Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

# Optimizing Energy Consumption Patterns in Southern California: An AI-Driven Approach to Sustainable Resource Management

Ayan Barua[1], Fazle Karim[2], Muhammad Mahmudul Islam[3], Niropam Das[4], Md Fakhrul Islam Sumon[5], Arifur Rahman[6], Pravakar Debnath[7], Mitu Karmakar[8], MD Azam Khan[9]

## Abstract

*Southern California is a special case scenario for any energy management study, given its sunny climate, sprawling urban landscapes, and economic strength. This research project focuses on how artificial intelligence can be applied in energy management by showing its potential toward optimum energy consumption and maximizing sustainability within Southern California. The dataset used for this study was accessed from the Kaggle website. The dataset encompassed various energy consumptions, and the data were collected across different building structures in Southern California between January 2018 and January 2024. These datasets included hourly records of electricity consumption for residential and commercial buildings and industrial buildings. Furthermore, it also provided a record of environmental and operating metrics. This dataset is useful to researchers and practitioners who work on forecasting electricity consumption, energy management, sustainability, and developing AI-based optimization models. To depict an insight into which variable affects strongly within the patterns of energy consumption, machine learning techniques used were logistic regression, Random Forest, and XG-Boost while considering a power outage data set. This study gives evidence that the AI-based models significantly enhance the forecast's accuracy and further allow integration of renewable energy resources, which in turn yield benefits through reduced operational costs and reduction of GHG emissions. The discussion has shown how such development implications could be translated into supportive policy frameworks of advanced studies in the future to electric vehicle charging and even energy storage solutions. Generally, this research underlines the crucial role of AI in changing energy management practices towards sustainable energy use.*

**Keywords:** *Energy Management, Power Outages, Renewable Energy, Artificial Management, Machine Learning, Optimization, Sustainability.*

## Introduction

*Background*

According to Chowdhury et al. (2024), the demand for sustainable energy consumption has become extremely pressing in the dispensation of climate change, resource scarcity, and escalating energy demands. Southern California is a special case for any energy management study, given its sunny climate, sprawling urban landscapes, and economic vitality. The heavy reliance on electricity for residential cooling, lighting, and commercial operations in the region adds to its environmental footprint. In simple fact, with its growing population and strong economic activities, Southern California uses up a lion's share of California's total energy consumption.

The significance of managing energy consumption can help find a solution to these challenges regarding sustainability. Active energy management will not only reduce costs for operational expenses among the consumers themselves but also mitigate environmental impact due to natural resource constraints, lower GHG emission rates, and offer more stabilized power grid functioning (Debnat et al., 2024). Advanced

[1] MBA in Business Analytics, International American University, Los Angeles California, Email: ayanbarua66@gmail.com, (Corresponding Author)
[2] MBA in Business Analytics, International American University, Los Angeles California.
[3] MBA in MIS, International American University, Los Angeles, California.
[4] MBA in Management Information System, International American University, Los Angeles California
[5] School of Business, International American University, Los Angeles, California, USA
[6] School of Business, International American University, Los Angeles, California, USA
[7] School of Business, Westcliff University Irvine, California, USA
[8] School of Business, International American University, Los Angeles, California, USA
[9] School of Business, International American University, Los Angeles, California, USA

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

technologies such as AI create new opportunities for the better consumption of energy and a greener, more sustainable future. This will be of particular interest to Southern California given its continued quest to achieve the ambitious targets contained in California's climate action plans, which require deep cuts in greenhouse gas emissions and an increased supply from renewable sources by 2045 (Hasan, 2024).

As per Nasiruddin et al. (2023), concerning the current trends of energy use in Southern California, there is great dependence on conventional grid systems, whereas there is a serious need for a wide array of renewable energy solutions. While solar and other renewable energies have begun to be integrated, efficiencies at the point of distribution, storage, and use continue to lag. Besides, increased air conditioning throughout the summer period creates peaking demand periods that stress the grid infrastructure of the region and result in rolling blackouts and increased energy prices. Such challenges require a holistic approach: technological innovation in combination with proactive policy measures.

*Problem Statement*

Rahman et al. (2024), reported that inefficient energy use in Southern California is a critical problem. While renewable energy technologies are increasingly advanced, the region still faces high levels of energy waste and excessive emissions of greenhouse gases. The inefficiencies are because of outdated infrastructure, behavioral patterns in consumers, and the limited application of data-driven energy optimization techniques. These are further exacerbated by the environmental effects of burning fossil fuels: air pollution and acceleration of climate change. The environmental and economic consequences of inefficient use of energy make the search for new solutions a pressing need. Badly optimized energy systems waste valuable resources and inhibit progress toward long-term sustainability. Today, the energy landscape in Southern California urgently requires a change of attitude toward smarter, adaptive patterns of energy consumption, which could work together with the region's sustainability goals (Shawon et al., 2023).

## Research Objectives

The present study aims to develop AI-driven strategies that will optimize energy consumption patterns in the residential and commercial sectors of Southern California. This research project, therefore, seeks to apply state-of-the-art AI-enabled methodologies and machine learning with real-time monitoring, using predictive analytics to spot potentials for inefficiency in the present utilization of energy consumption, forecast the demand for energy in historical and real-time data, propose actionable interventions to reduce energy waste, improve the integration of variable renewable sources into the grid, and support policymakers and stakeholders in their decision-making toward achieving sustainability targets. The overall objective will be to illustrate how AI might act as a transformative tool in the solution to energy challenges and sustainable management of resources in one of the most energy-intensive regions within the United States.

*Scope of this Research*

The prime focus of this study is on the residential and commercial sectors in Southern California, which collectively account for a substantial share of the region's total energy consumption. These sectors typically have typical different energy-use patterns and distinct challenges. The residential sector comprises households that use electricity for heating, cooling, lighting, and electronic devices. The amount of energy consumption depends upon various factors such as family size, level of income, and climatic conditions. The commercial sector is constituted by office buildings, retail outlets, and industrial firms that consume energy in lighting, heating and cooling ventilation systems, machinery, and other operations. Energy efficiency in the commercial sector becomes important for a reduction in operational costs and reduction of impacts on the environment.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

## Literature Review

*Energy Consumption Patterns in Southern California*

Sumon et al. (2024), posit that the unique combination of climatic, demographic, and economic factors in Southern California has shaped its energy consumption patterns. In the residential sector, energy use has been seasonal, peaking during the very hot summer months of the year due to the heavy reliance on air conditioning systems. Commercial energy use is rather constant throughout the year, influenced by lighting, HVAC, and other operation-specific industries and businesses.

Recent data shows that the residential sector is responsible for about 40% of the region's electricity use, while the commercial sector contributes close to 35%. Key trends indicate a gradual rise in energy efficiency measures, including the adoption of LED lighting and Energy Star-rated appliances. However, significant inefficiencies remain due to behavioral factors, outdated infrastructure, and low penetration of smart energy management systems. For instance, many households continue to use high-energy appliances during peak hours, further increasing grid stress and translating into higher energy costs (Sumsuzoha et al., 2024).

According to Zeeshan et al. (2024), the commercial sector also faces challenges in energy consumption. Office buildings and retail stores often operate inefficiently because the older facilities lack updated insulation or HVAC technologies. The shift to remote work during the COVID-19 pandemic has brought new dynamics into energy usage patterns: increased residential demand and reduced commercial energy use during business hours.

*AI Applications in Energy Management*

Alam et al. (2023), indicated that Artificial intelligence holds the key to unlocking far-reaching potential in the field of energy inefficiency and consumption optimization. AI techniques such as machine learning, deep learning, and predictive analytics are increasingly being employed in the monitoring, analysis, and management of energy systems in real time. These technologies enable the development of intelligent energy management systems that can perform demand forecasting, and anomaly detection, and recommend energy-saving interventions (Debnath et al., 2024b).

Case studies on different aspects have proved that AI can be successfully implemented in energy management. For example, AI-enabled smart grid systems have been deployed in different regions to improve the reliability of the grid and allow better integration of variable renewable energy sources (Chaloumis et al., 2024). AI-driven demand response programs in Southern California can demonstrate peak demand reduction by incentivizing consumption adjustment during critical periods (Hasan, 2024).

Machine learning algorithms have been used in several commercial buildings to optimize the operation of HVAC systems, thus allowing energy savings of up to 30%. Even with such progress, the scaling of AI applications in various settings remains a challenge. Major issues, such as the quality and availability of data, impact an AI model's performance (Bale et al., 2024). Large-scale investment and technical acumen are also required to integrate AI systems into the current infrastructure. Overcoming these challenges will be of paramount importance in reaping full benefits from AI-powered energy management.

*Sustainable Resource Management*

Kaur et al. (2024), asserted that these inventions promote technological, behavioral, and policy interventions for sustainable energy use. The best practices in sustainable resource management call for energy efficiency, adoption of renewable energy, and consumer participation. Some of the strategies that have worked well for residential consumers include energy-efficient home design, smart thermostats, and time-of-use pricing. Similarly, energy audits, retrofitting of older buildings, and investments in renewable energy installations such as rooftop solar panels will go a long way in helping commercial entities (Sumon et al., 2024b).

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

Notwithstanding, deploying these practices is not without challenges. Economic hurdles-for one, the initial capital regarding energy-efficient technologies adopting these difficult among consumers and businesses. Behavioral factors entail resistance to change and/or lack of awareness, complications that further worsen promotional efforts in sustainable practices (Hasanuzzaman et al., 2024). Policymakers have thus played a critical role in addressing these barriers through incentivizing, subsidizing, and spreading awareness of energy efficiency and renewable energy use. Southern California is underpinning its transition toward sustainable resource management with sound policy: the state boasts one of the strongest policies regarding a renewable portfolio and energy efficiency goals. Continuous innovation and collaboration among utilities, technology providers, and consumers will be needed, though (Karmakar et al., 2024)

*Related Research*

As per Khan et al. (2024), energy efficiency is deemed as one of the cheapest approaches to reducing energy demand and, subsequently, any further greenhouse gas emissions. As confirmed by empirical evidence, energy-efficient technologies and practices have been effective approaches in many contexts. Such new smart thermostats using machine learning optimize heating and cooling times for households, which might alone reduce household energy usage by up to 15% in research on residential energy use. In California, for example, studies have shown surprisingly high amounts of energy savings on retrofitting homes with advanced insulation and energy-efficient windows in areas where the weather is the most extreme (Olatunde et al., 2024).

Empirical evidence has also shown that, in the commercial sector, conducting energy audits and implementing targeted retrofitting programs have their benefits. A study of office buildings in New York City estimated that upgrading HVAC systems and lighting to energy-efficient systems achieved an average energy-use reduction of 25%. In the same vein, it has also been shown that energy management systems, driven by IoT and AI, can adjust energy consumption in real-time to avoid unnecessary waste, hence yielding financial savings in operating costs (Shawon et al., 2024b). However, high up-front costs of efficiency technologies and a general lack of consumer awareness persist as major barriers. Empirical studies highlight the need for economic incentives through tax credits and utility rebates, for example help overcome these barriers. The U.S. Department of Energy's Weatherization Assistance Program, for example, has installed energy-efficient technologies in low-income families' homes, saving an average of $283 annually per household (Shen et al., 2024).

Most empirical research has focused on the integration of renewable energy sources, particularly solar and wind energy, into the United States energy grid. One leading example is Southern California, where studies have documented progress made in the region by the use of solar energy (Sumsuzoha et al., 2024). Examples include the California Solar Initiative, a state-sponsored incentive program that has helped residential and commercial properties install more than 3,000 megawatts of solar capacity. Empirical data indeed reveal that solar installations in the State of California annually result in a reduction in the level of carbon dioxide emission by millions of metric tons. This trend is also reflected in research conducted concerning the integration of wind energy in the Midwest (Wen et al., 2024). In states like Iowa and Kansas, for instance, studies conducted by NREL have indicated that more than 30% of electric generation is represented by wind energy generation. The role that renewable energy could play in displacing fossil fuel-based power generation, and hence overall emissions, has been underlined in various such studies (Stecula et al., 2023).

*Data Collection and Preprocessing*

*Data Collection*

The dataset encompassed various energy consumptions, and the data were collected across different building structures in Southern California between January 2018 and January 2024. These datasets included hourly records of electricity consumption for residential and commercial buildings, as well as industrial buildings. Furthermore, it also provided a record of environmental and operating metrics. This dataset is useful to researchers and practitioners who work on forecasting electricity consumption, energy management, sustainability, and developing AI-based optimization models (Dataset-Engineer, 2024). This

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

dataset, due to its diverse features and real-world scenarios, can be applied to time-series analysis, regression tasks, and classification problems. The data was collected from over 100 facilities across Southern California, integrating information from smart meters, IoT sensors, building management systems, and regional utility companies. It covers different seasons, significant events (e.g., public holidays, extreme weather), and varying energy consumption patterns, allowing for robust analysis of electricity usage trends and energy-saving opportunities.

*Data Preprocessing*

Step 1 of the data preprocessing entailed handling missing values by dropping the rows containing missing values or imputing them with appropriate values. Step 2 comprised encoding categorical columns using a label encoder. Step 3 included rationalizing the target variable where "Energy Consumption (kWh)" was converted into classes like "Low", "Medium", and "High" depending on quantile thresholds. Step 4 included Checking the class distribution and removing classes with fewer than 2 samples to address any imbalance and choosing the "Timestamp" feature from the dataset. Step 3 entailed splitting the dataset into training-testing sets in step 3, including feature scaling according to the Standard scaling technique. The feature preprocessing techniques were very crucial in processing data so that it may take input directly from the user or serve as input for any model and save lots of time that might be wasted in solving it manually.

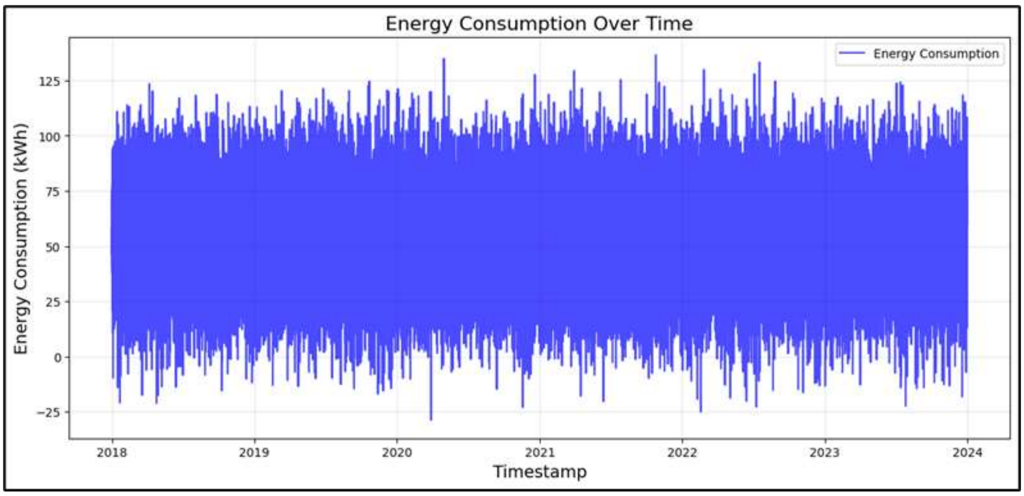
*Exploratory Data Analysis*

A suitable code snippet was applied as a general principle in the exploratory visualization of the dataset. The insights derived from this visualization were useful for understanding the data and possible subsequent analysis or modeling work. This time series visualization allowed the analyst to extract meaningful patterns and trends in energy consumption during the period under consideration. Besides, it revealed some informative patterns, like peaks, seasonality, or changes in the levels of consumption, which will add to further analysis or decision-making processes.

*Energy Consumption Over Time*

Appropriate code snippet was applied which focused on visualizing and analyzing the dataset, particularly the "Energy Consumption (kwh)" over time. The first code converted the "Timestamp" column to a datetime format, which was pivotal for time series analysis. The second step provided general information about the dataset, such as its description and other details. The main part of the code, the visualization step, did a line plot of "Energy Consumption " as a function of time, with appropriate labels, title, and font size as showcased from:

*Output*



Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

**Figure 1. Visualizes Energy Consumption Over Time**

The graph above displays the upward trend with huge fluctuations in energy consumption over time, from the year 2018 to the year 2024. While from 2018 to 2020 there was a gradual rise, from 2020 until 2022 there was a sudden increase in ups and downs, indicating quite a higher variability in energy demand. Similar volatility has continued in 2024, though the upward Consumption seems to have reached a plateau. It can result from several facts, including seasonal, influenced by the economic activities of mankind and technological changes, as well as external factors. For analysis of specific drivers that spur these trends and fluctuations to be reached, more additional overlays are needed to complement these data; that is to say, statistical analyses will form the bedrock upon which pinpointing is done.

*HVAC and Lighting Consumption Over Time*

Subsequently, python code utilized the Seaborn library for creating a line plot in which the variation of the energy consumption with time both for HVAC and Lighting. This code defined figure size, plotted the data on the same plot, assigned labels for x and y and defined a title for it. For better readability of labels of x-axis, rotation was done along x-axis, adding of grid in a plotting area, save as image with.png/.jpeg form. It displayed the trends in energy consumption by the HVAC and lighting systems through graphs that allow a comparison of energy usage by both segments for the given period of time as showcased below:

*Output*

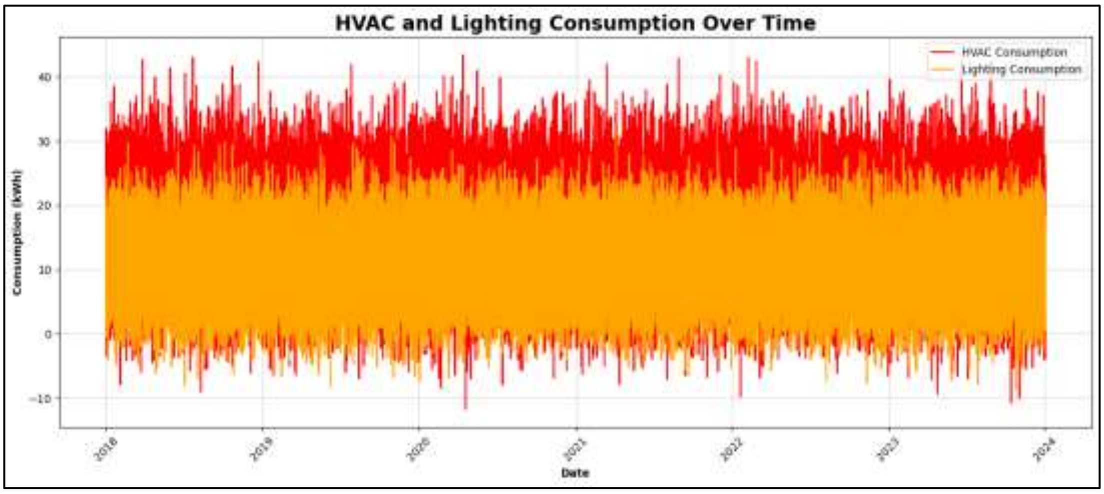



**Figure 2. Showcases HVAC and Lighting Consumption Over Time**

Figure 2 above portrays the Energy consumption of HVAC and Lighting over time from 2018 to 2024. The graph indicates high temporal variation for both HVAC and lighting energy consumption. HVAC remains mostly higher than lighting. Secondly, there is a similar kind of fluctuation in the pattern for both systems which may suggest that there exists some relationship between the two variables in respect to energy demand. It requires further analysis to find the exact influencers of these fluctuations, which range between seasonal variations, occupancies, and equipment efficiency.

*Power Outage Distribution*

Afterward, the utilized Python code snippet generated a bar chart to visualize the distribution of power outages. This code made use of the Seaborn plotting library and set the figure size. The sns.countplot() function plots a bar chart, counting the occurrences of each value in the column 'Power Outage Indicator' in the DataFrame df. The code enhanced the chart with a title and axis labels, turned on gridlines, and saved it as an image file. Finally, the code created a visualization of the power outage data in such a way that it instantly conveys how frequently the dataset contains power outages as showcased below:

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

*Output*

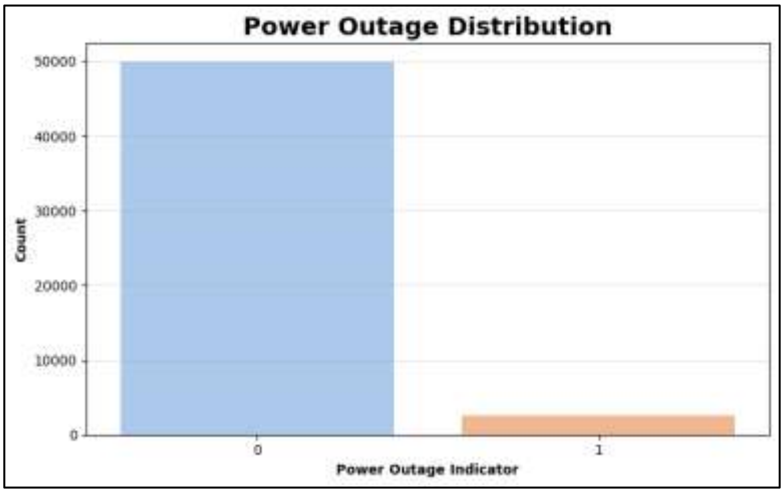



**Figure 3. Depicts Power Outage Distribution**

The bar chart above displays "Power Outage Distribution." It shows the distribution of power outages, ranging from "0" to "1." The bar for "0" is relatively high, implying that most of the data points reflect sites with no power outage. On the other hand, the bar for "1" is short, indicating that a small portion of the sites had power outages. This visualization would suggest that power outages are relatively rare within the dataset represented.

*Occupancy Rate by Building*

This code in Python showcased the distribution of the rate of occupancy across building use types as a box plot. It first imported a plotting library called Seaborn and set the figure size. The sns.boxplot() function created the box-and-whisker plot that illustrated graphically the distribution in the rates of occupancy for the different building types. The code then added a title, and axis labels, rotated x-axis labels for better readability, added gridlines, and saved the plot as an image file. Subsequently, the code effectively produced the visualization of the occupancy rate data, thereby allowing quick comparison and analysis of the occupancy rate distribution across different building types as showcased below:

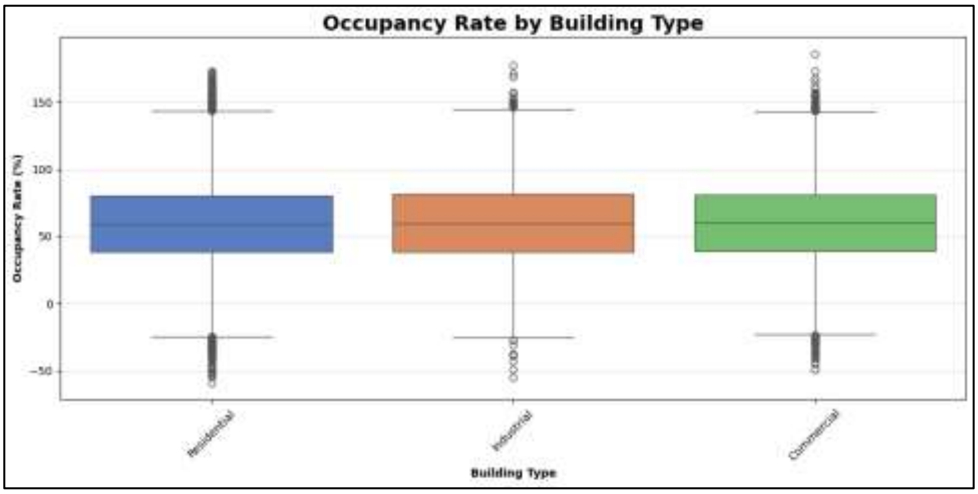



**Figure 4. Illustrates Occupancy Rate by Building Type**

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

The above box plot compared the distribution of occupancy rates across building types: Residential, Industrial, and Commercial. The analyst observed that residential buildings are usually lowly occupied within the range between 0 to 50%; for industries, there is a wider variability in the occupancy rate with some values indicating a high rate of occupancy. Commercial is similar to Industrial, but the distribution is broader and there are some high occupancy outliers. Generally speaking, this plot suggests that the distribution of occupancy varies greatly depending on the type of building: Residential buildings tend to have a lower occupancy compared to Industrial and Commercial buildings.

*Distribution of Carbon Emission Rate*

Python code snippet created a histogram showing the distribution of carbon emission rates. This script leverages the plotting library Seaborn and also sets the figure size. The sns.histplot() function created the histogram in 30 bins, colored in purple with slight transparency. It effectively created a visualization of the carbon emission rate data to understand the distribution and frequency of different rates across the dataset as showcased below:

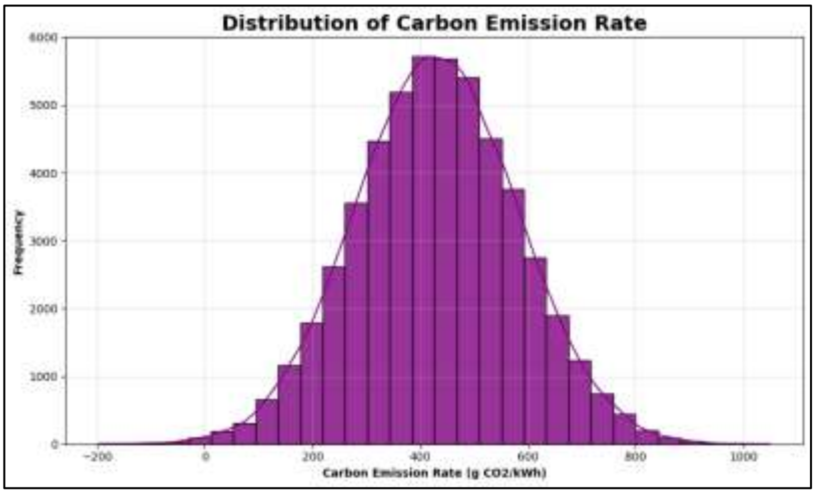



**Figure 5. Portrays Distribution of Carbon Emission Rate**

This histogram exhibits the different ranges of carbon emission rates according to their frequencies, in gram $CO_2$/kWh: In this histogram, the right skewed bell shape distribution peaks somewhere at approximately 400 g of $CO_2$/kWh-a pattern revealing the normal pattern seen as being very common. The observations of the variable are lesser toward both the lower and higher extremes of the distributions. It further indicates a normal distribution and has been overloaded on the histogram with a density curve, which is a continuous representation of data. From this graph, it is insightful to view the range in which carbon emission rates generally lie and how they are distributed.

## Methodology

*Feature Engineering and Selection*

As regards to the exploratory data analysis (EDA) of the power outage dataset, distinct feature engineering methods were applied to elevate the model's predictive capabilities. New variables were then derived based on those that already existed; these include average power consumption during peak hours and the frequency of outages over the previous months. We further did one-hot encoding on categorical variables to numerical forms with the method of one-hot encoding. This will avail a means through which such information might influence the model. Not only was this enrichment added to the data, but it gave more insightful granular insights into the contributing factors of the power outages.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

After feature engineering was complete, the focus turned toward feature selection on the most predictive variables that would suit our model best. Feature correlation analysis with the target variable was done to identify features that were either redundant or irrelevant. Besides the mentioned, other techniques include Recursive Feature Elimination and feature importance from tree-based models, enabling feature ranking regarding predictive power. We systematically assess the contribution of each feature toward the performance of our model, allowing us only to retain the most impactful features, which enhanced model accuracy and interpretability. The careful approach toward feature engineering and selection has gone a long way in ensuring that not only is the model parsimonious, but it is also robust in predicting power outages.

*Model Selection*

Proven machine-learning techniques have been used in the study of power outage prediction to capture a variety of patterns within the data. Logistic Regression was considered due to its simplicity and interpretability; it allowed us to understand the relationship between the independent features and the target variable. However, since most real-world data has nonlinear relationships, much more complex models were explored. The decision to use Random Forest was because of its capability to work with big data provided, the majority with higher dimensionality. Most of the time, ensemble methods are resistant to overfitting and generate pool predictions from many trees within their fold, which generally brings not only very accurate but also pretty stable models. Besides, another useful feature of using a random forest was feature importance that indicates for which variables the changes might cause more impact on power outages.

Furthermore, XG-Boost was used further to improve the predictive performance. Its efficiency and effectiveness in handling big datasets have been a major reason for choosing this approach. Considering that it is a tree-based, gradient-boosting framework, XG-Boost learns iteratively to capture complicated patterns in data, making it more appropriate for complex data with possibly nonlinear relationships. Its high performance with limited hyperparameter tuning has made it very popular in competitive machine learning. This work allowed a comprehensive analysis of the factors that influence power outages through the combination of these techniques, leveraging the interpretability of simpler models and the high performance of more advanced algorithms. In the end, this multilayered approach provided robust predictions and deep insights into power outage events.

*Model Development and Evaluation*

The models were developed and evaluated under the construction of a robust predictive system that helps in power outages. To enable our models to generalize well on unseen data, we adopted a structured approach for training and testing the model using cross-validation. K subsets were made from the data using the k-fold cross-validation methodology. The model was trained on k-1 of these subsets and validated on the remaining one while rotating this process until every subset had served as a validation set. This approach not only maximized the amount of data available for training but also gave a realistic estimate of the model's performance by reducing variance and mitigating the overfitting problem. This provided a better understanding of the actual performance of our models in a real-world scenario by averaging the performance metrics across all folds.

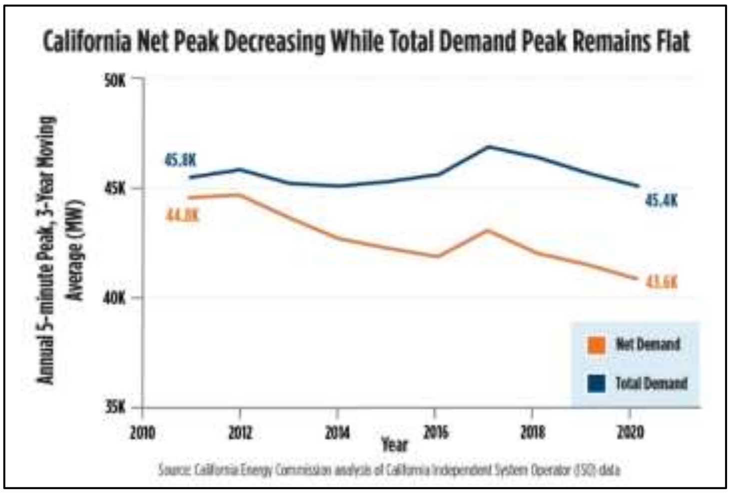
The performance of the trained models was then evaluated against an extended set of performance metrics-accuracy, precision, recall, F1-score, and Root Mean Square Error. Accuracy was a simple, direct measure of general correctness, while precision and recall were measures of the model's ability to correctly identify positive instances representing outages-relatively to its tendency to incorrectly predict such. The F1-score was the harmonic mean of precision and recall and thus gave a balanced view, something that is important in many such problems where class balance could be an issue. The RMSE was calculated for the regression-based models as an average magnitude of prediction errors, thereby providing us with how close the predicted values were to the actual outcomes. This evaluation was followed by hyperparameter tuning: a careful search using Grid Search and Random Search to come up with the best hyperparameters for our models.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

The reason for this is to make sure that, by systematically exploring various combinations of hyperparameters, we come up with a much more accurate and robust model that best suits our aim of effectively predicting power outages. This in-depth approach in model development and evaluation allowed for the creation of a reliable predictive system able to deliver actionable insights.

## Results and Analysis

*Energy Consumption Pattern Analysis*




The graph above compares the annual 5-minute peak net demand and total demand in California from 2010 to 2020. This graph shows us net peak demand trending down on-year by this interval within this period, while peaks of total demand remain consistently flat. This can be interpreted as the inference that California's energy system has gotten more efficient and depends less on peak-load plants to function. Other factors that may contribute to reducing the net demand peak would include increased energy efficiency, growth in renewable energy supplies, and demand-side management programs.

*AI Model Performance Evaluation*

*Logistic Regression*

The Python code snippet implemented the Logistic Regression model for classification. The code imported the class from the sci-kit-learn library and instantiated a LogisticRegression model. It fits the model on the training data (X_train, y_train) using the fit() method. The subsequent prediction of class labels makes use of this trained model on the test data X_test and the result is stored in the y_pred_log variable. Eventually, it printed performance metrics, such as the confusion matrix, classification report, and accuracy score, all to give an overview of Logistic Regression performance on test data.

*Output*

**Table 1. Exhibits Logistic Regression Classification Report**

| **Logistic Regression Results:** | | | | |
|---|---|---|---|---|
| | **precision** | **recall** | **f1-score** | **support** |
| | | | | |
| 0 | 0.33 | 0.50 | 0.40 | 3576 |
| 1 | 0.33 | 0.25 | 0.28 | 3470 |
| 2 | 0.34 | 0.25 | 0.29 | 3471 |
| | | | | |
| **accuracy** | | | 0.33 | 10517 |

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

| | | | | |
|---|---|---|---|---|
| **macro avg** | 0.33 | 0.33 | 0.32 | 10517 |
| **weighted avg** | 0.33 | 0.33 | 0.32 | 10517 |
| | | | | |
| **Accuracy:** 0.334220785395 07466 | | | | |

This classification report showcases relatively low performance for all classes with low precision, recall, and F1 scores. The precision was 0.33 for class 0, whereas recall was 0.50 with an F1-score of 0.40. In class 1, the values were 0.33, 0.25, and 0.28, while in class 2, these values became 0.34, 0.25, and 0.29 for precision, recall, and F1 scores, respectively. Moreover, the overall accuracy is just 0.33 for the model, meaning correct prediction of the class is seen only in about 33% of the cases. From this, it is determined that this model has difficulty classifying the instances into their appropriate classes and needs further adjustments.

*Random Forest*

The Python code snippet implemented a Random Forest classifier for a machine-learning task. It imports the necessary class from the sci-kit-learn library and creates an instance of the Random Forest Classifier with 100 trees and a specified random state for reproducibility. The model is then trained on the training data (X_train, y_train) using the fit() method. Subsequently, the trained model is used to predict the class labels for the test data (X_test), and the results are stored in y_pred_rf. Finally, the code prints evaluation metrics such as the confusion matrix, classification report, and accuracy score to assess the performance of the Random Forest model on the test data.

*Output*

**Table 2. Portrays Random Forest Classification Report**

| | | | | |
|---|---|---|---|---|
| Random Forest Results: | | | | |
| | precision | recall | f1-score | support |
| | | | | |
| 0 | 0.35 | 0.42 | 0.38 | 3576 |
| 1 | 0.34 | 0.31 | 0.32 | 3470 |
| 2 | 0.33 | 0.30 | 0.31 | 3471 |
| | | | | |
| accuracy | | | 0.34 | 10517 |
| macro avg | 0.34 | 0.34 | 0.34 | 10517 |
| weighted avg | 0.34 | 0.34 | 0.34 | 10517 |
| | | | | |
| Accuracy: 0.34182751735285727 | | | | |

The provided classification report showcases the performance of a Random Forest algorithm on a multi-class classification task. The algorithm exemplified relatively below-average performance across all classes, with low precision, recall, and F1 scores. Class 0, Precision: 0.35, Recall: 0.42, F1-score: 0.38, Class 1, Precision: 0.34, Recall: 0.31, F1-score: 0.32 Class 2 Precision: 0.33, Recall: 0.3 F1:0.31. Also, the overall accuracy of the model is low, standing at 0.34-which shows that it correctly predicts the class in only about 34% of the instances. This may be a sign of poor generalization by the model during the classification of instances in their respective classes.

*XG-Boost*

The Python code script deployed an XG-Boost classifier for a machine-learning task. The script imported a class from a library named xg-boost; after that, it instantiated a class of XG-Classifier with parameters: use_label_encoder=False, eval_metric='logloss', and then the fit() method is used on the model with the training data. Finally, the trained model has been used for the prediction of class labels on the test data X_test and is stored in y_pred_xgb. The code prints some evaluation metrics: the confusion matrix,

Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

classification report, and accuracy score that would help assess the performance of the XG-Boost model on unseen data.

**Table 3. Displays the XG-Boost Classification Report**

| **XGBoost Results:** | | | | |
|---|---|---|---|---|
| | **precision** | **recall** | **f1-score** | **support** |
| 0 | 0.35 | 0.37 | 0.36 | 3576 |
| 1 | 0.33 | 0.31 | 0.32 | 3470 |
| 2 | 0.33 | 0.32 | 0.32 | 3471 |
| **accuracy** | | | 0.34 | 10517 |
| **macro avg** | 0.33 | 0.34 | 0.33 | 10517 |
| **weighted avg** | 0.34 | 0.34 | 0.34 | 10517 |
| **Accuracy:** 0.3356470476371589 | | | | |

This classification report demonstrates the performance of the XG-Boost algorithm on a multi-class classification task. It performs modestly across all classes, with precision, recall, and F1-scores generally around 0.33. Specifically, for class 0, precision is 0.35, recall is 0.37, and F1-score is 0.36. For class 1, these values are 0.33, 0.31, and 0.32, respectively. Class 2 has 0.33 precision, 0.32 recall, and 0.32 F1 score. Generally, the performance of the model stands at 0.34 accuracy, correctly predicting the class in roughly 34% of cases. This indeed does reveal that the model is somewhat improved compared to the previous ones; it still seems to be struggling in the classification of instances into their correct classes and hence its optimization is of utmost welcome.

*Comparison of All Models*

This code snippet in Python compared the performance of three machine learning models: Logistic Regression, Random Forest, and XG-Boost. It creates a list of model names and then calculates the accuracy score for each of the models using the accuracy_score function from sci-kit-learn. Then, it creates a bar plot using the Seaborn library with the accuracy scores of different models. The plot then customized with a title, axis labels, and appropriate y-axis limits. Finally, the plot was displayed using plt.show() as showcased below:

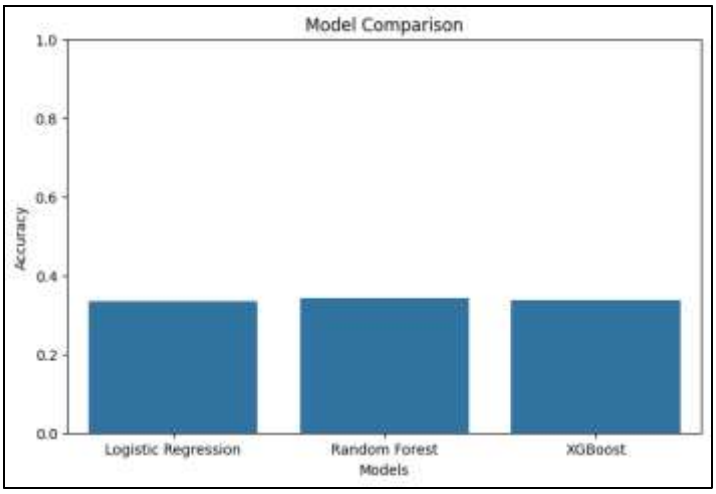



**Figure 6. Visualizes Model Comparison**

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

The bar chart above presents the accuracy scores for three machine learning models, namely Logistic Regression, Random Forest, and XG-Boost. All three models share very close accuracy scores at about 0.35. This means that at this metric of accuracy, no significant difference in performance may be identified among these models on the given dataset. Other metrics or techniques like cross-validation may be considered in such cases to come up with subtle differences in performance.

*Energy Savings Potential Estimation Using AI*

AI algorithms can analyze huge amounts of energy consumption data and find patterns and anomalies that human analysts may not find. By utilizing machine learning techniques such as regression, clustering, and anomaly detection, AI will accurately predict energy consumption under different conditions. This predictive capability enables the estimation of potential energy savings from different interventions. These may include AI simulations of energy-efficient measures such as LED lighting upgrades, HVAC system optimization, and building automation. In such cases, AI can quantify the expected energy savings by comparing the predicted consumptions against a baseline scenario and provide further valuable insights for decision-making.

*Case Studies*

Several case studies have been conducted in Southern California that outline how actual energy efficiency improvements have been influential in both the residential and commercial sectors. An example of such is the Energy Upgrade California program initiated by the California Energy Commission. The program aims at a reduction in energy consumption in homes through comprehensive home retrofits with energy-efficient appliances, better insulation, and better heating and cooling systems. For example, one case study reveals that a family living in Los Angeles, after retrofitting an HVAC system and adding insulation, reduced their energy bills by 30% and reduced their emissions of greenhouse gases by an amount that was quite substantial.

Another strong example involves the retrofitting of commercial buildings in downtown Los Angeles, wherein the LADWP partnered with local enterprises to make the buildings more energy-efficient under its Commercial Energy Efficiency Program. It provides incentives for projects with LED lighting, high-efficiency HVAC systems, and smart building technologies. One of the office buildings retrofitted its lighting and HVAC systems, recording energy savings of over 40 percent and decreasing operating costs while greatly improving comfort and productivity for tenants. In addition, greater integration of renewable energy resources, including solar panels, has also been important in enhancing energy efficiency in the region. For example, community solar projects allowed several families in San Diego to share in the benefits brought forth by solar energy, reducing, on the whole, their reliance on conventional sources of energy and lowering overall energy costs. The results from these case studies confirm that targeted energy efficiency programs are taking place across Southern California and are not only creating economic savings for residents and businesses, but their valuable contributions are also resulting in the environmental sustainability of the highest level, serving as a model for energy-conscious practices in Southern California.

## Discussion

*Implications of AI-Driven Energy Management*

The integration of AI into an energy management system has very significant advantages along with huge challenges. Among the primary benefits is real-time analysis of a large amount of data leading to more accurate energy demand and supply forecasting, enabling utilities to optimize energy distribution, reduce wastages, and improve reliability. For instance, AI algorithms can predict peak demand periods by studying historical consumption patterns and other external factors such as weather conditions. Additionally, AI can facilitate the integration of renewable sources of energy to optimize their usage and ensure that resources like solar and wind are put to good use. This leads to better energy efficiency and a reduction in consumer costs, while also being beneficial for environmental sustainability by reducing dependency on fossil fuels.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

Offsetting the benefits of deploying AI in energy management, however, is a set of challenges. Energy consumer data raises significant data privacy and security concerns-for one thing because data collection and analysis raise critical questions about consent and the potential for misuse. AI systems could be too complex for general adoption, especially by small utilities or organizations that are not very technical. Then, there is the issue of algorithmic bias, whereby AI systems could inadvertently favor one source of energy over another or one consumer group over another, creating unequal outcomes. The only way such challenges could be surmounted is by the stakeholders' concerted effort to make sure that AI is implemented responsibly and equitably.

*Policy and Regulatory Recommendations*

To promote sustainable energy in Southern California, there is a need for the policymaker to create an enabling regulatory framework that encourages innovation with the protection of consumer interests. For instance, it is important to encourage the adoption of AI-driven technologies through financial subsidies or tax credits for both residential and commercial users; this would help reduce the initial costs associated with installing advanced energy management systems, thus making them more accessible. Moreover, clear standards and policies on data privacy and security will be fundamental in trusting consumers and eliciting their participation in AI initiatives. This initiative would further enhance collaboration between utilities, technology companies, and research institutions in the rapid development of innovative AI solutions that are needed locally.

Policymakers are also encouraged to institute demand response programs using AI mechanisms that ensure efficiency in energy consumption at peak periods and, in turn, give financial incentives to consumers who reduce their consumption of energy. Finally, educative program design will create awareness among the public on the importance of AI in energy management; this will increase acceptance and participation in such programs, thus leading to better sustainable energy use across the region.

*Future Research Directions*

A few of the important areas where immense opportunity for future research can be undertaken are to further develop the integration of renewable energy sources, electric vehicle charging, and energy storage into AI models. Some of them are the development of AI algorithms to optimize the management of distributed energy resources like solar panels, wind turbines, and battery storage systems. With AI, it can analyze in real time a variety of data from these sources and help balance supply and demand, using renewable energy when it is available and storing energy for later use.

Besides, studies on AI-driven solutions in EV charging infrastructure are necessary amid the increasing adaptation of electric vehicles. Smart charging, powered by AI, could optimize charging times about grid demand, energy prices, and renewable energy supply to reduce stress on the grid and enhance overall efficiency. Further, AI can unleash a potential integration with energy storage technologies that might lead to better management of the energy reserve and ensure stored energy is used during peak demand periods or when renewable generation is low. Overall, AI and energy management stand out as one of the hotbeds of innovation, with tremendous potential to challenge conventional assumptions on how energy is harnessed and used. Southern California will be well on its way to a more efficient, fair, and sustainable energy future by overcoming the challenges and capitalizing on the opportunities identified here.

## Conclusion

In summation, the findings of this research project highlight the noteworthy potential of AI-driven energy management systems in optimizing energy consumption and enhancing efficiency across various sectors. Indeed, key findings imply that such AI technologies as predictive analytics, combined with real-time processing, lead to more accurate forecast cases concerning energy demand, and integration of renewable resources, and thus enable facilities with greater reductions in operational expenditure as well as minimized emissions of greenhouse gases. The wider ramifications of such developments extend beyond immediate economic benefits; in developing ever-smarter ways of consuming energy, AI models contribute to

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

sustainability by encouraging a shift toward cleaner energy and reducing dependence on fossil fuels. AI in energy management supports not only efficient resource use but also plays a very important role in the fight against climate change and long-term environmental objectives.

## References

Alam, M., Islam, M. R., & Shil, S. K. (2023). AI-Based Predictive Maintenance for US Manufacturing: Reducing Downtime and Increasing Productivity. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 541-567.

Bale, A. S., William, P., Kondekar, V. H., Sanamdikar, S., Joshi, P., Nigam, P., & Savadatti, M. B. (2024). Harnessing AI and IoT for optimized renewable energy integration and resource conservation. Library Progress International, 44(3), 1412-1426.

Challoumis, C. (2024, October). BUILDING A SUSTAINABLE ECONOMY-HOW AI CAN OPTIMIZE RESOURCE ALLOCATION. In XVI International Scientific Conference (pp. 190-224).

Chowdhury, M. S. R., Islam, M. S., Al Montaser, M. A., Rasel, M. A. B., Barua, A., Chouksey, A., & Chowdhury, B. R. (2024). PREDICTIVE MODELING OF HOUSEHOLD ENERGY CONSUMPTION IN THE USA: THE ROLE OF MACHINE LEARNING AND SOCIOECONOMIC FACTORS. The American Journal of Engineering and Technology, 6(12), 99-118.

Dataset-Engineer. (2024, October 24). Southern California energy consumption. Kaggle. https://www.kaggle.com/datasets/datasetengineer/southern-california-energy-consumption

Debnath, P., Karmakar, M., Khan, M. T., Khan, M. A., Al Sayeed, A., Rahman, A., & Sumon, M. F. I. (2024). Seismic Activity Analysis in California: Patterns, Trends, and Predictive Modeling. Journal of Computer Science and Technology Studies, 6(5), 50-60.

Debnath, P., Karmakar, M., & Sumon, M. F. I. (2024). AI in Public Policy: Enhancing Decision-Making and Policy Formulation in the US Government. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 169-193.

Egbemhenghe, A. U., Ojeyemi, T., Iwuozor, K. O., Emenike, E. C., Ogunsanya, T. I., Anidiobi, S. U., & Adeniyi, A. G. (2023). Revolutionizing water treatment, conservation, and management: Harnessing the power of AI-driven ChatGPT solutions. Environmental Challenges, 13, 100782.

Hasan, M. R. (2024). Revitalizing the electric grid: A machine learning paradigm for ensuring stability in the USA. Journal of Computer Science and Technology Studies, 6(1), 141-154.

Hasanuzzaman, M., Hossain, S., & Shil, S. K. (2023). Enhancing Disaster Management through AI-Driven Predictive Analytics: Improving Preparedness and Response. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 533-562.

Karmakar, M., Debnath, P., & Khan, M. A. (2024). AI-Powered Solutions for Traffic Management in US Cities: Reducing Congestion and Emissions. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 194-222.

Kaur, S., Kumar, R., Singh, K., & Huang, Y. L. (2024). Leveraging artificial intelligence for enhanced sustainable energy management. Journal of Sustainable Energy, 3(1), 1-20.

Khan, M. A., Debnath, P., Al Sayeed, A., Sumon, M. F. I., Rahman, A., Khan, M. T., & Pant, L. (2024). Explainable AI and Machine Learning Model for California House Price Predictions: Intelligent Model for Homebuyers and Policymakers. Journal of Business and Management Studies, 6(5), 73-84.

Nasiruddin, M., Al Mukaddim, A., & Hider, M. A. (2023). Optimizing Renewable Energy Systems Using Artificial Intelligence: Enhancing Efficiency and Sustainability. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 846-881.

Olatunde, T. M., Okwandu, A. C., Akande, D. O., & Sikhakhane, Z. Q. (2024). Reviewing the role of artificial intelligence in energy efficiency optimization. Engineering Science & Technology Journal, 5(4), 1243-1256.

Rahman, S., Islam, M., Hossain, I., & Ahmed, A. (2024). Utilizing AI and data analytics for optimizing resource allocation in smart cities: A US based study. International journal of artificial intelligence, 4(07), 70-95.

Shawon, R. E. R., Chowdhury, M. S. R., & Rahman, T. (2023). Transforming Urban Living in the USA: The Role of IoT in Developing Smart Cities. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 917-953.

Shawon, R. E. R., Rahman, A., Islam, M. R., Debnath, P., Sumon, M. F. I., Khan, M. A., & Miah, M. N. I. (2024). AI-Driven Predictive Modeling of US Economic Trends: Insights and Innovations. Journal of Humanities and Social Sciences Studies, 6(10), 01-15.

Shawon, R. E. R., Dalim, H. M., Shil, S. K., Gurung, N., Hasanuzzaman, M., Hossain, S., & Rahman, T. (2024). Assessing Geopolitical Risks and Their Economic Impact on the USA Using Data Analytics. Journal of Economics, Finance and Accounting Studies, 6(6), 05-16.

Shen, Q., Wen, X., Xia, S., Zhou, S., & Zhang, H. (2024). AI-Based Analysis and Prediction of Synergistic Development Trends in US Photovoltaic and Energy Storage Systems. International Journal of Innovative Research in Computer Science & Technology, 12(5), 36-46.

Stecuła, K., Wolniak, R., & Grebski, W. W. (2023). AI-Driven urban energy solutions—from individuals to society: a review. Energies, 16(24), 7988.

Sumon, M. F. I., Osiujjaman, M., Khan, M. A., Rahman, A., Uddin, M. K., Pant, L., & Debnath, P. (2024). Environmental and Socio-Economic Impact Assessment of Renewable Energy Using Machine Learning Models. Journal of Economics, Finance and Accounting Studies, 6(5), 112-122.

**Journal of Ecohumanism**
2025
Volume: 4, No: 1, pp. 2920 – 2935
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.6087

Sumon, M. F. I., Khan, M. A., & Rahman, A. (2023). Machine Learning for Real-Time Disaster Response and Recovery in the US. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 700-723.

Sumsuzoha, M., Rana, M. S., Islam, M. S., Rahman, M. K., Karmakar, M., Hossain, M. S., & Shawon, R. E. R. (2024). LEVERAGING MACHINE LEARNING FOR RESOURCE OPTIMIZATION IN USA DATA CENTERS: A FOCUS ON INCOMPLETE DATA AND BUSINESS DEVELOPMENT. The American Journal of Engineering and Technology, 6(12), 119-140.

Wen, X., Shen, Q., Zheng, W., & Zhang, H. (2024). AI-driven solar energy generation and smart grid integration a holistic approach to enhancing renewable energy efficiency. International Journal of Innovative Research in Engineering and Management, 11(4), 55-66.

Zeeshan, M. A. F., Sumsuzoha, M., Chowdhury, F. R., Buiya, M. R., Mohaimin, M. R., Pant, L., & Shawon, R. E. R. (2024). Artificial Intelligence in Socioeconomic Research: Identifying Key Drivers of Unemployment Inequality in the US. Journal of Economics, Finance and Accounting Studies, 6(5), 54-65.