

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.

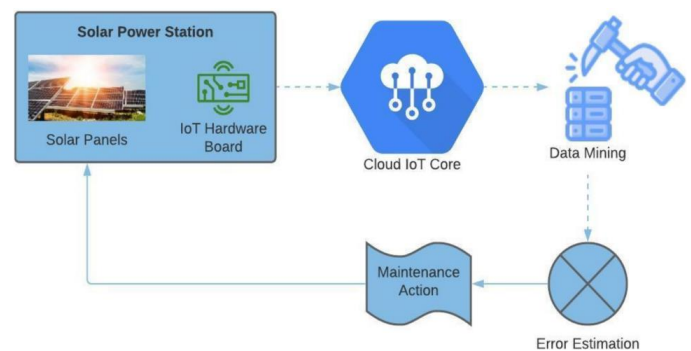


Fig.1 - Block diagram of solar system with cloud IoT [1]

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.

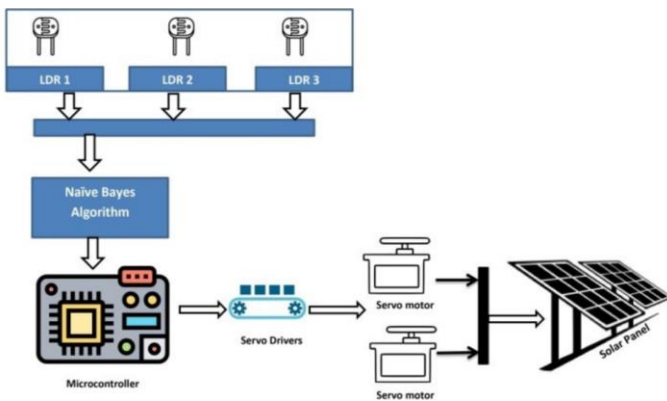


Fig. 2 - Naive Bayes Algorithm is automating the solar panel direction [3]

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 interface 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.

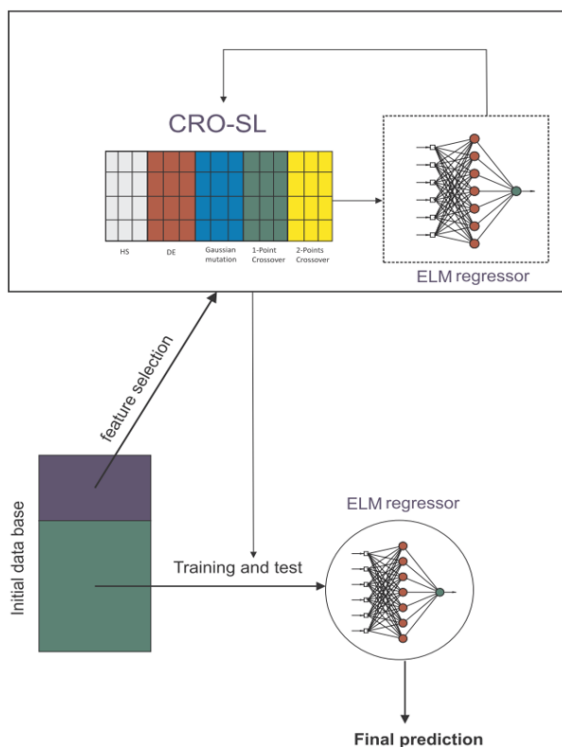


Fig 3. Using a hybrid CRO-SL-ELM system with feature selection to predict wind speed [7]

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.

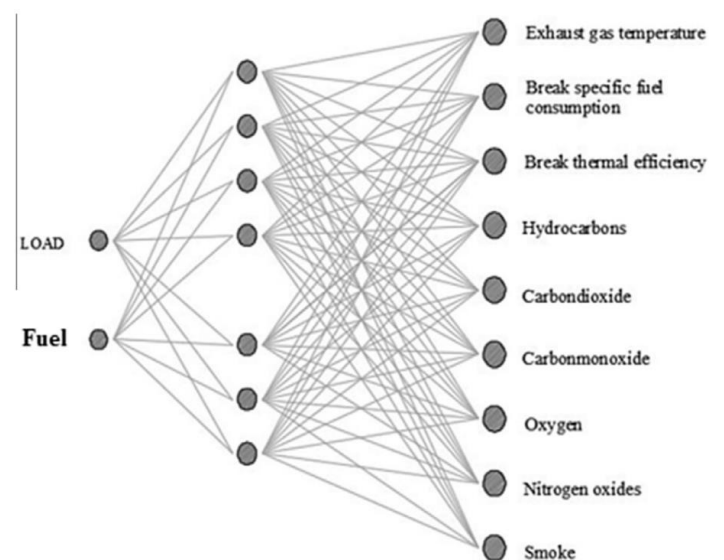


Fig. 4 Nine parameters for measuring engine performance are shown [8]



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.

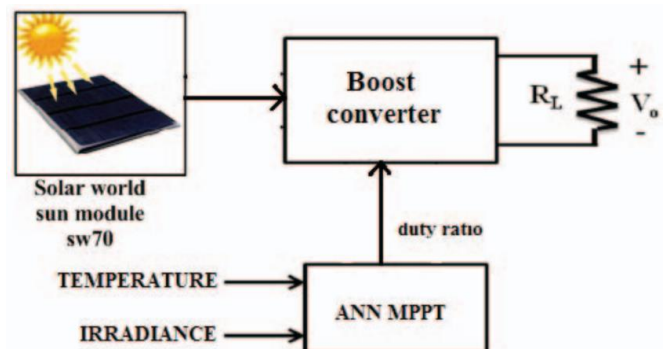


Fig. 5. ANN is integrated with MPPT and Boost Converter [16]

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

Permissions and rights

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References

- [1] I. M. Shirbhate and S. S. Barve, "Solar panel monitoring and energy prediction for smart solar system," *Int. J. Adv. Appl. Sci.*, vol. 8, no. 2, p. 136, 2019, doi: 10.11591/ijaas.v8.i2.pp136-142.
- [2] S. Shakya, "A Self Monitoring and Analyzing System for Solar Power Station using IoT and Data Mining Algorithms," *J. Soft Comput. Paradig.*, vol. 3, no. 2, pp. 96–109, Jun. 2021, doi: 10.36548/jscp.2021.2.004.
- [3] R. K. Kodali and J. John, "Smart Monitoring of Solar Panels Using AWS," in *2020 International Conference on Power Electronics and IoT Applications in Renewable Energy and its Control, PARC 2020*, Feb. 2020, pp. 422–427. doi: 10.1109/PARC49193.2020.236645.
- [4] S. Padma and P. U. Ilavarasi, "Monitoring of Solar Energy using IOT," *Indian J. Emerg. Electron. Comput. Commun.*, vol. 4, no. 1, pp. 596–601, 2017.
- [5] M. N. A. Mohd Said, S. A. Jumaat, and C. R. A. Jawa, "Dual axis solar tracker with iot monitoring system using arduino," *Int. J. Power Electron. Drive Syst.*, vol. 11, no. 1, pp. 451–458, Mar. 2020, doi: 10.11591/ijped.v11.i1.pp451-458.
- [6] I. D. Hashim, A. A. Ismail, and M. A. Azizi, "Solar Tracker," *Int. J. Recent Technol. Appl. Sci.*, vol. 2, no. 1, pp. 59–65, Mar. 2020, doi: 10.36079/lamintang.ijortas-0201.60.
- [7] M. Ali, M. P.-I. J. E. A. S. Technol, and undefined 2020, "An IoT based approach for monitoring solar power consumption with Adafruit Cloud," *ijeast.com*, vol. 4, pp. 335–341, 2020, Accessed: Jun. 29, 2022. [Online]. Available: <http://www.ijeast.com/papers/335-341,Tesma409,IJEAST.pdf>
- [8] S. K. Jha, J. Bilalovic, A. Jha, N. Patel, and H. Zhang, "Renewable energy: Present research and future scope of Artificial Intelligence," *Renew. Sustain. Energy Rev.*, vol. 77, no. April, pp. 297–317, 2017, doi: 10.1016/j.rser.2017.04.018.
- [9] P. C. Jena, H. Raheman, G. V. Prasanna Kumar, and R. Machavaram, "Biodiesel production from mixture of mahua and simarouba oils with high free fatty acids," *Biomass and Bioenergy*, vol. 34, no. 8, pp. 1108–1116, 2010, doi: 10.1016/j.biombioe.2010.02.019.
- [10] L. P. N. Jyothy and M. R. Sindhu, "An Artificial Neural Network based MPPT Algorithm for Solar PV System," *Proc. 4th Int. Conf. Electr. Energy Syst. ICEES 2018*, pp. 375–380, 2018, doi: 10.1109/ICEES.2018.8443277.
- [11] H. Qi, S.-C. Sun, Z.-Z. He, S.-T. Ruan, L.-M. Ruan, and H.-P. Tan, "Inverse Geometry Design of Radiative Enclosures Using Particle Swarm Optimization Algorithms," *Optim. Algorithms - Methods Appl.*, 2016, doi: 10.5772/62351.
- [12] O. Castillo, H. Neyoy, J. Soria, P. Melin, and F. Valdez, "A new approach for dynamic fuzzy logic parameter tuning in Ant Colony Optimization and its application in fuzzy control of a mobile robot," *Appl. Soft Comput. J.*, vol. 28, pp. 150–159, 2015, doi: 10.1016/j.asoc.2014.12.002.
- [13] A. Q. Mairizal et al., "Experimental study on the effects of feedstock on the properties of biodiesel using multiple linear regressions," *Renew. Energy*, vol. 145, pp. 375–381, 2020, doi: 10.1016/j.renene.2019.06.067.
- [14] S. O. Giwa, S. O. Adekomaya, K. O. Adama, and M. O. Mukaila, "Prediction of selected biodiesel fuel properties using artificial neural network," *Front. Energy*, vol. 9, no. 4, pp. 433–445, 2015, doi: 10.1007/s11708-015-0383-5.
- [15] T. F. Adepoju, B. E. Olatunbosun, O. M. Olatunji, and M. A. Ibeh, "Brette Pearl Spar Mable (BPSM): a potential recoverable catalyst as a renewable source of biodiesel from *Thevetia peruviana* seed oil for the benefit of sustainable development in West Africa," *Energy Sustain. Soc.*, vol. 8, no. 1, pp. 1–17, 2018, doi: 10.1186/s13705-018-0164-1.
- [16] M. E. Borges, L. Hernández, J. C. Ruiz-Morales, P. F. Martín-Zarza, J. L. G. Fierro, and P. Esparza, "Use of 3D printing for biofuel production: efficient catalyst for sustainable biodiesel production from wastes," *Clean Technol. Environ. Policy*, vol. 19, no. 8, pp. 2113–2127, 2017, doi: 10.1007/s10098-017-1399-9.
- [17] F. Ma and M. A. Hanna, "Biodiesel production: a review," *Journal Series #12109, Agricultural Research Division, Institute of Agriculture and Natural Resources, University of Nebraska–Lincoln*, vol. 70, no. 1, pp. 1–15, 1999, doi: 10.1016/s0960-8524(99)00025-5.