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ANN- ANFIS Based Forecast Model for Predicting PV and Wind Energy Generation

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***Abstract*- Carbon emissions from economic activity continue to rise and India is the third-largest emitter among individual countries. The Renewable Energy is the way forward and the problems in harvesting it should surmount through policy and technical approaches s. The prime disadvantage with most of the Renewable Energy resources is their susceptibility to the whim and vagaries of nature and becoming a variable random source of power. Predicting the power from these variable power sources define and determine the operation of these system. In this paper ANN- ANFIS based forecast model for predicting the PV Generation and Wind energy generation is presented. The designed forecast model is trained using historical data. The results of the proposed model are validated and compared by considering data sets from two power generating stations. The proposed model is designed using MATLAB and is presented in the form of a Graphical User Interface (GUI).**

***Index Terms*-Forecasting, Photovoltaic, Wind Energy, Artificial Neural Network, Adaptive Neuro Fuzzy Inference System**

I.INTRODUCTION

Energy is critical, directly or indirectly, in the entire process of evolution, growth and survival of all living beings and it plays a vital role in the socioeconomic development and human welfare of a country. Energy has come to be known as a strategic commodity' and any uncertainty about its supply can threaten the functioning of the economy, particularly in developing economies. Achieving energy security in this strategic sense is of fundamental importance not only to India's economic growth but also for the human development objectives that aim at the alleviation of poverty, unemployment and meeting the Millennium Development Goals (MDGs) [1].

In response to present scenario of energy consumption, India is gradually shifting the focus towards its renewable energy resources. The launch of Jawaharlal Nehru National Solar Mission (JNNSM) has created a lot of interest in the India solar sector. To create demand and attract investment in the sector, the government is providing various incentives.

India's solar PV market has grown by 75% in 2010 and 50% in 2011. India has huge potential for solar PV and with the right policy support from the Indian Government; India can become a major player in the solar market globally. One of the main features of the Mission is to make India a global leader in solar energy and the mission envisages an installed solar generation capacity of 20 GW by 2022. This could in fact be much larger due to private initiatives [2]. India is endowed with rich solar energy resources. Because of its location between the Tropic of Cancer and the Equator, India has an average annual temperature that ranges from 25^0C – 27.5^0C. Being a tropical country, India has huge potential for solar power generation. The average intensity of solar radiation received in India is 200 MW/km^2 with 250–300 sunny days in a year. As per government estimates, India receives 5,000tn kWh per year, with most parts of the country receiving 4-7 kWh per square meter per day [3].

Wind energy is the kinetic energy associated with movement of large masses of air. Wind energy has been the fastest growing renewable energy sector in the country. Along with good sunshine hours India is blessed with 7517 km of coastline and its territorial waters extend up to 12 nautical miles into the sea. India is the 3rd largest annual wind power market in the world and provides great business opportunities for both domestic and foreign investors. India is a prevailing market for the wind industry and Indian wind sector representing annual growth in 2.1GWof new installations. The global wind markets grew by an average 28% per year in terms of total installed capacity during the last decade. According to IEA projection India will needed 327 GW power generation capacity in 2020.Wind power would then produce close to 81 TWh every year by 2020 and 174 TWh by 2030. Research and development activities are being undertaken through research institutions, national laboratories, universities and industry for the development of cost effective technologies and systems to improve the quality of power generation from wind Grid parity is also implemented in wind power where it depends on the wind quality and distribution factor. Forecasting the output power of these renewable resources is a significant problem for electric power departments to adjust dispatch planning in time, boost the reliability of electric system operation and the connection level of renewable power plants and reduce spinning the reserve capacity of generation systems [4, 5].

The primary disadvantage with wind and solar energy resources is that they are unpredictable which limit their capacity to act as primary energy sources. An alternative is to combine one or more renewable energy sources to form a hybrid system. The complimentary behavior of wind and solar power sources can be used to design a reliable hybrid energy system. In the past few years; PV power forecasting has been widely studied. Short-term power prediction methods for PV power plants mainly include two categories: physical methods and statistical methods. Physical methods mean that a physical equation is established for forecasting according to the PV power generation process and system characteristics and in combination with forecast weather data [6, 7]. Statistical

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methods aim to summarize inherent laws to forecast the output power of PV power plants based on historical power data [8, 9, 10, 11, 12, 13, 14]. The above methods have their respective advantages, but the non-stationary characteristics of PV power output have an important influence on the convergence and properties of the above methods. Since solar irradiance received at a site on the Earth's surface shows periodicity and non-stationary characteristics due to the influence of Earth's rotation and revolution, output power data of PV plants shows one day periodicity. In other words, the power output presents a rising trend before noon, and presents a declining trend after noon. If an effective method to reduce the non-stationary characteristics of PV output power is not adopted, conventional power prediction methods cannot guarantee the precision of forecasting results, or even the convergence of the method [15]. Relevant research has achieved good results in wind power prediction [16].

Artificial neural network (ANN) has been viewed as a convenient way to forecast solar radiation intensity and power output of PV system, which can be trained to overcome the limitations of traditional methods to solve complex problems, and to solve difficult problems which are hard to model and analyze [15]. In this work a comprehensive model to predict the solar power output and output of a wind energy systems based on historical data is presented. The work explores the option of using prediction methods based on Artificial Neural Networks (ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting the power output.

II. DETERMINATION OF INPUT VARIABLES FOR THE POWER FORECASTING MODEL

Generally, sufficiently accurate solar irradiance data can be input into a formula to derive predicted output power. Predicting power output from renewable energies is closely related to weather forecast predictions. To predict the amount of solar irradiance or power generated, various environmental factors, such as solar irradiance, cloud cover, atmospheric pressure, and temperature, along with the conversion efficiency of PV panels, installation angles, dust on a PV panel, and other random factors must be considered. All these factors affect PV system output. Hence, in choosing input variables for a prediction model, one should consider deterministic factors strongly correlated with power generation. Additionally, time-series data for PV power generation are strongly auto correlated and therefore these historical data should be the input data of the forecasting model. To establish an accurate and reliable output power prediction model for a PV power plant, it is necessary to analyze the effect factors for the PV power plant output. In the physical sense, global solar irradiance received on the ground is a direct influencing factor on the voltage effect of PV cells. The Pearson product-moment correlation coefficient, also known as r, can measure the direction and strength of the linear relationship between two variables, which is a method to quantify non-deterministic relationship. The value of PPMCC ranges between -1 to +1, where 1 is total positive correlation, 0 is no correlation, and − 1 is total negative correlation. Table I provides the Pearson product-moment correlation coefficient between PV output and environmental factors under typical weather conditions.

It can be seen from Table I that the correlation coefficient between the power output of a PV power generator and solar irradiance is greater than 0.8, which means they are highly correlated, while the correlation coefficient between PV power generation output and temperature is greater than 0.3, which means these factors are positively and low-level correlated

TABLE I
PEARSON PRODUCT-MOMENT CORRELATION COEFFICIENT BETWEEN PV OUTPUT AND ENVIRONMENTAL FACTORS

Weather Condition	Pearson Product-Moment Correlation Coefficient			
	Irradiance	Temperature	Humidity	Wind Speed
Clear	0.966	0.322	-0.527	-0.229
Cloudy	0.891	0.441	-0.511	-0.025
Overcast	0.987	0.409	-0.478	0.125
Rainy	0.923	0.410	0.039	-0.178

The correlation coefficient of humidity indicates a low but negative correlation. The correlation between PV power generation output and wind speed is small. Table II provides the Pearson product-moment correlation coefficient between wind speed and power output. Pearson correlation of power and wind speed is 0.816. According to Table II, there is a high correlation between wind speed and power output.

TABLE II
PEARSON PRODUCT-MOMENT CORRELATION COEFFICIENT BETWEEN WIND SPEED AND POWER OUTPUT

Wind Condition	Pearson Product-Moment Correlation Coefficient
None	0 -0.09
Low	0.1-0.3
Medium	0.3-0.5
High	0.5-1.0

III.DESCRIPTION OF THE PROPOSED FORECASTING SYSTEM

In this work, both Artificial Neural Networks (ANN) and ANFIS (Adaptive Neuro Fuzzy Inference System) have been employed to forecast power for PV and Wind Energy Systems. Both the systems are trained using historical data sets.

An artificial neural network (ANN) includes selection of inputs, outputs, network topology and weighed connection of node. Input features will correctly reflect the characteristics of the problem [18]. Another major work of the ANN design is to choose network topology. This is done experimentally through a repeated process to optimize the number of hidden layers and nodes according to training and prediction accuracy. In this work 9 Environmental Parameters namely Global horizontal irradiance, Global diffused irradiance, Ambient Temperature, Precipitation, Wind Speed, Air pressure, Sun shine duration, Relative Humidity and Surface Temperature. Another network is designed by considering 4 inputs like Global horizontal irradiance; Global diffused irradiance, Ambient Temperature and Surface Temperature. Similarly to

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forecast the wind energy, wind speed and angle of wind direction relative to the turbine blades are considered as inputs.

In this work a Feed – Forward Back Propagation network is used. A TRAINLM training function along with LEARNGDM adaptive learning function is used of training and adaptation of the network. MSE is used to compute the performance measure. The total network comprises of 2 layers with layer one having 9 neurons and using a TANSIG transfer function.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a class of adaptive networks that is functionally equivalent to fuzzy inference system. Sugeno type ANFIS [16] uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference system. It applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. An ANFIS works [17] by applying neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). There are several features of the ANFIS which enable it to achieve great success in a wide range of scientific applications. The attractive features of an ANFIS include: easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving. According to the neuro-fuzzy approach, a neural network is proposed to implement the fuzzy system, so that structure and parameter identification of the fuzzy rule base are accomplished by defining, adapting and optimizing the topology and the parameters of the corresponding neuro-fuzzy network. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data, and as a connectionist architecture provided with linguistic meaning.

Global horizontal irradiance; Global diffused irradiance, Ambient Temperature and Surface Temperature form the input vectors for the network and similarly to forecast the wind energy, wind speed and angle of wind direction relative to the turbine blades are considered as inputs. In the proposed work both Back propagation and Hybrid methods of optimization are employed.

IV.DATA SETS USED FOR THE ANALYSIS

In this work 9 environmental parameters namely Global horizontal irradiance, Global diffused irradiance, Ambient Temperature, Precipitation, Wind Speed, Air pressure, Sun shine duration, Relative Humidity and Surface Temperature are considered as inputs to train the proposed forecast system. The Data pertains to 10 MW power plants in Kalipi, Andhra Pradesh, India. The model is scaled down to 10 KW for simplification of analysis. The Latitude of the site is: 13.9928873^0 and Longitude is: 77.4587239^0. The site is located at an altitude of 548 meters from the mean sea level. The Data format considered to train the proposed model comprises of 3960 individual data sets pertaining to hourly data for 365 days .The data hour is considered from 7 am to 6 pm. Each individual data set comprises 9 data points pertaining to different parameters being employed in the forecast system. The sample data set used in the training of ANN PV forecast model is given in the Table III.

In order to train the forecast for the wind energy system, the data is obtained from Sotavento Galicia experimental wind energy farm [19]. The data considered include wind speed and angle of wind direction relative to the turbine blades.

TABLE III
SAMPLE DATA SET USED IN TRAINING THE ANN FORECAST MODEL

G_Gh (Global Horizontal)	119	76	70	237	78	341	660	345
G_Dh (Global Diffused)	75	76	70	227	78	312	350	289
Ambient Temperature	24.5	24.7	24.7	25.5	25.4	26.3	27.8	28.2
Precipitation	0	0	0	0	0	0	0	0
Wind speed	1.5	0.8	3.3	1.8	1.5	1.8	2	1.3
Air pressure	940	940	940	940	940	940	940	940
Sunshine Duration	30	1	0	3	0	5	46	10
Relative Humidity	62	63	68	62	63	59	55	51
Surface Temp	25.2	24.9	24.8	27.3	25.6	29.1	33.9	31.3

The main technical details of wind system data are as follows [19]

- Number of wind turbines: 24
- Technologies present: 5
- Different models: 9
- Power rating of the wind farm: 17.56 MW
- Average annual generation: 33,364 MWh
- Prevailing winds: on the east-west axis
- Average wind speed at the site: 6.41 m/s

In order simplify the forecast system; again the considered data of PV generating station is scaled down to 10 KW systems. A total of 1440 data sets pertaining to hourly monitoring for a 60 day period are considered to train the forecast system. The sample data set is given in the Table IV and Table V summarizes the details about the data base used in this study. The wind generation is scaled down to 17.56 KW for the simplification analysis.

Table V summarizes the database of PV and Wind generating stations used in this study for forecasting the PV and wind energy systems.

TABLE IV
SAMPLE DATA SET USED IN TRAINING THE FORECAST MODEL FOR WIND ENERGY

Wind Speed (m/s)	6.54	9.89	12.68	14.35	10.84	11.43	13.23	15.3	14.65	14.15
Angle (degrees)	147	150	144	145	150	165	187	207	231	238

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TABLE V
DATABASE UTILIZED IN THIS STUDY

Data Sources	Installed Capacity	Sampling Data	Measurement Item	Total number of data points
Kalipi Solar Power Installation	10 MW	Average values for 60-minute	(i) PV generation (ii)Atmospheric temperature (iii) Solar irradiance (Global and Diffused) (W/m^2) (iv) PV module temperature (v) Ambient temperature (vi) Wind speed (vii) Precipitation (viii) Duration of sunshine (ix) Atmospheric Pressure	71280
Sotavento Galicia wind energy farm	17.56 MW	Average values for 60-minute	(i) Wind generation (ii) wind speed (iii) Wind Angle	2880

V.FORECASTING RESULTS AND DISCUSSIONS

The forecasting tool is designed in the form of a Graphical User Interface (GUI). The GUI is coded using MATLAB R 2012a and the simulations are run in a Pentium i3 system with a RAM of 4 GB. The screen shot of the proposed system is depicted in the figure 1.The proposed GUI has the following functions

a) It has provision to feed the different environmental factors related to both the wind energy and the PV cell

b) It has provisions to enter the site data, in terms of latitude,

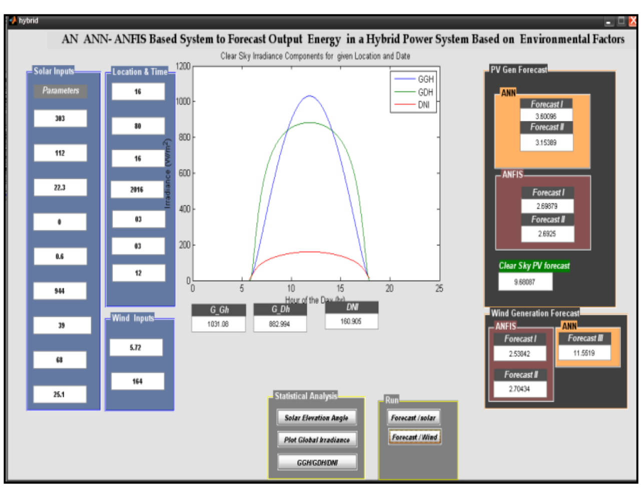

Fig 1. Graphical User Interface of the proposed system

Longitude, altitude and also the time, day, month and year of prediction

c) It has a built in clear sky based forecast model to predict the irradiation for a particular geo location for a specific day and time.

d) It has two forecast for both ANN and ANFIS

(d1) In the case of ANN : Forecast I is the Forecast arrived at by considering all 9 environmental factors and Forecast II is the one arrived at by considering 4 factors like Global diffused and normal irradiance , ambient temperature and surface temperature.

TABLE VI
DATA POINTS USED IN THE VALIDATION FOR PV FORECAST

	SD1	SD2	SD3	SD4	SD5
G_Gh (Global Horizontal)	34	98	532	836	973
G_Dh (Global Diffused)	34	52	134	147	101
Ambient Temperature	28.1	20.5	24.4	29.7	28.3
Precipitation	0	0	0	0	0
Wind speed	1.5	0.2	0.7	4.1	0.3
Air pressure	941	944	944	947	949
Sunshine Duration	2	17	55	59	60
Relative Humidity	54	78	63	35	40
Surface Temp	27.9	20.9	29.8	36.1	39
Actual Generation Scaled to 10 KW (KWh)	0.20574	1.175237	5.9933	8.8797	9.9185

(d2) In the case of ANFIS Forecast Iis arrived at by having Hybrid optimization and Forecast II is arrived by having Back propagation optimization. The ANFIS system for solar forecast considers only 4 factors like (Global diffused and normal irradiance, ambient temperature and surface temperature)

In order to validate the results of the proposed work, the forecast is tested against 5 data points for both PV and Wind energy. The data points being considered for validation are sampled to represent high, medium and low values of the parameters being considered in the forecast model.

The data points being considered for analysis of the PV system is given in the table VI.

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The result of the forecast for the above data set is discussed in the following section; the results are being described through a series of tables

TABLE VII
FORECAST FOR PV GENERATION BY ANN – FORECAST I

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.35521	0.94286	6.106	8.75604	9.84484
% Error	-72.649	19.7729	-1.8804	1.39261	0.74265

TABLE VIII
FORECAST FOR PV GENERATION BY ANN – FORECAST II

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.3688615	0.910558	5.35801	8.58571	10.0603
% Error	79.2853	22.52133	10.6	3.31081	-1.42965

TABLE XI
FORECAST FOR PV GENERATION BY ANFIS – FORECAST I

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.364641	0.797184	5.31916	8.08136	10.7236
% Error	-77.2339	32.16824	11.24823	8.990619	-8.11715

TABLE X
FORECAST FOR PV GENERATION BY ANFIS – FORECAST II

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.37844	0.78824	5.40998	8.10273	10.6893
% Error	-83.94	32.929	9.73287	8.74996	-7.7713

From the table VII, table VIII, table XI and table X following observations can be inferred

a) For very low insolation values all the forecast methods results in very high error percentage, this can be evident from the fact the least error percentage is 72.64 % being delivered by the forecast by ANN Forecast I (which considers all the 9 parameters for forecast)

b) As there is increase in the insolation values, there is substantial and appreciable increase in the prediction accuracy and subsequently a decrease in the error percentage. It can be observed that the error percentage stands at 19.79 for SD2 as predicted by ANN Forecast I

c) At higher insolation values the percentage of error drastically falls and the best forecast being delivered by ANN Forecast I. It has given a forecast with an error as less as 0 .74265 % for SD5.

d) When the comparison is inferred between different forecasting methods, between ANN and ANFIS, ANN delivers better results. In particular the forecast delivered by ANN Forecast I which considers all the 9 parameters for forecast is superlative.

The data points being considered for analysis of the wind energy system is given in the table XI.

TABLE XI
DATA POINTS USED IN THE VALIDATION FOR WIND ENERGY FORECAST

Data Points	WD1	WD2	WD3	WD4	WD5
Wind Speed (m/s)	6.54	9.87	10.86	18.85	19.93
Angle (degrees)	147	221	195	216	216
Actual Energy Generated (KWh)	5.68851	6.6161557	6.5060	14.5263	15.2027

It can be inferred from the table XII, table XIII and table XIV, except for one odd high error % for the forecast produced by the ANN, the other forecast have relatively small error percentages. When the performance of the forecast by ANN and ANFIS is compared the forecast delivered by the ANFIS method is relatively better. When the comparison is done between the hybrid mode of optimization and back propagation mode of optimization in ANFIS, there is no appreciable difference between the forecast delivered by the two optimization approaches.

The results of the forecast of the wind energy are illustrated using the following tables

TABLE XII
FORECAST FOR WIND GENERATION BY ANN

Data Point	WD1	WD2	WD3	WD4	WD5
Actual Value	5.68851	6.61616	6.506	14.5263	15.2027
Predicted Value	10.1	6.90156	6.03	13.92	13.94
% Error	-77.551	-4.3137	7.31632	4.17381	8.30576

TABLE XIII
FORECAST FOR WIND GENERATION BY ANFIS FORECAST I

Data Point	WD1	WD2	WD3	WD4	WD5
Actual Value	5.68851	6.61616	6.506	14.5263	15.2027
Predicted Value	5.83	7.165	6.99	14.32	14.15
% Error	-2.48729	-8.29552	-7.43929	1.420183	6.924428

TABLE XIV
FORECAST FOR WIND GENERATION BY ANFIS FORECAST II

Data Point	WD1	WD2	WD3	WD4	WD5
Actual Value	5.68851	6.61616	6.506	14.5263	15.2027
Predicted Value	5.92	7.163	6.91	14.34	14.18
% Error	-4.0694	-8.2653	-6.2097	1.2825	6.72709

There are several evaluation criteria for forecasting models, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and others. In this work, the Normalized Root Mean Square Error (NRMSE) was utilized because it can provide the comparative analysis for different installed-capacity cases. It is defined as follows:

$$NRMSE = 100\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(P_a^i - P_j^i)^2}{P_{install}}}\% \qquad (1)$$

Where $P_{install}$, P_a, P_f, indicate installed capacity, actual power output, and power forecast value, respectively, and N is the total number of samples.

VI.CONCLUSION

As the search for clean energy continues to grow, PV and Wind energy systems will be one of the most important contributors towards delivering the required energy. In this we have implemented a forecast method based on ANN and ANFIS for predicting the output power with help of ANN and ANFIS models trained using historical data. It can be inferred from the results that in regard to predicting the PV generation ANN based forecast delivers better results when compared to the ANFIS based forecast. On the other hand the ANFIS based model delivers better result for forecasting the wind generation. It is also observed that in a hybrid system involving PV and wind energy different forecast approaches can be employed to predict the power output from different sources. The outputs of the forecast models have multiple applications including serving as inputs for energy management system for hybrid PV systems.

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