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Research in the field of environmental protection and energy issues

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EDITORIAL

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Editorial

On behalf of the entire Editorial Board, I am very pleased to announce the launch of a new journal called the Journal of Environmental and Energy Science. It is a journal that addresses issues related to environmental technologies and innovations in many industrial areas, with a particular focus on energy. As part of the Journal of Environmental and Energy Science, the publication will cover the following areas of environmental and energy transition technologies, technologies improvements, energy efficiency, environmental protection, energy sources, storage, and applications, energy and environmental transition, sustainable development, energy conversions, fundamentals, and buildings, economy and policy aspects on energy and environment, energy usage and savings.

In today's world, ecology, as well as environmentally friendly technologies, play an important role. Their use is influenced by a wide variety of factors. The results of studies [1] show that the application of restrictive pro-environmental policies, the introduction of environmental taxes, as well as the development of pro-environmental technologies, are influencing greater interest in the use of renewable energy sources. Of course, this process is a long one, and various factors influence energy innovations that limit the use of fossil fuels. However, successfully implemented innovations can in turn contribute to reducing environmental pollution, including greenhouse gas emissions into the atmosphere. Certainly, a transition toward a cleaner environment requires appropriate environmental management at production facilities. In turn, at national levels, changes toward the introduction of cleaner technologies require the restructuring of environment-related policies to introduce incentives for citizens to abandon outdated solutions that negatively affect the environment in favor of using cleaner energy sources. As shown in [1], taxing all polluting activities will not only discourage pollution but also improve environmental quality in the long run. Of course, it is important to have real incentives that can influence, if not in the short time horizon, then in the longer period, the implementation of the modernization strategy in companies.

We are observing a growing environmental awareness among the public, which is why progress related to research in the field of clean energy technologies, as well as other solutions that can have an impact on improving environmental quality, is so important.

Available research [2] indicates that the reduction of greenhouse gas emissions, which have a negative impact on the climate, is influenced by factors such as the production of electricity from renewable sources, as well as ecological innovations. Industrialization, on the other hand, has an impact on increasing greenhouse gas emissions, hence the transformation towards technological change, mainly in the energy sector, is recommended to counteract the negative effects of climate change.

Modeling of various scenarios using carbon capture and utilization, in which carbon dioxide is captured from the atmosphere and used to produce synthetic fuels that can replace fossil fuels, has indicated clear advantages in minimizing changes in energy demand sectors such as transportation, however, it has also been pointed out that the technology is cost-intensive compared to existing scenarios, and that it is based on a technology still in development [3].

The high cost of technologies can reduce companies' incentives to implement them. Research results show [4] that government subsidies can serve as an effective way to reduce the financial burden on companies to improve technology. In addition, government subsidies are conducive to expanding the market for green products and improving social welfare.

The ongoing energy transition requires the involvement of various sectors in more efficient use of resources. The continuous evolution of industrial operations and productivity requires the development and implementation of energy efficiency measures [5]. However, choosing the right technology for a specific industry that is acceptable in terms of cost remains a major challenge for many companies.

We hope that the publications contained in this journal will be useful and interesting to our readers and will influence pro-environmental decision-making. For the authors of the publications, the journal will at the same time become a useful channel for the distribution of research results, which, given the above, are of great importance to many societies.

Types of articles, objectives, and scope

The new open-access journal, established under the title of Journal of Environmental and Energy Science, is an international peer-reviewed open-access journal, which allows readers to access the content of the articles free of charge, and consider for publication articles covering all the areas described above. We highly encourage academic authors from around the world to publish their research results in this journal. All articles undergo

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a thorough review process to ensure the highest quality of published content for readers.

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Enhanced Power Demand Forecasting Accuracy in Heavy Industries Using Regression Learner – based Approched Machine Learning Model

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Abstract

For effective management of power systems in heavy industries, accurate power demand forecasting is essential. Traditional statistical models have been tried for this goal, but they frequently struggle to capture the intricate patterns and connections in the data. This paper proposes a method for predicting these power demand, it involves preparing the baseline data, training a surrogate model using a machine learning algorithm, and performing cross-validation to evaluate the performance of the model. To address the diversity in load behaviors and demand spike patterns, a statistical analysis-based machine learning algorithm selection approach is proposed to guide the accurate development of the surrogate model. This study provides a comprehensive framework for predicting the power demand, selecting appropriate machine learning algorithms, and avoiding overestimation. Results enable management to make better decisions, optimize energy usage, and reduce costs and avoid penalties, and surcharges.

Keywords: power demand, forecasting, heavy industries; load; power generation; load; forecasted demand

1. Introduction

Power is essential to the economy, in the most electrical grid that spans large geographical areas. It is typically made up of a few large networks and within those electrical networks electricity flows freely among secondary distribution system of many electrical systems directly to various customers [6].

In the process of bringing power from generation delivery points to the customers and transforming the same to a lower voltage that supplies all the loads, particularly in heavy industries, it is important to identify the exact contacted demand to avoid penalties and charges for instances of exceeding actual consumption versus actual and overspending for extremely high contracted demand under Philippines energy framework system which both scenarios are expenses to the organization.

Accurate load forecasting is crucial for efficient energy management since heavy businesses use a lot of energy to run their activities [4][7]. In load forecasting, the future power demand is predicted using historical data and other pertinent variables. Complex temporal correlations and patterns in the data are difficult to capture using conventional forecasting techniques, such as statistical models. Machine learning models, such as the Regression – learner neural network, have demonstrated tremendous potential in recent years for enhancing load forecasting accuracy in a variety of domains.

In this study, we propose an innovative Regression – learner neural network model-based method for load forecasting in heavy industries. To increase the precision of load forecasting, we offer a model that considers pertinent factors such as kilowatts, kVA, kVAR, power factor, and the maximum demand spike each day. The proposed Regression Learner model has the capacity to capture long-term dependencies and patterns in the data, which is significant in the context of heavy industries where the energy consumption is influenced by various factors such as production schedules, weather conditions, and modifications in industrial processes. Below is the load profile of the plant as baseline data.

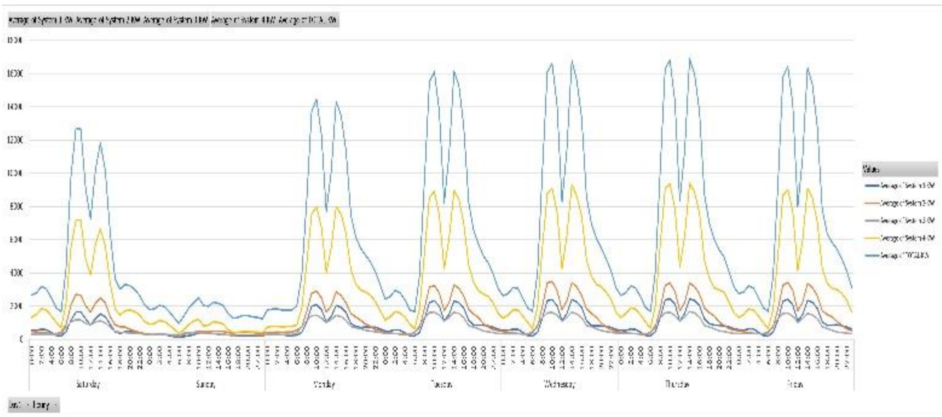

Fig. 1. – Plant historical data

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The primary goal of this study is to show how well the suggested Regression Learner neural network model performs load forecasting in heavy industries. The historical load data was initially preprocessed with the pertinent parameters included. The Regression Learner model was then trained and tested using the preprocessed data, and its performance was compared to that of conventional forecasting techniques.

2. Regression Learner Model

Regression models used to predict data can be easily created with the help of the Regression Learner app. Its user-friendly interface enables simple data exploration, feature selection, specification of validation schemes, model training, and model evaluation [2]. Additionally, it offers automated training options for choosing the best regression model type, including support vector machines, regression trees, Gaussian process regression, linear regression, kernel approximation models, ensembles of regression trees, and neural network regression models [2],[5].

The application uses supervised machine learning to train models, which entails using a known set of observations of input data (predictors) and known responses to teach the model how to produce expected responses for new input data.

If the predictions are done with only one single variable, then it is treated as simple linear regression whose expression is given below which is also called as Hypothesis equation and the same analysis is presented in this paper [10].

$$Y=a+bX+\varepsilon \qquad (1)$$

Where, Y is the response or output or dependent variable, a is the intercept, b is slope of linear regression line, X is independent variable and ε is the error or residual of model.

Similarly, if the same predictions are carried out for more than one variable, then it is referred as multiple linear regressions and the expression goes as follows [10]:

$$Y=a+bX1+cX2+dX3+\ldots\ldots\ldots.+\varepsilon \qquad (2)$$

Where, Y is the response, X1, X2, X3 and b, c, d are independent variables and their slope respectively as it has multiple regression lines, a is the intercept and ε is sum of residual errors calculated for all regression lines. The most common factor in both simple and multiple linear regression lines is error 'ε'. The error should be minimum as such as it can, as it may result to better accurate model [10].

Certain mathematical methods are adopted to reduce the error. Some of the techniques include Root Mean Squared Error (RMSE), Minimum Squared Error (MSE), Minimum Absolute Error (MAE), R squared, Ordinary least squares method, Sum of absolute errors, Gradient descent method. Out of all these methods, the most common and comfortable method is RMSE method which is the root of squares of difference between predicted and true values of a model and the same technique has been carried over in this paper. However, the equations for calculating errors in different methods and their formulae is as listed below [1],[3].

$$RMSE = \sqrt{\frac{1}{n}\ \sum_{i=1}^{N}(Ypred - Ytrue)^2} \qquad (3)$$

Where, N is the number of observations or iterations to calculate error, Ypred is the predicted values of dependent values and Ytrue or actual value. True values are the values which are fed as input to trained model and predicted values are the values obtained after performing LR analysis. Mean Absolute Error (MAE) is expressed as the difference between predicted and true responses and Mean Squared Error (MSE) is defined as the squares of difference between predicted and true responses which are given below [3].

$$MAE = \frac{1}{n}\sum_{i=1}^{N}(Ypred - Ytrue) \tag{4}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{N}(Ypred - Ytrue)^2 \tag{5}$$

Regression Learner is a powerful tool that can be used to create regression models, such as linear regression models, regression trees, Gaussian process regression models, support vector machines, kernel approximation, ensembles of regression trees, and neural network regression models. It not only allows you to train models but also provides the ability to explore your data, select features, specify validation schemes, and evaluate results. You can export a model to the workspace to use it with new data or generate MATLAB® code for programmatic regression [5],[8].

3. Methodology

The process of training a model in Regression Learner can be divided into two parts: Validated Model and Full Model. The Validated Model trains a model with a validation scheme that protects against overfitting by applying cross-validation. Alternatively, you can choose holdout validation. The validated model is visible in the app. The Full Model trains a model on the entire dataset, excluding the test data. The app trains this model simultaneously with the validated model. However, the model trained on full data is not visible in the app. When you choose a regression model to export to the workspace, Regression Learner exports the full model [3].

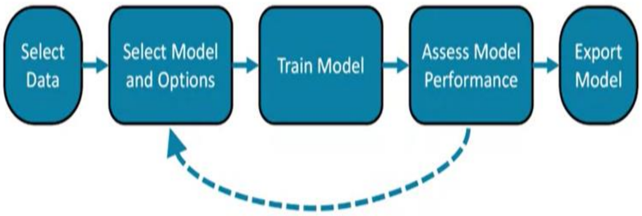

Fig. 2. Regression learner work flow

Collect historical power demand data, including kilowatts (kW), reactive power, apparent power, power factor, and maximum demand spike in a day. Additional relevant data such as weather data, economic indicators, and industrial activity data may also be collected. Second, is to clean and preprocess the data by handling missing values, outliers, and other data quality issues. Normalize the data to improve model performance. Third, select the relevant features for the Regression Learner model based on their importance in predicting power demand. Fourth, train the model using the preprocessed data. The model may be trained using various hyperparameters such as the number of layers, the number of neurons per layer, the learning rate, and the number of epochs. Fifth, validate the model using a holdout set of data or cross-validation. Evaluate the model's performance using various metrics such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), including fine-tune the model by adjusting the hyperparameters based on the validation results [2], [3].

4. Power Load Forecasting Based on Regression Learner Model

The baseline data are extracted in the smart metering from the previous year, after the extraction and validation, important parameters are set to be considered to a trained variable. These are actual kilowatt (kW), kilowatt – hour (kWh), the reactive power in kVAR, reactive power - hours in kVARh, apparent power in kVA and apparent power – hours in kVAh.

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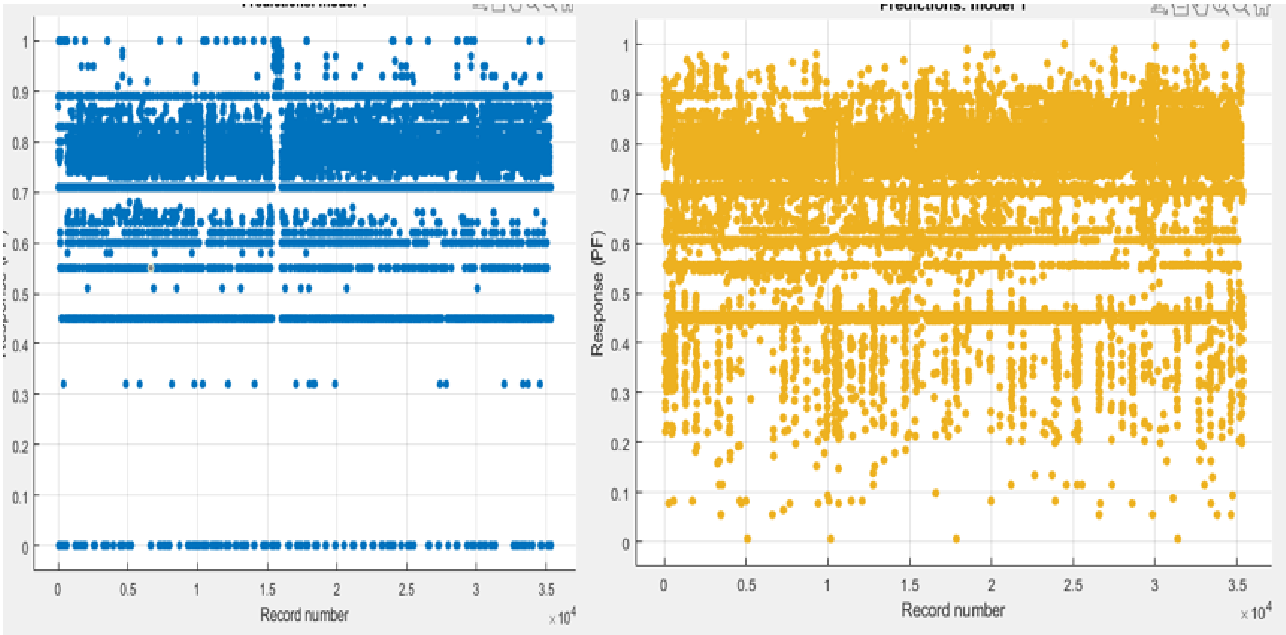
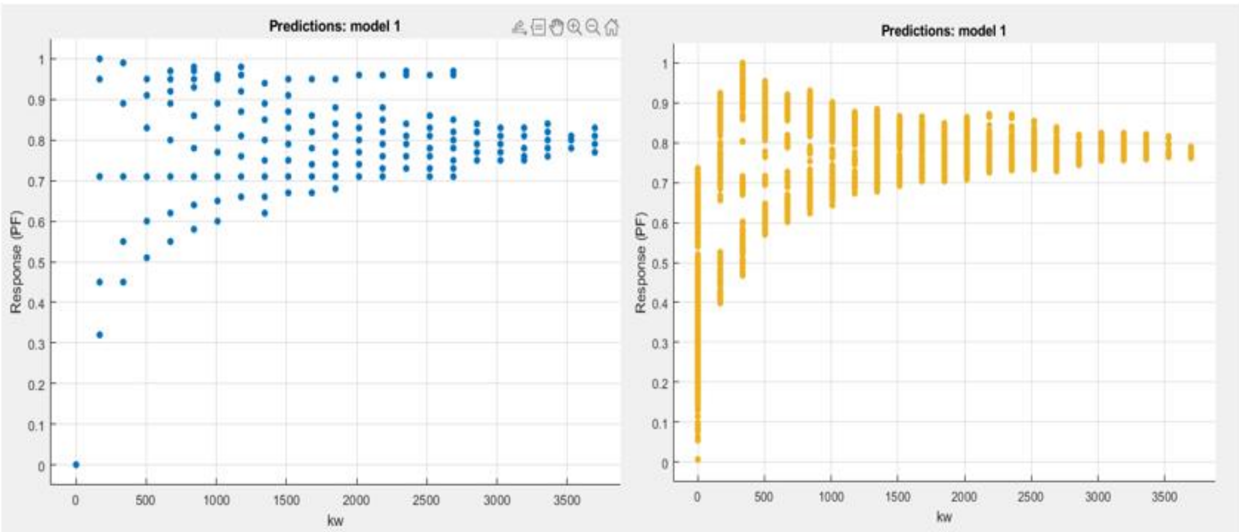


Baseline data Trained data

Fig. 3. Combined graph of the baseline & trained data

Individual parameters considered in this study graphically presented to provide an overview of the baseline data with the trained data. This graphs comparison presents the similarities and differences between these two sets of data into how the model predict the future load profile of the plant [9].



Baseline power in kW Predicted power in kW

Fig. 4. Power in kW graph of the baseline & trained data

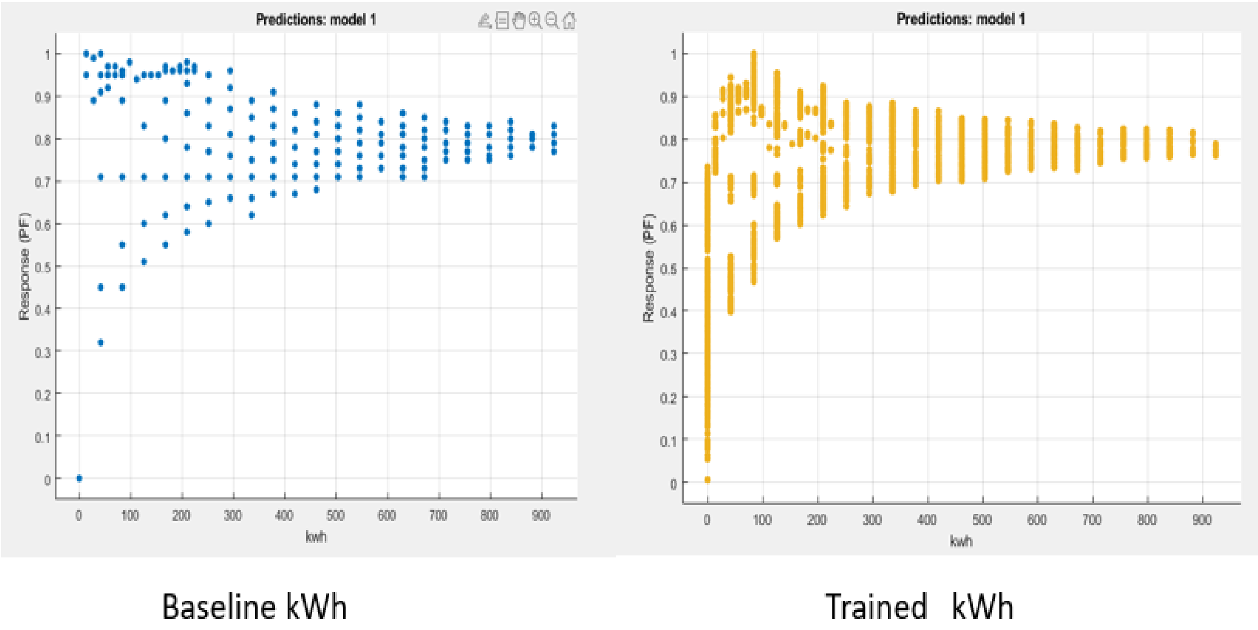


Fig. 5. kWh graph of the baseline & trained data

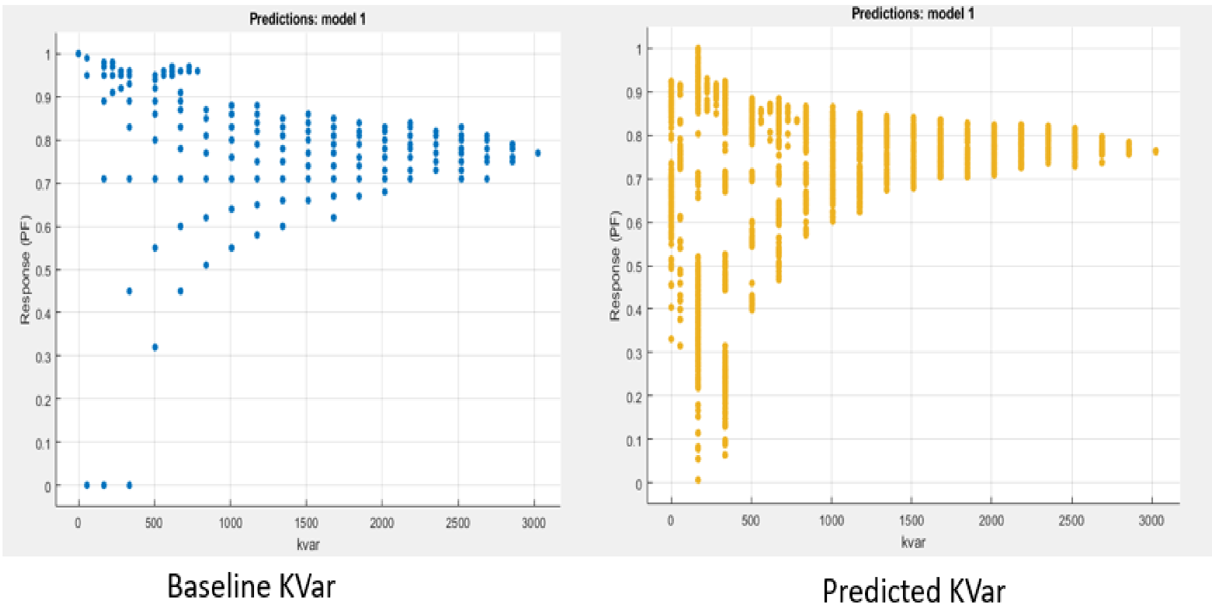
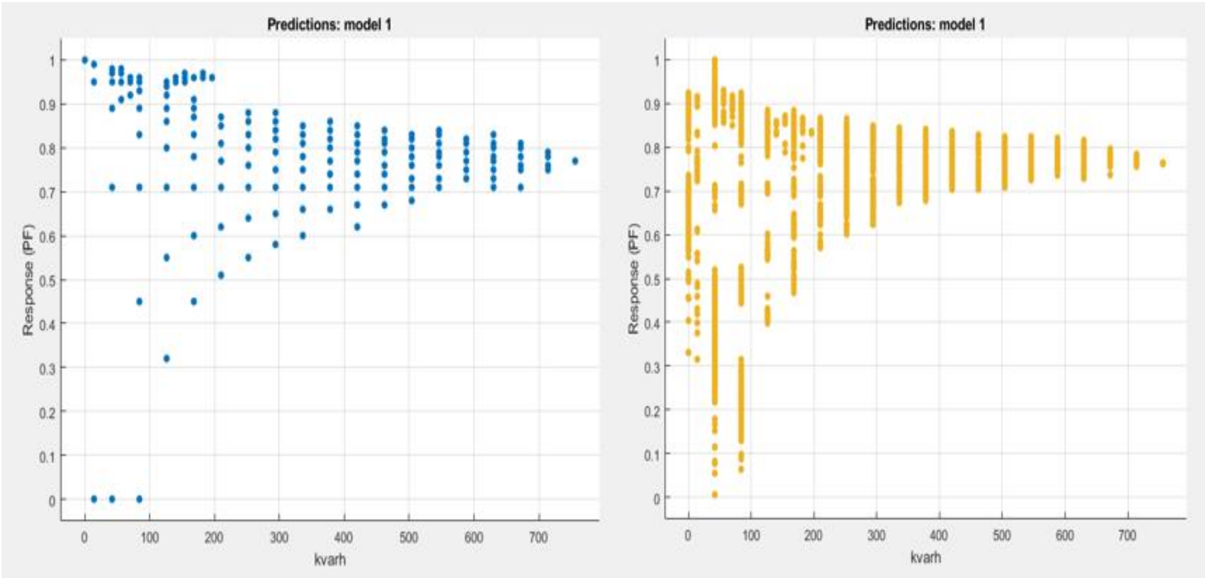


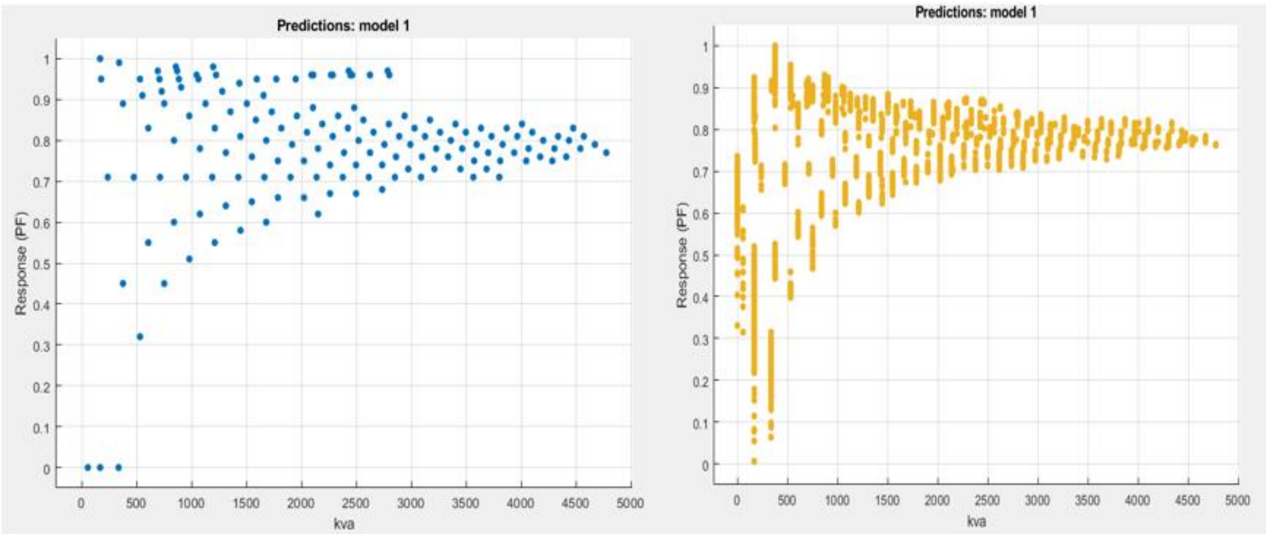
Fig. 6. kVar graph of the baseline & trained data



Baseline KVarh

Predicted KVarh

Fig. 7. kVar-h graph of the baseline & trained data



Baseline kVA

Predicted KVA

Fig. 8. kVA graph of the baseline & trained data

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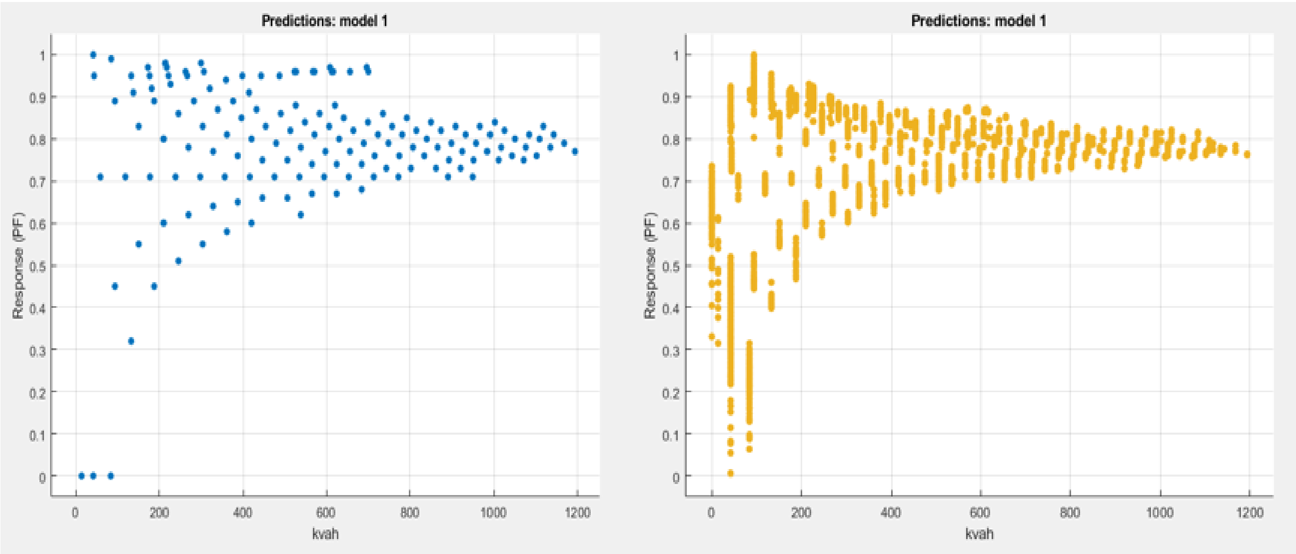

Baseline kVAh Predicted kVAh

Fig. 9. kVAh graph of the baseline & trained data

5. Analysis and Experimental Results Summary and conclusion

A measure of how well a model fits the data is R-squared. The target variable's variance is 84% explained by the model, according to the R-squared value of 0.84 found in this experiment. MSE is a different way to quantify the discrepancies between the target variable's predicted and actual values. In this experiment, the mean of the squared errors, or MSE, was calculated to be 0.0044997. The target variable's expected and actual values are separated by an absolute amount known as the MAE. The average absolute error of the model's predictions from the actual values is 0.018981 units, according to the MAE value this experiment yielded.

Overall, the model appears to be performing reasonably well with an R-squared value of 0.84 indicating that the model is able to explain most of the variance in the data. The RMSE score of 0.067079, however, indicates that there is still some room for the model's predictions to be improved.

6. Conclusion

The model with an automated box constraint, an epsilon value, and a kernel value of 0.66 performed reasonably well in terms of predicting the target variable. The RMSE value of 0.067079 and the MAE value of 0.018981 show that there is still space for improvement in the model's predictions, but the R-squared value of 0.84 indicates that the model is able to explain the majority of the variance in the data. The experiment's findings show that the model is a viable strategy for power demand forecasting with comparable predictions and better than the traditional methods. With the help of the results, management is able to improve judgments, use energy more efficiently, cut costs, avoid fines and surcharges, and reduce costs through energy usage optimization.

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Conflict of interest

The authors declares no conflict of interest

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Integration of Renewable Hybrid Energy System: A State of Art

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Abstract

The presence of sunshine, air, and other resources on Earth must be used in a manner that promotes human well-being while safeguarding the environment and its inhabitants. The use of sunlight and air as a significant Renewable Energy (RE) source has been a critical area of innovation or new product development in recent years. But integrating AI and ML with renewable energy can be a breakthrough for the whole world. Artificial intelligence (AI) and machine learning (ML) have the potential to significantly contribute to the effectiveness, efficiency, and cost-cutting in the production of solar and biodiesel energy. The output of solar energy may be analyzed and expected based on weather patterns using ML algorithms, and the distribution of biodiesel fuels might benefit from AI's assistance in improving the supply chain. Artificial intelligence and machine learning will help the renewable energy industry expand, which will have a beneficial effect on the planet. So, the major focus of this paper is Artificial neural networks (ANN). The primary emphasis of the introductory section on ANNs in Renewable Energies is on their usage in Solar and Biodiesel. In the realm of Renewable Energies, ANNs have shown to be invaluable instruments for the prediction, control, and optimization of a wide range of systems. Advanced technologies like, Photovoltaic power prediction, maximum power point tracking, and optimum size of photovoltaic systems are just some of the ways that ANNs have been put to use in the Solar Energy sector. Artificial neural networks (ANNs) have been employed in the biodiesel industry for a variety of purposes, including the forecasting of fuel qualities, the improvement of the transesterification process, and the forecasting of engine performance. These examples show how ANNs may be put to good use in the Renewable Energy sector, where it can address a wide range of problems in an efficient and effective manner.

Keywords: Artificial Neural Networks (ANN); Photovoltaic system; Solar energy; Smart grid; Biodiesel energy; irrigation system; Wind energy; Renewable energy; Hybrid Energy Storage System

1. Introduction

The use of solar energy has been validated as a kind of renewable energy. Keeping tabs on and anticipating photovoltaic energy production may assist cut down on energy waste and free up resources for greater use. [1] Due to variations in solar radiation and weather, forecasting solar energy is difficult. Intelligent solar system development is greatly aided by the use of Machine Learning methods. The input utilized to predict solar power output includes data like, such as temperature, humidity, and photovoltaic panel data. The experimental findings demonstrate the success in identifying the dead states of individual panels, and the time series-based solar energy forecast is a close approximation of the actual power output. [1] The solar panel real-time tracking system developed is capable of recording and analyzing real-time data pertaining to various parameters such as current, voltage, power, light intensity, and position of the solar panels. The system operates effectively, seamlessly transmitting measurements to the server. The precision of the current and voltage sensors integrated into the solar panel performance monitoring system plays a crucial role in determining the accuracy of the readouts for the solar array's output parameters. A solar tracking system that uses GPS and an image sensor to determine the sun's azimuth angle using ANN-based Image Processing (IPT) Techniques. With the use of IP algorithms and an AI decision-making process, we can tell whether the sky is clear or overcast just by looking outside. To some extent, the sun-tracking system may be used to validate the applicability of scientific computations based on the observed data. The suggested high-tech setup is tested and proven effective using experimental findings that are shared through a cloud storage service for synchronization purposes. So, Hemmati [2] investigated about the ease of installation and maintenance of solar power systems has led to their extensive use in both residential and industrial settings. Solar power, on the other hand, is notoriously high-maintenance once it's up and running. The paper's suggested work seeks to offer a service warning based on the current and voltage produced by the solar panels. The adjusted values of the solar panel are evaluated to the data from the solar panel systems under varying solar radiation conditions. When there is a significant shift in the solar panels' output, the suggested model will send out a warning to the service crew. So, the below figure-1 represents the smart solar system integrated with the IoT could system with the error estimation feedback.

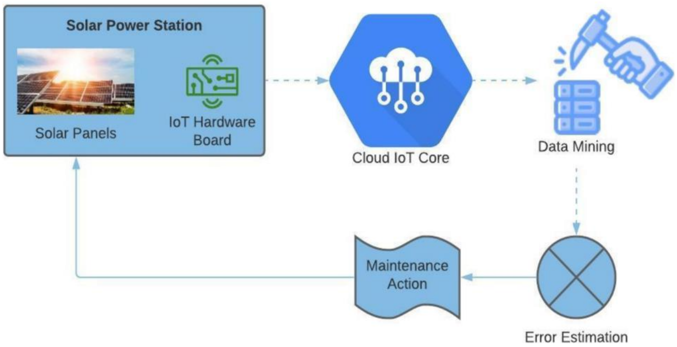

Fig.1 - Block diagram of solar system with cloud IoT [1]

So [2] **,** [3] the best practices for using photovoltaic power and learning about single and dual axis tracking systems are summarized in this paper.

The LDR's resistance and conductivity are what allow for the estimation of brightly lit regions. As compared to the status quo, the proposed strategy increases electricity generation by 25%. A total of 200 watt-hours per day are generated by the system. This new model will be compared to the present one at a power consumption level of 100 watts per day. So, the below figure-2 presents the Naïve Bayes Algorithm is automating the solar panel direction.

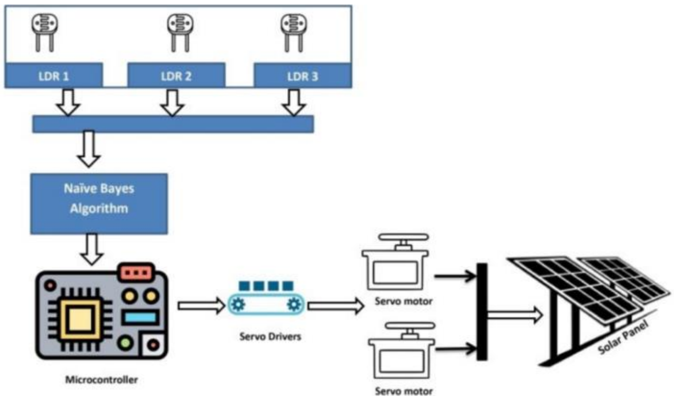

Fig. 2 - Naïve Bayes Algorithm is automating the solar panel direction [3]

So, there are some project's significance lies in its potential to boost solar panel efficiency through the use of locally sourced solar tracking technology. [4] When putting this technology into practice, precise control is essential for creating a sophisticated tracking system. Here, with the integration of GPS and ANN, the sun's azimuth angle has been calculated. Even nowadays the solar panels are getting protected from the heating issue using the IoT technologies.

2. Introduction to AI and ML in Renewable Energies Solar and Biodiesel

Basically, machines that exhibit intelligence similar to that of human beings are said to have artificial intelligence (AI). It incorporates a wide range of AI methods, from heuristic algorithms and machine learning to fuzzy logic and the semantic web. The goal of AI is to have robots do tasks traditionally performed by the human brain and to reduce the human intereface to increase the efficiency [4][5][6]. It is largely used to anticipate supply chain modelling, optimization, the performance of end-use systems for bioenergy, the performance of conversion processes, and the properties of biomass and biofuels. Artificial neural networks (ANN), regression, and analytical approaches are now popular modelling tools in internal combustion engine research. Optimization strategies recommended include Response Surface Methodology (RSM), Genetic Algorithms, and Taguchi Methods.

The most important branch of artificial intelligence, machine learning (ML) algorithms are designed to analyse data behaviour and are [6] usually used to carry out specialised learning and logical reasoning tasks without the need for explicit instructions. Machine learning (ML) algorithms have been used in many fields in the last several decades. These fields include internet search, autonomous vehicles, voice recognition, and even human genome mapping., extreme learning machines (ELM), support vector machines (SVM), recurrent neural networks (RNN), Artificial neural networks (ANN) ensemble learning (EL), and random forests are only some of the ML methods we found to be widely used for solar energy prediction. Even, May et.al [6] has proposed an idea about the artificial neural network approach that is presented in this paper for microgrid optimization through load prediction and management using renewable energy sources. The hybrid energy system comprises several components, including a photovoltaic array, wind turbines, the public power grid, electric loads, and a battery bank for energy storage. In order to minimize costs and enhance efficiency, an advanced dynamic neural network is employed to determine the optimal energy harvesting strategy for each source. Through extensive simulations, the results demonstrate the effectiveness of the proposed design in efficiently generating energy from all available sources. So, in this way AI and ML have become so important in the renewable energy sector. Sanz et.al [7] has discussed that in machine learning, feature selection is crucial for solving both classification and regression issues. In the most major renewable energy sources, such wind, solar, and marine resources, feature selection seems linked to prediction systems. For better performance, wrapper FSP methods are the most popular. They consist of several algorithms, the most popular of which are those that facilitate rapid learning. This method integrates several search techniques into a unified algorithm, yielding a powerful, comprehensive search across multiple levels. An Extreme Learning Machine has been used for forecasting. Comparisons are made with other regression methods to determine how well the system performs in a problem of wind speed prediction utilizing input from numerical models and actual data from a wind farm in Spain. And so, the below figure-3 is describing the process of Predicting wind speed using a hybrid CRO-SL-ELM system with feature selection.

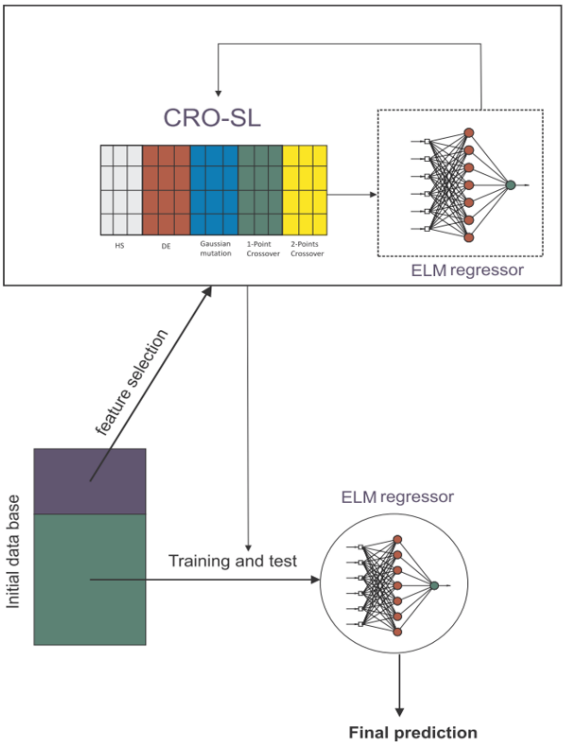

Fig 3. Using a hybrid CRO-SL-ELM system with feature selection to predict wind speed [7]

2.1. Artificial Neural Network (ANN)

Inspired by the structure of neurons in the human brain, artificial neural networks (ANNs) are a collection of nonlinear models built to process information. Artificial neural networks (ANNs) are made up of many individual nodes that are linked together to form a larger network that generates a desired output via some activation function. The output of an ANN is affected by the strength of the weights assigned to the connections between the nodes. An ANN's memory and computational prowess are the result of its network's weights, activation functions, and other configuration parameters. Due to its amazing approximation of nonlinear connections, ANNs have found widespread application in solar energy forecasting. The bulk of these data-driven strategies, on the other hand, have a low level of transparency, which is the main rationale for referring to the entire spectrum of models as "theory-free." Simply simply, ANN-based modelling systems are inspired by the brain's neurological processing capabilities. As a result, the accompanying figure-4 illustrates how ANN is employed in the automotive industry, particularly in engine operations, and how many parameters depend on ANN.

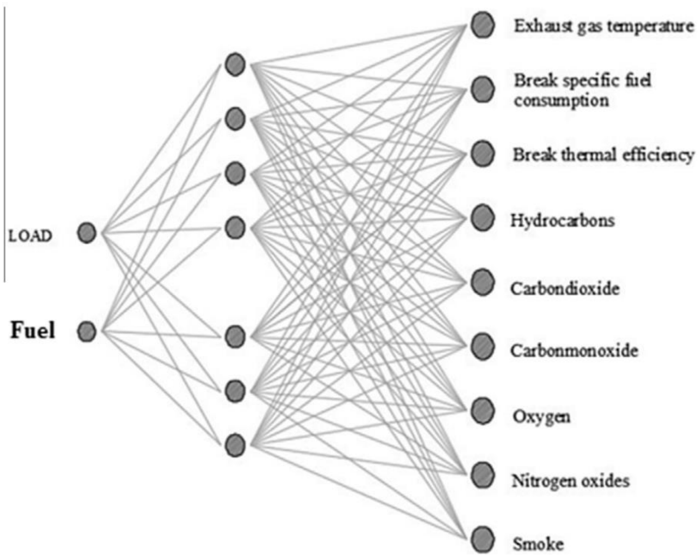

Fig. 4 Nine parameters for measuring engine performance are shown [8]

2.2. Fuzzy logic and Evolutionary Algorithm

Now if we talk about Boolean logic, which only allows for true or false answers, fuzzy logic allows for a "degree of truth" to be assigned to a statement's truth value. FL mimics human decision-making in this way. FL uses conditional "if-then" In order to define systems, there are rules that govern how components interact. Due to its simplicity and adaptability, this approach can deal with ambiguous and incomplete information in real-world issues. This technique has mostly been used to control issues in CST technology. The image is a more modern example. The work of Rubio et al.[9] who used fuzzy logic to control the temperature of the fluid that exits the receiver tube using a dispersed collector field, is an example of the work done by Xu et al.[10] who developed a Direct Steam Generation (DSG) parabolic trough plant's outlet steam temperature control approach. Fuzzy logic can act as the brain's clever emulation in coping with ambiguity in the natural world. It employs fuzzy sets and membership functions as well as qualitative data and experience with hazy boundaries to carry out regular reasoning. Fuzzy logic can handle the issue using normal fuzzy information and is good at forming judgments based on erroneous non-numeric data.

2.3. Simulated Annealing

Also, there are many algorithm like genetic so, Genetic algorithms imitate the natural processes of reproduction and selection. First, a randomly selected starting population of candidates for the issue is made. The fitness function evaluates each candidate's "fitness," and the best responses are chosen to create the subsequent population of responses using certain heuristics, such as crossover and mutation operators. The pairing-up and DNA-exchange mechanisms utilised by two chromosomes are comparable to the crossover operator. The mutation operator is used to preserve diversity in the population by altering a few genes in the DNA sequence. For instance, Cabello et al. [11] suggested a condensed GA-based model to maximize annual profit by optimizing the size of a parabolic trough collector, which was inspired by the inaccuracy of standard approaches. The algorithm was also utilized to reduce expenses and losses related to solar power plants using parabolic dishes Cumpston and Pye [12] Simulated annealing (SA) is a stochastic technique for roughly estimating the global optimum of given functions, in the same way. It is driven by thermodynamic principles. The parameter space may be effectively searched for multiple probable local minima using these sorts of techniques.

3. Biodiesel

Biodiesel is chemically similar to diesel fuel, which makes it a drop-in replacement for diesel engines. When used in diesel engines, biodiesel can help to reduce greenhouse gas emissions and other air pollutants, as well as promote energy independence by reducing the need for imported petroleum. The production of biodiesel involves a process called transesterification, in which the glycerol and fatty acids in a bio-oil are separated and recombined to form a new substance with improved combustion properties. This process also removes impurities and improves the stability of the fuel. One of the main advantages of biodiesel is that it is made from renewable resources, which makes it a sustainable alternative to diesel fuel. Unlike petroleum, which is a finite resource that will eventually run out, it can be produced from crops and waste products that can be continuously replenished.

Table 1 *Comparison of deep learning algorithm*

Algorithms	Advantages	Disadvantages	Relevant situations
CNN[7]	capable of processing picture data and strong feature extraction abilities.	Calculation was inefficient; the features could have been better predetermined.	Images are either already present in the solar energy data or can be created from it.
DBN[9]	Ability to extract features unsupervised; high computing effectiveness.	impede the processing of data about solar energy in several dimensions.	Unrecognizable characteristics of solar energy.
SAE [10]	Possibility of unsupervised feature extraction; simplicity of implementation.	Network optimization is challenging.	Data about solar energy has to be reduced in dimension.
GAN [11]	capacity to produce fresh data with distribution according to the supplied data;	not being able to adequately explain the characteristics of the incoming data;	There are several gaps in the solar energy statistics. low efficiency of computing

3.1 An Introduction to the Production of Biodiesel

Clean burning, a pleasing aroma, and the capacity to decompose naturally all contribute to biodiesel's attractiveness as a diesel alternative fuel. It's eco-friendly since it may be made from recycled oil and animal fat. Biodiesel may be used as a heating oil, plasticizer, power generator, high-boiling absorbent for industrial pollution removal, lubricants and solvents, in addition to its core usage as a transportation fuel. Biodiesel is mechanically interchangeable with regular diesel in all respects, including cetane rating, viscosity, energy content, and phase transitions. Also, by opening up new markets for agricultural goods, the use of biofuels has the potential to revitalise rural communities.

3.2 Utilizing machine learning in the manufacturing of biodiesel

According to ASTM, biodiesel is a blend of fatty acid alkyl esters that are made from sustainable resources, including recycled animal fat, vegetable oil, and other oils. [13] Oil extraction, biodiesel washing, trans-esterification reaction, glycerin neutralization, product separation, unreacted alcohol recovery, and biodiesel purification are all steps in a typical biodiesel manufacturing process. Many ML applications are investigated and evaluated throughout the crucial steps of biodiesel manufacturing in this investigation.

3.2.1 Hydrolysis and fermentation

All reviewed AI studies centre on enzymatic hydrolysis, one of the most common methods for converting biomass into sugar, which is then fermented to make bioethanol. All AI studies for enzymatic hydrolysis had the objective of predicting sugar yields, even if additional metrics like the yields of glucose, xylose, or total reduced sugar were also used. Different enzyme data (such as xylanase, cellulose, -amylase, and -glucosidase) were utilised in each study's input variables depending on the kind of enzyme used Astray et al.[14]. Traditional modelling techniques, such as those created for enzymatic hydrolysis and mechanistic kinetic models, typically fall short when attempting to simulate prolonged response periods Jeoh et al.[15]. Traditional modelling techniques, such as those created for enzymatic hydrolysis and mechanistic kinetic models, typically fall short when attempting to simulate prolonged response periods. Traditional modelling techniques, such as those created for enzymatic hydrolysis and mechanistic kinetic models, typically fall short when attempting to simulate prolonged response periods.

4. Application of ANN in Renewable Energies Solar and Biodiesel

In this research, P.N and Sindhu [16] has researched a maximum power point tracking (MPPT) strategy that makes use of an artificial neural network and then evaluate its performance in comparison to that of three more traditional MPPT algorithms. The sun irradiance and temperature are sent into the ANN, and the duty ratio for the boost converter is the output. "nntool" is a MATLAB/SIMULINK tool used for ANN training. The findings of this comparison demonstrate that ANN based MPPT controller outperforms the other maximum power point tracking algorithms in terms of performance metrics like steady state error and speed of reaction to rapid changes in solar temperature and irradiance. Based on the findings, it is determined that ANN-based MPPT outperforms traditional MPPT methods in terms of output power, steady-state oscillations, and settling time.

So, the below figure-5s is representing the block diagram of the MPPT integrating with the ANN.

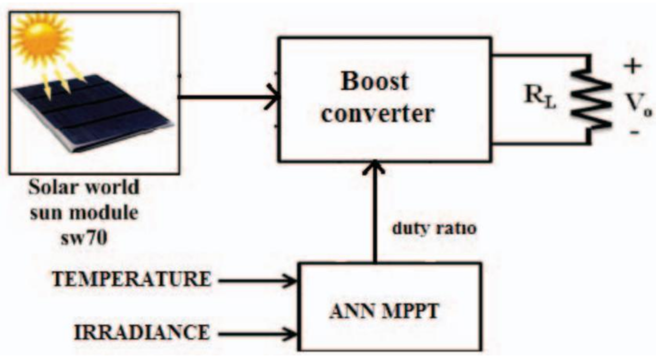

Fig. 5. ANN is integrated with MPPT and Boost Converter [16]

So, in the same way Sun et al. [17]has presented a single-phase residential solar PV system that uses artificial neural networks and adaptive dynamic programming for maximum power point tracking control and grid integration of a solar photovoltaic array through an LCL-filter based inverter. The optimum control based on approximative dynamic programming is implemented by the suggested artificial neural network controller. The simulation and hardware experiment results show that the ADP-based artificial neural network controller provides superior performance to proportional resonant and conventional standard vector control techniques for solar PV systems.

5. Summary and conclusion

The renewable energy research community has been successful in applying industry 4.0 methods to several steps in biofuel production, but has yet to create an AI or ML-driven feedstock-to-pump conversion model. Previous research indicates that a smart biofuel manufacturing process is possible; however, a bigger dataset for biofuel production is required for the proposed technique to effectively reduce costs. While the full potential of the proposed MI-based framework for cost reduction has yet to be realized, it shows promise. This research aimed to identify examples of AI-ML use in renewable energy production and better understand best practices by looking at the use of AI in biofuels production and Industry 4.0 initiatives. Energy and biofuels production-centric advanced manufacturing techniques have been investigated. Although most examples demonstrated the value of incorporating AI into certain stages of the process, it is clear that the technology will only live up to its full potential when it is used to oversee and direct the whole operation. Before the mentioned approaches are used commercially, considerable emphasis should be placed on improving the conversion technology in order to increase the technology's scalability. Several reasons contribute to the increasing enthusiasm for using the ML method to biodiesel systems. Superior biodiesel quality, lower operating costs, less water and fewer chemicals, automated biodiesel plants, testing biodiesel's compatibility with engines, standards compliance, diesel engine tuning with biodiesel blends, and peak performance are all goals to strive for. The use of ML technologies to mimic small-scale biodiesel systems for use in the lab has received a lot of attention. However, there are no ML-based techniques for real-time observation or management of running biodiesel systems. Since it is generally known that ML techniques, especially cutting-edge deep learning approaches, are sufficient for basic modelling of future lab-scale biodiesel systems, it appears that more research on the issue is not essential. Instead, researchers need to look at how to monitor, manage, and optimise industrial biodiesel systems in real-time using ML technology. Before implementing the suggested ML-based monitoring and control systems in larger-scale industrial applications, it is advised to evaluate them on lab-scale small-scale biodiesel systems. In spite of ML technology's reliability and advantages over more conventional modelling techniques, it is not a silver bullet for addressing all problems and knowledge gaps in the biodiesel field. This technology may work best as an adjunct to existing procedures rather than as a substitute for them.

As compared to ML models, which may provide easily digestible results, black-box approaches are preferred. As a result of their advantages over pure ML models in interpolation and extrapolation, hybrid ML methods are being considered as viable solutions for biodiesel system monitoring, control, and optimization. To further improve the precision and consistency of ML models, sophisticated stochastic metaheuristics should be utilised to optimise and modify the topology and training parameters. Current hardware and software improvements will allow for the development of reliable and accurate ML-based soft-sensors for use in real-time monitoring and management of biodiesel systems. The present review paper aims to inspire further study into the development and use of advanced measuring techniques are combined with real-time ML-based monitoring and controlling systems for biodiesel plants. Nevertheless, their hefty initial investment is preventing their widespread use in biodiesel systems. ML technology has the potential to be used successfully across the whole of the biodiesel supply chain, from initial feedstock selection and oil extraction through final product refinement and quality control, accumulation, gearbox, and combustion. Extremely advanced machine learning are far more successful and valuable than it is already in practically all fields of biodiesel research.

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Conflict of interest

The author declares no conflict of interest

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