Analysis of Renewable Energy Demands using AI

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Abstract: Sustainable energy includes all kinds of renewable energy which is obtained through the natural resources of our earth that are infinite or non-exhaustible, which includes mainly wind energy and solar energy. The future energy will be renewable energy which will be replacement for the traditional form of the energy which mainly depends on the fossil fuels which are detrimental to the environment. This paper mainly addresses the analysis of sustainable energy requirement for the future using artificial intelligence. Various types of renewable energy such as hydroelectric, wind and solar are taken into consideration for different seasons. Machine learning-based techniques will be used to preprocess the data and evaluate it for associations and trends. The total data is divided into two sets training and testing in the ratio of 80:20. The analysis of AI is done using python programming language. Finally, various types of machine learning techniques are compared for getting optimal results and tested also for accuracy. This paper can help analyze the renewable energy demands of future using machine learning and deep learning to deliver insightful information.

Keywords: Sustainable Energy, Artificial Intelligence, Solar, Wind, Machine Learning Techniques.

Introduction

Application of Machine learning for Analyzing and predicting energy consumption has been the latest trend. We continue to utilize more electrical energy generated by fossil fuels, which results in higher greenhouse gas emissions. The techniques and algorithms used in machine learning is advancing at a greater pace. Applying Machine learning techniques in energy sector will help in accurately predicting energy use and the performance of renewable sources[1].

The artificial intelligence (AI) technology that powers the new digitalization paradigm is crucial in integrating renewable energy sources, energy supply, and demand into the power grid. This provides a practical baseline for policymaking in Energy Industry. In terms of energy efficiency optimization and computational efficiency AI techniques beat conventional models. If the independent power producers want to create outcomes to stay competitive, they may need to concentrate more on AI technologies. Regulations for new services and goods can be implemented as rapidly and effectively with data analysis using artificial intelligence [2].

The combination of sunlight and air as a substantial source of renewable energy has been a focus of study and development over the past few years. Various studies have employed statistical and biologically inspired AI approaches to achieve current and upcoming renewable energy goals [3].

The cost of the electricity generated, the availability of renewable sources, the efficiency of energy conversion, greenhouse gas emissions over the technology's entire life cycle, the amount of land and water required, and the social impacts were some of the criteria used to evaluate non-combustion based renewable electricity generation technologies. Solar energy, geothermal energy, hydropower, wind energy is the least sustainable, according to the study's findings. Wind power has been demonstrated to have the lowest relative greenhouse gas emissions, the least amount of water consumption requirements, and the best social outcomes when compared to other technologies, but it requires more land and has higher relative capital costs [4].

Natural gas power plants, which also significantly contribute to greenhouse gas emissions and the accompanying climate change, generate close to a quarter of the world's electricity.

In this paper study of various types of non-renewable energy like gas fired and coal fired and renewable energy such as wind and solar are taken into consideration for different seasons and analyzed using K-Nearest Neighbor (KNN) and Naive Bayesian algorithm and accuracy of the algorithms are compared.

Literature Survey

“Renewable energy is the future, and technical and policy solutions should be used to overcome harvesting challenges. The main drawback of the majority of renewable energy sources is that they are unpredictable and subject to the whims and caprices of nature. The operation of the system is defined and determined by forecasting the power from various variable power sources. Elodie Guillard (2020) presented a forecast model for the PV generation based on ANN and ANFIS [1]. Utilizing past data, the forecast model that was created and trained. By considering the PV power generating station data set, the outcomes of the proposed model are verified and contrasted. To assess the effectiveness of the proposed system, a simulation model is created in MATLAB [5].

When compared to nuclear and fuel-based energy, renewable energy (RE) has significant economic and environmental advantages. Various predictive models have been created to enhance prediction accuracy for improved energy management. However, current research ignores the time complexity of its approaches in favor of boosting prediction accuracy, which is a prerequisite for power systems. A lightweight ESNCNN model for precise RE prediction was developed by Z. A. Khan et al. (2012), in which an ESN learns the relationship between the nonlinear mapping and a CNN extracts the spatial data from the RE data. The best ESNCNN features are enhanced and chosen in order to forecast future energy production using fully connected layers. Additional tests are conducted on electricity consumption datasets to thoroughly evaluate the proposed ESNCNN's generalizability. These experiments show a significant reduction in error rates compared to existing state-of-the-art methods [6].

Forecasting renewable energy accurately is difficult for the power system's planning, management, and operations because of the ambiguous and frantic nature of renewable energy data. K. M. Shahiduzzaman (2021) explores efficacy, efficiency, competency, and application potential by providing a thorough and comprehensive analysis of the renewable energy forecast based on several machine learning algorithms. In their study, a time series forecasting model for renewable energy using linear regression, support vector machines (SVM), and long short-term memories (LSTM) for twelve different countries were analyzed. It is concluded in this study that Smaller mean and standard deviation countries are better suited for SVM-based forecasting models, whereas bigger mean and standard deviation countries are better suited for linear regression-based techniques. These forecasting algorithms allow us to predict the daily generation of renewable energy over the next two years [7]. It should be noted that various models for various nations were created [10]-[12].

Using solar and wind energy in hybrid energy systems will reduces CO2 emissions. Energy management of hybrid energy systems has been extensively studied by several research since faults in EM might cause HES blackouts. A reliable forecasting model for one hour before EM has been produced by recent research by Musbah (2021) using energy management strategy (EMS) to obtain optimal EM.

This study's primary goal is to choose the energy source that meet the demand. To do this a variety of machine-learning techniques including Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbors (KNN) Gaussian Naive Bayes (Gaussian NB) has been employed. The second goal is to compare these algorithms' outputs in order to select the one that performs the best and rank them according to performance and accuracy [8].

It is found that in comparison to the RF and Gaussian NB algorithms the DT method has the best performance. The KNN algorithm, particularly for class 3, provides the lowest accuracy [13]-[15] .

According to [9], a novel method to search alternative design in an energy simulation tool was suggested. The alternative design is searched using a classification algorithm. In this experiment, three classifiers Naive Bayes, k-Nearest Neighbor and Decision Tree were utilized. It was found Decision Tree outperforms k-Nearest Neighbor in terms of speed. Decision Tree categorization is quick because there are no calculations involved. The Weka data mining tool is used outside of the application to construct the tree model. And before being implemented into the application, the model is transformed into rules. Classification using the tree rules is quicker than methods that require calculation, like Naive Bayes and k-NN. As a result of the direct relationship between classification time and data volume, k-Nearest Neighbor is the slowest classifier. The size of the data will determine how large of a distance calculation is required. As a result, the classification process moves quite slowly. Despite being a straightforward technique, Nave Bayes can outperform more complex classification techniques [16]-[17].

Proposed System

Modelling for forecasting is also known as A statistical architecture with a high degree of accuracy in forecasting is created using predictive modelling. The machine learning techniques are used for foreseeing the crime based on the dataset. Regression and pattern categorization represent two of the forecasting techniques. The dataset values, which are taken to be constants, are used to predict the data. Patten classification seeks to assign discrete class labels to a given value of data as an output of a prediction, in contrast to regression models.

a) Type of forecasting Model Algorithms

- Decision Trees

The decision tree is an algorithm that uses a graph or tree-like representation of decisions, including costs, utility, and outcomes of random events. That is one way to demonstrate an algorithm.

- Naive Bayes

Machine learning makes use of a group of straightforward probabilistic classification algorithms known as naive Bayes classifiers. They are based on erroneous assumptions about feature independence and the Bayes theorem implementation.

- KNN

The K-NN algorithm works by finding the K nearest neighbors to a given data point based on a distance metric, such as Euclidean distance. The class or value of the data point is then determined by the majority vote or average of the K neighbors. This approach allows the algorithm to adapt to different patterns and make predictions based on the local structure of the data.

b) Data Preprocessing

This method includes steps for getting rid of any empty or ambiguous values that can compromise the system's accuracy. The main steps are formatting, cleaning, and sampling. The cleaning process can be used to remove or correct any missing or incorrect data. If enough data are used for sampling, the algorithm's execution time might be shortened. The preprocessing is done in Python.

c) Proposed system

The proposed system can be divided into 4 modules such as, Data modeling, estimating performance, Data analysis that is descriptive, and Data treatment.

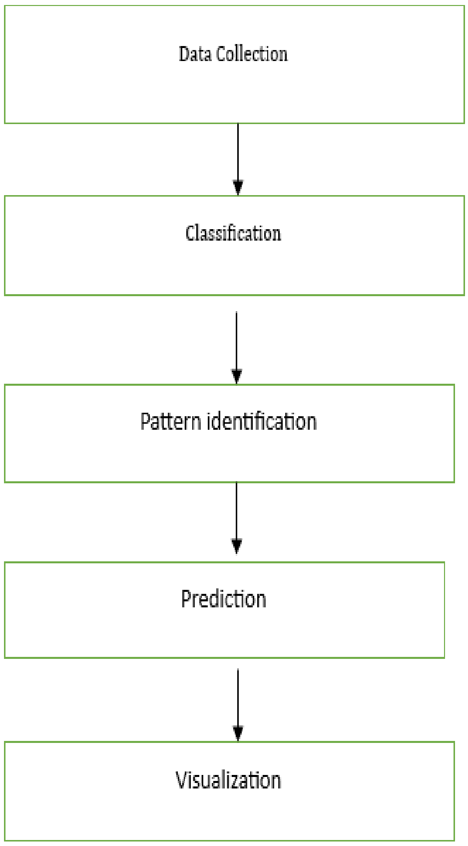

Fig 1 – System Architecture

The data must be prepared for analysis in the correct format at this stage. data transformation, cleansing, and variable analysis. One of the aforementioned procedures, such as Standardization, normalization, or the absence of values, may be required in order to modify the variables.

d) Data Sampling (Train and Test)

Training data: This sample will be used to build the model. This is where 80–90% of the data is kept.

Testing data: The performance of the model will be verified using this sample. 20% or 40% of the data is utilized in this case.

- Training the Model

Learning appropriate values for each weight and bias from labelled instances is all that is required to train a model. In supervised learning, an algorithm uses a large number of instances to develop a model in an effort to discover the model with the lowest possible loss. It also refers to assessing the correctness and error of the model's performance. Train the model using the initial sample, which is the population or database of data that is accessible, and test the algorithm's assumptions.

- Testing the model

Model testing is the procedure where a fully trained model's performance is assessed through testing. Utilize a test sample to ascertain and project, and then assess the model's accuracy and other performance metrics.

Implementation

This project's dataset was obtained from various sources across Oman. The following steps make up the project’s implementation.

a) Data collection

The dataset is in CSV format is used in fig 2.

year	average_dem	distribution_l	Annual_Energy	peak_demand
2017	3578	3157	31	6116
2018	3899	3309	34	6520
2019	4241	3471	37	7000
2020	4614	3634	41	7430
2021	4905	3835	43	7830
2022	5203	4033	46	8300
2023	5421	4211	47	8670
2024	5614	4402	49	9107

Fig 2. Dataset sample

b) Data Preprocessing

Utilizing Label Encoder, the categorical attributes (Location, Crime Type, and Area) are transformed to number values. The date has been divided into new properties like month and hour that can be used as model features.

c) Prediction selection

The employable model-building qualities are selected. The selection criteria for characteristics are Block, which was Location, District, place, X, Y, Latitude, Longitude, Hour, and Month.

d) Developing and Training Model

The attributes for the model are month and year. The dataset is separated into two pairs:

x_test, y_test, and x_train, y_train. It imports the algorithms model from Sklearn. Models are used to construct models. (X_train, Y_train) Fit.

e) Forecasting

The Model. Predict (x test) is used to make predictions after the model has been created using the procedure. The accuracy is determined using the metrics. accuracy_ score (y test) import of accuracy _score.

f) Visualization

Utilizing the Sklearn mathpoltlib library. The dataset is analyzed using graphs.

Results and Discussion

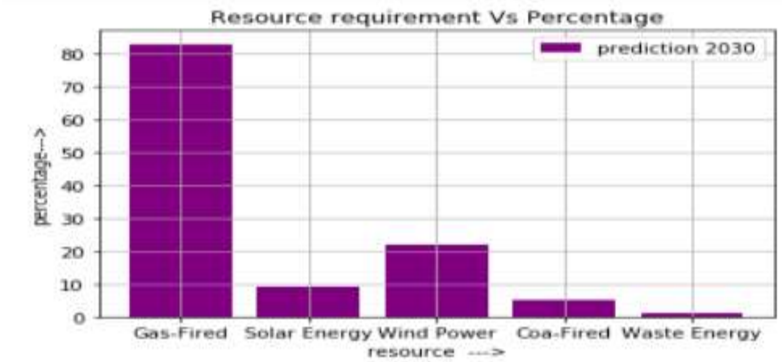

Fig.3. Resource Requirements

The figure 3 shows the resource requirement in terms of percentage for different types of resources as shown in the plot above renewable energy will contribute around 10% by 2030.There is still sharp hike in the requirement of Gas-Fired which is around 80% by 2030.

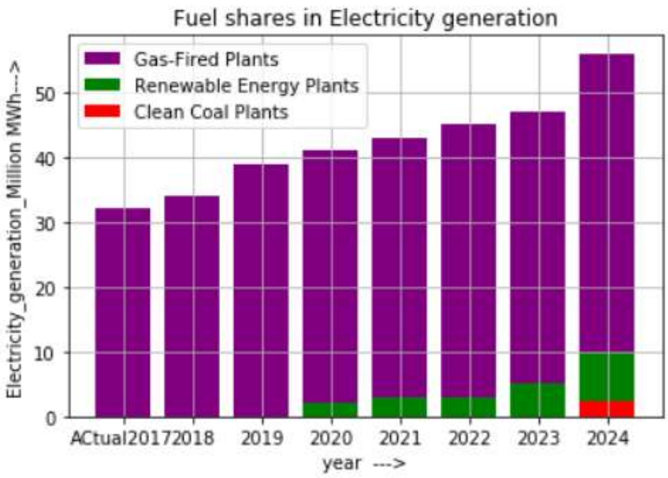

Fig.4.Fuel share in Electricity Generation

The shares of fuel in generation of electricity until the year 2024 shown in figure 4. The comparison is done for three types of plants, which are Gas-Fired Plants, Renewable Energy plants and clean coal plants. The analysis is predicted in terms of Million MWh for different types of plants and above plot clearly reflects by 2024 renewable energy fuel shares in generation of electricity is above 10 Million MWh.

```
plt.xlabel("Algorithm --->")
plt.ylabel("percentage(%)--->")
plt.scatter(algorithm,percentage,label="Accuracy comp
plt.plot(algorithm,percentage,color="red")
plt.bar(algorithm,percentage,width=0.3,color="orange"
plt.legend(loc=5)
plt.show()
```

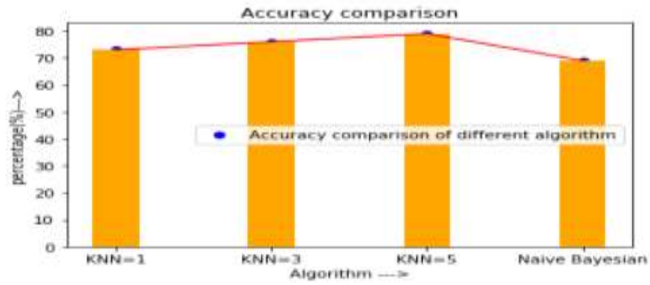

Fig.5. Accuracy comparison

The figure 5 shows the accuracy prediction of different types of machine learning algorithm. The percentage of accuracy is more for KNN=5. Accuracy testing is nothing but creation of confusion matrix.

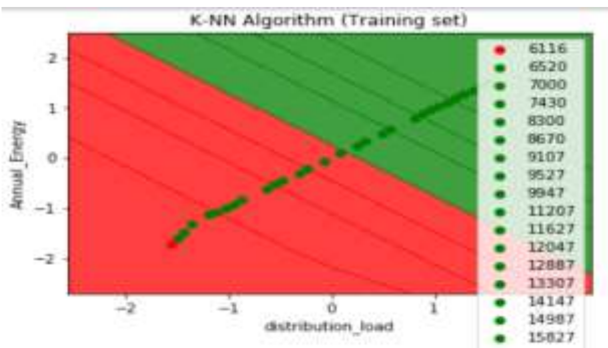

Fig.6. (a) K-NN training set

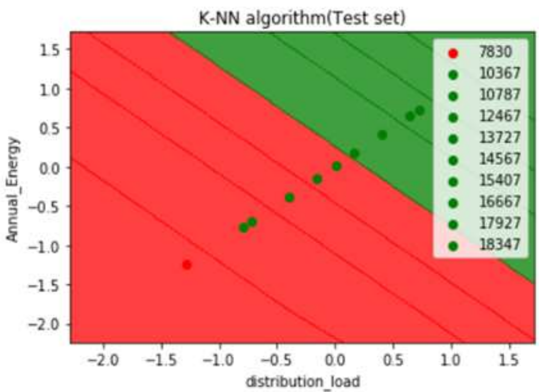

Fig.6. (b) K-NN test set

The distribution load and annual energy are indicated in figure 6. In the above output training set and testing sets were taken in the ration of 80:20. When we compare the both the plots the results reflect the correct prediction using the KNN algorithm.

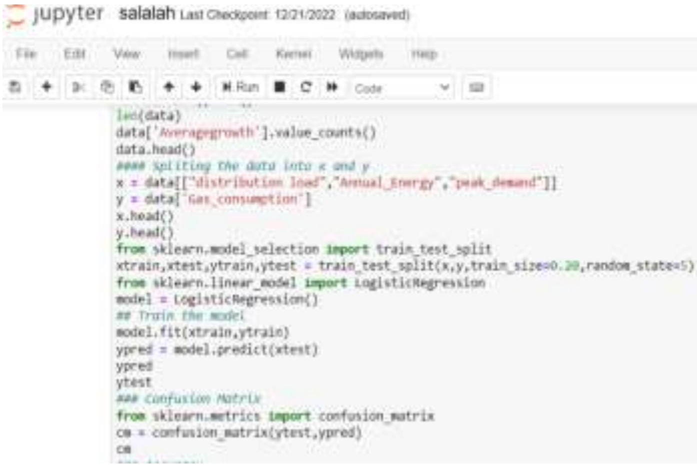

Fig.7.Sample Python Program

A sample python program for accuracy calculation is shown in figure 7. The total data set is divided into two, training data set and testing data set in the ratio of 80:20. Based on the samples, the AI is smart enough to predict the requirement of load for the future and peak demand for different seasons.

For the analysis purpose different types of machine learning algorithm such as KNN and Naïve Bayesian are used. Based on the outputs obtained from the proposed different machine learning algorithm, it reflects a better accuracy is achieved in KNN with neighbor value of five.

Conclusions

The analysis of results shows clearly the future energy will be renewable energy which will be replacement for the traditional form of the energy which mainly depends on the fossil fuels which are detrimental to the environment. The proposed work reflects the analysis of sustainable energy requirement for the future using artificial intelligence. The total data was divided into two sets training and testing in the ratio of 80:20 and the analysis of AI is done using python. Finally, the accuracy using various types of machine learning techniques are compared for the getting optimal results.

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