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An Optimal Model to Meet the Hourly Peak Demands of a Specific Region With Solar, Wind, and Grid Supplies

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ABSTRACT The objective of the work is to make Rameswaram, a region in Tamil Nadu self-sufficient for its energy needs by making use of hybrid energy to the maximum and utilizing fossil-based energy to the minimum. To calculate the wind and solar energy for a particular region, the wind speed and solar irradiance of that region are to be forecasted. Then the peak load requirement for a year of that region is identified and the installation capacities of wind and solar farms are fixed. Storage devices like batteries, are not used in this work. Hence all the power drawn from installed array of solar panels are utilized first to meet the hourly peak demands. If the power drawn from solar panels are insufficient to meet the demand, then the wind turbines are operated. The number of wind turbines to be operated will differ from time to time based on the demand that could not be met with solar power alone. The grid supply is used only in case of any deficiency from solar and wind power to meet the peak demand requirements. A new algorithm is proposed which will help in estimating the number of wind turbines to be operated to meet the hourly peak demands. Later the costs of utilizing energy from grid and renewable energy are estimated separately and the results compared. The entire process is automated for ease of operation using the proposed algorithm. This model can be extended to any region where this type of configuration is proposed.

INDEX TERMS Predictive model, wind and solar energy, optimal operation, cost analysis.

I. INTRODUCTION

The increase in prices of petroleum products has made hybrid renewable energy more popular and needy. Two or more renewable energy sources are combined to form hybrid energy systems, which will maintain a greater balance in energy supply and provide increased system efficiency. The main aim of this paper is to make use of the predicted results of wind speed and solar irradiance from which an algorithm is developed for maximum utility of wind turbines to meet out the peak demands at various times of a day. Power from wind turbines and solar panels can be predicted in advance but it has been decided to optimize the use of wind turbines alone as per the requirements from the power producers. No information is available in the literature for the above said type of configuration. Hence the proposed method is not compared with any other method and it can be considered to be a benchmark for this kind of configuration. From the environmental point of view, the main objective of the proposed study is to focus towards the green energy by bringing down the usage of fossil fuel based energy.

Yang *et al.,* [1] have analyzed how text mining can be an effective way of reviewing literature pertaining to solar irradiance and power forecasting. In the review paper, Voyant *et al.,* have [2] discussed various solar irradiation forecasting methods using machine learning techniques. Apart from popular methods like Neural Networks and Support Vector Regression, other methods like Gradient Boosting, Random forest, Regression tree, and many other methods are also discussed. It is difficult to compare the performances

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of these methods as the data set are geographically diverse and different. Bae *et al.,* [3] have proposed a very short term prediction of solar irradiance using K-means clustering and Support Vector Regression. In [4], Fatih *et al.,* have proposed a two-step model for forecasting solar radiation in which Mycielski model is based on the assumption that solar data has a pattern that repeats itself and Markov chain model is used to find the probabilistic relations of the data. Khosravi *et al.,* [5] have applied different machine learning algorithms for solar forecasting for two different datasets and compared their results. In [6], Ravinesh *et al.,* have proposed a hybrid model for wind speed prediction, where the Multilayer Perceptron is integrated with bio-inspired fire fly optimizer algorithm. Mohanty *et al.,* [7] have discussed solar power forecasting and its implications in India. Khosravi *et al.,* [8] have adapted three different machine learning models for wind forecasting and compared their performances. In [9], Moustris *et al.,* have developed one day ahead wind speed prediction of Tilos Island, Greece, using Artificial Neural Network (ANN). In [10], G. W. Chang *et al.,* have identified an upgraded neural network model for wind speed prediction with an error feedback scheme.

Daniel O'Leary and Joel Kubby [11] have used an innovative method for solar power forecasting based on image processing and acoustic classification techniques. A review paper by Wan *et al.,* [12] has dealt with forecasting methodologies for solar resource and PV power. The authors have discussed the merits and demerits of different types of prediction methodologies. Parsi [13] has applied three different methods for solar radiation forecasting such as exponential smoothing, seasonal forecasting and ANN. The results show that the exponential smoothing is said to have less mean error when compared to other methods. Khondaker [14] has compared variants of prediction models like multiple regression techniques, Support Vector Machines (SVM) and linear least squares using multiple kernel functions for day ahead solar radiation prediction. Of the three different kernel functions such as Linear, Polynomial and RBF, RBF kernel performs better than the other methods. Various Machine Learning (ML) algorithms were utilized in [15] for forecasting solar power in Sri Lankan island. In this research work, the proposed ML model outperformed the solar power forecast than the SP model. In [16], Xiangyun Qing and Yugang Niu have proposed hourly day ahead solar irradiance prediction model and have used Long Short Term Memory (LSTM) networks for training their model. Salfate *et al.,* [17] have proposed a short term wind speed forecasting for 12h and 24h ahead using ANN with Back Propagation (BP) approach. To train their model they have used three years data and to validate their model, they have used one year data. To predict the time-series wind speed data Khosravi et al., [18] have developed the following algorithms for wind speed prediction and are listed as follows: Support Vector Regression (SVR), Multilayer Feed-Forward Neural Network (MLFFNN), Fuzzy Inference System (FIS), Group Method of Data Handling (GMDH) type neural network, Adaptive Neuro-Fuzzy Inference System (ANFIS), ANFIS optimized with Genetic Algorithm (ANFIS-GA) and ANFIS optimized with Particle Swarm Optimization algorithm (ANFIS-PSO). The classification of wind speed based on the cut-in-speed of the wind turbine is given in [19]. The wind speed prediction for Coimbatore region of Tamil Nadu is done using Neural Network and is given in [20].

To cater to the electrical demands of a particular building, a Hybrid Renewable Energy Systems (HRES) is presented in [21]. Optimum performance on HRES is obtained by applying fuzzy logic rule on Hybrid Optimization Model for Electric Renewable (HOMER) software program. Initially, an analytical model of solar, wind and hydropower plants are proposed [22] and later merged with cost criteria to create an objective function. Gioutsos *et al.,* [23] have given levelized cost of systems for electricity generation and observed that the cost has decreased considerably with increased renewable energy penetration with no added cost. In [24], the authors examine the financial effects of a renewable energy scenario for the Java-Bali grid. Initially the operation and maintenance costs are only considered and later on the capital cost is also considered and the total system cost and power generation cost are determined. To analyze the random power generation from the renewable energy resources in the District Energy System (DES), Monte Carlo study [25] is used. PSO algorithm is used for optimizing the DES for a day-ahead. In the first model, a Weibull distribution for wind [26] is considered to search the minimal energy cost that relates to the design parameters of a single wind turbine. In the second, a composite optimization algorithm is developed, which consists of an iterative method and an improved PSO algorithm which is adopted for optimizing the layout of the wind turbines iteratively. A combined pricing model [27], i.e., Real Time electricity Price (RTP) with Inclining Block Rate (IBR) has been used to minimize the cost along with reducing the peaks. This model incorporates user preferences and energy resources to optimally schedule load demand. Budischak *et al.,* [28] have proposed a model with two purposes. The first one is to look for combinations of various renewables at various sites with storage that are not intermittent and satisfy the need within a given fraction of hours. Second purpose is to obtain minimal cost, considering the actual cost of electricity which excludes subsidies and includes external costs. HRES is to meet the load requirement with minimum cost using Sequential Linear Programming (SLP) algorithm [29] as an optimization tool. Khare *et al.,* [30] have used HOMER software for modelling optimization of HRES. The results are compared with Particle Swarm Optimization (PSO) and chaotic PSO algorithms.

The HOMER software is used [31] for designing and analyzing hybrid power systems, which contain a mix of conventional generators, co-generators, wind turbines, solar photovoltaic, hydropower, batteries, fuel cells, biomass and other inputs. HOMER is able to calculate the best option that would give the best energy efficiency. The state of the art energy usage from renewable sources is summarized in [32]. For physical modeling of renewable energy systems, several methodologies and criteria for optimization of the HRES are discussed. Some work done for optimization of renewable energy systems is provided by the authors in [33] and they have given a gap analysis to develop a general model to find an optimal combination of energy components. Also they have selected a typical rural community to minimize the total cost of the system for the entire life time of the project. Because of its advantages PSO algorithm [34] is preferred over the other techniques for reducing the Levelized Cost of Energy (LCE). For the probability of the loss of power supply for a load at a typical house at USA, an optimum number of PV modules and batteries are provided for the minimum cost of the power system [35]. Different power management, control strategies and multi-objective optimization methods used for hybrid wind-solar systems are discussed in [36]. To find the best configuration of the system and for sizing the components, the Multi Objective PSO method [37] is used and the power management algorithm is applied to the load. For generation unit-sizing, a simple numerical algorithm has been developed [38] to determine the storage needed for a stand-alone, wind, PV, and hybrid wind/PV systems and optimum generation capacity for a site in a remote area in Montana in USA with a typical residential load. A harmonic search-based chaotic search has been proposed [39] for optimizing a hybrid solar-wind powered reverse osmosis water desalination system. The author [40] has proposed an improved bee algorithm for optimizing off-grid solar-wind reverse osmosis desalination systems with two different storage methods. A new hybrid optimization algorithm consisting of chaotic search, harmony search and simulated annealing is proposed by Zhang *et al.*, [41] for optimal sizing of a stand-alone hybrid solar and wind energy system. Discrete Simulated Annealing (DSA) algorithm has been used [42] for optimizing a PV/WT/FC/diesel system for a grid independent electrification of a remote area. Zhang *et al.*, [43] have proposed a design optimization method for hybrid reverse osmosis desalination plant powered by solar and wind energy. Maleki [44] has applied PSO algorithm to evaluate the effect of a grid-connected fuel cell based Combined Heat and Power (CHP) systems. Tabu search for optimizing a small independent hybrid power scheme is discussed in [45]. Almehizia *et al.*, [46] have proposed a novel way of storage of energy which will solve the issues in integrating renewable energy with grid. The objective of the study [47] is to predict the thermal performance of the cavity receiver for varying cavity depths and tube diameter using ANN and numerical modelling. The results reveal that the ANN method is more beneficial than the numerical modeling. A machine learning model namely Least Square Support Vector Machine (LSSVM) is used to predict the output power and shaft torque of stirling engines in [48]. Using LSSVM model the performances of stirling engines are measured using several statistical measures and the results indicate that the LSSVM model can predict with reasonable accuracy.

In this proposed work, considering the two broad areas of literature survey conducted (1. Wind and solar irradiance prediction. 2. Cost optimization of hybrid energy), it is attempted to device a hybrid (wind and solar) system along with grid supply to judiciously utilize the available solar and wind power incurring minimal cost to meet the hourly peak demands for a specific region. Solar irradiance and wind speed for Rameswaram region of Tamil Nadu are predicted and then the total wind and solar power available in that region are estimated. The prime goal of this work is to meet the peak demands by wind and solar power alone, instead of using the grid power which is mostly fossil-fuel based. A new algorithm has been introduced to minimize the cost of power utilized by properly selecting the wind turbines in conjunction with solar power and grid to meet the maximum demand throughout the day at one hour intervals. Finally, the costs of producing energy from three different energy sources are analyzed. The optimum power to be generated from these energy sources are made to meet the demands at various time zones, which will ultimately reduce the cost of energy utilized.

II. PROPOSED METHODOLOGY

A. WIND SPEED AND SOLAR IRRADIANCE PREDICTIONS

In order to develop a hybrid model for Rameswaram region, models for predicting wind speed and solar irradiance are separately developed. After training and testing the wind and solar parameters with different machine learning algorithms, it was decided to apply Artificial Neural Network (ANN) for prediction as there were no significant differences in the performances of all other algorithms. First, a model for wind speed prediction is developed. All the parameters which contribute to the wind speed [49] are explored and the following parameters are identified for the study in this work. The wind parameters considered for training are Temperature in °C, Pressure in hPa, Humidity in %, Rainfall in mm and Visibility in km. The target is the Wind speed or Velocity in km/h. The above data are collected for a period of five years (2012-2016). The neural network toolbox of MATLAB is utilized to train the network for wind speed prediction. The user has to select network type, input data, target data, training algorithm, performance measure, number of layers, number of neurons in each layer and activation functions. Once the user selects all the parameters then the network is trained till the performance measure is reached or the number of set iterations is complete. If the performance is satisfactory, the network object model is tested using the test data set, otherwise the performance has to be checked with different training algorithms, transfer functions, number of layers and number of neurons. The network object is now ready for simulation and can be simulated for any new data set.

Next, a model for solar irradiance prediction is developed using the ANN toolbox available in MATLAB. The solar parameters [50] considered for training are Elevation and Azimuth angles, Air temperature in °C, Humidity in % and Pressure in hPa. The target is the Global Horizontal Irradiance (GHI) accumulated for an hour expressed in W/m^2. The solar data was obtained from National Institute of Wind

Energy (NIWE), an autonomous R&D institution by the Ministry of New and Renewable Energy (MNRE), Government of India. It contains three types of irradiance parameters such as Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI) and Global Horizontal Irradiance (GHI). Since GHI includes both DNI and DHI, it has been decided to use only GHI values for calculating solar irradiance. It has been ascertained that the data provided by NIWE are as per the prescribed standard for measuring solar irradiance. Hence the data has been used as it is for the study. Similar to wind data, five years of solar irradiance data are considered for developing a model using ANN. The ANN is trained and the performance of the network is checked. If the MSE value is satisfactorily low, then the network model is saved for future use. The test data, which has not been used for training the ANN model is used for simulation. The simulated results are compared with the desired values and checked for the validity of the network model. The predicted solar irradiance is considered for a period of 12 hours at an interval of one hour, commencing from 6:00 am to 6:00 pm for each day.

To ascertain the validity of the proposed model in predicting the future wind speed, the data pertaining to the year 2017 (which is not considered for training) is applied to the network object and the wind speed outputs are predicted for the year 2017. The predicted wind speeds are compared with the actual wind speeds available for the year 2017, to check the accuracy of prediction. If accurate, the model is ready for future predictions. Similar procedure is adapted to check the accuracy of the developed solar network object and use the model for future predictions of solar energy.

B. POWER CALCULATIONS

From the results obtained, the favorable periods of operating wind turbines for Rameswaram region is ascertained. Wind speeds for operating wind turbines are categorized as follows:

- 8 km/h (2 m/s) is the speed where small wind turbines start rotating.
- 12.6 km/h (3.5 m/s) is the cut-in speed where wind turbines start generating power.
- 36–54 km/h (10–15 m/s) is the speed at which a turbine reaches its maximum capacity.
- At 90 km/h (25 m/s) is the cut-out speed where a turbine is brought to a halt.

After predicting the average wind speed per day, the days during which the wind speeds are more than the cut-in-speed and less than the cut-out-speed, are utilized for calculating wind power. The wind power generated per day is calculated using the standard formula available in [51]. The parameters used for calculating wind power are of air density, velocity and swept area of the wind turbine. After predicting solar irradiance, the total solar power captured per day is calculated by applying the existing formula in the literature [52].

C. OPTIMAL USE OF WIND, SOLAR AND GRID POWER

Rameswaram a coastal region of Tamil Nadu, is chosen for this research, as it is a potential region for harnessing

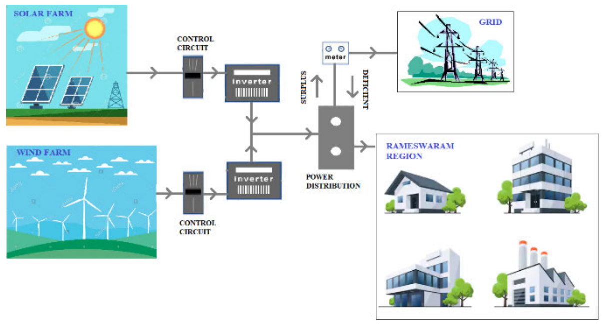

FIGURE 1. Block Diagram of wind-solar hybrid system.

both wind and solar energies. Tourism and fishery are the major sources of income among Rameswaram residents. Coral and handicraft, hotel, sea food processing and sea shell crafting are the main occupations of Rameswaram people. Industry relating to the above areas are quiet prevalent in Rameswaram. Hence, we consider only the domestic, commercial and industry loads of Rameswaram for research purpose. The block diagram of the hybrid system is given in Fig. 1.

The power from wind and solar farms are converted from DC to AC using inverters. The generated power is distributed to the town of Rameswaram to fulfill the needs of domestic, commercial and cottage industries. Any surplus energy from the renewable energy is fed to the grid and any deficiency in power to meet the peak demand is drawn from the grid. Since the aim is to build a model which is self-sufficient for Rameswaram region, the day on which the daily peak demand is the highest out of 365 days within a year of that region [53] is collected. After visiting various solar and wind farms across Tamil Nadu and considering the feedbacks received from the wind and solar power plant operators, it was decided to keep the power from solar panels fixed, whereas the operation of wind turbines are kept varying according to the requirement whereas the rest of the wind turbines are put to halt. A new algorithm namely Operation_Decision_Algorithm () which contains two major functions, which are i) Hybrid_Operation () ii) Only_Solar_Operation (), is developed. The algorithm will make its decision whether to go for Hybrid_Operation() or Only_Solar_Operation() based on the wind speed. If the wind speed is more than the cut-in-speed (3.5 m/s), then power from both wind turbine and solar panel can be utilized. If the wind speed is less than the cut-in-speed, then power from solar panel is utilized. If both wind and solar power are not available, the total demand is to be met by the grid power only.

Considering all the energy sources (solar, wind and grid supplies) available for Rameswaram region, the combinations of these energy to meet the peak demand at a particular time of the day has to be evaluated. Most of the days in a year, during day times, all the three energy sources are available. Rameswaram is mostly sunny throughout the year except for a brief period of two months (Oct, Nov) in a year. The solar panels need sunlight which is available in Rameswaram for almost all the 365 days in a year. Even on cloudy days, it is also possible to extract sufficient amount of solar power from this region. The model developed has to take into account the energy available from the three sources and the hourly peak demand at various times of the day. Energy has to be properly distributed so that the power needs are met with the minimal usage of energy from grid with the motive of reducing the overall cost.

Since the electrical appliances are used at different times of the day and for different durations, the hourly peak demands vary. The hourly peak demands of the region are considered for predicting the operation of the wind, solar and grid supplies to meet the requisite amount of power. Even though it is possible to extend the proposed method for 10-15 minutes duration or a lesser period of peak demand, it is found that the hourly peak demands do not vary widely and hence hourly peak demands are considered for predicting the wind turbine usage and minimizing the cost of utilizing power. If need arises, the system can be designed based on 10-15 minutes interval peak demand of the region. At any point of time, if all the available appliances are operative, the proposed design will ensure that the requisite power will be supplied because the maximum hourly demand that may occur during any one of the 365 days of the year has been estimated.

For the proposed wind and solar farms, Rameswaram region is chosen for optimizing the cost of power using the solar, wind and grid supplies. All wind turbines are assumed to have the same generating capacity. Similarly the array of solar panels are also of identical generating capacity. According to Green Rameswaram Report [53], the peak power demand for the whole year is 7.5 Mega Volt Amperes (MVA) which is roughly equivalent to 6 MW considering an average power factor of 0.8. In order to meet this demand, the installation capacities for wind and solar power generators are planned. Considering the cut-in-speed of wind turbine, wind energy of around 20 kW per turbine is obtained. Therefore, in order to meet the peak demand of 6000 kW, around 300 turbines each of 250 kW capacity are required.

So depending on the wind energy forecasted, the number of turbines to be operated on a particular day is decided. The wind and solar power generators are assumed to be installed in the ratio 2:1. 300 turbines each with a capacity of 250 kW can produce a maximum of 75 MW. So the capacity of total solar panels is fixed to be 40 MW, which could be obtained from 160 array of solar panels where each array of panel is of 250 kW capacity. Since wind energy is variable in nature, it is preferable to have more number of wind turbines than solar panels to balance out the varying power availability from wind turbines. It is viable to harvest wind power if the wind speed is more than 3.5 m/s. During the days, when the wind speed does not reach the cut-in-speed, then only solar power is relied upon and if solar power is inadequate to meet the peak demand, power is drawn from grid to augment the deficiency and with the limitation that solar resource will not be available during the night time. To optimize the power supply, the following algorithm is developed to distribute the energy generated from wind turbines and solar panels and utilizing the grid supply in the event of deficiency in meeting the peak demand and also feeding back to grid in case of surplus solar power. The algorithm is represented in flowcharts given in Figures 2, 3 and 4.

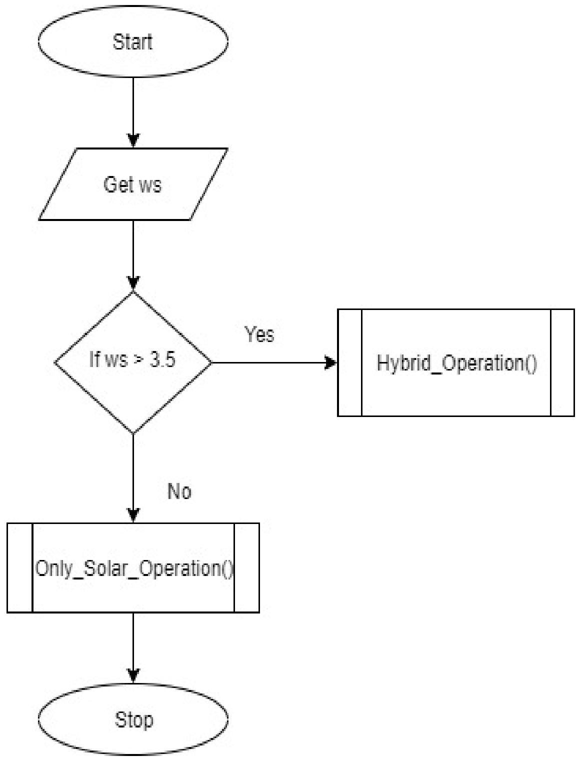

FIGURE 2. **Operation_Decision_Algorithm.**

In Figure 2, the wind speed defined by the variable *ws* is taken as input. If the wind speed is greater than the cut-in-speed, then Hybrid_Operation () is chosen. If the wind speed is less than the cut-in-speed, then Only_Solar_Operation () is chosen. Hybrid_Operation () is called when both wind turbine and solar panels are operative. Only_Solar_Operation () is called when only solar panel is operative, since the wind speed is not sufficient for the operation of wind turbines.

In Figure 3, three inputs such as solar power, demand and wind power per day from a single turbine, given by variables *sp*, *d* and *w* are considered. If solar power generated is greater than zero, then the demand is primarily met by solar energy. If solar power generated is greater than the demand, the excess solar power is supplied to the grid. If solar power generated is not sufficient to meet the entire demand, partial demand is met by solar power and the remaining power needed is met by operating the required number of wind turbines. If the solar power is less than zero, then the entire demand has to be met by wind power by operating the required number of wind turbines. To augment the hourly demand, additional turbine(s) are operated in addition to the required number of wind turbines. The power generated from the excess wind turbines operated is supplied to the grid. The total solar power generated, number of wind turbines

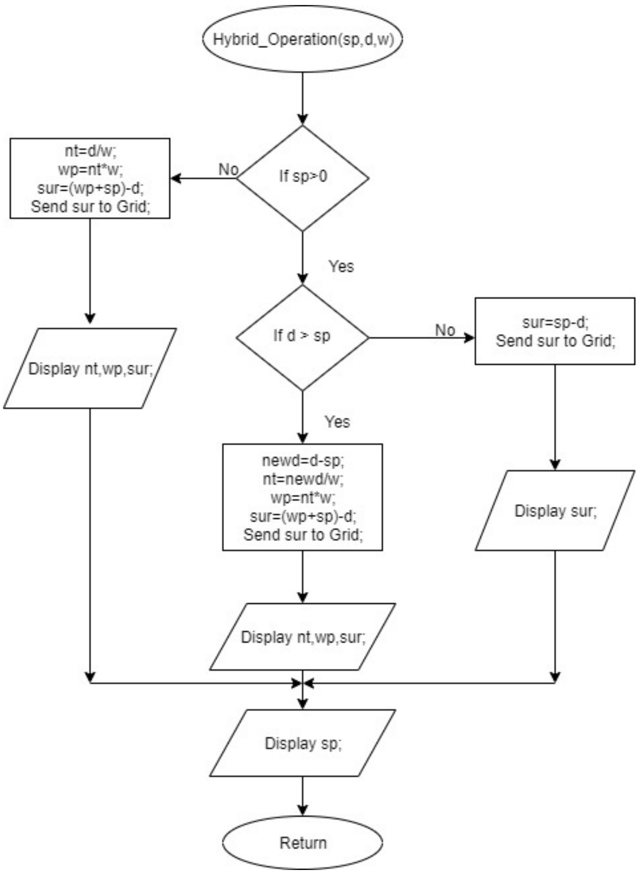

FIGURE 3. **Hybrid_Operation.**

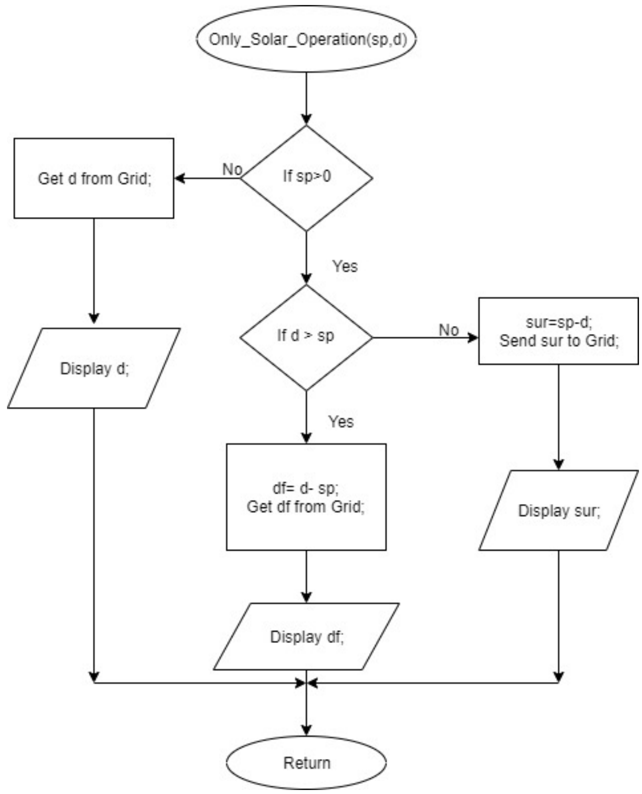

FIGURE 4. **Only_Solar_Operation.**

operated, the total wind power generated and surplus power supplied to the grid are displayed for every hour.

In Figure 4, solar power generated and demand given by variables *sp* and *d* are considered as input. If solar power generated is less than zero, then the entire demand has to be met only by the grid, since the wind speed is not conducive for operating wind turbine. If solar power generated is greater than zero, the demand is met primarily by solar power. If the solar power generated is greater than the demand, then the surplus power is supplied to the grid. If the solar power generated is less than the demand, then the deficit power is drawn from the grid. The hourly demand, the surplus power supplied to the grid, the deficit power drawn from the grid are displayed for every hour.

D. COST ANALYSIS

The prime motive of this proposed work is to develop a model which should be able to select the combination of energy resources to provide sufficient power at the requisite time with minimal cost. Any shortage of power can be met from the grid. The unit cost of, solar power is INR 3.11 [54], wind energy is INR 2.86 [55], grid power is INR 7.00 [56] and power supplied back to grid is INR 3.00 [57]. Initially, the energy generated from the solar panels is catered to meet the hourly peak demands. If the peak demand is higher than the solar power generated, then the demand is to be augmented by the energy generated from wind turbines. At any point of time, when solar and wind energy are unavailable, then the entire power is drawn from the grid source only to meet the hourly maximum demands. In this study, backup storage devices are not considered to accumulate any excess power generated from the solar panels and wind turbines. The cost of utilizing energy from grid alone and the cost of utilizing energy from renewable sources are estimated separately and a cost analysis was made. Since there are no models available for such type of configuration which has been used or adopted, a suitable model similar to the proposed model could not be found for exact comparison. Justifications are given through the proposed algorithm and its several functions to show that the cost of power utilization is minimal under the stated conditions such as power availability, type of power available, the usage pattern and the cost of utilizing different types of energy.

III. RESULTS AND DISCUSSIONS

The wind data was trained and tested with some of the machine learning algorithms such as Gaussian Process, Linear Regression, k-Nearest Neighbour (k-NN), Random forest and ANN. The Root Mean Square Errors (RMSE) for various algorithms are given in Table 1. Though the RMSE vary widely for training data, they gave almost nearly equal RMSE for test data. Hence it has been decided to use ANN for prediction as it is easy to implement using Neural Network Tool Box in MATLAB.

Algorithm 1 Operation_Decision_Algorithm(ws)

```
Initialisation:
  ws ←Wind Speed in m/s per day
Hybrid_Operation () // when wind turbines and solar panels can operate together
Only_Solar_Operation () // when only solar panels can operate
Cut_in_Speed for Wind Turbines to operate← 3.5 m/s
Iterations:
  IF (ws > 3.5) THEN
    GOTO Hybrid_Operation ( )
  ELSE
    GOTO Only_Solar_Operation ()
  ENDIF
Operation_Decision_Algorithm( )
Only_Solar_Operation (sp,d)
Initialisation:
  d ←Demand at a point of time
  sp←Solar Energy in kW
  df ←Deficiency Power in kW
  sur←Surplus Power in kW
Iteration:
  IF ( sp > 0 ) THEN
    IF ( d>sp) THEN
      Compute df←d-sp
      Grid←Get(df)
    ELSE
      Compute sur←sp-d
      Grid← Send(sur)
    ENDIF
  ELSE
    Grid←Get(d)
  ENDIF
Only_Solar_Operation()
Hybrid_Operation (sp,d,w)
Initialisation:
sp ← Solar Power in kW
nt ← Number of wind turbines
d ← Demand at a point of time in kW
w ← Wind Power per day from a single turbine in kW
wp ←Wind Power from 'n' turbines in kW
newd ←New Demand in kW
sur ← Surplus Power in kW ( Excess power)
Iteration:
  IF (sp > 0) THEN
    IF (d > sp) THEN
      Compute newd←d-sp
      Compute nt←newd/w
      Compute wp←nt×w
      Compute sur←(sp+wp)-d
      Grid ←Send (sur)
    ELSE
      Compute sur ←sp-d
      Grid ←Send (sur)
```

Algorithm (Continued) Operation_Decision_Algorithm(ws)

```
      ENDIF
    ELSE      Compute nt ← d/w
        Compute wp ←nt×w
  Compute sur←(sp+wp)-d
  Grid ←Send (sur)
      ENDIF
  Hybrid_Operation( )
```

TABLE 1. Root mean squared error for wind data.

Machine Learning algorithms	Training	Testing
Gaussian Process	0.19	0.32
Linear Regression	0.19	0.32
k-NN	0.0011	0.41
Random forest	0.08	0.32
Neural Network	0.51	0.35

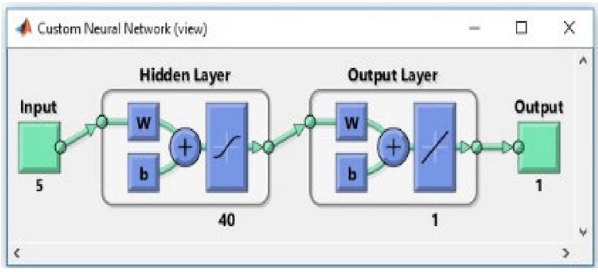

FIGURE 5. Neural network architecture for wind data.

To predict the wind speed for the year 2017, the previous five years data (2012-2016) are taken to train the neural network model. In order to predict the wind speed for a specific month, the five years data of the same month are considered for training, and a model is developed. For instance, the data for the months of September are taken for all the five years. The daily average data of all the parameters pertaining to wind speed prediction are taken and so there will be 30 rows of observation for the month of September. Hence for five years, it will be 150 rows of observation with 5 columns of attributes for the training data. The target is the wind speed which will be represented by a single column of 150 rows. The target is normalized using 'minmax′ normalization function. The ANN architecture consists of 40 neurons with 'tansig' activation function in the first hidden layer and 'purelin' activation function in the output layer and the architecture is shown in Fig. 5.

Different training algorithms such as Levenberg Marquardt (LM), Resilient Back Propagation (RP), Scaled Conjugate Gradient (SCG) and Gradient Descent with Momentum (GDM) back propagation were applied and it was found that LM training algorithm has given less error as compared to

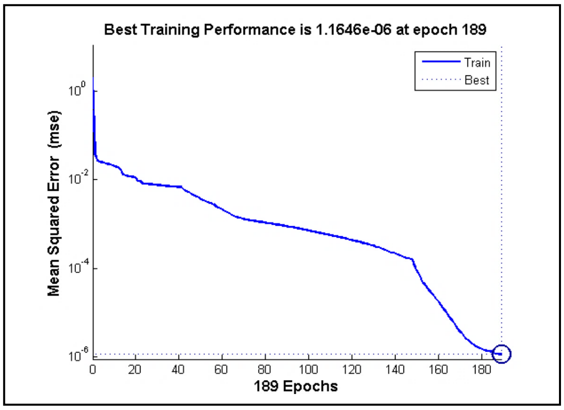

FIGURE 6. Performance of LM algorithm.

TABLE 2. Simulation results.

Training data (2012-2016)		Test data (2017)	
Actual wind speed in km/h	Predicted wind speed in km/h	Actual wind speed in km/h	Predicted wind speed in km/h
15.40	10.66	4.80	10.20
8.00	8.25	3.90	9.67
11.70	11.25	3.10	9.81
17.60	10.93	6.50	8.79
18.90	11.06	6.10	5.83
20.00	13.59	5.90	8.30
10.20	11.83	9.10	10.46
0.90	4.50	5.60	6.88
2.80	10.00	2.40	16.57
13.30	13.28	4.30	6.90

TABLE 3. Root mean squared error for solar data.

Machine Learning algorithms	Training	Testing
Gaussian Process	0.1437	0.0951
Linear Regression	0.1336	0.0973
IBk	0	0.1169
Random forest	0.0383	0.0697
Neural Network	0.098	0.0697

the other training algorithms and the performance graph of LM algorithm is given in Fig. 6. Table 2 shows the comparisons of actual and predicted wind speeds both for the training (2012-2016) and the test data (2017) and the results are depicted graphically in Figures 7 and 8.

The solar data was trained and tested with some of the machine learning algorithms as was done for wind data and the results are given above in Table 3. To predict the solar irradiance, five years (2012-2016) data have been considered for training the network. Since the month of September is taken for predicting wind speed, the same month's data is used for solar irradiance prediction. For a single day in September, there are 12 hourly data, starting from 6:00 AM to 6:00 PM. So, for 30 days, there would be 360 rows of data for a year. For 5 years, there are 5 columns of attributes (Elevation, Azimuth, Temperature, Humidity and Pressure) and 1800 rows of training data. The target which is GHI, consists of a single column of 1800 rows. The target is normalized using 'minmax' normalization function. The network is trained and the network object model is stored for later use. The chosen ANN architecture consists of 40 neurons with 'tansig' activation function in the first hidden layer and 'purelin' activation function in the output layer and is shown in Fig. 9.

TABLE 4. Simulation results.

Training data(2012-2016)		Test data (2017)	
Actual solar irradiance in W/m^2	Predicted solar irradiance in W/m^2	Actual solar irradiance in W/m^2	Predicted solar irradiance in W/m^2
29.70175	33.63	39.93	38.18
148.55	191.57	176.56	185.98
449.2833	343.18	400.26	329.85
683.85	566.83	633.34	531.10
855.7	703.75	789.93	646.90
929.6667	689.49	815.54	630.17
649.5833	670.80	637.69	531.01
279.4833	535.66	600.80	479.37
277.85	458.07	568.16	500.57
434.0167	387.33	504.42	411.26
294.9	216.62	288.44	219.94
90.3	69.42	109.82	79.31

Different training algorithms were applied and the training performance is shown above in Fig.10. Here also the Mean Squared Error (MSE) for LM is found to be less when compared to that of SCG, RP and GDM. Table 4 show the comparisons of actual and predicted solar irradiances both for the training (2012-2016) and the test data (2017) and the results are depicted graphically in Figures 11 and 12.Once the wind speed is predicted, the operating range of the wind speed for generating wind power is to be checked. If the wind speed falls below or goes above the operating range, the data is ignored and the wind speed that falls within the operating range of the wind turbine alone is considered.

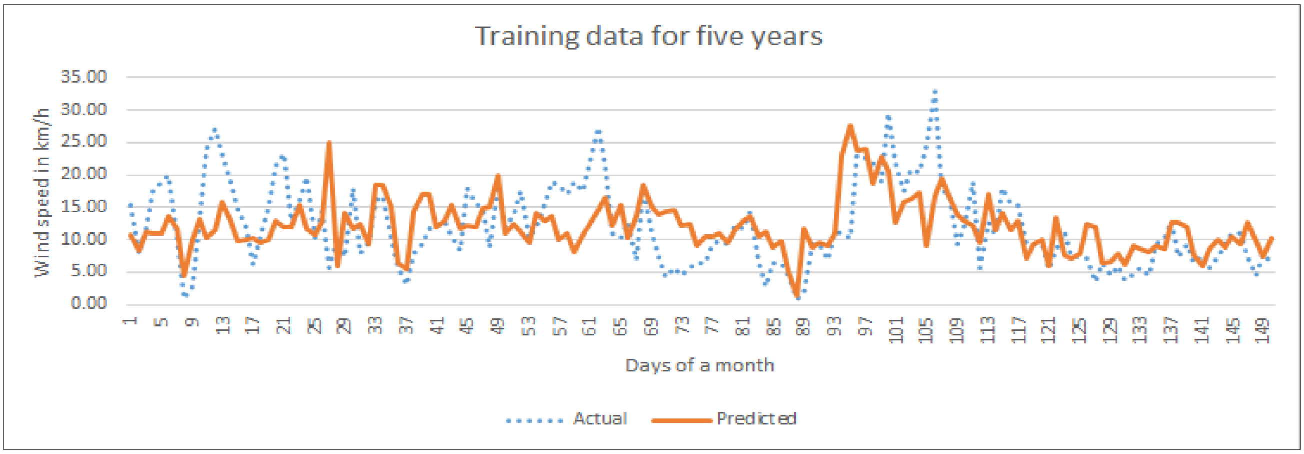

FIGURE 7. Training data for the months of September for the years 2012-2016.

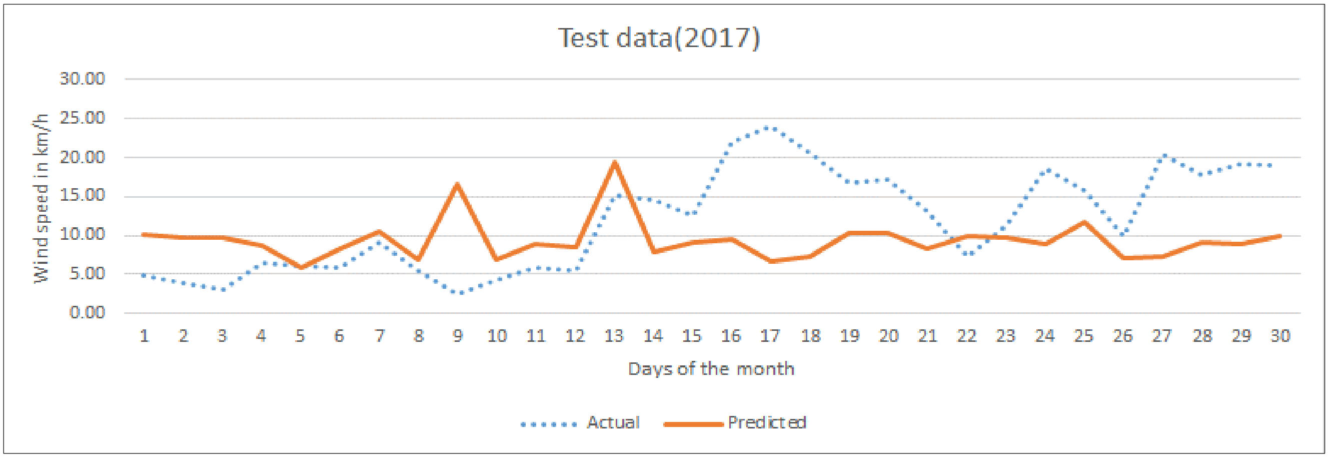

FIGURE 8. Simulation results for test data for the year 2017.

Analyzing the wind speed data of a region, the days in which wind turbines can be operated are identified. The formula for calculating wind power (P) in kW generated by a wind turbine is given in (1).

$$P = 0.5 \times \rho \times A \times C_p \times V^3 \times N_g \times N_b, \quad (1)$$

where

ρ is the air density in kg/m^3, a constant value of 1.20 is assumed,

A is the swept area given by the formula: Πr^2, where r is the radius of the turbine blade,

C_p is the performance Coefficient, a constant value of 0.35 is assumed,

V is the wind velocity in m/s,

N_g is the Generator efficiency, which ranges between 50% and 80% and

N_b is the Gearbox efficiency assumed to be of 95%.

Typical data which is used for calculating wind power for five days in a month is given in Table 5. The formula given in equation (1) is applied to this data set. In the original data, wind speed is given in km/h and hence it is converted it into m/s. This power calculated is for a single turbine of 250 kW capacity.

After calculating the power generated from a wind turbine, next the power generated from a solar panel is calculated.

TABLE 5. Wind power calculation.

V(m/s)	ρ (kg/m^3)	A	C_p	N_g	N_b	P (Watts)	P (kW)
6.09	1.20	2826	0.35	0.80	0.95	102073.36	102.07
6.68	1.20	2826	0.35	0.80	0.95	134182.38	134.18
5.71	1.20	2826	0.35	0.80	0.95	83800.38	83.80
4.63	1.20	2826	0.35	0.80	0.95	44647.15	44.65
4.76	1.20	2826	0.35	0.80	0.95	48778.64	48.78

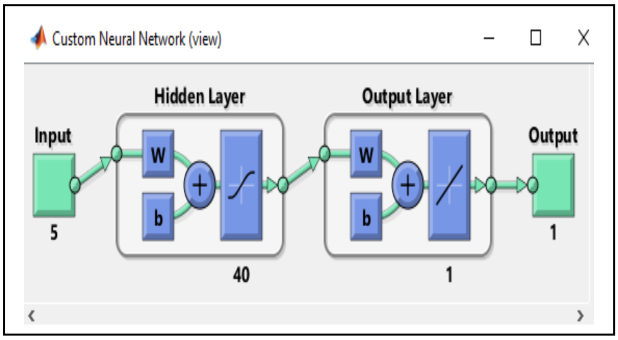

FIGURE 9. Neural Network Architecture for solar data.

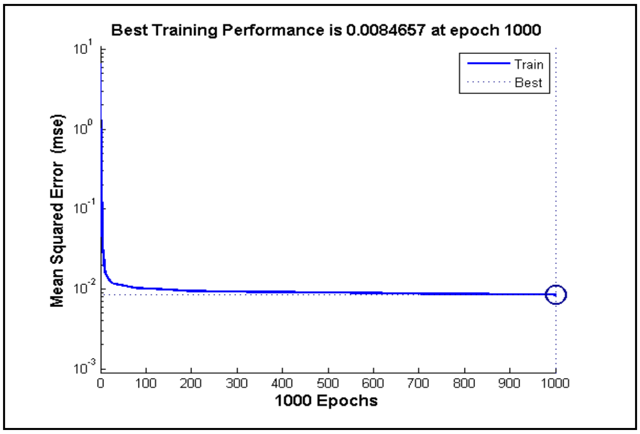

FIGURE 10. Performance of LM algorithm.

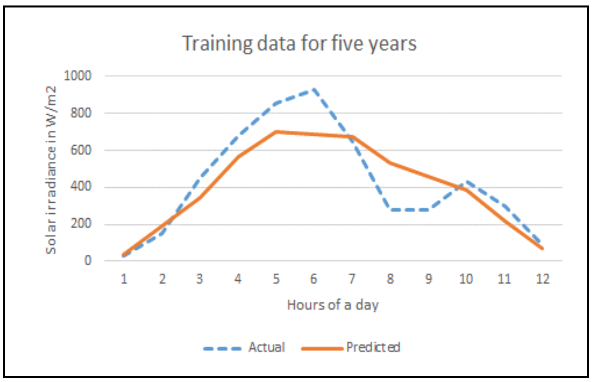

FIGURE 11. Simulation results of training data for five years (2012-2016).

The formula for calculating the solar energy output from a solar panel is given in (2).

$$E = H \times r \times A \times PR, \tag{2}$$

where

H is solar irradiance in kWh,
r is the % of panel efficiency,
A is Panel area in m^2,
PR is the performance ratio (default value 0.75) and
E is Energy in kWh

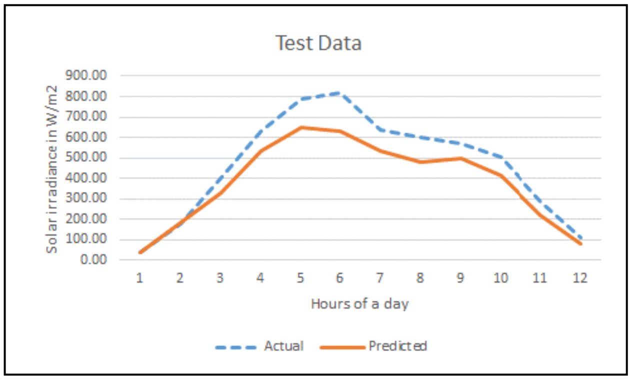

FIGURE 12. Simulation results of test data for the year 2017.

TABLE 6. Solar power calculation for a day.

H (Watts)	*H (kW)*	*r (%)*	*A (m^2)*	*PR*	*E in kWh*
26.55	0.03	15	2322	0.75	6.93
157.41	0.16	15	2322	0.75	41.12
370.00	0.37	15	2322	0.75	96.65
430.14	0.43	15	2322	0.75	112.36
574.53	0.57	15	2322	0.75	150.08
672.11	0.67	15	2322	0.75	175.57
485.45	0.49	15	2322	0.75	126.81
477.95	0.48	15	2322	0.75	124.85
454.56	0.45	15	2322	0.75	118.74
411.41	0.41	15	2322	0.75	107.47
237.15	0.24	15	2322	0.75	61.95
73.72	0.07	15	2322	0.75	19.26

The solar power is calculated for 12 hours, from 6:00 AM to 6:00 PM for the data set given in Table 6. The solar energy is calculated using Equation (2) for the given data sets.

Using the proposed algorithm, the demand supply table is filled and later the cost of using the energy from grid only and cost of using energy from renewable sources are worked out. If power is drawn only from the grid, the cost is calculated by (3).

$$\text{Cost of using grid power} = \text{Demand} \times \text{INR } 7, \tag{3}$$

If the power is drawn from renewable energy as well as from grid, the cost is calculated by (4).

$$\begin{aligned} &\text{Cost of using renewable energy} \\ &\quad = (\text{Solar} \times \text{INR } 3.11) \\ &\qquad + (\text{Wind} \times \text{INR } 2.86) \\ &\qquad - (\text{Surplus} \times \text{INR } 3) - (\text{Deficiency}^{*}\text{INR } 7), \end{aligned} \tag{4}$$

If the wind and solar power put together is surplus, then the cost of the surplus power is deducted from the total

TABLE 7. Demand-supply data for a day in September.

Time (1)	Solar power in kW (2)	Number of turbines (3)	Wind power in kW (4)	Hourly peak Demand in kW (5)	Surplus power in kW [(2)+(4)-(5)]	Deficiency in kW [(2)+(4)-(5)]	Cost of using Grid power in INR	Cost of using Renewable energy in INR
0	0.00	62	5045.56	5043.00	2.56	0.00	35301.00	14422.62
1	0.00	62	5045.56	5002.00	43.56	0.00	35014.00	14299.62
2	0.00	61	4964.18	4920.00	44.18	0.00	34440.00	14065.01
3	0.00	60	4882.80	4879.00	3.80	0.00	34153.00	13953.41
4	0.00	62	5045.56	4969.20	76.36	0.00	34784.40	14201.22
5	0.00	65	5289.70	5231.60	58.10	0.00	36621.20	14954.24
6	0.00	68	5533.84	5526.80	7.04	0.00	38687.60	15805.66
7	1109.59	56	4557.28	5658.00	8.87	0.00	39606.00	16458.04
8	6579.15	0	0.00	5637.50	941.65	0.00	39462.50	17636.21
9	15464.59	0	0.00	5658.00	9806.59	0.00	39606.00	18675.11
10	17978.06	0	0.00	5617.00	12361.06	0.00	39319.00	18828.59
11	24013.10	0	0.00	5596.50	18416.60	0.00	39175.50	19430.94
12	28091.40	0	0.00	5555.50	22535.90	0.00	38888.50	19756.55
13	20290.00	0	0.00	5576.00	14714.00	0.00	39032.00	18959.90
14	19976.49	0	0.00	5555.50	14420.99	0.00	38888.50	18863.91
15	18998.71	0	0.00	5572.93	13425.79	0.00	39010.48	18808.63
16	17195.43	0	0.00	5674.40	11521.03	0.00	39720.80	18914.70
17	9912.07	0	0.00	5756.40	4155.67	0.00	40294.80	18359.53
18	3080.99	34	2766.92	5822.00	25.91	0.00	40754.00	17417.54
19	0.00	74	6022.12	5986.00	36.12	0.00	41902.00	17114.90
20	0.00	74	6022.12	5945.00	77.12	0.00	41615.00	16991.90
21	0.00	72	5859.36	5822.00	37.36	0.00	40754.00	16645.69
22	0.00	71	5777.98	5699.00	78.98	0.00	39893.00	16288.08
23	0.00	69	5615.22	5596.50	18.72	0.00	39175.50	16003.37
				Total Cost in INR			926098.78	406855.38

cost of renewable energy. If the wind and solar power put together is deficient, then the cost of the deficient power which is derived from the grid is added to the total cost of renewable energy. For instance, a day in September is taken where the wind speed is 5.65 m/s. For example, referring to Table 7, row 0, the wind power in Column (4) is evaluated by multiplying the number of turbines in Column (3) with wind power of 81.38 kW per turbine, when the wind speed

TABLE 8. Demand-supply data for a day in February.

Time (1)	Solar power in kW (2)	Number of turbines (3)	Wind power in kW (4)	Hourly peak Demand in kW (5)	Surplus power in kW [(2)+(4)-(5)]	Deficiency in kW [(2)+(4)-(5)]	Cost of using Grid power in INR	Cost of using Renewable energy in INR
0	0.00	0	0.00	5018.40	0.00	-5018.40	35128.80	35128.80
1	0.00	0	0.00	4879.00	0.00	-4879.00	34153.00	34153.00
2	0.00	0	0.00	4756.00	0.00	-4756.00	33292.00	33292.00
3	0.00	0	0.00	4735.50	0.00	-4735.50	33148.50	33148.50
4	0.00	0	0.00	4772.40	0.00	-4772.40	33406.80	33406.80
5	0.00	0	0.00	4911.80	0.00	-4911.80	34382.60	34382.60
6	0.00	0	0.00	5272.60	0.00	-5272.60	36908.20	36908.20
7	198.92	0	0.00	5535.00	0.00	-5336.08	38745.00	37971.21
8	5301.82	0	0.00	5514.50	0.00	-212.68	38601.50	17977.41
9	15139.90	0	0.00	5535.00	9604.90	0.00	38745.00	18270.39
10	25132.63	0	0.00	5453.00	19679.63	0.00	38171.00	19123.59
11	32424.64	0	0.00	5412.00	27012.64	0.00	37884.00	19802.71
12	38597.91	0	0.00	5350.50	33247.41	0.00	37453.50	20297.27
13	40413.95	0	0.00	5309.50	35104.45	0.00	37166.50	20374.03
14	38526.16	0	0.00	5268.50	33257.66	0.00	36879.50	20043.38
15	33153.98	0	0.00	5283.88	27870.11	0.00	36987.13	19498.56
16	25030.93	0	0.00	5354.60	19676.33	0.00	37482.20	18817.20
17	15222.10	0	0.00	5469.40	9752.70	0.00	38285.80	18082.63
18	5303.22	0	0.00	5535.00	0.00	-231.78	38745.00	18115.49
19	0.00	0	0.00	5473.50	0.00	-5473.50	38314.50	38314.50
20	0.00	0	0.00	5330.00	0.00	-5330.00	37310.00	37310.00
21	0.00	0	0.00	5125.00	0.00	-5125.00	35875.00	35875.00
22	0.00	0	0.00	4961.00	0.00	-4961.00	34727.00	34727.00
23	0.00	0	0.00	4817.50	0.00	-4817.50	33722.50	33722.50
			Total Cost in INR				875515.03	668742.78

is 5.65 m/s. Since the wind speed is greater than cut-in-speed, the function Hybrid_Operation () is selected. Since solar power is available from 6 am to 6 pm, the remaining hours of a day are filled with zero values.

Solar power per day in Column (2) of Table 7 is evaluated by multiplying the solar irradiance with the number of array of panels. During the period where solar power is unavailable, the wind turbines are operated. When solar power is still

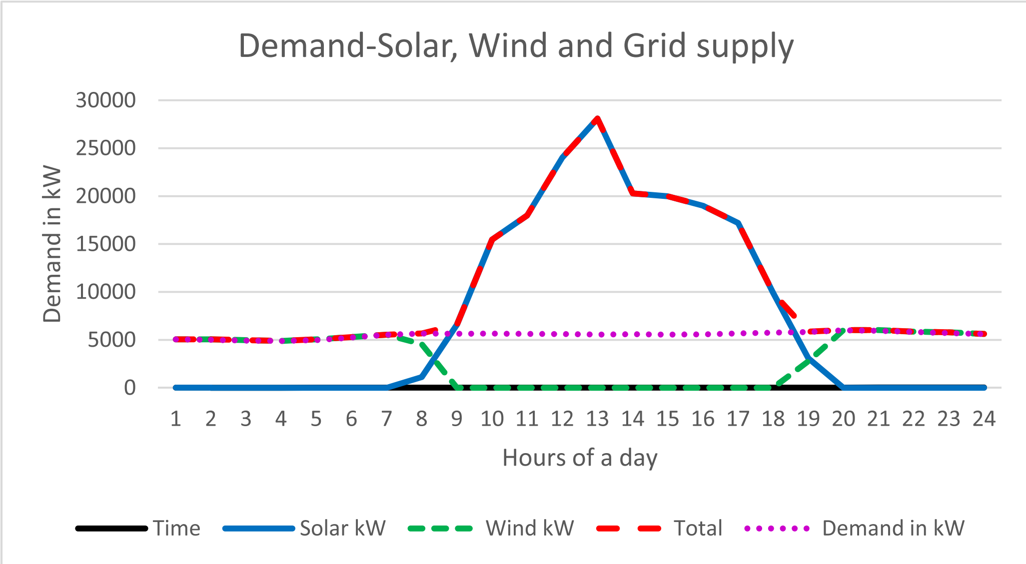

FIGURE 13. Demand supply chart for a day in September.

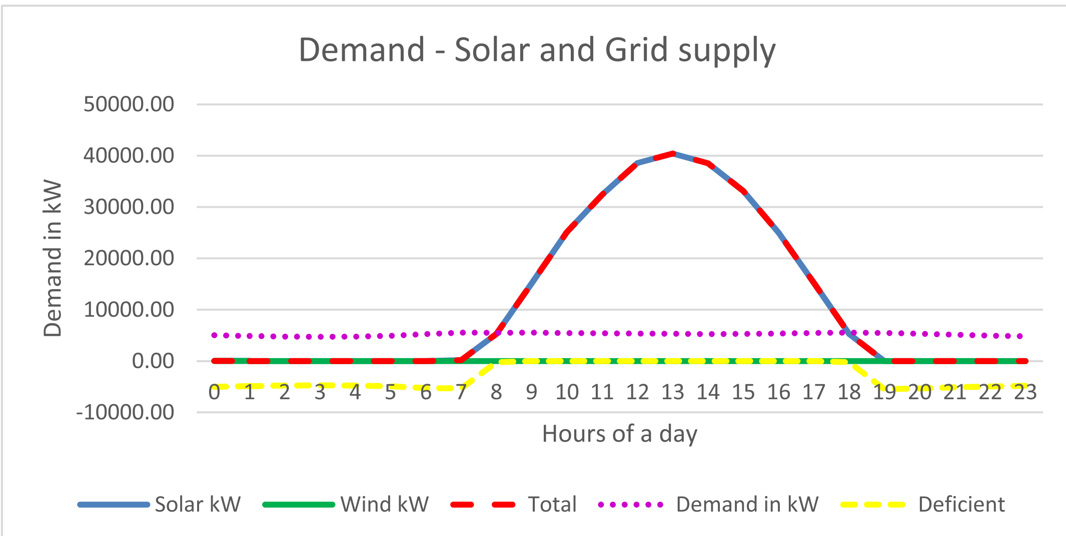

FIGURE 14. Demand supply chart for a day in February.

available, but could not meet the demand, then the wind turbines are operated, else they are put to halt. The demand-supply data and plot are shown in Table 7 and Fig. 13 respectively. The total cost that is likely to incur out of using grid power alone amounts to INR 926098.78 per day and the total cost of using renewable energy sources works out to be INR 406855.38 per day and is given in Table 7. Hence, for this particular scenario the total cost saving per day is INR 519243.40.

Another scenario, where the monthly average wind speed is below the cut-in-speed, is discussed. When wind speed is less than the cut-in-speed, Only_Solar_Operation () function is chosen. A day in February is considered and the demand-supply data and plot are shown in Table 8 and Fig.14 respectively. The total cost that is likely to incur out of using grid power alone amounts to INR 875515.03 per day and the total cost of using renewable energy sources works out to be INR 668742.78 per day and is shown in Table 8. Hence, in this scenario, the total cost saving per day is INR 206772.25.

The IF function in MS-EXCEL, can perform a logical test and return one value for a TRUE result and another for a FALSE result. The syntax for IF function is = IF (logical_test, [value_if_true], [value_if_false]). If power drawn from solar and wind energy put together is greater than the total demand, then the surplus energy is calculated by adding both the energies drawn from solar and wind and the sum is deducted from the total demand. This gives the surplus energy, which has to be supplied to the grid. In Tables 7 and 8, the surplus power in Column (6) is calculated by the formula given below in (5).

$$\text{IF}(((\text{Column }(2)+\text{Column }(4) > \text{Column }(5)), (\text{Column }(2)+\text{Column}(4)-\text{Column}(5), 0) \quad (5)$$

If power drawn from solar and wind energy put together is less than the total demand, then the deficit energy is calculated by adding both the energies drawn from solar and wind and the sum is deducted from the total demand. This gives the deficit energy, which has to be drawn from the grid. In Tables 7 and 8, the deficit power in Column (7) is calculated by the formula given below in (6).

$$\text{IF}(((\text{Column }(2)+\text{Column }(4) < \text{Column }(5)), (\text{Column }(2)+\text{Column}(4)-\text{Column}(5), 0) \quad (6)$$

The cost of using only grid power given in Column (8) in Tables 7 and 8 is given by the formula given below in (7).

$$\text{Column }(5)*7 \quad (7)$$

The cost of using renewable energy given in Column (9) in Tables 7 and 8 is given by the formula given below in (8).

$$(\text{Column }(2)*3.11)+(\text{Column }(4)*2.86) - (\text{Column }(5)*3)-(\text{Column }(6)*7) \quad (8)$$

IV. CONCLUSION

Wind and solar energy are drawn from natural sources and are available freely in plenty. These renewable energy have no greenhouse gas emissions. They are non-pollutant and have less impact on the environment. The main objective of this work is to provide uninterrupted power supply to the consumers at minimal cost by incorporating solar panels and wind turbines in addition to the existing power supply from the grid. The overall work is divided into four phases. In the first phase, neural network models are developed for predicting wind speed and solar irradiance. In the second phase, the predicted wind speed and solar irradiance are used for calculating wind and solar power generated respectively. In the third phase, the load forecast for Rameswaram region is analyzed and the peak demand for the entire period of one year is identified. The installation capacities of wind turbines and solar panels are fixed based on the peak demands. This decision is based on the feedbacks received from solar and wind farm operators in which they suggested to fix the solar panels and vary the number of wind turbines to optimize the power utilization since the wind power is unpredictable to a larger extent. The energy from solar panels is either utilized to meet the peak demand or supplied to the grid if it is surplus. When there are situations where neither wind nor solar energy is available, the entire demand is met by the grid source only. To reduce the maintenance and operational expenditure, the minimum number of wind turbines to be operated is decided based on the hourly peak demands. A scenario is considered where peak demand for every hour is met by any one of the three sources of energy or a combination of these energy. For all the 24 hours in a day, the energy demands are met by meticulously sharing the three available energy sources. If solar power is insufficient to meet the demand or not available, then the demand is met from wind energy. If both solar and wind energy put together are either insufficient to meet the demand or not available then the power has to be necessarily drawn from the grid. In the last phase, the loads are distributed to solar, wind and grid amicably based on the hourly peak energy demands. This will minimize the total cost involved and also provide uninterrupted power supplies to consumers. This procedure can be extended to any other region by making use of the proposed algorithm and any organization can use this framework to optimally use wind, solar and grid supplies.

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