculated using Eq. (2):

$$EIU = \frac{\text{Annual Electricity Consumption [kWh]}}{\text{Total Gross Plant Area [ft}^2\text{]}} \quad (2)$$

The Annual Energy Savings (AES) represents the amount of money saved annually from implementing energy-saving measures per unit of electrical consumption rate. It is calculated using Eq. (3):

$$AES = \frac{\text{Recommended Savings (\$)}}{\text{Unit Cost (\$)}} \quad (3)$$

Percentage of Annual Energy Savings (%AES) quantifies the efficiency of energy-saving measures in reducing electricity consumption, expressed as a percentage of the annual energy savings divided by the annual energy consumption. It is calculated using Eq. (4):

$$\%AES = \frac{AES}{\text{Annual Energy Consumption } [Ec]} * 100\% \quad (4)$$

The data needed for those parameters need to be precise to utilize them in the desired manner, which contributes to obtaining adequate results that lead to coming out with useful recommendations about knowing the effect of two main (SEC and EIU) variables and how they could correlate with the AES% of the research cases under study. [45].

### 2.3 Data Collection

The collected data comprised 138 industrial facilities in the field of fabricated metal products; all of those companies operate in the Mid-West region of the United States of America. They have almost similar production capabilities and organizational structures that contain engineering divisions to manage the production of food products, with various types and production units. The products vary from automotive parts, can lids, hose reels, steel parts, metal cans, metal bars, valves, springs, pipe coatings, metal stamping, steel and aluminum coils, bottled beverages, cables, cable trays, steel pressure tanks, chimney covers, heat exchangers and many more products. According to the statistical data from the Department of 'Energy's Industrial Training and Assessment Centers, the open-source website uses the Standard Industrial Classification (SIC) 34, specific to the fabricated metal products sector for entities operating with the same economic activity. That website has more than 21,194 assessments and 157,927 recommendations [46].

The data was collected from eight diverse ITAC centers covering the Midwest region, operating within Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. Those states fall under the jurisdiction of a total of eight ITAC centers such as the University of Chicago Illinois, Indiana University-Purdue University, Michigan State University, University of Missouri-Columbia, University of Nebraska—Lincoln, University of Dayton, University of Wisconsin, Milwaukee, and University of Louisville. Table 1 shows a breakdown of the number of assessments done by each ITAC center operating within the Mid-west region.

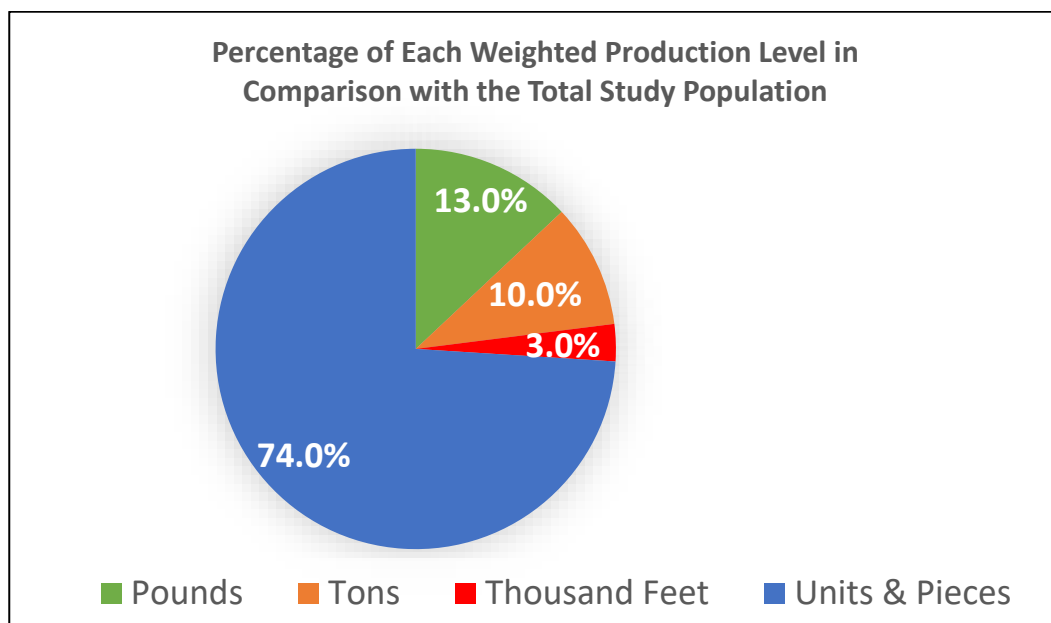
**Table 1**

The number of assessments performed by the ITAC centers in the fabricated metal products for the past decade

No.	Industrial Training and Assessment Centers	Assessments
1	University of Chicago, Illinois	13
2	Indiana University-Purdue University	25
3	Michigan State University	4
4	University of Missouri-Columbia	33
5	University of Nebraska—Lincoln	8
6	University of Dayton	28
7	University of Wisconsin, Milwaukee	20
8	University of Louisville	7

With more than 19,846 recommendations and over 2,614 assessments completed by the Industrial Assessments Centers nationwide, the fabricated metal products industry came at second place on the list of assessments completed since the ITAC began its operations in the eighties, which highlights its significance to the energy sector [47]. Since the amount of available data from assessments was vast, the study focused on the last ten years, which limited the number of assessments under study compared with the total number of assessments made in that industry. Moreover, the study emphasized data from the Industrial Training and Assessment Centers operating in the 12 states in the Midwest region.

The case under study consisted of 138 manufacturing facilities within the study population and are represented by the extracted data from the SIC index (34XX) of the fabricated metal products. After thoroughly studying and analyzing the data, it turned out that the production level of the various entities under study differs according to the product type, as some of the manufacturing units vary from Pieces, Thousand Feet, Pounds, Units, and Tons. Where only three percent (3%) of those 138 facilities produce products that are quantified by Thousand Feet (Tfeet), with four (4) facilities. Ten percent (10%) of those facilities under study have production levels in Tons, with fourteen facilities (14). The facilities, which have pounds as units for production, have 18 facilities, representing thirteen percent (13%) of all the assessments. Thus, a remarkable portion of those assessments was related to the facilities that had units or pieces as their production level, with a total of one hundred and two facilities (102), representing seventy-four percent (74%) a total of total facilities under study, as shown in Fig. 3.



**Fig. 3.** Percentage of each weighted production level facilities in comparison with the total study population

A normalization technique was utilized to address any unit fluctuations or differences to ensure that every production level unit had the same baseline. As a result, the facilities with common production level units that could be measured using measurable units like pieces and units were chosen within this study to serve as the study population.

#### 2.4 Study Population

The study population was selected to include the one hundred and two (102) facilities that have measurably counted units or pieces for their production levels, as well as most of the facilities, due

to the homogeneity of the data and consistency of the production level. The study excluded dismissible or unrealistic data points in the data collection process for more reliable statistical analysis and accurate results. Leaving the study population with 94 facilities instead of 102, as mentioned earlier. The study sample used for this research case study was based on two Eq.s: the first one was for the Cochran equations [26] for large populations, as shown in Eq. 5, and the second one was for small populations, as shown in Eq. (5):

$$n_0 = \frac{Z^2 pq}{e^2} \tag{5}$$

The confidence level represented by Z in this research study was aimed at (97%). Table 2 shows the critical (Z) values used in the calculation of confidence intervals in the Cronbach Alpha analysis are equal to 2.17. The value (p) represents the value estimated by the researchers for the true proportion of the study population and equals 0.5. It represents the maximum that can be used in the Cochran equation for large populations, and q represents the product of the subtraction of p from one (1). It is equal to (0.5), and finally, he represents the permissible error limit and is equal to (0.03), as shown in Table 2. Therefore, it was assumed that the study sample size n is more than 1308 facilities, more than 3% of the study population. Therefore, the Cochran equation for small communities shall be applied as stated below in Eq. (6):

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \tag{6}$$

Where N represents the size of the study population and is equal to 94,  $n_0$  represents the assumed sample size and is equal to 384. By applying the equation, the approved size of the study sample n is approximately 88 facilities. However, the study included the complete 94 facilities instead as a study sample to increase the accuracy of the results. The Cochran sample sizing theory is shown and illustrated by the tables that are utilized in the data needed for Eq. 6. This sampling technique is frequently employed for both small and large population selection as in [48].

**Table 2**  
 Critical (z) values used in the calculation of confidence intervals

Confidence Level	Critical (z) value to be used in confidence interval calculation
90%	1.64485
95%	1.95996
97%	2.17009
99%	2.57583
99.90%	3.29053

**Table 3**  
 Sample size required for sampling

Estimated Population Size	Margin of error						
	Confidence Level 97%				Confidence Level 99%		
	10%	5%	2.50%	1%	5%	2.50%	1%
100	50	80	94	99	87	96	99
500	81	217	377	475	285	421	485
1,000	88	278	606	906	399	727	943

### 2.5 Study Tool

To analyze data statistically, this research study utilized a statistical software called the Statistical Package for Social Sciences (SPSS). Two statistical models were created. The first was a linear regression analysis to determine the correlation between two variables—Energy Intensity Usage (EIU) and Specific Energy Consumption (SEC)—with EIU as the independent variable and SEC as the dependent variable. Considering that the energy footprint of any industrial plant is reflected by those two metrics, which have been deemed significant in the energy-auditing industry. The second model, in which SEC and EIU are the independent variables, and AES% is the dependent variable, evaluated the relationship or correlation between SEC and EIU and Annual Energy Savings percentage (AES%), where the Annual Energy Use of the Facility ( $E_c$ ) in kWh is divided by the AES to get the AES%.

### 3. Results and Data Analysis

Despite the natural dispersion of data, in addition to the trials of consistent and ordinal data points, computations for averages, standard deviation, percentage, and correlation analysis between the various variables were done to assess the consistency and quality of the raw data provided. Depending on the variables and kind of data, two models of linear regression analyses have been run in addition to a reliability test for each model to ensure detailed and real-life reflection of data values. Social Statistical Packages Program (SPSS) package software was utilized to serve that purpose.

#### 3.1 Tests the Validity and the Reliability of the Study Tool

Cronbach's Alpha test and the self-validity coefficient are two essential and trustworthy techniques for determining how logical and predictable the link between the statistical data of different variables  $i$  [49]. The results in Table 4 show that the SEC and EIU variables data  $i$ -0.015s coherency,  $i$ , less than the statistically suggested minimum Cronbach's Alpha coefficient value of 0.6 [50]. Those results make sense, given that the two parameters are entirely distinct and separate factors are used in their computations. Furthermore, since the EIU is based on the ratio of  $E_c$  values to plant area, and the SEC is based on  $E_c$  values and normalized production levels, they are not regarded as raw data.

**Table 4**  
 Cronbach's alpha result based on standardized items

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
-0.015	-0.231	2

#### Using Linear Regression Analysis to Study the Effect of EIU on SEC

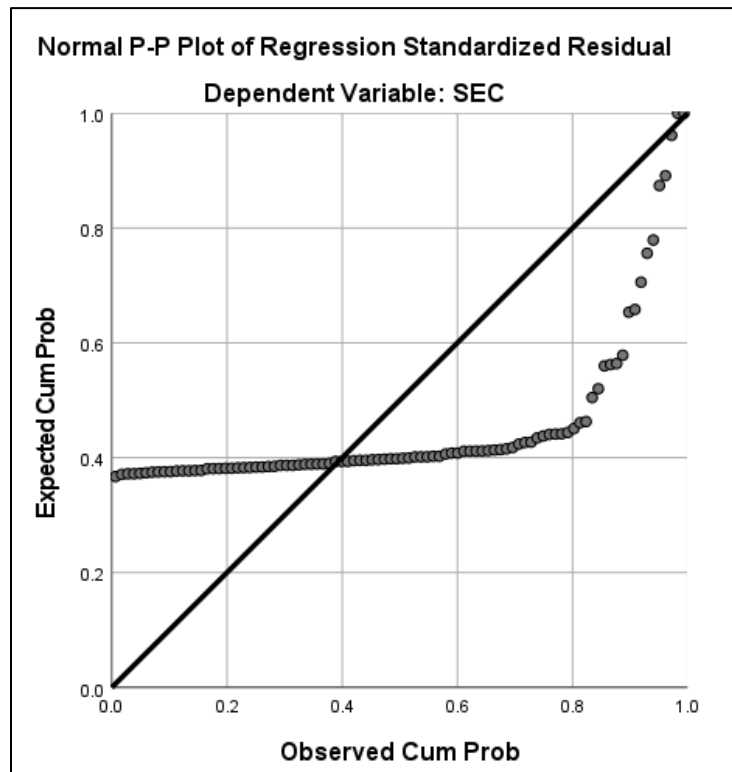
A linear regression study was done to look into how EIU, an independent variable, affected SEC, a dependent variable. The comparison of 94 data points related to the previously mentioned independent (EIU) variable with additional data points related to the dependent variable (SEC) served as the foundation for this regression analysis. The following outcomes are demonstrated in Table 5, which shows that the R-value (Pearson's correlation coefficient) equals 0.103, which is 10.3% of the variance in the dependent variable, which is a statistically acceptable finding, as it is more than zero value. R is a correlation coefficient that measures the strength of the relationship between two variables and the direction on a scatterplot, as shown in Fig. 4 below, proving a nearly linear relationship between the dependent and independent variables [51].

**Table 5**  
 Shows the r-value for the linear regression analysis between SEC and EIU

Model Summary b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change
1	0.103a	0.011	0	1123.887	0.011

a. Predictors: (Constant), EIU

b. Dependent Variable: SEC



**Fig. 4.** Nearly linear relationship between the dependent variable (SEC) and the independent variable (EIU)

### 3.2 Using Linear Regression Analysis to Study the Effect of EIU And SEC On AES%

A linear regression analysis was performed to look into the effects of SEC and EIU as independent factors on AES percentage, the dependent variable. Comparing 94 data points related to the previously mentioned independent variable (EIU) with additional data points related to the other independent variable (SEC) was the foundation for this regression analysis. The following outcomes are shown in

Table 6, which shows that R-Value (Pearson's correlation coefficient) equals 0.195, which is 19.5% of the variance in the dependent variable, which is a statistically adequate finding, as it is more than zero value. R is a correlation coefficient that measures the strength of the relationship between two variables, as well as the direction on a scatterplot, as shown in Figure 5 below, which proves that there is a linear correlation between the dependent variable AES% and the independent variables (EIU and SEC).

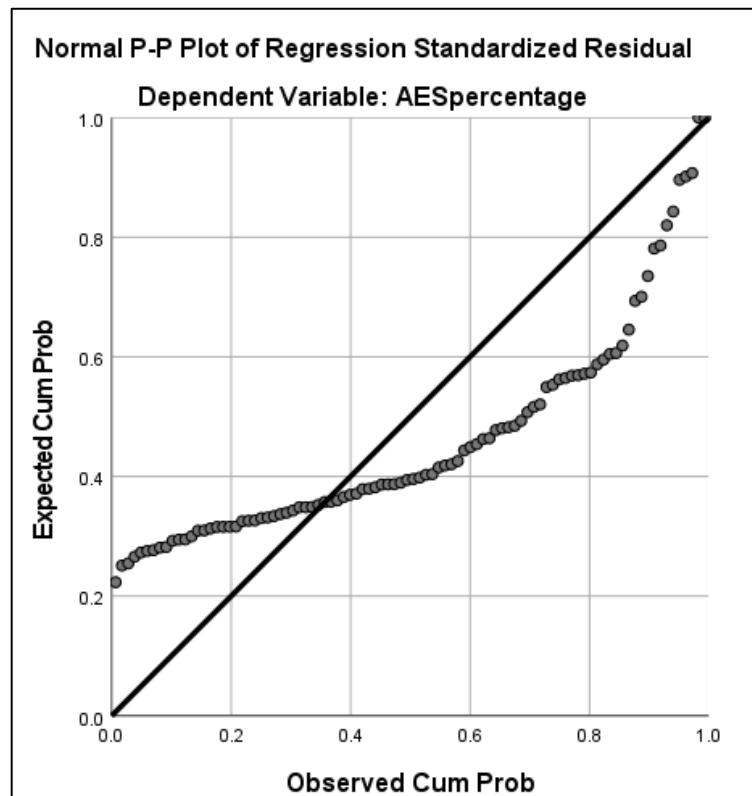


Fig. 5. Linear correlation between the dependent variable (AES%) and the independent variables (EIU, SEC)

Table 6

R-value for the linear regression analysis between SEC, EIU, and AES%

Model Summary b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change
1	.195a	0.038	0.017	0.00231	0.038

a. Predictors: (Constant), EIU, SEC

b. Dependent Variable: AESPERC

### 3.4 Artificial Neural Network

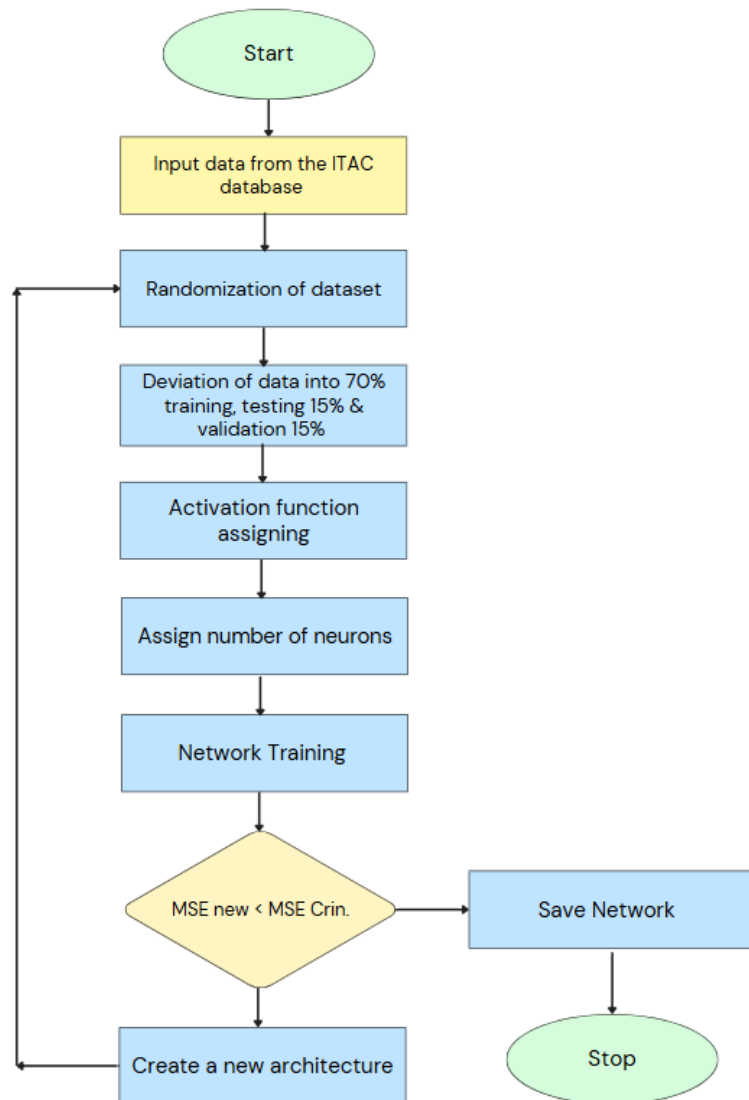
An artificial neural network has been utilized as a second validation tool for the SPSS. This approach has been used to check if utilizing machine learning could affect the predictive results from a standard multi-regression analysis calculation. The data set has been Split into three main datasets with a percentage of (70%) training, (15%) validation, and (15%) test. The main purpose of the training data set is to contemplate the relationship between variables or inputs and outputs. At the same time, the validation is utilized to ensure that the model does not overfit or underfit the dataset but rather to understand its interdependencies and correlations. The testing data set is used to measure the performance of the Artificial Neural Network (ANN) dataset without training or validation to give a reliable outcome from the 'variables' interdependencies [52].

Since only the midwestern states and a single industry are covered by the data, the number of accessible data points is somewhat small compared to the ITAC data source. Therefore, the best design for this study is to employ a few hidden layers, with the first layer using three neurons. Fig. 6 shows the specific steps that were taken in order to produce the ideal ANN structure. We'll talk

about more specifics on the ANN setup and assessment. The X-axis of Fig. 7 is the Epoch, which shows that the number of iterations of the data set has been passed through the Neural Network for Training, Validation, and Testing. The Y-axis shows the main metric used to validate the model, the Mean Square Error, as mentioned in Eq. (7). Different numbers of Epochs were used for training, and the results have shown that in all these cases, the model is underfitting, as shown in the Fig. 7 sample case at 200 Epochs. Underfitting occurs when the data model cannot accurately capture the relationship between the input and output variables. The reasons for the underfitting are that the data points are small (95 data points) for a neural network, and the complexity of the model is very simplistic for a machine learning application.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \tag{7}$$

Where,  
 MSE = mean squared error  
 n = number of data points  
 Y<sub>i</sub> = observed values  
 Ŷ<sub>i</sub> = predicted values



**Fig. 6.** A flowchart that shows the steps to obtain the optimized ANN model

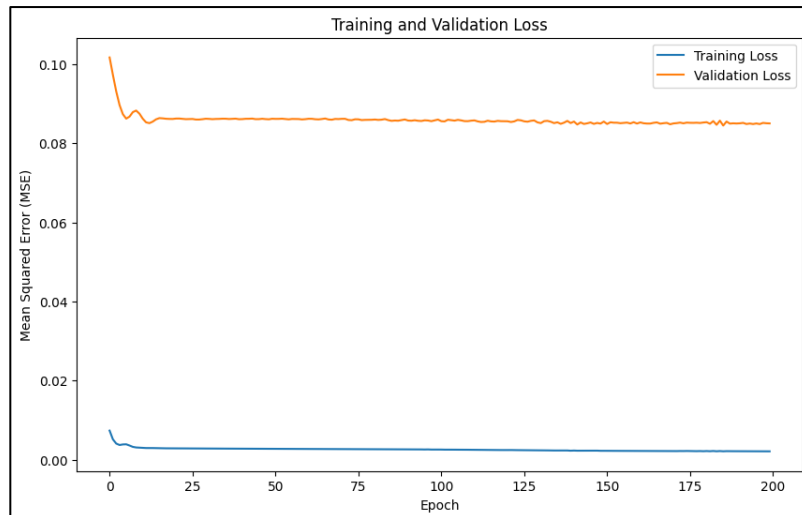


Fig. 7. Shows the training process of the artificial neural network (ANN)

Fig. 6 shows the specific steps that were used to get the ideal ANN construction, setup, and assessment. Figure 8 shows the model's performance over testing data sets, representing only 14 data points (15%) out of the 95 data points. Also, the figure demonstrates that the scatter points representation is intact for most of the data set, while there is a minimal divergence from the regression line by one data point, which is acceptable as one of the data points has a very high SEC value from the other as explained in the aforementioned linear regression analysis.

Fig. 9 shows the model's performance over the entire data set, representing a 100% value of the whole 95 data points. Also, the figure demonstrates that the scatter points representation is intact for most of the data set. At the same time, there is a minimal divergence from the regression line by one data point, which is acceptable as one of the data points has a very high SEC value from the other, as explained in the linear regression analysis. Table 7 shows the averages of the mean square error, the root mean square error, and the mean average error. These differ from the values obtained from the SPSS tool, which is explainable as machine learning generally needs more data points to develop a proper predictive analysis.

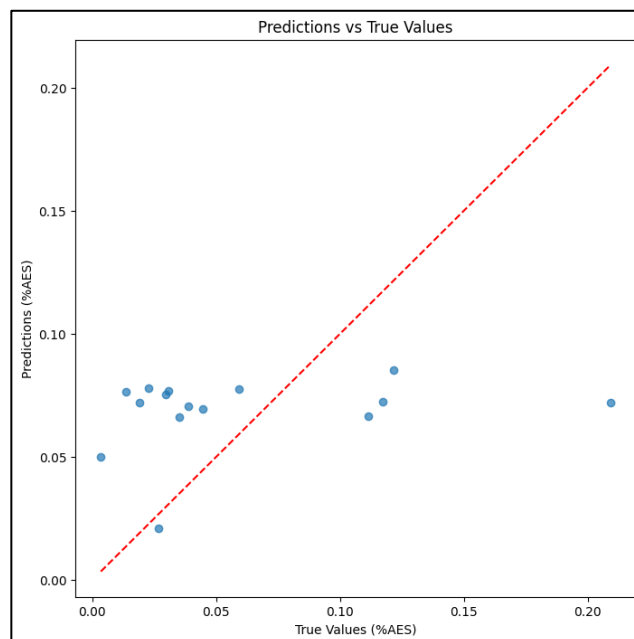
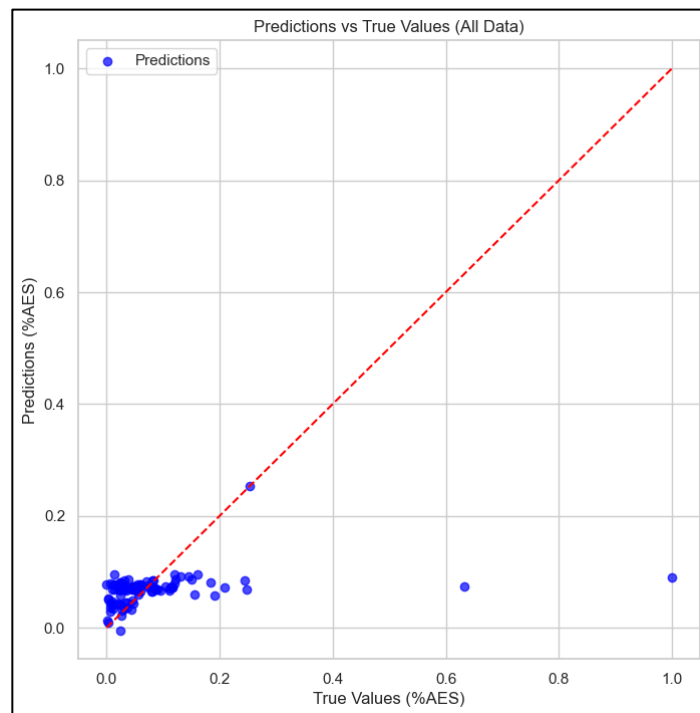


Fig. 8. Performance of the model over testing data sets

**Table 7**  
Shows the evaluation metrics of the whole data set

Mean Square Error (MSE)	0.0145
Root Mean Square Error (RMSE)	0.1206
Mean Average Error (MAE)	0.0519



**Fig. 9.** Predictions of the ANN model over the entire dataset

#### 4. Conclusions

Starting with the primary research question is to investigate the impact of EIU as an independent variable on SEC as the potential effect and the implications of these findings to be used as a baseline or a benchmarking reference to all the stakeholders who are invested in the Fabricated metal products work field. It was concluded that there is an acceptable significance of those two variables and their interdependence on one another, as they are considered to be two of the significant energy evaluation parameters. When it came to studying the correlation between the dependent variable (AES%) and the independent variables (EIU) and (SEC), it was concluded that there is adequate significance for those two variables and their interdependence on (AES%).

When it comes to the utilization of the Artificial Neural Network (ANN), it was concluded that when the data model cannot effectively depict the link between the input and output variables, underfitting takes place. The model's simplicity for a machine learning application and the short number of data points (95 data points) for a neural network are the causes of the underfitting. Therefore, more data points were needed to develop a proper predictive model for such relationships between variables. This will be inevitably valuable for the extensive study that shall be undertaken to cover a wider range of industries and a broader aspect of the geographical representation, including a national case study for all the industrial training and assessment centers across all the states.

There is the possibility of having a more comprehensive study, which includes Nationwide facilities all over the U.S., to have a better perspective on the energy footprint for fabricated metal products and other industrial work fields.

### **Author Contributions**

M.I.Y. led the conceptualization, data collection, and treatment, playing a key role in the investigation and formal analysis. In addition to participating in the literature review and ensuring the study's strategic direction and quality. K.K. conducted an extensive literature review, managed reference collection, and handled formatting, ensuring the manuscript's overall structure and clarity. Q.A. contributed to drafting the introduction and integrating relevant references. R.S.A. provided overall supervision, project administration and supporting the writing of the original draft. Asma Khasawneh contributed to data treatment. All authors have read and agreed to the published version of the manuscript.

### **Funding**

This research was funded by the Department of Energy DE-EE0009728.

### **Data Availability Statement**

The data supporting the results of this study were collected from the publicly available ITAC open source database, which is accessible at <https://iac.university/indexSic>. All data were systematically extracted from this resource for analysis. The statistical analyses were conducted using SPSS software, and all graphs and visual representations of the data were generated within this platform. Further details regarding the data collection and analysis procedures are available upon reasonable request.

### **Conflicts of 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. Furthermore, the funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

### **Acknowledgement**

US Department of Energy (DOE) funds this research under DE-EE0009728.

### **References**

- [1] Kluczek, A., & Olszewski, P. (2017). Energy audits in industrial processes. *Journal of Cleaner Production*, 142(4), 3437–3453. <https://doi.org/10.1016/j.jclepro.2016.10.123>
- [2] Maache, M., Kada, C., Amano, R., Kumano, H., Selim, O., & Kada, K. (2024). Experimental & mathematical investigation of thermochemical conversion for horse manure. *ASME Journal of Energy Resources Technology*. <https://doi.org/10.1115/1.4065956>
- [3] Kada, C., Maache, M., Kada, K., Selim, O. M., Youssef, M. A., & Amano, R. S. (2025). Pyrolysis treatment for sludge and animal manures: Impact of heating rate. *Journal of Energy Resources Technology*, 1(3). <https://doi.org/10.1115/1.4067509>
- [4] U.S. Energy Information Administration. (2023). Monthly energy review. <https://www.eia.gov/totalenergy/data/monthly/>
- [5] U.S. Energy Information Administration. (2023). Independent statistics & analysis. <https://www.eia.gov/energyexplained/us-energy-facts/>
- [6] Statista Research Department. (2024, October 25). Global energy transition statistics. <https://www.statista.com/statistics/267081/electricity-consumption-in-selected-countries-worldwide/>

- [7] Barbetta, G. P., Canino, P., & Cima, S. (2015). The impact of energy audits on energy efficiency investment of public owners: Evidence from Italy. *Energy*, 93(1), 1199–1209. <https://doi.org/10.1016/j.energy.2015.09.117>
- [8] Patterson, M., Singh, P., & Cho, H. (2022). The current state of the industrial energy assessment & its impacts on the manufacturing industry. *Energy Reports*, 93, 7297–7311. <https://doi.org/10.1016/j.egy.2022.05.242>
- [9] Abdelhadi, A., Salem, A., Abbas, A., Qandil, M., & Amano, R. (2021). Study of energy saving analysis for different industries. *Journal of Energy Resources & Technology*, 143(5), 9. <https://doi.org/10.1115/1.4048249>
- [10] Giacone, E., & Mancò, S. (2012). Energy efficiency measurement in industrial processes. *Energy*, 38(1), 331–345. <https://doi.org/10.1016/j.energy.2011.11.054>
- [11] Krarti, M. (2020). *Energy audit of building systems: An engineering approach*. Taylor & Francis. ISBN 9780367619725
- [12] Kalantzis, F., & Revoltella, D. (2019). Do energy audits help SMEs to realize energy-efficiency opportunities? *Energy Economics*, 83, 229–239. <https://doi.org/10.1016/j.eneco.2019.07.005>
- [13] Bosu, I., Mahmoud, H., & Hassan, H. (2023). Energy audit, techno-economic, and environmental assessment of integrating solar technologies for energy management in a university residential building: A case study. *Applied Energy*, 341. <https://doi.org/10.1016/j.apenergy.2023.121141>
- [14] Worrell, E., Price, L., & Martin, N. (2001). Energy efficiency and carbon dioxide emissions reduction opportunities in the US iron and steel sector. *Energy*, 26, 513–536. [https://doi.org/10.1016/S0360-5442\(01\)00017-2](https://doi.org/10.1016/S0360-5442(01)00017-2)
- [15] Al Nawafah, Q., Al Nawafah, H., Amano, R., & Abousabae, M. (2024). Enhanced thermal performance in evacuated tube solar collectors using titanium oxide nanoparticle: A computational fluid dynamics (CFD) investigation. In *ASME 2024 Power Conference*. Washington, District of Columbia, USA. <https://doi.org/10.1115/POWER2024-137203>
- [16] Khokar, I., Farghaly, O., Kothari, A. N., & Deshpande, P. (2024). Towards precision diagnosis: Integrating lexical analysis and deep learning for uncertainty detection and quantification in clinical reports. In *IEEE Symposium on Computer-Based Medical Systems*. Guadalajara. 10.1109/CBMS61543.2024.00051
- [17] Matsunaga, F., Zytkowski, V., Valle, P., & Deschamps, F. (2022). Optimization of energy efficiency in smart manufacturing through the use of cyber-physical systems. *International Journal of Electrical and Computer Engineering*, 15, 1–14. <https://doi.org/10.1115/1.4053868>
- [18] Kristi, A. A., Susanto, E., Risdiyanto, A., Junaedi, A., Darussalam, R., Rachman, N. A., & Fudholi, A. (2025). Energy analysis of active photovoltaic cooling system using water flow. *International Journal of Electrical and Computer Engineering*, 15(1), 1–14. <http://doi.org/10.11591/ijece.v15i1.pp1-14>
- [19] Angappan, S., Nataraj, A., Krishnan, L., & Palanisamy, A. (2025). Development of an Internet of Things based smart cold storage with inventory monitoring system. *International Journal of Electrical and Computer Engineering*, 15(1), 89–98. <http://doi.org/10.11591/ijece.v15i1.pp89-98>
- [20] Amano, R., Khalil, A., Abousabae, M., & Kada, K. (2025). Numerical & experimental analyses of the serpentine channel cooling for a turbine blade in stationary and rotational modes. *International Journal of Energy for a Clean Environment*, 26(1). 10.1615/InterJEnerCleanEnv.2025056629
- [21] Alvianingsih, G., Hashim, H., Jamani, J., & Senen, A. (2025). Determination of biomass energy potential based on regional characteristics using adaptive clustering method. *International Journal of Electrical and Computer Engineering*, 15(1), 46–55. <http://doi.org/10.11591/ijece.v15i1.pp46-55>
- [22] Saade, M., El-Eissawi, H., & Nada, A. S. (2025). Enhancing the reliance of emergency power supply systems for nuclear facilities using hybrid system. *International Journal of Electrical and Computer Engineering*, 15(1), 36–45. <http://doi.org/10.11591/ijece.v15i1.pp36-45>
- [23] Kumar, R., Krishnapillai, S., & Venkatarath, G. (2023). Optimization of flow paths of air-cooled heat exchanger. *International Journal of Electrical and Computer Engineering*, 24(4), 53–65. 10.1615/InterJEnerCleanEnv.2022043633
- [24] Boyd, G., & Lee, J. (2019). Measuring plant level energy efficiency and technical change in the U.S. metal-based durable manufacturing sector using stochastic frontier analysis. *Energy Economics*, 81, 159–174. <https://doi.org/10.1016/j.eneco.2019.03.021>
- [25] Takayabu, H., Kagawa, S., Fujii, H., Managi, S., & Eguchi, S. (2019). Impacts of productive efficiency improvement in the global metal industry on CO2 emissions. *Journal of Environmental Management*, 248. <https://doi.org/10.1016/j.jenvman.2019.109261>
- [26] Aslanova, N. R., Abdullayeva, E. J., & Beloglazov, A. (2023). Development of methods for managing energy consumption and energy efficiency in a common system. *International Journal of Electrical and Computer Engineering*, 13(2), 1306–1313. <http://doi.org/10.11591/ijece.v13i2.pp1306-1313>

- [27] Uchaipichat, N., Wibunsin, C., Chokjulanon, K., & Tanthanuch, N. (2025). Computer vision-based sun tracking control for optimizing photovoltaic power generation. *International Journal of Electrical and Computer Engineering*, 15(2), 1251–1261. <http://doi.org/10.11591/ijece.v15i2.pp1251-1261>
- [28] Qutaina, B., Shehada, A., Yasin, A., & Alsayed, M. (2023). Geographical information systems based site selection methodology for renewable energy systems in Palestinian territories. *International Journal of Electrical and Computer Engineering*, 13(4), 3622–3630. <http://doi.org/10.11591/ijece.v13i4.pp3622-3630>
- [29] Noriega, A. E., Sousa, S. V., Donolo, P. D., & Quispe, E. C. (2024). Assessing power quality in individual circuits of industrial electrical system. *International Journal of Electrical and Computer Engineering*, 14(5), 4888–4896. <http://doi.org/10.11591/ijece.v14i5.pp4888-4896>
- [30] Lee, J., & Park, G. L. (2022). Renewable energy allocation based on maximum flow modelling within a microgrid. *International Journal of Electrical and Computer Engineering*, 12(2), 1180–1188. <http://doi.org/10.11591/ijece.v12i2.pp1180-1188>
- [31] Haidi, T., & Cheddadi, B. (2022). Wind energy integration in Africa: Development, impacts and barriers. *International Journal of Electrical and Computer Engineering*, 12(5), 4614–4622. <http://doi.org/10.11591/ijece.v12i5.pp4614-4622>
- [32] Kavanathottahil, D. M., Jones, T. A., & Pushpa, M. (2024). A novel and optimized computational framework for energy efficient data dissemination in wireless sensor network. *International Journal of Electrical and Computer Engineering*, 14(3), 3045–3054. <http://doi.org/10.11591/ijece.v14i3.pp3045-3054>
- [33] Carabalí, D. M., Forero, C. R., & Cadavid, Y. (2018). Energy diagnosis and structuring an energy saving proposal for the metal casting industry. *Applied Thermal Engineering*, 137, 767–773. <https://doi.org/10.1016/j.applthermaleng.2018.04.012>
- [34] Abbas, I., Saravani, M., Al-Haddad, M., Qandil, M., & Amano, R. (2018). A comparative study of industrial energy assessments for small and medium-sized industrial facilities. 12th International Conference on Energy Sustainability, Lake Buena Vista. <https://doi.org/10.1115/ES2018-7550>
- [35] Ke, J., Price, L., McNeil, M., Khanna, N. Z., & Zhou, N. (2013). Analysis & practices of energy benchmarking for industry from the perspective of systems engineering. *Energy*, 54, 32–44. <https://doi.org/10.1016/j.energy.2013.03.018>
- [36] U.S. Department of Energy. (2015). Archtoolbox. <https://www.energy.gov/sites/prod/files/2015/02/f20/Energy%20Intensity%20Baselining%20&%20Tracking%20Guidance.pdf>
- [37] Maddox, D., Zhang, J., Xie, Y., Xu, W., Liu, X., Wang, S., & Rosenberg, M. (2022). Energy and energy cost savings analysis of the 2021 IECC for commercial buildings. U.S. Department of Energy. [https://www.energycodes.gov/sites/default/files/2022-09/2021\\_IECC\\_Commercial\\_Analysis\\_Final\\_2022\\_09\\_02.pdf](https://www.energycodes.gov/sites/default/files/2022-09/2021_IECC_Commercial_Analysis_Final_2022_09_02.pdf)
- [38] Bahr, M. T., Immonen, J., Billings, B. W., & Powell, K. M. (2023). Intelligent control of thermal energy storage in the manufacturing sector for plant-level grid response. *Processes*, 11(7), 1–22. <https://doi.org/10.3390/pr11072202>
- [39] Kim, J. B., Wang, F., Khanna, S., Balakrishnan, B., Uddin, M., & Aman, J. (2023). Digital twin framework for smart campus to reduce greenhouse gas emission. *IEEE Smart World Congress (SWC)*, 1–8. 10.1109/SWC57546.2023.10448799
- [40] Farghaly, O., & Deshpande, P. (2024). Leveraging machine learning to predict National Basketball Association player injuries. 2024 IEEE International Workshop on Sport, Technology and Research (STAR), 216–221. 10.1109/STAR62027.2024.10636005
- [41] Youssef, M. I., & Webster, B. (2022). A multi-criteria decision making approach to the new product development process in industry. *Reports in Mechanical Engineering*. 10.31181/rme2001260122y
- [42] Więckowski, J., & Sałabun, W. (2025). Comparative sensitivity analysis in composite material selection: Evaluating OAT and COMSAM methods in multi-criteria decision-making. *Spectrum of Mechanical Engineering and Operational Research*, 2(1), 1–12. <https://doi.org/10.31181/smeor21202524>
- [43] Mishra, A. R., & Rani, P. (2025). Evaluating & prioritizing blockchain networks using intuitionistic fuzzy multi-criteria decision-making method. *Spectrum of Mechanical Engineering and Operational Research*, 2(1), 78–92. 10.31181/smeor21202527
- [44] Sandra, M., Nishanthini, C., Narayanamoorthy, A., & Almakayeel, N. (2025). A smart decision framework for sustainable management of C&D waste using picture fuzzy decision model. *Spectrum of Mechanical Engineering & Operational Research*, 130–146. <https://doi.org/10.31181/smeor21202533>
- [45] Amano, R., Youssef, M. A., & Youssef, M. I. (2025). Employing linear regression analysis: Investigating the relationship between energy intensity and specific consumption in U.S. Midwest plastic production facilities. *International Journal of Energy for a Clean Environment*, 26(4), 60–72. 10.1615/InterJEnerCleanEnv.2025054764

- [46] U.S. Department of Energy. (2024, February 1). Industrial Assessment Center SIC Index. <https://iac.university/indexSic>
- [47] Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001). Determining appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal*, 19(1), 43–50.
- [48] Youssef, M. I., & Hausawi, Y. M. (2024). Utilizing the enterprise architecture model to develop the structure of public sector entities in Saudi Arabia. *Journal of Engineering Management and Systems Engineering*, 3(3), 164–174. <https://doi.org/10.56578/jemse030304>
- [49] Gliem, J. A., & Gliem, R. R. (2003). Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. <https://api.semanticscholar.org/CorpusID:146359317>
- [50] Bougie, R., & Sekaran, U. (2006). *Research methods in business: Skill building approach*. John Wiley & Sons. ISBN: 978-1-119-56124-8
- [51] Amano, R., Youssef, M. I., & Youssef, M. A. (2025). Exploring the correlation between energy intensity and specific energy consumption in food and kindred industry for the Midwest states. *International Journal of Energy for a Clean Environment*, 26(4). 10.1615/InterJEnerCleanEnv.2025054884
- [52] AbuShanab, Y., Al-Ammari, W. A., Gowid, S., & Sleiti, A. K. (2023). Accurate prediction of dynamic viscosity of polyalpha-olefin boron nitride nanofluids using machine learning. *Heliyon*, 9(6), e16716. <https://doi.org/10.1016/j.heliyon.2023.e16716>