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Renewable Energy Consumption Forecasting Using Machine Learning Models

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ABSTRACT :

Forecasting energy consumption is essential for system stability, renewable energy integration, and effective resource management. For this, machine learning (ML) models such as ensemble approaches (e.g., Random Forest), neural networks, and linear regression are effective tools. Large dataset analysis, pattern recognition, and non-linear energy trend prediction are all areas in which these models shine. Demand-side management, smart grids, and renewable energy forecasts are a few examples of ML applications that allow for real-time grid choices and optimal resource allocation. But issues like resource demands, feature engineering, and data quality continue to exist. Enhancing these areas will increase machine learning's contribution to energy forecasting and the advancement of sustainable energy solutions.

Keywords: Energy Consumption Forecasting, Machine learning (ML), Renewable energy, Neural networks, Ensemble methods, Smart grids, Energy management, Data quality, Feature engineering, Resource allocation

1. Introduction :

The essence of humanity is energy. Everywhere, energy conservation is a popular topic, and as the world economy grows, certain nations' energy problems are getting worse. At around one-third of the overall energy consumption, the construction industry is one of the top three energy consumers in society and is expected to keep growing. Due to the country's growing economy and urbanization, China's energy consumption is increasing daily, making it a major global factor. In many ways, energy permeates every aspect of our existence. Because of the energy in the food we eat, humans are able to move, talk, lift objects, and throw frisbees. As long as humans and animals have existed on Earth, using food as fuel has greatly aided in survival.

1. It might be somewhat hectic to get meals for nourishment and energy. task that occupies the majority of people's waking hours in several developing nations.Despite the fact that obtaining food is a necessity in developed countries, the increased mechanization of agricultural production means that only a comparatively limited number of people actively participate in this process. Most people are therefore free to pursue other hobbies for the remainder of their life. Estimating energy consumption can help with resource allocation, shore-side electrical system sizing, and energy-saving measure evaluation. Reduced energy consumption and higher energy production are the two main factors impacting national economies.
2. The agricultural sector in Turkey, for instance, uses a lot more energy in the form of engine fuel than it generates in the form of useable calories from food. Massive amounts of energy are also used to make goods, heat homes, run cars, provide electricity, and carry out a variety of other tasks. For our civilization to operate as it does now, a significant amount of coal, natural gas, and oil must be taken out of the soil and consumed. Although we also use energy from nuclear reactors, wind turbines, hydroelectric facilities, and geothermal plants, their contributions are less significant. We also receive a lot of energy directly from the sun. Artificial Intelligence (AI), especially machine learning (ML), has recently improved the predicting of energy use and performance.

This research is divided into five parts. The several forms of energy are covered in Section Two after this introduction. An overview of predicting energy use is given in Section Three. diverse machine learning techniques are described in Section Four, along with examples of how they are applied in diverse industries to predict energy consumption, both renewable and non-renewable. Section Five presents the conclusions at the end.

2. Types of Energy :

2.1 Non-Renewable Energy

All fossil fuels, such as coal, oil, and natural gas, as well as nuclear fuels, such as uranium-235 for fission and deuterium for fusion, and some types of geothermal energy, are considered non-renewable energy sources. The size, pace of use, and availability of a non-renewable resource all affect when it will run out. For example, it is estimated that a vigorous nuclear fission energy program could take centuries to exhaust the fossil fuel supply, decades to exhaust the heat energy from some nearby geothermal locations, and a comparable amount of time to exhaust the ground's uranium-235 reserves. Geothermal energy is therefore likewise categorized as non-renewable. In Turkey, fossil fuels like coal, natural gas, and oil provide about 85% of the country's energy. Under extreme heat and pressure under the Earth's surface, plant and animal matter decomposed and changed into hydrocarbon molecules hundreds of millions of years ago, giving rise to these resources. Fossil fuels have become more and more important to industrial societies since the beginning of the industrial age. About 150 years ago, firewood provided the majority of the thermal energy in the Turkish economy, which was mostly dependent on human and animal work. The use of firewood now makes up less than 1% of all energy used, and manual labour is no longer as prevalent.

2.2 Renewable Energy

Nezhnikova et al. claim that a number of advantages have helped explain the notable rise in the usage of renewable energy sources in recent years. First, renewable energy sources present chances to vary fuel combinations from the standpoint of energy security. Second, their broad use lessens the effects on the environment, such as reduced air pollution and CO_2 emissions. Third, in reaction to the global economic crisis, recovery plans actively include renewable energy sources. Finally, they can be a workable answer to the current energy dilemma. Armstrong and Hamrin go on to classify renewable energy sources into a number of categories, including geothermal (using the heat from the Earth), biomass (made from plant materials), wind, sun, hydropower, and ocean energy (which includes wave, tidal, and sea current energy).

3. Machine Learning :

One important use of artificial intelligence (AI) is machine learning (ML), which allows systems to learn from their experiences and get better without explicit programming. The foundation of this learning strategy is in-depth data investigation. Reinforcement learning, supervised learning, unsupervised learning, and semi-supervised learning are the four main machine learning learning techniques, and each is designed to handle a particular kind of issue.A classification of machine learning algorithms can be found in the following categories:

3.1. Supervised Learning

Giving the computer training data that consists of observations and the associated known output values is known as a supervised learning problem. In order to forecast results for new, unseen data when the input values are known but the outputs are not, it is necessary to create generic rules, or a "model," that can map inputs to outputs. The two primary categories of supervised learning are (i) classification, which yields categorical output values, and (ii) regression, which yields numerical output values.

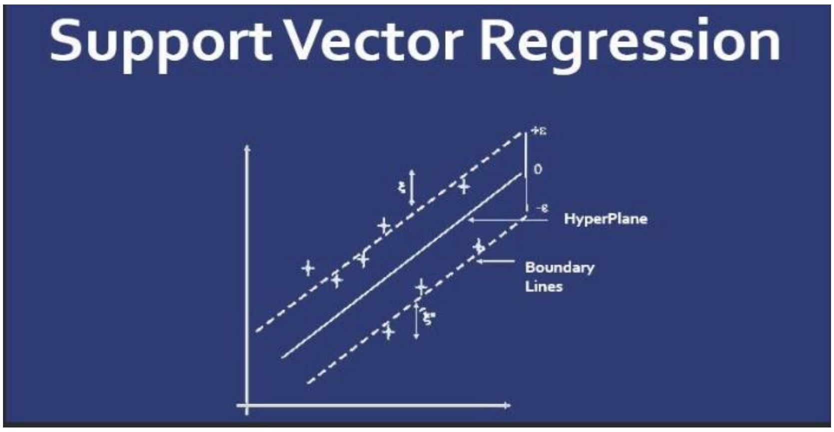
3.2. Unsupervised Learning

We frequently don't know what the "labels" on exploratory data actually mean, or we can just be looking for any patterns that organically develop. Unsupervised learning techniques like clustering, frequent pattern recognition, and dimensionality reduction can be used to accomplish this. In this method, the algorithms are in charge of finding and displaying the interesting patterns in the data. A small number of features are usually extracted from the data by unsupervised learning algorithms, which then use these learnt features to categorize newly introduced data.

4. Examples of Machine Learning Models :

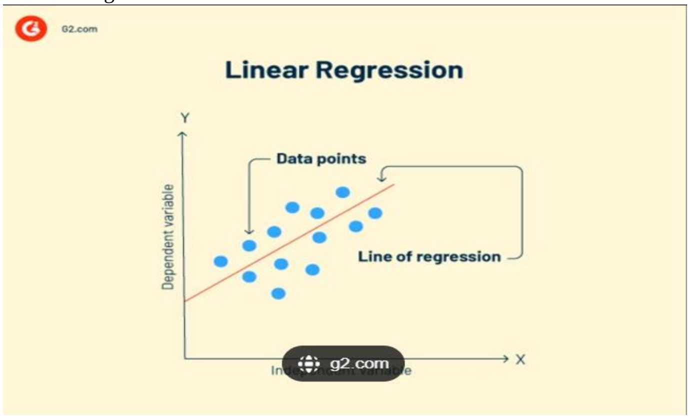
4.1 Support Vector Regression

A supervised machine learning approach called Support Vector Regression (SVR) is founded on the ideas of Support Vector Machines (SVM). SVR is intended for regression issues, not classification jobs, and predicts continuous values instead of discrete classes. It ensures robustness against outliers by finding a hyperplane that matches the data within a specified margin of tolerance. SVR effectively models non-linear interactions by mapping input data into higher dimensions using a kernel function (such as a linear, polynomial, or radial basis function). It is frequently used in financial forecasting, energy consumption forecasts, and other situations that call for accurate and reliable numerical estimations.



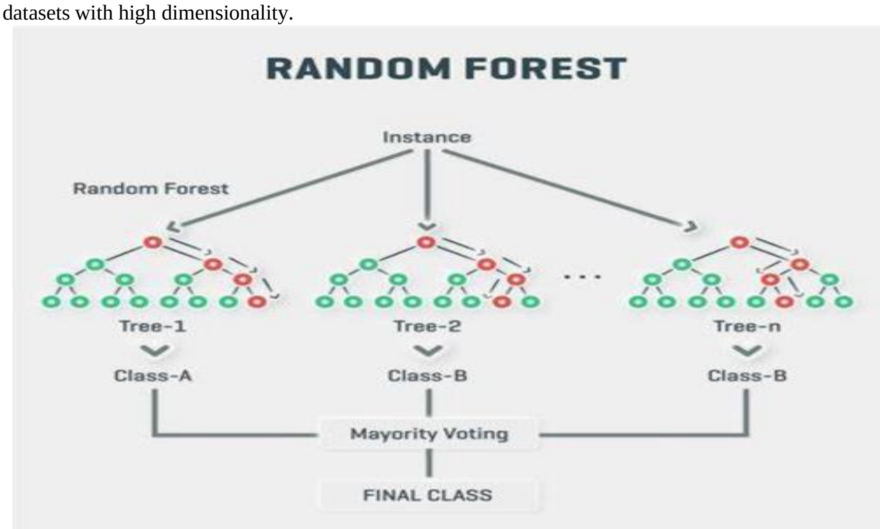
4.2 Linear Regression

A basic statistical and machine learning technique for simulating the relationship between a dependent variable and one or more independent variables is linear regression. The equation $y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n + \epsilon$ assumes a linear relationship, with y representing the dependent variable, $x_1, x_2, \dots, x_n$ representing the independent variables, β_0 serving as the intercept, $\beta_1, \beta_2, \dots, \beta_n$ as the coefficients, and ϵ as the error term. Because of its ease of use, interpretability, and effectiveness in spotting trends and formulating forecasts when data exhibits a linear pattern, linear regression is frequently employed. In machine learning tasks, it can also be used as a baseline model to compare more intricate algorithms.



4.3 Random Forest

In order to increase accuracy and manage overfitting, Random Forest, an ensemble learning technique for classification, regression, and other problems, generates numerous decision trees during training and combines their outputs. Every tree in the forest chooses the best feature from a random selection of features at each split after being trained on a random subset of the data. Compared to individual decision trees, this unpredictability improves the model's resilience and lowers the possibility of overfitting. Random Forest averages the trees' predictions for regression and employs majority vote among the trees for classification. Random Forest is a potent option for addressing challenging machine learning issues because of its adaptability, scalability, and capacity to manage huge datasets with high dimensionality.



4.4 XG Boost

Extreme Gradient Boosting, or XGBoost, is a popular gradient boosting-based machine learning algorithm for classification and regression applications. Iteratively, it creates a group of decision trees, each of which optimizes a particular loss function to fix the mistakes of the ones before it. In order to avoid overfitting and enhance generalization, XGBoost uses strategies including regularization, parallel processing, and tree pruning. It is built for efficiency and scalability. It functions effectively with big, complicated datasets and allows handling missing data. In competitive machine learning competitions and real-world applications that demand accurate forecasting and sound decision-making, XGBoost has gained popularity due to its speed and predictive ability.

4.5 Deep Learning

In order to represent intricate patterns in data, deep learning—a type of machine learning—focuses on multi-layered neural networks, or deep neural networks. It employs layers of interconnected nodes (neurons) to process data hierarchically, learning both low-level features and high-level representations, drawing inspiration from the composition and operations of the human brain. Deep learning is particularly good at applications like picture recognition, natural language processing, audio recognition, and time series analysis that require huge, unstructured datasets. Transformers for text and language tasks, recurrent neural networks (RNNs) for sequential data, and convolutional neural networks (CNNs) for picture tasks are important architectures. Deep learning has fueled AI achievements, allowing systems to function like humans thanks to increases in processing power and massive data accessibility.

5. Development in Methodology :

A study by Akash Talwariya, Pushpendra Singh, Jalpa H. Jobanputra, and Mohan Lal Kolhe was published in 2023. It used machine learning approaches to improve energy consumption management and forecasting for renewable energy. Using historical meteorological data, such as wind speed and solar radiation, they used Convolutional Neural Networks (CNN) to forecast the production of solar and wind energy. Furthermore, by examining past usage trends, Long Short-Term Memory (LSTM) networks were employed to predict energy consumption. Energy loads were divided into fixed, shiftable, and non-shiftable categories to increase efficiency and enable better demand management. Using error metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), the study confirmed that its predictions were true, showing very accurate results.

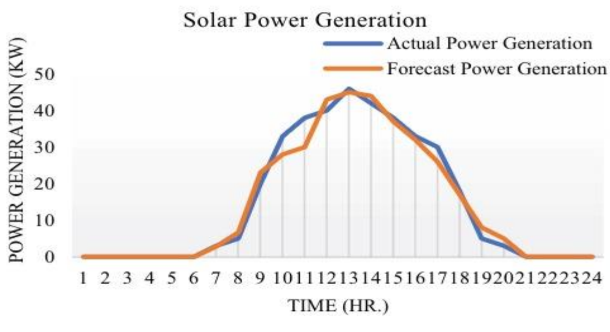
5.1 Solar-Wind Energy Generation Forecast Model

For the purpose of predicting energy generation, the study took into account a solar and wind farm with a maximum capacity of 60 kW for solar power and 40 kW for wind power at a typical site in Rajasthan, for a total plant capacity of 100 kW. The following inputs were used to anticipate historical generation data: temperature, humidity, wind direction, wind speed, solar radiation, and rainfall. A typical day's energy generation is predicted by the suggested CNN model, as shown in Figures 3 and 4 for wind and solar power generation, respectively. Table 1 displays the error predictions for Mean Absolute Error (MAE), RMSE, and MSE: For solar power generation, the MSE is 6.122, RMSE is 2.474, and MAE is 1.495; for wind power generation, the values are MSE of 78.25, RMSE of 3.034, and MAE of 5.41.

5.2 Energy Consumption Forecast Model

A created pricing mechanism is used to supply the generated electricity to consumers; consumer-end consumption projections for fixed, non-shiftable, and shiftable loads are displayed in Figures 5, 6, and 7, respectively. With MSE, RMSE, and MAE values of 0.0007, 0.027, and 0.0175 for stable loads, respectively, Figure 5 compares actual and predicted energy use in kWh. With an MSE of 0.0045, RMSE of 0.067, and MAE of 0.049, Figure 6 compares the actual and expected energy usage of uninterruptible (non-shiftable) loads. With an MSE of 0.047, RMSE of 0.21, and MAE of 0.13, the model produces good results for consumption prediction at the consumer end. Figure 7 shows the link between actual and predicted energy usage for interruptible (shiftable) loads.

Figure: Solar power generation curve



The table shows the aggregated error report for energy forecasts for various appliance types at the consumer end. The findings show that the suggested approaches enhance forecast accuracy for energy consumption and solar and wind power generation. These approaches can be used for load estimates and predictions of renewable energy in a variety of categories. In order to improve energy balancing, the results can also be applied to demand-side management in combination with forecasts for renewable energy. Additionally, these findings help guide plans for maximizing sustainable energy production while coordinating demand-side control initiatives by employing suitable energy storage capacities to optimize energy throughput.

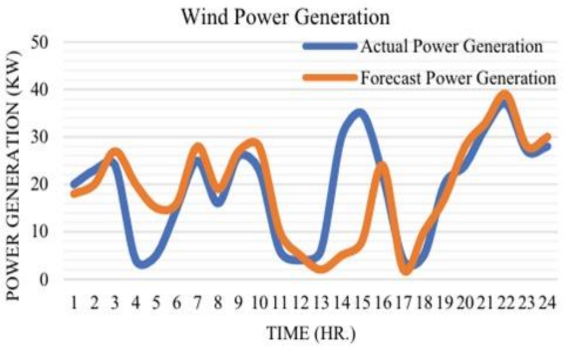


Figure: Wind power generation curve

Generation Source	MSE	RMSE	MAE
Solar PV Generation	6.122	2.474	1.495
Wind Power Generation	78.25	3.034	5.41

Table : Error for solar PV and wind power generation.

6. Applications of Machine Learning Methods :

6.1 Machine learning in industry

Because industrial objectives tend to focus on more pressing issues, energy efficiency (EE) is frequently not given priority inside enterprises. However, as Industry 4.0 and AI become more integrated, there is a growing interest in exploring the possibilities of machine learning (ML) technologies across a variety of sectors. ML includes a variety of potent methods, like class prediction and pattern recognition, that make it easier to glean insightful information from unstructured data. Businesses can greatly benefit from these insights when it comes to improving their operational and strategic decision-making procedures.

6.2 Machine learning in Electric Vehicles

In order to create fully intelligent electric vehicles (EVs) that can make quick, unprogrammed judgments based on real-time data while guaranteeing minimal electricity usage, machine learning (ML) is increasingly being applied to the efficient management of electric vehicles' energy consumption (ECEV). Because there is so much dispersed data, traditional statistical techniques like simple linear regression sometimes fail to produce reliable predictions. On the other hand, by reducing the discrepancy between actual and anticipated values, machine learning algorithms that combine supervised and unsupervised learning approaches improve prediction accuracy. For example, EVs' remaining charge and driving range have been predicted using Simple Linear Regression (SLR). Extreme Gradient Boosting (XGBoost) and Support Vector Regression (SVR) are two machine learning methods that have recently become more well-liked since they can predict outcomes with high accuracy and speed.

6.3 Machine Learning in buildings

About 40% of energy use in the commercial and residential sectors of the US is attributed to building demand, which accounts for a sizeable amount of worldwide energy consumption. Additionally, buildings must be constructed and operated efficiently to support sustainable energy practices because they will need energy for at least 50 years. One of the most important aspects of energy management, planning, and conservation is predicting building energy use. A number of machine learning (ML) models, including XG Boost, Support Vector Regression (SVR), Extreme Learning Machines (ELM), and Artificial Neural Networks (ANNs), have shown promise in predicting patterns of building energy use. Energy predictions have been made using these models, which include SVR, ELM, ANNs, Deep Recurrent Neural Networks (DRNN), and Generative Adversarial Networks (GAN).

6.4 Machine learning in ships in ports

Numerous ports worldwide have put in place a number of strategies to cut down on ship emissions and diesel use, including slowing ship speeds and using cold ironing or renewable energy sources. At the moment, scientists are concentrating more on calculating how much energy ships use when at sea. Statistics, Monte Carlo simulations, Multiple Linear Regression (MLR), polynomial regression, Artificial Neural Networks (ANN), the LASSO regression algorithm, Support Vector Machines (SVM), Gaussian Process Metamodel (GPM), non-linear ANN, and Multi-Resolution Analysis of Wavelet Neural Networks (MRAWNN) are some of the techniques that have been used for this purpose. The goal of these methods is to precisely forecast how much energy a vessel will need while doing marine operations.

7. Advantages :

1. Accuracy in Prediction: ML models such as artificial neural networks (ANN), support vector regression (SVR), and deep learning frameworks (e.g., LSTM) can model nonlinear patterns in energy data, providing higher accuracy compared to traditional statistical models.
2. Scalability: ML models can handle large datasets efficiently, enabling predictions across various time scales, from hours to years.
3. Adaptability: These models are adaptable to different types of energy consumption data, including renewable sources (solar, wind) and conventional systems.
4. Automation: ML algorithms can automate feature selection, parameter tuning, and real-time forecasting with minimal manual intervention.
5. Hybrid Model Flexibility: Combining ML with optimization algorithms (e.g., genetic algorithms, PSO) or other methods like empirical mode decomposition improves model robustness.

8. Limitations :

1. Data Dependency: ML models require large, high-quality datasets for training. Missing or noisy data can reduce prediction accuracy.
2. Overfitting Risks: Models like deep learning can overfit small datasets, leading to poor generalization on unseen data.
3. Computational Demand: Training advanced ML models, such as deep neural networks, requires significant computational resources and time.
4. Interpretability: Black-box models (e.g., neural networks) lack transparency, making it challenging to understand or justify predictions to stakeholders.
5. Expertise Domain: Effective implementation often requires domain-specific knowledge to preprocess data, select features, and interpret results.

9. Applications and Examples :

1. Renewable Energy Integration:

- **Example**: Predicting solar irradiance using hybrid models like LSTM combined with wavelet decomposition.
- **Benefit**: Helps grid operators balance supply and demand efficiently.

2. Smart Grid Management:

- **Example**: Real-time load forecasting with ANN or SVR.
- **Benefit**: Enables dynamic pricing and efficient grid operations.

3. Industrial and Building Energy Management:

- **Example**: Predicting hourly energy use in smart buildings with ensemble methods like random forests or Cat Boost.
- **Benefit**: Reduces operational costs and energy wastage.

4. Policy and Decision Making:

- **Example**: Long-term energy demand forecasting using deep belief networks (DBN).
- **Benefit**: Supports government planning for renewable energy transitions.

5. Microgrid Optimization:

- **Example**: Short-term wind energy predictions using hybrid ANFIS models.
- **Benefit**: Enhances microgrid reliability and reduces dependence on fossil fuels.

10. Conclusion :

Energy is essential to our society and is the foundation of all economic activity. As a result, interruptions in the energy supply may have profound and far-reaching economic effects. Governments are motivated by this reality to guarantee the availability of secure and dependable energy sources. In many nations, renewable energy systems are in a prime position to lessen the existing reliance on imported fuels and lower the dangers of supply disruptions. Heat, electricity, and transportation fuels can all be produced using these widely dispersed renewable energy sources.This study uses machine learning (ML) models to analyze energy consumption in the building, business, and residential sectors. Modern technologies like Big Data (BD) and the Internet of Things (IoT), which can handle enormous volumes of data from sensors and energy meters, are especially well-suited for the building energy industry.

The use of machine learning (ML) models has increased significantly over the last ten years, with hybrid and ensemble approaches becoming increasingly popular in addition to more conventional approaches like support vector machines (SVMs), multi-layer perceptrons (MLPs), and artificial neural networks (ANNs). With these hybrid techniques, researchers hope to increase efficiency and accuracy. Future studies will concentrate on creating hybrid models that are more accurate and faster.

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