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Original Article

Customized IoT Hardware and Artificial Neural Network-Assisted System for Prediction of Solar Radiation and Wind Speed

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Abstract *- Renewable sources are essential in fulfilling affordable, clean, and sustainable energy requirements. Consistent wind speed forecasting and accurate solar radiation prediction are required to minimize economic losses and enhance the security of power usage. Predicting solar radiation and wind speed is difficult due to their uncertain behaviour. Motivated by these aspects, this study implemented an Internet of Things (IoT) and artificial neural network (ANN) based system for predicting solar radiation and wind speed. Initially, IoT and long-range (LoRa) enabled hardware was developed for obtaining real-time data. In this study, customized hardware was developed with the amalgamation of LoRa, WI-Fi and many sensors. Solar grid and windmill sensor nodes are customized hardware deployed to collect real-time data to create datasets that predict solar radiation and wind speed using wind speed, solar radiation, humidity, temperature, voltage, and current parameters. For the prediction, in this study, we have employed the ANN techniques, i.e., Levenberg Marquardt (LM) and Bayesian regularization (BR) methods. We have found that the proposed ANN framework using the LM algorithm provides accuracy in the prediction compared to the BR algorithm with less root mean square error (RMSE), mean square error (MSE), fast convergence speed, and more significant Correlation coefficient (R).*

Keywords *- ANN, IoT, LoRa, Renewable energy, Solar radiation, Windmill.*

1. Introduction

The United Nations (UN) sustainable development goals (SDGs) '7' ensure universal access to affordable, reliable, renewable, and modernized energy for all by 2030 [1]. To expand energy access, it is crucial to enhance energy efficiency and invest in renewable energy such as solar, wind, and thermal [2]. In addition, using renewable energy contributes to climate change mitigation and disaster risk reduction. About 11% of the World's electricity will provide by solar energy, according to the International Energy Agency (IEA), by 2050 [3]. About 1458 MW of total power capacity was installed by renewable energy as of 1999 [4]. In 2019, about 11% and 22% of the total energy generated annually is from wind and solar [5]. The utilization of renewable energy has increased by about 4.4% in the decade from 2009 to 2019 annually [6]. Generally, India mainly utilizes coal for power generation, and to minimise carbon emissions, India initiated to implementation renewable energy. By 2030, India aims to produce 60GW of electricity from wind and 100GW from solar power [7]. There is an increase in the cumulative capacity of wind power from 2001 to 2020, where it concludes that there is a rise in wind power installation from 24 GW (2001) to 743 GW (2020) [8]. The cumulative installed solar energy capacity from 2001 to 2020 where describes that solar energy capacity increases per year from 0.90GW (2001) to 707.50GW (2020) [9].

Now, India is the third largest renewable energy producer in the World. India aims to generate about 500 GW of renewable energy capacity by 2050. In India, renewable energy resources install 40 per cent of electricity capacity. Figure 1 represents the Installed capacity of non-conventional energy resources in India till 2022 from solar 48.55 GW (31%), wind 40.03 GW (25%), small hydro 4.83 GW (3%), large hydro. 46.51 GW (30%), biopower 10.62 GW (7%) and nuclear 6.78 GW (4%). Our country's target is to achieve zero emissions of greenhouse gases by 2070 by using non-fossil fuel resources [10].

Many parameters such as grid frequency, the output power of wind turbines, voltage stability and stable operation of power systems are affected due to the fluctuations in the wind speed. Hence, these parameters mainly depend upon accurate wind speed prediction [11]. The variation in the temperature and changes in air pressure in different places also affected wind speed. Wind speed becomes faster when the pressure difference is increased. Different seasons conditions, such as summer, winter, spring, and autumn, have different sources of wind energy [12]. Similarly, solar emissions depend on various parameters like solar elevation angle, the incidence angle of sunlight and the sun's height above the horizon and daytime. The elevation angle is zero after sunset and before sunrise; hence solar radiation is absent at that time [13].

Sometimes predictions go less accurate due to insufficient datasets, inefficient prediction methods, and systematic errors [14]. A real-time system and an effective ANN algorithm are necessary to accurately predict wind speed and solar radiation. In previous studies, most are highly focused on adopting the available data for prediction [15]. However, applying prediction to real-time data enables one to take immediate action as the data is updated continuously. Motivated by these aspects, this research aims to implement an IoT eco-system at the solar panel and windmill to obtain real-time data through sensors connected to it and predict the solar and wind speed depending on real-time data [16, 17]. In this study, we designed a low-cost IoT-based customized hardware for real-time solar radiation and wind speed prediction. We implemented ANN techniques, i.e., the LM and BR algorithms. Algorithms applied on real time data for improving accuracy of prediction. By comparing both models, the LM model generates better results with minimum errors and faster speed. The significant contribution of this work is stated as follows:

- Proposed architecture for customized hardware with solar sensor node, windmill sensor node, and gateway based on LoRa.
- To develop an ANN design for solar and wind speed prediction.
- To apply an efficient LM algorithm & BR algorithm to the input environmental parameters for accurate, fast, stable prediction with minimal errors.

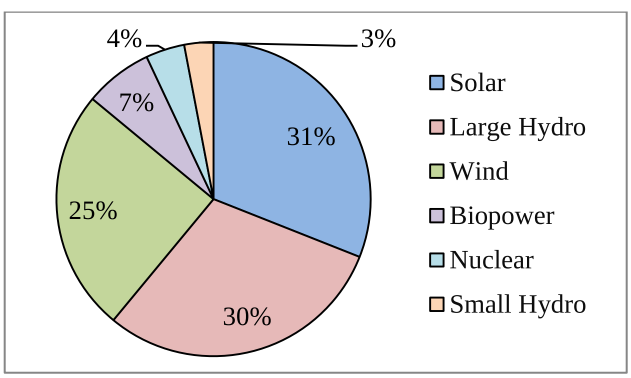


Fig. 1 Installed renewable energy capacity in India, 2022 [10]

The article's structure is as follows: Section 2 explains the work for predicting solar radiation and wind speed using ANN & IoT, and section 3 presents the ANN model. In section 4, we discussed the system architecture. Section 5 covers hardware description, Section 6 covers hardware implementation with results, and the conclusion and future work are explained in Section 7.

2. Related Work

ANN is important for wind energy prediction for sustainable development and power generation. Environmental parameters depend upon each other, and they have a correlation coefficient between them, such as monthly wind speed and atmospheric pressure have a relation with each other but depend upon location. Solar radiation received on Earth depends on various factors such as altitude, Sunshine duration, daytime, Atmospheric condition, latitude, dust particles, clouds, aerosols, humidity temperature, pressure and cloud cover. These factors enhance variation in solar radiation. Solar radiation decreases at the poles, and increases with altitude increases [18-19]. When temperature and average solar radiation increase, solar power generation increases. However, solar power is not much more dependent upon the change in wind speed [20].

Many equations and methods were used to measure the daily and monthly wind speed and solar radiation. Hargreaves' method of empirical equations, ANN method [21], and multi-linear regression (MLR) method were predicting solar radiation. When parameters such as extra-terrestrial radiation & the square root of the daily difference in temperature were used in the MLR and ANN techniques, the accuracy was improved [22]. The adaptive neuro-fuzzy model is used to optimize the design of wind farms and wind turbines. ANN is used for fault detection in a wind turbine with more excellent reliability and maintenance planning [23].

ANN technique has given better performance and accuracy than the linear and non-linear regression methods for wind speed forecasting [24]. NAR and NARX models are the two ANN techniques that performed better than the persistence method for wind speed prediction. The NARX method gives a low mean square error and accurate results compared to the NAR model [25]. Hybrid methods provided more stability and improved accuracy than individual forecasting models [26].

Hybrid models of Recurrent Kalman Filter (RKF), Wavelet and Artificial Neural Network (WNN), and Time Series (TS) provided wind speed prediction improved accuracy of the complete forecasting system [27]. A single ANN technique does not give better results than a hybrid ANN model. A Hybrid method improves the stability of a single ANN model for long-term and short-term wind speed prediction. The Hybrid generative adversarial network (HGANN) framework is used for ultra-short-term wind speed forecasting to improve generalization problems, increase prediction power, minimize computational cost, and reduce error convergence [28].

A hybrid model of particle swarm optimization (PSO) and Extreme Learning Machine (ELM) predicted daily global solar radiation as associated with the other ML algorithms such as extreme learning machine, SVM, M5 model tree, autoencoder and generalized regression neural networks [29]. ANN models such as cascaded forward neural network (CFFN), Elman forward neural network (EMNN) and Feedforward neural network (FFNN) are employed to predict global horizontal irradiance prediction. These models provided better prediction with more accuracy and less RMSE, MBE and MAPE error than the satellite data.

FFNN was found better performed for the daily prediction of global horizontal irradiance (GHI), whereas EMNN performed better for monthly and annual prediction of GHI [30]. ANN implemented with the combination of long short-term memory (LSTM) and convolutional neural network (CNN) for estimating hourly worldwide solar radiation for East and North Africa provided minimum error and long-term computational dependency. The hybrid CNN-ANN model provided the best result for Southern, West, and Central Africa [31]. The LSTM model designed with genetic algorithm (GA) and attention mechanism (AM) gave accuracy in prediction and speed of the model. The AM determines the attention degree of various features. The GA provided an optimal solution, and the LSTM model reduces problems such as slow parameter update and too long training time [32].

Different sensors and control units are used to measure and control environmental parameters. Depending upon the application, we are using different sensors and control units. IoT technology-based systems are used for checking the state of wind turbines and finding the faults in wind turbines [33]. IoT-based systems can increase power levels and improve the efficiency of power systems. Using IoT, things are connected through the internet. In IoT, the technology consists of sensors, protocols, nanotechnology, and intelligent technology. We can achieve brilliant work, tracking, and monitoring through this technology. Innovative IoT-dependent monitoring system for power generation improves reliability and stability [34].

IoT technology is applied for wind prediction with the help of a wireless sensor network (WSN). The input parameters of wind are collected in real-time, and prediction is made using accurate data. Data parameters such as pressure, humidity, temperature, and wind direction are used for prediction. So that power is predicted more efficiently and accurately [35]. Data transmission is also done by ZigBee technology. ZigBee technology has low energy consumption, but its range is small, i.e. 10 to 100 m. LoRa also has a low power consumption, but its range is extensive compared to ZigBee, i.e. urban areas have 2 to 5 km, and suburban areas is 15 km. Therefore, we are using LoRa for transmission. Wireless communication is better than wired communication as it is cost-effective and does not have limitations of distance range [36]. We have used IoT platforms for prediction because it provides the best choice for selecting reliable and cost-effective technology for our application. We have used real-time analytics to provide visualisation using a cloud server. Cloud computing used is the combination of two services, internet and processing services. We use cloud computing to process big data and complex computations [37].

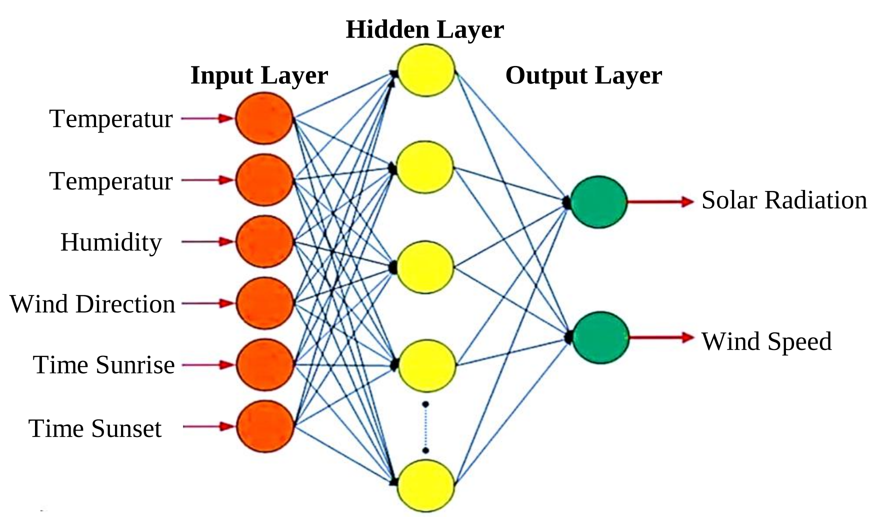


Fig. 2 ANN model

After reviewing many research papers in Table 1, we have observed that artificial neural network models enhance reliability, accuracy, stability, and system optimization compared to other models. It helps to detect faults and minimize errors in solar and wind prediction low-cost customized hardware designed using a LoRa modem and different sensors. BR and LM learning algorithms were implemented for predicting accurate solar radiation and wind speed. These machine-learning algorithms provide better results than other models discussed in a detailed review regarding speed, accuracy, reliability, curve fitting and generalization. IoT platforms are also used for the collection of real-time environmental parameters.

3. Artificial Neural Network

ANN is a biological neural network that resembles the human brain. It consists of neurons that relate to each other. Its structure is like the biological system. In the case of artificial neural networks, dendrites consider as input, cell nucleus are named nodes, synapses are the weights, and axons are known as output [38]. Like the human brain, ANN understands things, make decisions, and learns by example. The ANN model consists of the input, hidden, and output layers. The input layer accepts input according to the programmer used. The middle-hidden layer performs mathematical calculations, and the output layer provides output. It consists of one input layer of four neurons. Input parameters are temperature, humidity, pressure, sunrise, sunset, and wind direction. Two outputs are solar radiation and wind speed. There is one hidden layer shown in Figure 2. Hidden layers can have many numbers of neurons depending upon the application used. Artificial neural network output depends upon various parameters such as bias, weights, batch size, and learning rate. Every network node has weights and transfer functions for calculating the sum of weights and bias. The output (equation 1) is given by inputs multiplied by their weights and passes through the transfer function.

$$y = \sum_{i=1}^{n} w_i * x_i + b \quad (1)$$

The log sigmoid function is a transfer function for generating output between 0 and 1. This transfer function reduces the computational burden in the training process. We have analyzed many research papers in which various ANN techniques are used. In Table 1, we have discussed the conclusion of some ANN techniques. By observing various statistical parameters such as MSE, MAE, R, MAPE, and RMSE, we can find an ANN-efficient algorithm for wind and solar prediction.

Table 1. Previously used ANN techniques and their comparison

Techniques	Prediction Parameter	MAPE	RMSE	R
Empirical equations, such as Multi-linear regression methods (MLR), Hargreaves method, ANN[22].	Solar radiation	---	3.166 3.314 3.840	0.940 0.934 0.910
ANN Linear Regression (LR) Non-Linear Regression (NLR) [24]	Wind speed	7.9244 9.069 9.1144	0.2027 0.2080 0.2077	0.9076 0.8875 0.8889
Support Vector Machine (SVM) Multilayer Perceptron (MLP) [39]	Daily and monthly global solar radiation	8.940 8.950	1.524 1.596	0.986 0.970
Persistence model, gradient boosting regression tree LSTMDE-HELM ANN [40]	wind speed	5.13162 5.17290 4.84868 5.33199	0.69814 0.70315 0.6582 0.71869	0.95910 0.95851 0.96334 0.95814
Deep learning [41]	Solar radiation	--	0.78	0.980
RRBFNN [42]	Wind speed prediction	1.0165e-05	1.2715e-06	---
Autoregressive Integrated Moving Average (ARIMA), ANN, ARIMA-ANN [43]	Wind Speed	---	---	---
Persistence, BPNN [44]	Wind Speed	---	---	---

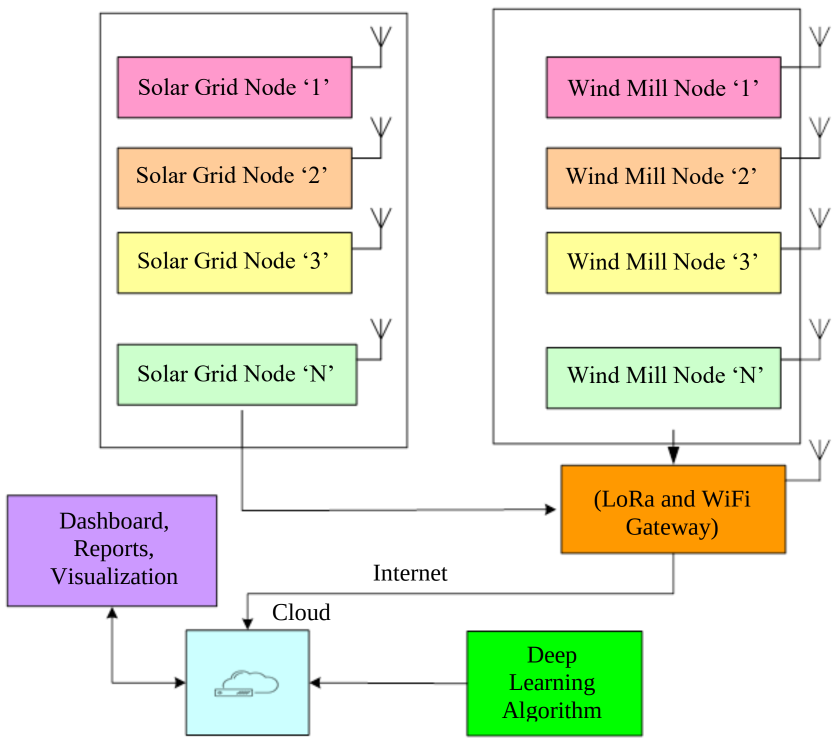


Fig. 3 System architecture

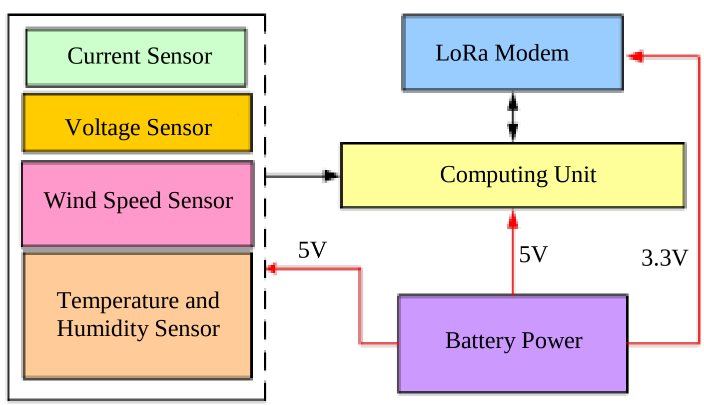


Fig. 4(a) Windmill node

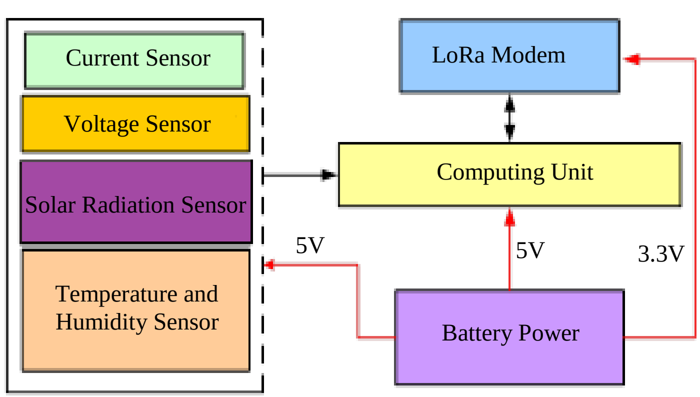


Fig. 4(b) Solar grid node

Table 2. Technical specifications of ATMEGA 328P [42]

Parameters	Details
Controller	8-bit Microcontroller
Pins	32
Architecture	Advanced RISC
Serial communication interface	• Programmable serial USART • Master/slave SPI serial interface • I²C
Operating voltage	2.7 V-5.5 V
Current	Power-down mode: 1µA at 3V Active mode: 1.5mA at 3V - 4MHz
Temperature limit	-40°C to +125°C
PWM channels	6

Table 3. Specifications of ATMEGA 2560

Characteristics	Specifications
Controller	CMOS 8-bit Microcontroller
Pins	100
Architecture	Advanced RISC
Serial communication Interface	• Programmable serial USART • Master/slave SPI serial interface • Byte-Oriented 2-wire Serial Interface
Current	Active 4MHz, 3.2 mA and max. 5mA at 3V Power-down mode: WDT enabled <5µA and max. 15 µA at 3V
PWM channels	12
ADC Channel	8

It is observed that solar radiation and wind speed are changing non-linearly. ANN is the best technique to analyze non-linear parameters for accuracy. LM algorithm is the best learning algorithm among other previously used ANN techniques.

4. System Architecture

Implementing IoT network infrastructure in monitoring the solar panels and windmill is highly significant for the prediction [45, 46]. Figure 3 presents the proposed architecture, in which the windmill node and solar grid node are embedded with LoRa-based communication protocol to transmit the real-time sensor data to the cloud for prediction. Both windmill and solar grid nodes are integrated with multiple sensors to obtain environmental data. The Windmill and solar grid nodes communicate the sensor's information to the LoRa-enabled gateway, which is also embedded with a Wi-Fi module.

Table 4. Specifications of SX1278 LoRa [56]

Characteristics	Specifications
Antenna	50 ohm
Pins	14
Frequency	433 MHz
Operating Voltage	1.8V to 3.6V
Modulation	FSK, GFSK, MSK, GMSK, LoRa™ and OOK modulation
RSSI	127dB
maximum link budget	168 dB
Programmable bit rate	300 kbps
Network Topology	Point-to-Multipoint, Point-to-Point, Mesh and Peer-to-Peer

The received information from both nodes is in the form of radio frequency (RF) packets; the Wi-Fi modem in the gateway converts the RF packet data into an internet protocol (IP) packet and logs it into the cloud server via internet connectivity. In order to predict, a deep learning-based ANN technique is applied to the sensor data on the cloud server.

5. Hardware Description

This section will discuss the hardware implemented for monitoring the solar grid and windmill. Here we have customized solar grid nodes and windmill mode for IoT-based real-time monitoring of environmental parameters shown in Figures 4(a) and Figure 4(b). Sensors like DHT11, voltage and current sensors are embedded in the solar grid node to monitor the temperature, humidity, voltage and current. The computing unit processes and computes weather station sensor data to increase efficiency and accurately measure data [47-49]. ATmega 328 is a computing unit in solar and windmill nodes. ATmega 2560 computing unit used in LoRa gateway. DHT11 sensor deployed to measure humidity and temperature. BH1750 sensor used for measuring light intensity in Lux. Cup-type anemometer used for measuring wind speed.

5.1. Computing Unit

ATmega328 computing unit is an 8-bit CMOS-based AVR microcontroller used as a computing unit consisting of 32 pins. It is primarily used in embedded systems and projects. It is mainly used due to its simplicity, low cost, and low power consumption [41]. Atmega328 TQFP micro controller is used in solar and windmill node. It has self-programmed flash program memory. ATmega328 micro controller chip is based on advanced RISC architecture. The operating voltage range of ATmega328 is from 2.7V to 5.5V. Its program memory (flash memory) size is 32KB, internal SRAM is 2KB, and EEPROM is 1024B.

It comprises one UART, two SPI and one I2C digital communication peripherals [42]. The specifications of ATmega 328P are given in Table 2. The ATmega2560 computing unit is used as a computing unit based on advanced RISC architecture that provides high performance. It has USART serial communication port. USART has TXD and RXD pins for serial communication with an indicator LED. It operates on voltage from 1.8V to 5.5V. It comprises four USART, 5 SPI and one I2C digital communication peripherals. Its program memory (flash memory) size is 256KB, internal SRAM is 8192B and EEPROM size is 4096B [50]. It collects inputs from the sensors and processes the information. After that, data will be sent to the Wi-Fi module [51]. The specifications of ATMega 2560 are shown in Table 3.

5.2. Sensors

In this study, the authors are using different sensors with their specifications. Different environmental parameters measurement sensors are deployed, such as the current sensor (ACS712), voltage sensor and Temperature & humidity sensor (DHT11). The Current sensor ACS712 is used for AC and DC measurement. It operates on a 5V power supply. It has zero magnetic hysteresis. It is used in communication systems and for industrial purposes. It provides electrical isolation without the use of optoisolators.

The voltage sensor is simple and based on the principle of the resistor voltage divider. This sensor can make the input connector voltage five times smaller. The voltage at the analogue input pin is 5V. Hence the detected voltage should not be larger than 5V× 5= 25V. Its voltage input range for DC is from 0-25V. The resistor tolerance is 1%. It can be easily used with Microcontroller. The DHT11 sensor consists of a thermistor of negative temperature coefficient used for temperature measurement and a humidity sensing capacitor for humidity measurement. Its temperature ranges from 0-50 ^{0}C with an accuracy of ±2 degrees and humidity from 20% to 95% with an error of ±5% [52]. It is used for measuring environmental variations. It is applicable mainly due to its advantages like cost effectiveness, excellent quality, good stability and fast response time. A light intensity sensor (BH1750) is connected to measure the intensity of sunlight, as shown in Figure 7. It consists of 16 bits analog to a digital converter, directly providing a digital output. The light intensity sensor consists of a lux meter which measures light intensity in Lux. It is better than an LDR because the BH1750 sensor does not require calculations. Its operating voltage range is from 3V to 5V. It supports the I2C interface; the data range is 0-65535.

A cup-type anemometer is preferred for measuring wind speed and wind direction. It can detect wind speed and direction. An anemometer is used for measuring wind speed depending on the rotation of cups. When the wind speeds increase, the cups also spin faster. The number of rotations determines the wind speed. The three-cup anemometer is better than the four-cup anemometer due to its advantages, such as being fast, providing high aerodynamic torque and more uniform response [39]. It has been observed that air temperature and humidity can affect the wind speed. If there is friction between cups and air, the value of wind speed decreases for higher-density locations [40]. It is used in various applications such as Weather, ocean, Environment, Industry, Laboratory and Agriculture.

5.3. Wireless Communication

LoRa is used as a protocol for data transmission. LoRa consumes low power and provides long-range transmission [53, 54]. Without cable, this network connects to the internet; the data storage may be locally or in the cloud. The production cost is low than the commercial data logger. Data logger uses long-range wireless digital communication to transmit the data through RF bands. LoRa communication transmits over 10 km of long-range data transmission and has minimum power consumption [55]. LoRa transreceiver module (SX1278) consist of 14 pins.

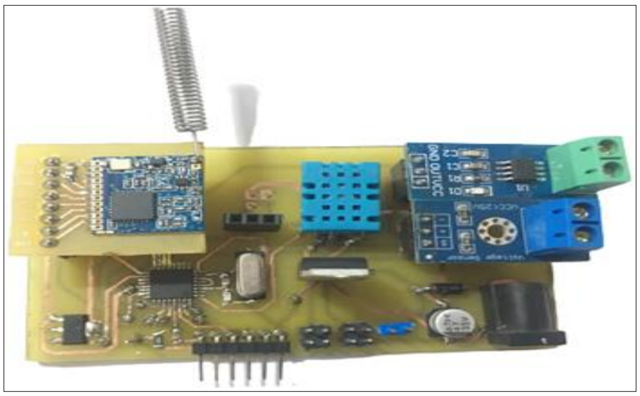
Its operating frequency range is 433 MHz. It consists of an SPI interface. The operating voltage range is approximately 1.8V to 3.6V, and the packet size is 256 bytes. A 50-ohm antenna is used in its 14-pin. It has excellent blocking immunity and a built-in temperature sensor [56]. The specifications of SX1278 LoRa are shown in Table 4. It is used in many applications such as agriculture, IoT communication, and to create mesh star topology. The data is obtained at the LoRa gateway and NuttyFi Wi-Fi, and the gateway connects to the internet. Gateway is a physical device connected between the sensor node and the cloud server. As illustrated in architecture, measuring environmental parameters from various sensors is implemented using open-source software. Coding is done by using Proteus software and Arduino IDE. The hardware porotype of the windmill node and solar grid is shown in Figure 5.

6. Hardware Implementation with Results

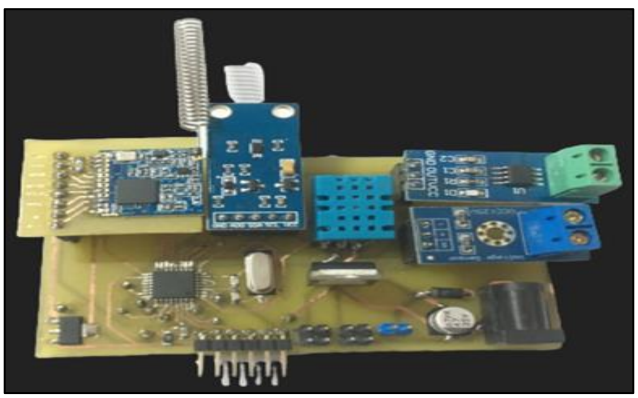
Firstly, sensors must measure current, voltage, light intensity, temperature, wind speed, and humidity. Realistic data is used for prediction. After that, we collect data through the gateway and can implement a deep learning algorithm for accurate prediction. The predicted data will give to the cloud. Figure 6 shows measured environmental parameters using solar grid nodes 1 and 2 at different climatic conditions. In Figure 6, various climatic parameters are measured using a windmill sensor node. Measured data is displayed on the graphical display unit. Blynk IoT app can monitor and control devices at weather forecast stations through smartphones. It controls and monitors sensors using NodeMCU based on the Blynk IOT framework. As a server, Raspberry Pi is used. It is also used as a bridge connected to the internet.

Table 5. Environmental parameters and their units

Parameter	Unit
Voltage	Volt (V)
Current	Ampere (A)
Wind Speed	Kilometre/ hour (Km/hr.)
Solar Radiation	Lux (Lx)
Temperature	Celsius (^{o}C)
Humidity	Percentage (%)



(a)



(b)

(c)

Fig. 5 Hardware of (a) Windmill node, (b) Solar grid node, and (c) LoRa Gateway

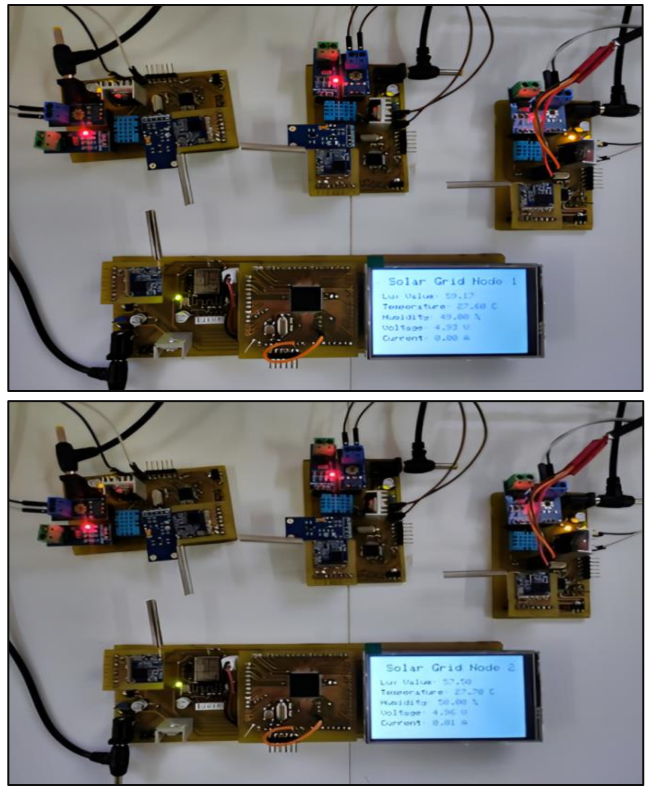


Fig. 6 Real data collection using solar grid node1 and solar grid node 2

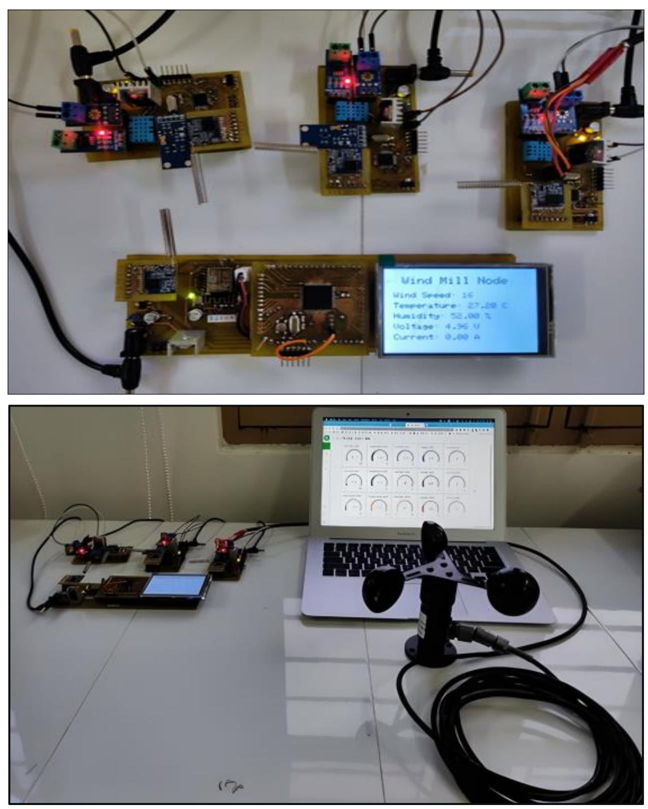


Fig. 7 Real data collection using windmill node

Table 6. Environmental parameters used for prediction

Meteorological Parameters	Units
Solar Radiation	W/m^2
Time Sunrise	hh:mm: ss
Humidity	Percentage
Temperature	Degree Fahrenheit
Barometric Pressure	Hg
Wind Speed	Miles/hr.
Wind Direction	Degrees

The NodeMCU microcontroller linked sensors and equipment at weather stations with the help of Raspberry Pi. The sensor data read by NodeMCU. After that, data will be sent to the server. The server responded to the requests for smartphones. The complete hardware set up with sensor nodes and LoRa gateway is shown in Figure 7. The parameters shown in Table 5, such as voltage, wind speed, solar radiation, current, temperature, and humidity, are measured with the help of sensors fabricated on the solar grid and windmill sensor nodes. The sensor node sends the sensing real-time data to the gateway node. After measuring environmental parameters, the real-time information is sent to the LoRa gateway. It has been found that LoRa is a long-range wireless transmission implemented to transmit real-time data to the cloud through Wi-Fi internet connectivity after applying a deep learning algorithm for predicting data accuracy.

Figure 8 shows the real-time data collection using customized hardware. PCB layout is designed using a proteus software tool. Real-time data is collected and predicted by Python and Google colab. We have used the IoT platform because IoT is used for various industrial applications such as monitoring of the environment, agriculture monitoring, industries, intelligent Buildings/smart homes, smart grids, management of disaster, robotics, health care, and automation industries. It provides many solutions to reduce the consumption of resources for Intelligent Energy Control in buildings. We have found that an IoT-dependent framework can enhance scalability and reliability, remove organizational barriers, and minimize energy costs.

6.1. Observations using the ANN Model

Levenberg-Marquardt and Bayesian Regularization algorithms are used for prediction using MATLAB R2021b software. The dataset used for prediction includes solar radiation, wind speed, wind direction, temperature, time sunrise, time sunset, humidity and pressure shown in Table 6.

The hourly meteorological datasets have been taken from the HI-SEAS weather station for four months, from September to December 2020, every 5 minutes time duration. The hidden layer neurons are 20. It also depends upon the designed model. There are two outputs, i.e., solar radiation and wind speed. Input datasets are 30962, and testing target data sets are 1724. Both algorithms are implemented by using Log sigmoid transfer function.

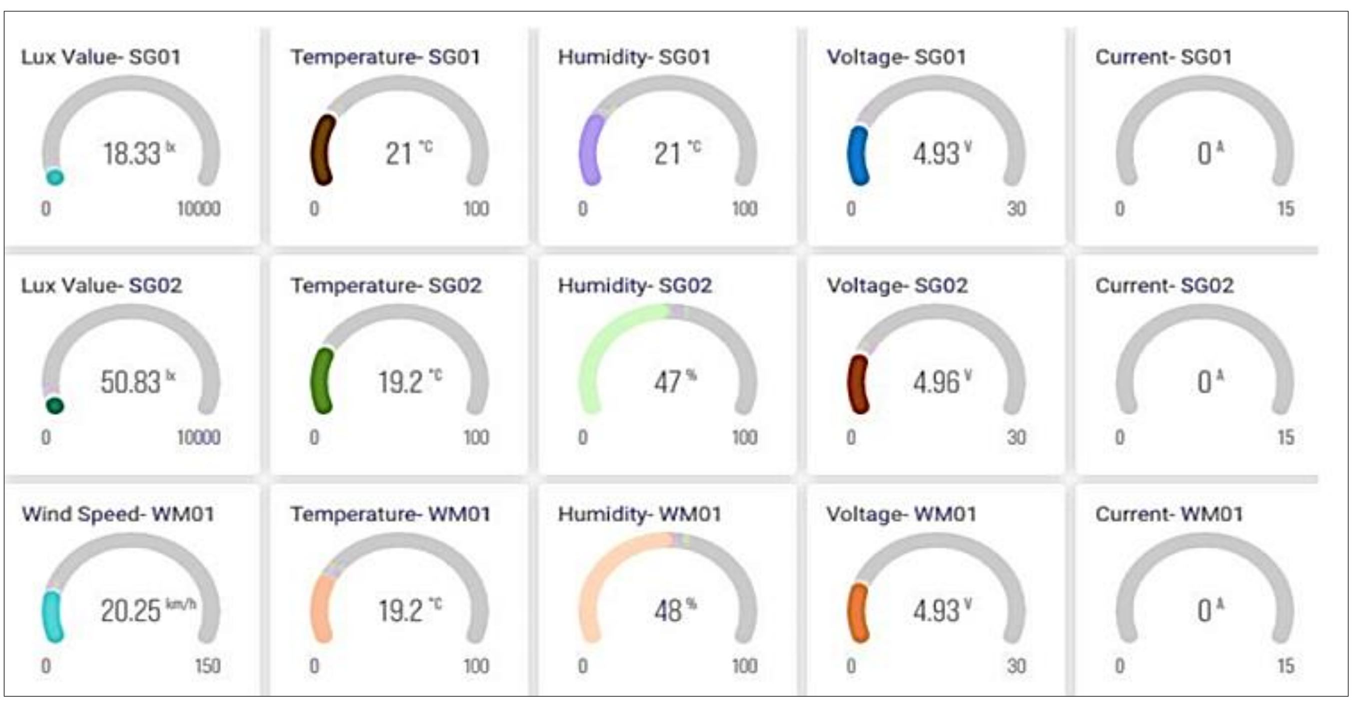


Fig. 8 Real-time data collection

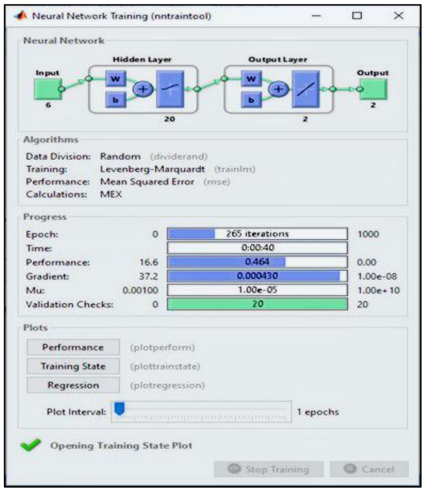


Fig. 9(a) Neural network training using LM

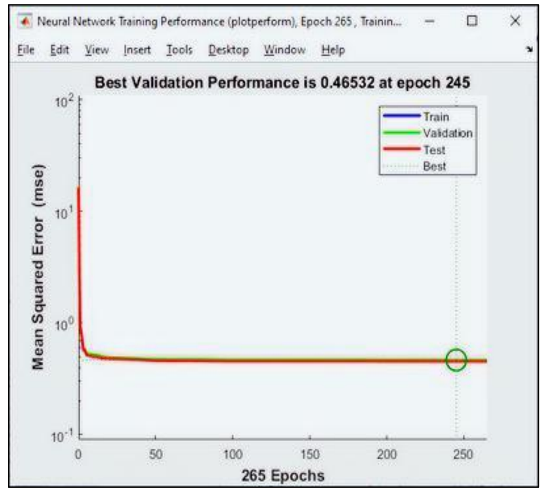


Fig. 9(b) Performance plot using LM

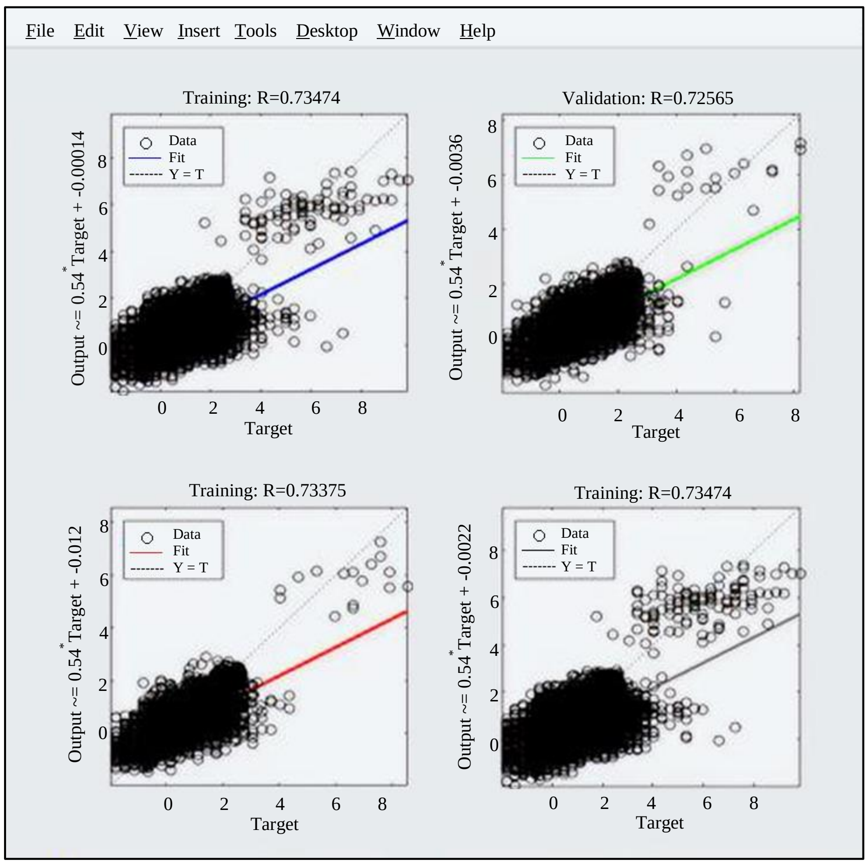


Fig. 10 Regression plot using LM

Firstly, train the network using the Levenberg Marquardt method. The neural network stage is implemented with performance under specific constraints of 10000 epochs. The minimum performance gradient is set to 0.00000001, the learning rate is 0.4, and the maximum validation failures are set to 20. When the training is complete, the network's performance will be checked. After training, check the plot by clicking the respective buttons in the training window. The result improved by increasing the hidden layer neurons until the desired result was achieved. We used 'trainlm' as a training function, i.e., Levenberg Marquardt back-propagation. Figure 9(a) shows the network training stage implemented by the Levenberg Marquardt algorithm.

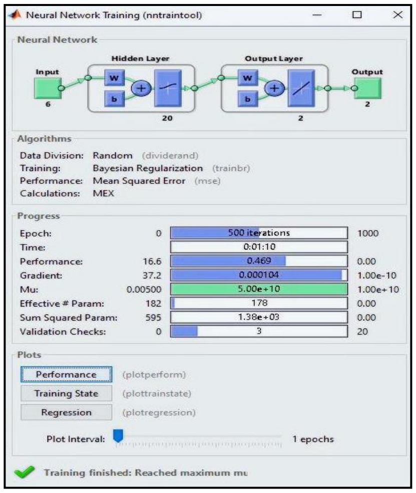


Fig. 11(a) Neural network training using BR

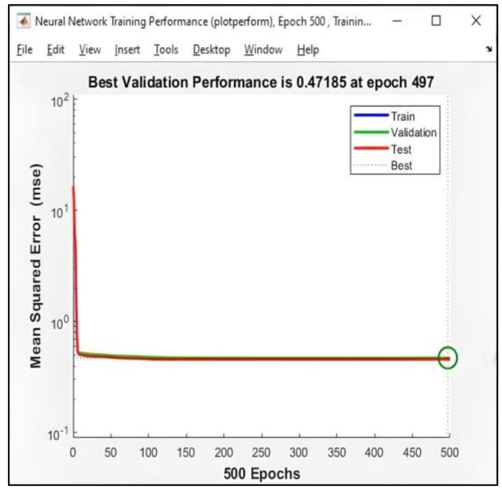


Fig. 11(b) Performance plot using BR

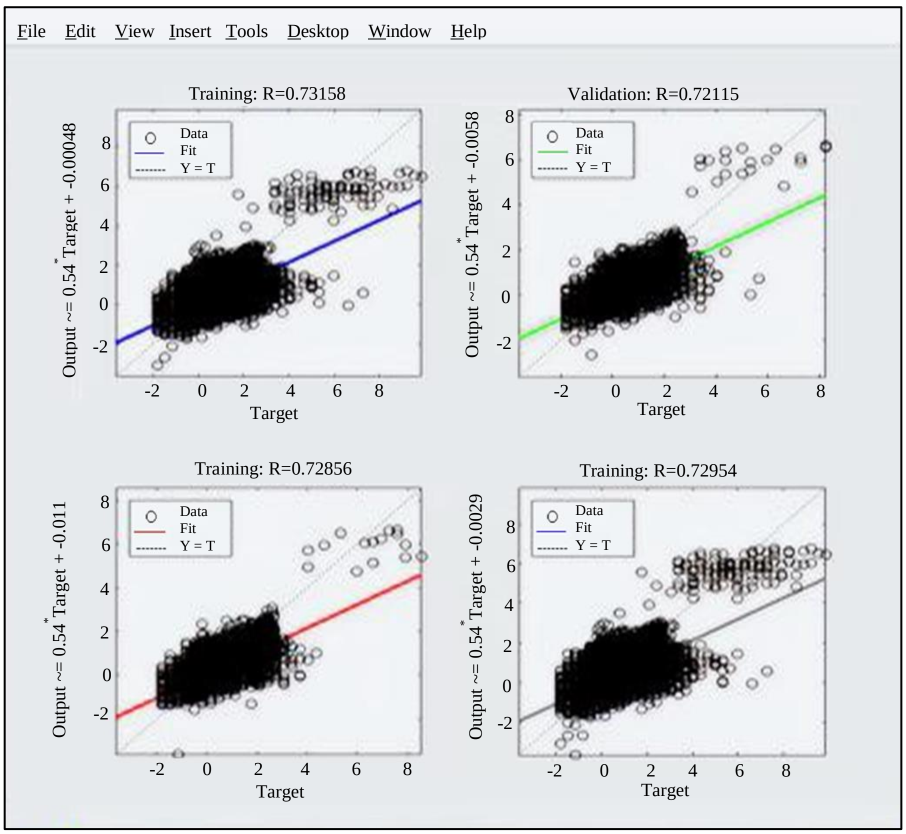


Fig. 12 Regression plot using BR

Figure 9(b) shows a performance plot using the LM training process. The correlation Coefficient (R) value for training data is 0.73474, validation data is 0.72565, testing is 0.73375, and all is 0.7332, as shown in Figure 10. Secondly, train the network using the Bayesian Regularization method. The neural network stage has a maximum of 10000 epochs. The minimum performance gradient is set to 1.0000e-010, the learning rate is 0.0001 and no. of hidden neurons is 20. The training function for the Bayesian regularization method is 'trainbr'. Figure 11(a) shows the training stage of the network using the BR algorithm. Figure 11(b) shows a performance plot using the BR training process. This shows that the best performance in the form of mean square error (MSE) of the LM model is 0.46532 at epoch 245; RMSE is 0.8246, whereas for the BR model mean square error (MSE) is 0.47185 at epoch 497, root mean square error (RMSE) is 0.8317 as shown in Table 7.

Table 7. Performance analysis of using LM and BR algorithm

Evaluation Metrics	LM	BR
MSE	0.46532	0.47185
RMSE	0.8246	0.8317
Iterations	245	497
Hidden Neuron	20	20
R	0.7332	0.72954

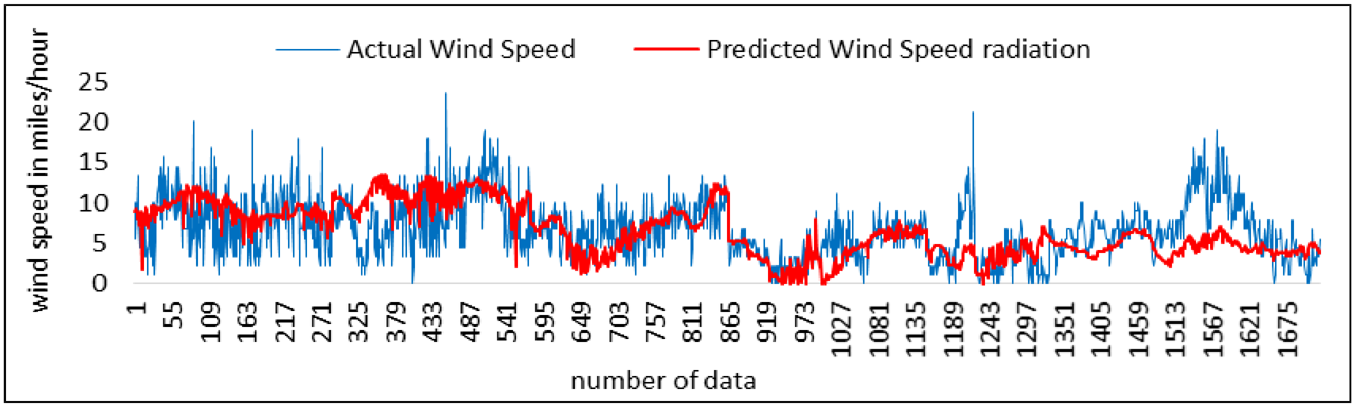


Fig. 13 Actual v/s observed wind speed using levenberg-marquardt algorithm

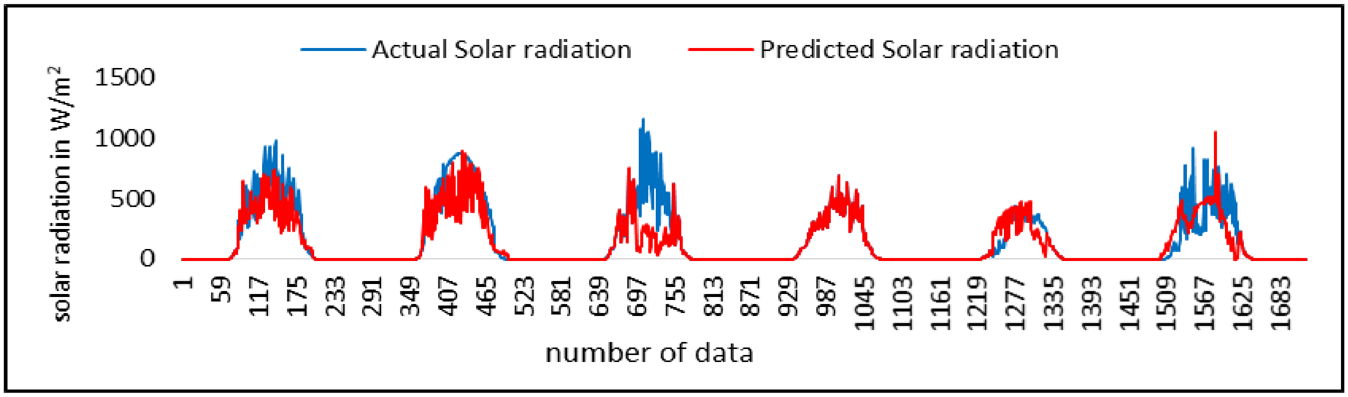


Fig. 14 Actual v/s observed solar radiation using levenberg-marquardt algorithm

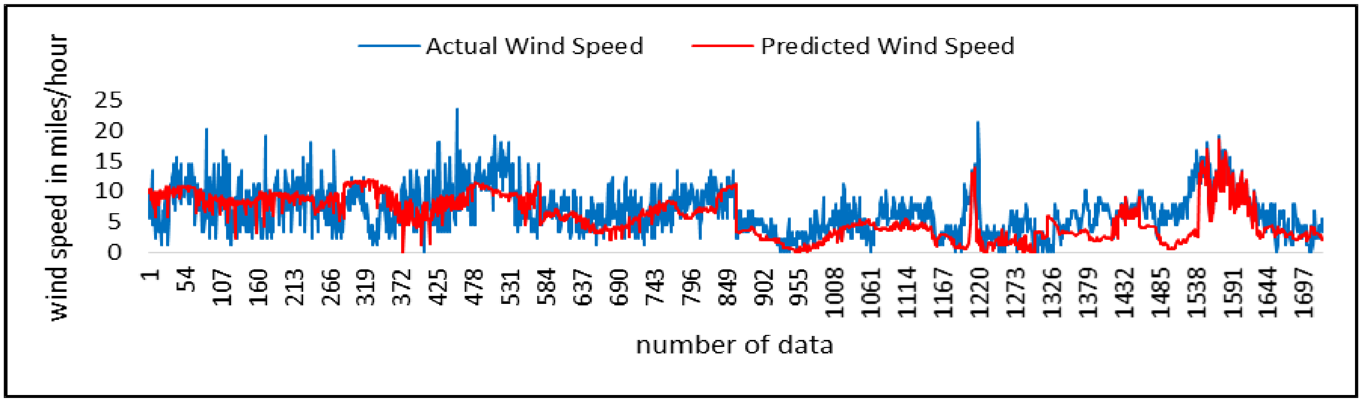


Fig. 15 Actual v/s observed wind speed using Bayesian regularization

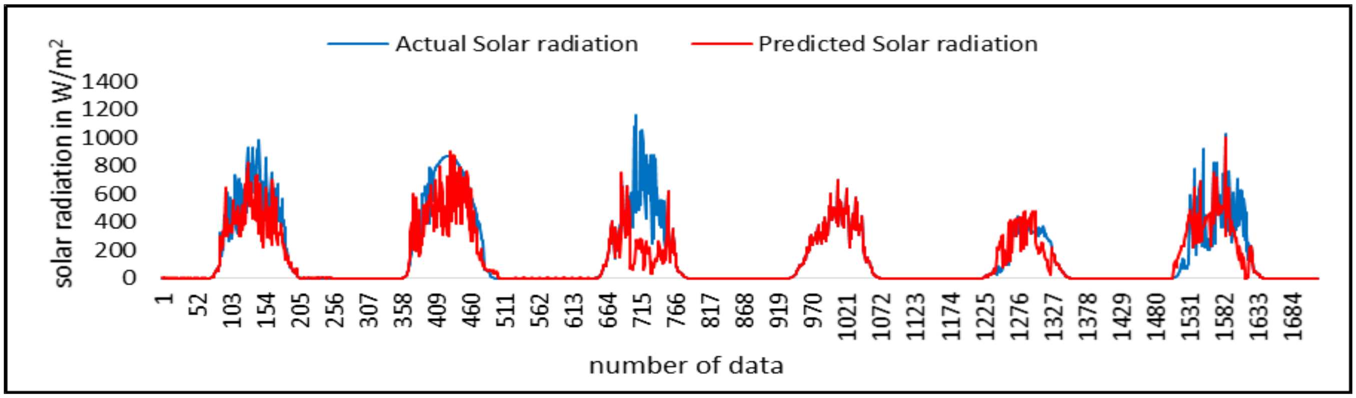


Fig. 16 Actual v/s observed solar radiation using the bayesian regularization algorithm

The correlation coefficient (R) value using the BR model for training (0.73158), validation (0.72115), testing (0.72856), and all (0.72954) is shown in the regression plot in Figure 12. From the above discussion, we have found that the LM model gives less MSE and RMSE than the BR model. BR model also provides good results, approximately similar to the LM model, but there is a difference in the number of iterations reached. The BR model takes more time to converge than the LM model. Prediction is done for five days in December 2020. Figure 13 and Figure 14 show the actual v/s predicted value of wind speed and solar radiation using the Levenberg Marquardt method. Figure 15 and Figure 16 shows the actual v/s predicted value of wind speed and solar radiation using the Bayesian Regularization method. A graph plotting between the actual and observed values shows a high degree of similarity between them for the ANN model using the LM algorithm. It provides a good prediction than the BR algorithm.

7. Conclusion and Future Work

Currently, renewable energy plays an essential role in generating electricity and sustainable development. Solar and wind energy are abundant, clean, replenished energy resources readily available. Both solar radiation and wind speed are primarily affected by other atmospheric parameters and show nonstationary behaviour. It is very challenging to predict these parameters accurately. Customized hardware designed based on IoT has low-cost sensors connected to it and collects real-time datasets. We are also implementing ANN techniques i.e., levenberg marquardt and bayesian regularization, on existing datasets for prediction to enhance the accuracy of the proposed model. It is observed that the LM model outperformed the BR model regarding MSE, R-value and RMSE. LM shows superior performance by providing prediction at a higher speed. LM has the lowest mean square error of 0.46532, root mean square error of 0.8246 and R-value of 0.7332, whereas BR has an MSE of 0.47185, RMSE of 0.8317 and R-value 0.72954. LM takes 254 iterations, and BR takes 497 for the best validation performance. BR also performed nearby similarly to LM regarding MSE and RMSE, but the BR model is slow to give accurate results.In future, we will implement efficient ANN techniques on real-time data sets collected by designed customized hardware. In addition, a comparison is made by predicted output using real-time data and prediction done by existing datasets. This will help to find the designed IoT-based customised hardware's accuracy and efficiency.

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