Soft Computing Techniques for Forecasting Issues in Grid Connected Solar Power System

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Abstract— This paper analyses the operation of an adaptive neuro-fuzzy inference system (ANFIS)-based maximum power point tracking (MPPT) for solar photovoltaic (SPV) energy generation system. The MPPT works on the principle of adjusting the voltage of the SPV modules by changing the duty ratio of the Quasi-z-source inverter. The duty ratio of the inverter is calculated for a given solar irradiance and temperature condition by a closed-loop control scheme. The closed-loop control of the qZSI regulates the duty ratio and the modulation index to effectively control the injected power and maintain the stringent voltage, current, and frequency conditions. The ANFIS is trained to generate maximum power corresponding to the given solar irradiance level and temperature. The response of the ANFIS-based control system is highly precise and offers an extremely fast response. The main objective for a grid-connected Photovoltaic (PV) inverter is to feed the harvested energy from PV panels to the grid with high efficiency and power quality.

Keywords: Solar Power System, Soft Computing Techniques, ANFIS

I. INTRODUCTION

The term Soft Computing (SC) encompasses many techniques which include: Fuzzy Logic (FL), Neuro-Computing (NC), Probabilistic Reasoning (PR), Evolutionary Computing (EC) or Genetic Algorithms (GA), Chaotic Systems (CS), Belief Network (BN) and part of Learning Theory (LT) (Zadeh, 1965, 1994, 1995; Mellit and Kalogirou, 2008). SC techniques are different from analytical approach in that they employ computing techniques that are capable of representing imprecise, uncertain and vague concepts (Voracek, 2001a; Kulak et al., 2005; Kahraman, 2007; Guarino et al., 2009). Analytical, also called hard computing, approaches on the other hand use binary logic, crisp classification and deterministic reasoning. In their editorial review, (Hoffmann et al., 2005) observed that: “In contrast with hard computing methods that only deal with precision, certainty, and rigor, soft computing is effective in acquiring imprecise or sub-optimal but economical and competitive solutions. It takes advantage of intuition, which implies the human mind-based intuitive and subjective thinking is implemented here”.

Techniques in SC are able to handle non-linearity and they offer computational simplicity when compared with the analytical methods. These techniques have been shown to be able to manage large amount of information and mimic biological systems in learning, linguistic conceptualization, optimization and generalization abilities. Soft computing techniques are finding growing acceptance in materials engineering and three of them are popular, namely: (i) Fuzzy Logic (FL), (ii) Artificial Neural Networks (ANN) and (iii) Genetic Algorithms (GA). There are well established methodologies for integrating SC techniques to realise synergistic or hybrid models with which better results could be obtained (Zadeh, 2001). The use of hybrid techniques is also growing. The literature on the application of soft computing to materials engineering (ME) is so vast and so rich that it will be impractical to attempt a complete review in a journal article. To this end, we focus on those papers that we consider to be of interest, not only in terms of their contribution ton knowledge and good practice, but also those that help us to draw attention to some observed or perceived lapses in the application of SC techniques.

Real world problems have to deal with systems which are non-linear, time-varying in nature with uncertainty and high complexity. The computing of such systems is study of algorithmic processes which describe and transform information: their theory, analysis, design, efficiency, implementation, and application. Conventional computing/Hard computing requires exact mathematical model and lot of computation time. For such problems, methods which are computationally intelligent, possess human like expertise and can adapt to the changing environment, can be used effectively and efficiently. Soft computing utilizes computation, reasoning and inference to reduce computational cost by exploiting tolerance for imprecision, uncertainty, partial truth and approximation. Soft Computing with its roots in fuzzy logic, artificial neural network, and evolutionary computation has become one of the most important research field applied to numerous engineering areas such as Aircraft, Communication networks, computer science, power systems and control applications. Soft Computing Techniques comprises of core methodologies: Fuzzy Systems (FS), including Fuzzy Logic (FL); Evolutionary Computation (EC), including Genetic Algorithms (GAs); Artificial Neural Networks (ANN), including Neural Computing (NC); Machine Learning (ML); and Probabilistic Reasoning (PR). Where PR and FL systems are based on knowledge-driven reasoning, whereas, ANN and EC, are data-driven search and optimization approaches. List of various problem Solving Techniques are as shown in Figure.

These techniques can be deployed as individual tools or be integrated in unified and hybrid architectures. The fusion of Soft Computing techniques causes a paradigm shift in engineering and science fields, which could not be solved with the conventional computational tools. Soft Computing has gain importance in the application fields for wireless communication in the last decade.

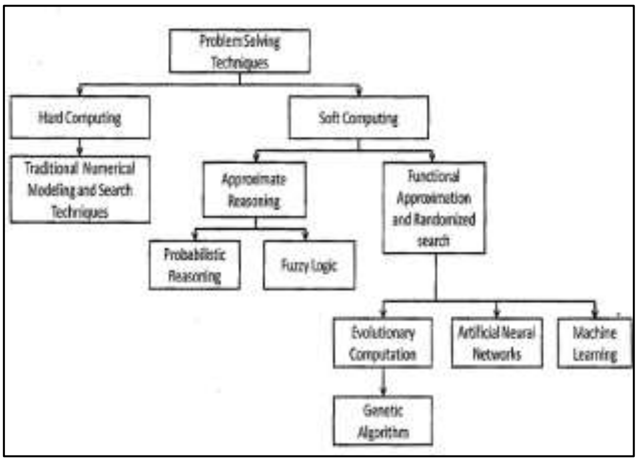

Fig. 1: Various Problem Solving Techniques

Uncertainties arising due to incomplete modeling and measurements are handled using fuzzy logic, either in stand-alone manner or in conjunction with the optimization and prediction algorithms. Various methods of using the tools for application oriented programming techniques is briefly discussed here.

II. Fuzzy Logic System

Fuzzy systems are based on fuzzy logic, a generalization of traditional Boolean logic which is extended to handle the concept of partial truth i.e values between "complete true" and "complete False". Fuzzy Logic provides a set of mathematical methods for representing information in a way that resembles natural human reasoning and deals with system uncertainty and vagueness. Concepts of fuzzy sets, fuzzy logic and fuzzy control have been introduced and developed by L.Zadeh in a series of articles spanning several years. Fuzziness is imprecision or vagueness, a fuzzy proposition may be true to some degree.

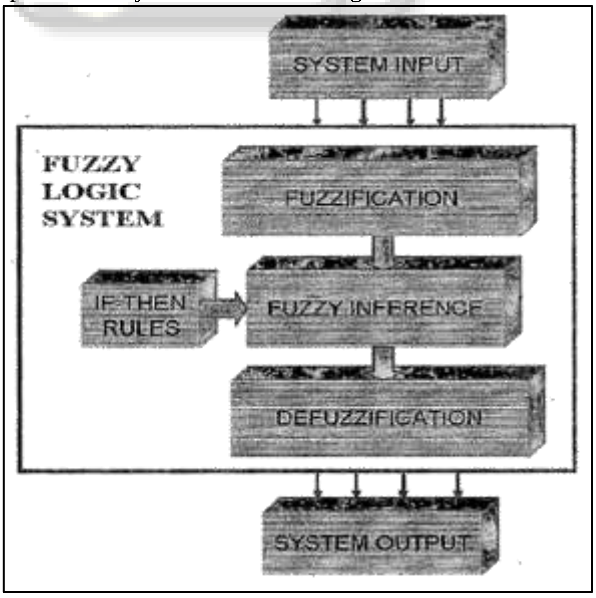

Fig. 2: Fuzzy Logic System

A Fuzzy Logic System is an expert system that uses a collection of fuzzy membership functions and fuzzy IF-THEN rule base, instead of Boolean logic, to reason about data. The rules in a Fuzzy Logic System are of a form as following:

IF (a is LOW) AND (*y* is HIGH) THEN (*z* is MEDIUM), IF (premise) THEN (Conclusion)

where *x* and *y* are input variables for known data values, *z* is an output variable for an output data to be computed, LOW is a membership function (fuzzy subset) defined on the set of x, HIGH is a membership function defined on the set of y, and MEDIUM is a membership function defined on the set of z. The antecedent (the rules premise, between IF and THEN) describes to what degree the rule applies, while the consequent (the rules conclusion, following THEN) assigns a membership function to each of one or more output variables. The set of rules in a Fuzzy Logic System is known as the rule base or knowledge base. Figure 2 shows the Fuzzy Logic System Block Diagram.

- Fuzzification: The membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.
- Fuzzy Inference Engine: The truth value for the premise of each rule is computed, and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule. The aggregation method min or product is used as inference rules. After Inference, the composition of all fuzzy sets is carried out. Under composition, all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable. Usually max or sum is used.
- Defuzzification: It convert the fuzzy output set to a crisp number. There are many defuzzification methods.

III. Artificial Neural Networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the biological neural networks, which consists of massively parallel computing systems with large number of simple processors with many interconnections. ANN methodologies consists of basic architecture known as ''Neurons". A neuron or nerve cell is a special biological cells that processes information in human brain. ANNs are applied to solve various challenging problems like Classification, Clustering, Function Approximation, Prediction/Forecasting, Medical Imaging Application, Optimization and Control related applications.

$$\sum_{i=1}^{N} W_i X_i = W_1 X_1 + W_2 X_2 + \dots + W_N X_N$$

A. Artificial Neuron

The science of ANN has its first significance appearance during the 1940's, when researchers McCulloch and Pitts tried to emulate the functions of human brain by developing physical model of biological neuron and their interconnections. Their work was focus on a simple neuron, which were considered to be binary with fixed thresholds as shown in Figure 3.

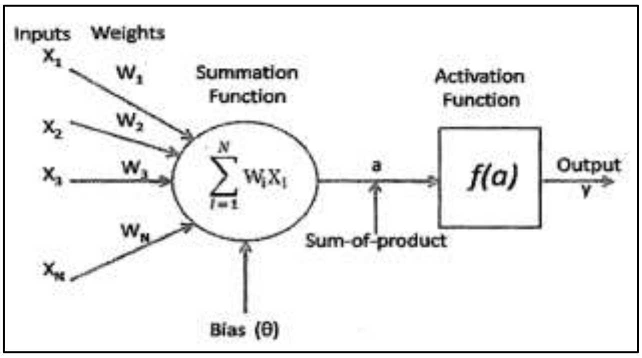

Fig. 3: Artificial Neuron

If this value is below threshold t, the output of the unit is 1 and 0 otherwise. The McCulloch- Pitts model of a neuron is so simple that it only generates a binary output and also the weight and threshold values are fixed. But, it has substantial computing potential. The neural computing algorithm has diverse features for various applications. Thus, we need to obtain the neural model with more flexible computational features. In the first stage, the linear combination of inputs is calculated. Each value of input array is associated with its weight value, which is normally between 0 and 1. Also, the summation function often takes an extra input value Theta with weight value of 1 to represent threshold or bias of a neuron. The summation function will be then performed as:

$$a = \sum_{i=1}^{N} W_i X_i + \theta$$

The sum-of-product value is then passed into the second stage to perform the activation function which generates the output from the neuron. The activation function "squashes" the amplitude the output in the range of [0,1] or [-1,1] alternately. The behavior of the activation function will describe the characteristics of a neuron model.

In learning process, ANN updates network architecture and connection weights from training patterns. ANNs learn the underlying rules (like input-output relation) from the given collection of training data. Learning algorithms adjusts the weights of ANN using learning rules. Based on learning process there are three types of learning paradigms:

– Supervised learning: also known as learning with a "teacher", means the network is provided with the correct output for every input pattern. Connection weights are then determined so as the allow the network to produce output very close to the correct answers. Examples of supervised learning algorithms are Boltzmann learning algorithm, Learning vector quantization, Back-propagation Adaline algorithm and Perception learning Algorithms.
– Unsupervised Learning: also know as learning without "teacher", do not require correct output answers for each input pattern in the training set provided. It explores the network structure in data or correlations between input patterns, and organizes input patterns into categories from these correlations. Unsupervised Learning algorithms include Principal Component Analysis, Associative memory Learning, Kohonen's SOM, Adaptive resonance theory (ART) algorithms.
– Hybrid learning: It combines supervised and unsupervised learning i.e. part of the weights are determined through supervised learning and the remaining are obtained through unsupervised learning. Radial Basis Function (RBF) Learning algorithm used for learning in RBF networks using Error-correction and competitive learning rule is an example of Hybrid learning.

B. Neuro-fuzzy

The neuro-fuzzy model, which involves the integration of ANN and FL techniques are perhaps the most popular hybrid technique used in materials engineering. Neurofuzzy models are able to take advantage of the fuzzy inference mechanism capabilities in fuzzy logic and the learning ability of neural networks. The ANN technique is usually used as the learning algorithm for the defuzzification process in FL based models. Neuro-fuzzy models are regarded as black-box models which provide little insight to help understand the underlying process. Figure 4(a) illustrates a simple configuration of a neuro-fuzzy model.

C. Fuzzy-genetic

When the FL and GA techniques are combined to develop a solution, the fuzzy-genetic model results. The aim here is to exploit the ability of the fuzzy logic at knowledge description and the optimisation capability of the genetic algorithm. Usually, the defuzzification process in fuzzy logic based model are developed using optimal selection of elements from a fuzzy set. Aside from GA, techniques that employ the concepts of interaction, variability, and voting techniques are also used to optimise the defuzzification and membership generation process. Figure 4(b) illustrates a simple configuration of a fuzzy-genetic algorithms model.

D. Neuro-genetic

When the ANN and GA techniques are combined to develop a solution, the neuro-genetic model results. The aim here is to take advantage of the learning ability of the ANN and optimisation ability of the genetic algorithm. Figure 4(c) illustrates a simple configuration of a neurogenetic algorithms model. No application of neuro-genetic algorithms model in materials engineering has been reported in the literature we reviewed.

E. Neuro-fuzzy-genetic

When the three SC techniques discussed here are combined to develop a solution, the neuro-fuzzy-genetic model results. Usually, the GA approach is used to optimise the performance of a neuro-fuzzy system. The development of this approach is usually guided by heuristics, based on the experiences of an expert materials engineer. In (Huang, Gedeon, and Wong, 2001) the architectture in Figure 19 was proposed for developing a neurofuzzy-genetic model for predicting the permeability in petroleum reservoirs. The vector Xc and matrix Zc are the training pattern and Yc is the target output.

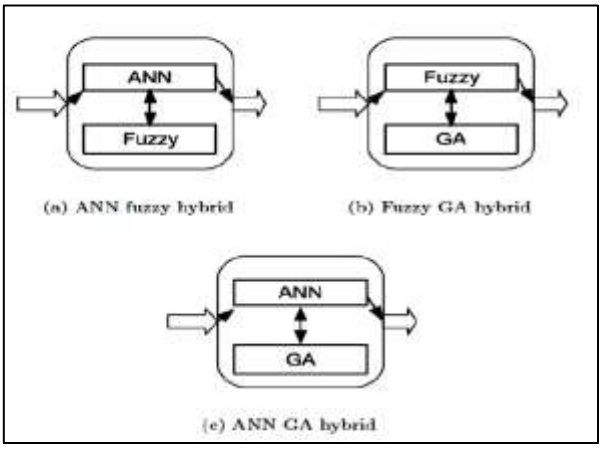

Fig. 4: Hybrid soft computing models

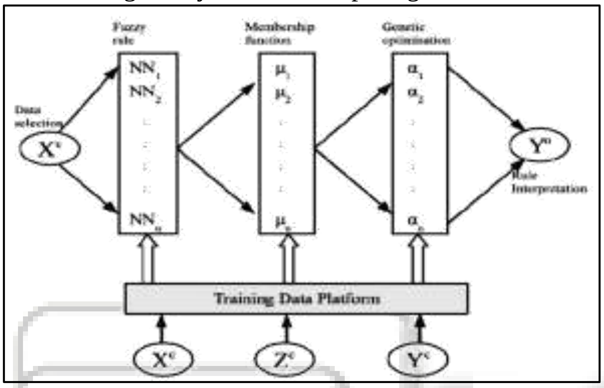

Fig. 5: ANN –fuzzy-GA hybrid

This paper analyses the operation of an adaptive neuro-fuzzy inference system (ANFIS)-based maximum power point tracking (MPPT) for solar photovoltaic (SPV) energy generation system. The MPPT works on the principle of adjusting the voltage of the SPV modules by changing the duty ratio of the Quasi-z-source inverter. The duty ratio of the inverter is calculated for a given solar irradiance and temperature condition by a closed-loop control scheme. The closed-loop control of the qZSI regulates the duty ratio and the modulation index to effectively control the injected power and maintain the stringent voltage, current, and frequency conditions. The ANFIS is trained to generate maximum power corresponding to the given solar irradiance level and temperature. The response of the ANFIS-based control system is highly precise and offers an extremely fast response. The main objective for a grid-connected Photovoltaic (PV) inverter is to feed the harvested energy from PV panels to the grid with high efficiency and power quality. The simulation results show that the proposed ANFIS MPPT controller is very efficient, very simple and low cost.

It is well known that the output power of photovoltaic (PV) panels holds highly non-linear characteristic. For a certain temperature and irradiation, there will be a specific maximum power at certain voltage so-called maximum power point (MPP). The voltage of MPP changes with the irradiation and especially the temperature varying. Thus, the system needs to operate at the MPP of PV array by controlling the inverter, no matter how much irradiation, what temperature or other conditions. Moreover, the generated energy from the PV system, which is mostly provided to the utility grid, not only should be of sinusoidal current, but also must satisfy the requirements of the power grids, such as no DC component of the inverter output current, minimization of the harmonics, as a result of no harmonic pollutions on the power grids, and so on. These requirements impose the inverter with a high-grade control. The challenge is how to meet the above requirements with minimum cost, which has to be faced for the majority of designers.

AI based methods are most suitable for improving the dynamic performance of maximum power point tracking. Considering the non-linear characteristics of solar PV module, the AI methods provide a fast, flexible and computationally demanding solution for the MPPT problem. Fuzzy logic controller and artificial neural networks are two main AI methods used for MPPT. In this paper, designing and implementation of ANFIS based MPPT scheme which is interfaced with Quasi-Z-Source Inverter presented.

ANFIS combines the advantages of neural networks and fuzzy logic and hence deals efficiently with non linear behavior of solar PV modules. Designing of Quasi-Z-Source Inverter is also carried out which is used for impedance matching and maximum power transfer between load and solar PV module.

IV. SOFT COMPUTING TECHNIQUES FOR FORECASTING ISSUES

In last few years, Renewable Energy is introduced as a alternative source of energy. Especially in Indian context solar Energy is an important issue and unlimited source of energy. However, solar radiation is varies with time and geographical locations and meteorological conditions. In this literature survey, artificial neural network and generalized neural network are used as a powerful tool for Renewable Energy Forecasting. With the help of metrological data such as wind velocity, solar irradiation, and temperature as input to the model we can predict the changes in generated solar power, which is very useful for integration of solar power into grid. Here these soft computing techniques are able to prediction the solar power generation accurately and fast compare to conventional methods of forecasting. Solar power forecasting is very useful and key component as planning of solar power plant. It plays an important role in 21st century which is having a energy's supply and demand problem due to peak load and shortage of power at the peak hours. Solar power forecasting motivates studies of integration of renewable grid to conventional grid. In India we found heavy fluctuations in solar power generation with respect to time and places. So Solar Energy output is needed to forecast reliably and accurately for a successful integration in the electricity grid. This is also important because solar energy is clean energy and does not produce CO2 and pollute the environment. Therefore solar power is one of the best options for the alternative energy source. Because of fluctuation of solar irradiation and weather parameter solar power fluctuates. Therefore this solar power forecasting is very useful tool for a solar power plant and planning for storage battery which is the feasible measure to stable power output of PV standalone system. This short term power forecasting helps in the following power system areas such as:

1) Control
2) Unit Commitment
3) Security Assessment
4) Optimum planning of power generation
5) Energy exchange
6) Grid integration

There are many factors which affect the short term solar power forecasting. These factors are given below

a) Meterological
b) Climate
c) Light intensity
d) Dust particle

A number of conventional techniques used for forecasting which is given below:

– Multiple linear regressions.
– Stochastic time series.
– General exponential smoothing.
– State space and kalman filter and
– Knowledge based approach.

These conventional techniques includes non-weather sensitive and weather sensitive models. In our Indian continent, there are sudden variations in climate. so accurate prediction are essential. The short term solar power forecasting techniques may further divided as follows:

1) Model independent of weather parameters.
2) Model including weather parameters.
3) Stochastic methods.

These all techniques are work on increase the accuracy of solar power forecasting. Forecasting is a richest application field of artificial neural network. Neural network central unit works as the human brain and biological neural network. On the basis of brain, neural network grouped or connected by a huge number of processing elements those are work as biological neurons which is able to work in parallel mode to solve a particular problem. Neural network always try to learn from past event or experiments. Actually in neural network past data or events play an important role. So past data must be chosen carefully. Because of wrong or disturbed input data can perform incorrectly.

The present neural network techniques have some technical drawbacks such as it takes a large training time and huge data requirement to train for a non-linear complex power forecasting problem and the relatively large number of hidden node required.

V. DEVELOPMENT OF AN ARTIFICIAL NEURON MODEL

In development of ANN model in Matlab Ver. R2010 for solar power forecasting and the following steps are taken:

1) Data preparation.
2) Selection of neural network structure.
3) Selection of appropriate training algorithm.
4) Selection of training parameter.

A. Data Preparation

In solar power forecasting the selection of input variable is very important part. The four input variables namely, Temperature, solar radiation, wind velocity, and solar power have been considered for the ANN model development. The data has been acquired at Indian Institute of Technology Jodhpur, India in energy Lab. The main aim of the neural network is to recognize these factor and solar power. The selected input variables have been pre-processed and the used for ANN training.

B. Selection of Neural Network:

Framing of neural network development.

1) Number of input variable = 4
2) Number of output = 1
3) Number of input layer neurons = 4
4) Number of Hidden layer neurons = 10
5) Number of Hidden layer = 1

The ANN structure is given below:

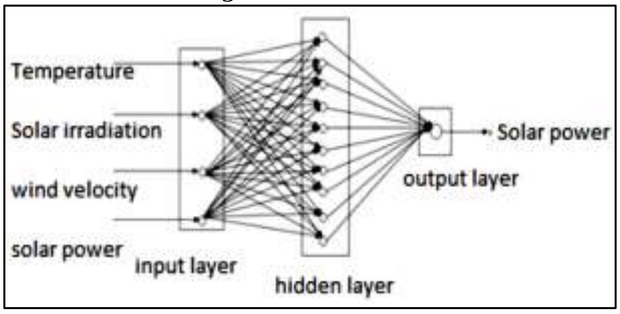

Fig. 6: Neural Network solar power forecasting model

C. Selection of Appropriate Training Algorithm:

In general back propagation training algorithm is used with learning and momentum factors. During the training sum squared error is fed back to change the weight.

D. Selection of Training Parameter

1) Number of epochs = 500(number of iterations required to reach to the final goal)
2) Error tolerance = .001(for the accuracy)
3) Learning rate = 0.9
4) Momentum factor = 0.1

VI. RESULT AND DISCUSSION

The result of training data from ANN model shown in figure 7 graphically for solar power

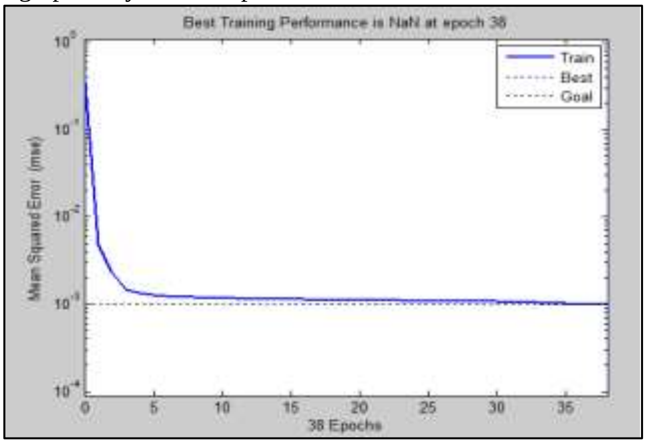

Fig. 7: performance graph

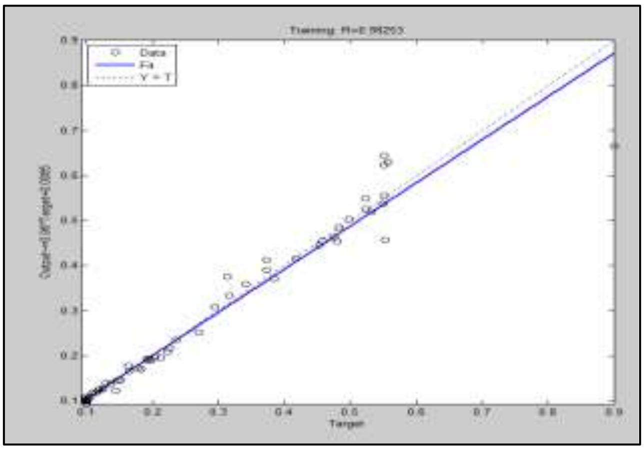

Fig. 8: regression plot

VII. MODEL DEVELOPMENT

A. *Fuzzy Logic Model*

The short term solar energy forecasting for 1hrs ahead by fuzzy logic model is developed and presented and the developed fuzzy logic model followed by specific set of rules which are being made for qualitative descriptions. The fuzzy linguistic variables are described as high, medium and low. Here, the main concern for the development of fuzzy systems is the appropriate membership functions. Generation of membership function depends upon intuition, experience or probabilistic methods and further it have been defined such as six membership functions like L (low), L1 (Extreme low), M (Medium), M1 (Medium High), H (High) and H1 (extreme High) all values lies in between the ranges 0.1 to 0.9 .IN fuzzy model, rules may be fired with some degree using fuzzy inference but in conventional expert systems, a rule is either fired or not fired. For the short term solar energy prediction problem, certain set of rules are described to determine the accuracy in terms of Absolute Relative Error (ARE). Such rules are expressed in the below following form.

IF premise (antecedent), THEN conclusion (consequent)

For the short term solar energy prediction purposed are followed by certain sets of multiple antecedent fuzzy rules. The input to the rule is solar energy during 8 a.m., 9 a.m., 10a.m., and 11a.m., of September, 2017 and output is 12noon.

B. *Adaptive Neuro Fuzzy Inference System*

Accordingly, the hybrid approach converges much faster since it reduces the dimension of the search space of the original back-propagation method. For this network created fixes the membership functions and adapt only the consequent part; then ANFIS can be viewed as a functional-linked network where the enhanced representation, which take advantage of human knowledge and express more insight. By fine-tuning the membership functions, we actually make this enhanced representation. The data set is available from the IMD centre .A complete data set of September month of one hour ahead global solar irradiance data (8 a.m., 9 a.m., 10 a.m., 11a.m,) are used for prediction of global solar irradiance for 12noon, output. The triangular type of membership function (trimf) is used for input and linear type function is used for output. The number of correct outputs is noted till the error is minimized.

In solar power applications of solar energy forecasting plays a vital issue because solar power is fluctuating in nature and it depends on several meteorological parameters. So, considering the above fact and Keeping in view the aforesaid, general fuzzy based model and ANFIS model are generated for short term solar energy predicted. The proposed ANFIS has effectively forecasted the global solar radiation and then becomes utilise preferably for any design of conversion solar energy application. The ANFIS model shows better results in comparison with other models. The evaluation results of solar radiation shows a significant improvement in statistical parameters and depicts better accuracy than other models. The comparative results deduce the forecasting ability of Adaptive-Neuro fuzzy inference system model and its compatibility for any location with different atmospheric conditions.

VIII. SHORT TERM SOLAR POWER FORECASTING FOR SMART-GRID

In last few years, Renewable Energy is introduced as a alternative source of energy. Especially in Indian context solar Energy is an important issue and unlimited source of energy. However, solar radiation is varies with time and geographical locations and meteorological conditions. With the help of metrological data such as wind velocity, solar irradiation, and temperature as input to the model we can predict the changes in generated solar power, which is very useful for integration of solar power into grid.

Solar power plays an important role in distributed power system. Photovoltaic systems have been increasingly installed worldwide in recent years. Because it produces clean energy, moreover the development of technology is continued therefore the reliability is increasing and the price is decreasing in opposite. To implement the PV system, however, a significant limitation of PV system is the uncertainty of power from the sun. This will affect the quality of the electrical system that connected.

Solar power forecasting is playing a key role in solar PV park installation, operation and accurate solar power dispatch ability as well as scheduling. Solar Power is varies with solar radiation and weather parameters such as ambient temperature, wind velocity, cloud coverage. In order to effectively achieve a high-penetration of commercial solar power into the grid, useful forecasting methodologies must be developed for integration of solar power in electric grid. The existing electric grid was designed and created to safely and reliably distribute power from a few concentrated power generation sources through highly monitored and controlled transmission lines to typically radial distributed loads. So we better monitoring and control system for performance analysis and operation of SPV system.

The forecasting challenges involve a combination of Weather parameters, Solar Radiation, Mathematical modeling, and Solar PV Power generation monitoring data. For the day ahead period, the challenges involve forecasting the dynamic changes in weather parameters and cloud cover. One challenge affecting solar power forecasts for all time-scales is the need for solar plant models that accurately convert irradiance values to power forecasts. In order to effectively support the solar power providers and grid managers, the meteorological community needs to prioritize the current shortfalls in solar forecasting and identify opportunities to improve them.

The new management tools, and the joint coordination of photo voltaic generation and storage at the building and micro-grid levels, require the use of solar power forecasts for several hours ahead. The time-horizon of interest for power system operations and electricity markets can be divided into two classes.

A. *Short-term*

For short-term load forecast in a smart grid environment, Borges et al. propose three different methods: (top-down) adding up single-observed consumptions and perform a global forecast; (bottom-up) adding up the sum of individual forecasts for each load in order to create a global forecast; (regression method) regression of the individual loads recorded by the meters. The main goal was to evaluate combined forecasting.

B. *Very short-term*

For the very short-term horizon, two different classes of models can be found. The first class is based on satellite images. It described an algorithm based on cloud-index images that are predicted with motion vector fields derived from two consecutive images.

The second class consists of univariate time-series models. Researchers compared the performance of different machine-learning algorithms (i.e., ARIMA, kNNs, NN, and NN optimized by genetic algorithms), which only use past observations of the time-series as inputs. The NN, combined with genetic algorithms, obtained the best performance.

The forecasting framework presented here paper addresses the very short-term horizon and is included in the second class of models.

IX. Conventional Models for Solar Power Forecasting

In distributed power generation solar power forecasting play an important role and it has amplified day by day. Several recent studies deal with the problem. Many of these consider forecasts of the global irradiance which is essentially the same problem as forecasting solar power. For solar power forecasting following conventions models are discussed here:

A. *Clear Sky Models*

Here we only choose two clear sky models, one which is a based on a polynomial regression and the other based on the European Solar Radiation Atlas (ESRA) clear sky model, so that the sensitivity of the methods for forecasting of clear sky days can be examined. The sensitivity should be small since short-term forecasting involves the use of previous irradiance values that can be used to adjust the clear sky forecasting.

B. *Persistence Models*

Clear sky persistence models are defined as having the clear sky conditions (ratio between the measured irradiance to the clear sky irradiance) persist for the next time-step.

$$k(t+\Delta t)=k(t)=(I(t))/I(t)clr$$

X. Input Selection of the PV Power Forecasting Model

Solar energy is one of most popular renewable energies, which comes from the sun in the form of solar irradiance. The solar cells made up of semiconductors in the PV module converts the solar irradiance to electricity through the photovoltaic effect. The PV power generation mainly depends on the amount of solar irradiance. In addition, other weather parameters, including atmospheric temperature, module temperature, wind speed and direction, and humidity, are considered as potential parameters for estimating the PV power output.

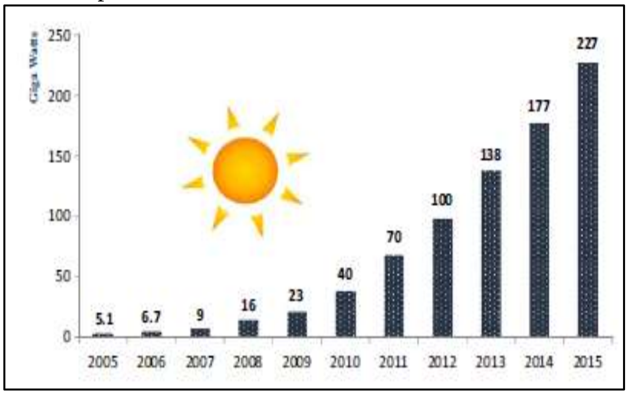

Fig. 9: Total installed PV power system from 2005 to 2015 worldwide.

A significant number of historical time series data of PV power output and corresponding meteorological variables are used to establish the forecasting model of PV power generation. The historical series data are divided in two groups: the training and testing data. The training data (almost 70% of the total data) are used for the learning of the model to forecast future values, whereas the testing data are used to validate the PV power forecasting model.

XI. Correlation between PV Power Output and Input Variables

The variation of meteorological parameters depends on the geographical location, as well as the weather condition; thus, no similar impact of a meteorological parameter exists on the PV power generation at different geographical locations. Consequently, the correlation of the meteorological parameters and PV power output will not be the same in different locations. However, the performance of a forecasting model is highly dependent on the correlation of the input and output values of the model. The study of the correlation of the different meteorological inputs, such as solar irradiance, atmospheric temperature, module temperature, wind speed and direction, and humidity, with PV power output, is important. The correlation might be positive or negative. The strongly correlated input variables should be used as an input vector to the forecasting model, and the weakly correlated input vector data should be refused. Fig. 2 shows the pattern of the solar irradiance and PV power output of a particular day. In a clear-sky day means a normal day, the PV power output is highly strongly matched with the solar irradiance curve. The PV power output is not highly strongly matched with the solar irradiance in an abnormal day, like cloudy or rainy day, but it is strongly matched.

Therefore, a similar pattern is observed for PV power output and solar irradiance in any weather condition. Fig.10 shows the strong positive correlation between solar irradiance and PV power output. Therefore, solar irradiance is an important input vector in developing an appropriate PV power forecasting model due to its high correlation coefficient (R2 = 0.988).

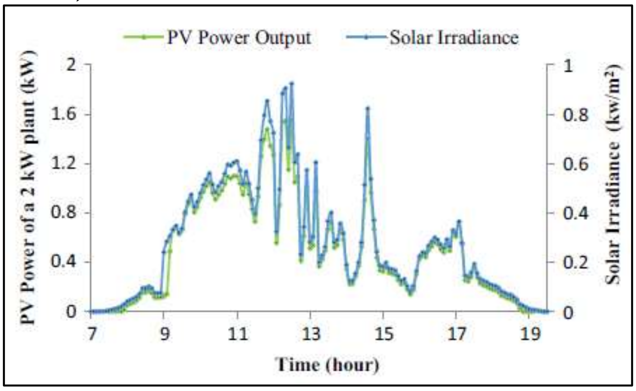

Fig. 10: Solar irradiance and PV power output pattern for a particular day

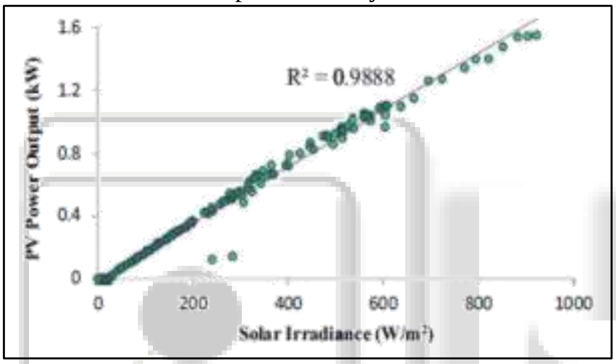

Fig. 11: Correlation between solar irradiance and PV power output

XII. CLASSIFICATION OF PV POWER GENERATION FORECASTING

Researchers have classified the forecasting of PV power generation in different categories based on different factors. However, no fixed criteria exist to classify the PV power forecasting. Most of the researchers classify the PV power forecasting depending on the forecasting horizon, historical data of solar irradiance and other meteorological data pattern, and methods used to forecast. An extensive review has been performed based on different classifications of PV power generation forecasting as presented in the following subsections.

A. Classification of PV power forecasting based on forecast horizon

The span of time into the future for which the PV power outputs are to be forecasted is called the forecast horizon. The purpose and accuracy of a PV power forecasting model depends on the forecast horizon. Lipperheide et al. analyzed the performance of PV power forecasting over the different forecast horizons, such as 20, 40, 60… 180 s. The forecast error (RMSE) of the proposed forecasting model is in the range of 3.2–15.5% for forecast horizons from 20 s to 180 s. Lonij et al. designed a PV power forecasting model where the errors have been changed with respect to forecast horizons ranging from 15 min to 90 min. The forecasting accuracy varies with the change of forecast horizon in the same model with the identical model parameters. Therefore, the forecast time horizon should be considered before designing the proper forecasting model. No well-defined criteria exist to classify the forecasting model based on the forecast horizon. Nevertheless, according to most of the researcher's reports, the forecasting of PV power generation can be divided into three categories based on time horizon, as shown in Fig.12.

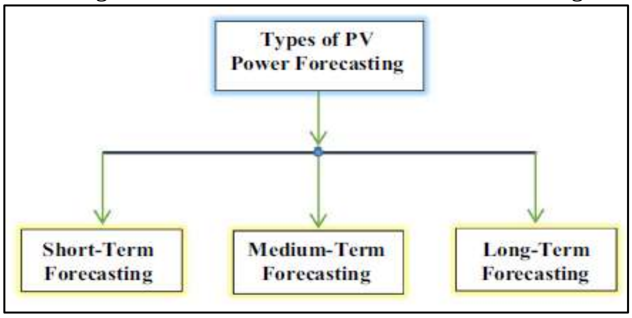

Fig. 12: Classification of PV power forecasting based on time horizon.

B. Short-term forecast

The forecasting of PV power generation done for one hour, several hours, one day, or up to seven days is known as short-term forecasting. The short-term forecasting of PV power generation ensures unit commitment, scheduling, and dispatching of electrical power. This type of forecasting model is useful in designing a PV-integrated energy management system. Short-term forecasting also enhances the security of grid operation.

C. Medium-term forecast

Medium-term PV power forecasting is done for more than one week to one month. This type of forecasting smooths the planning of the power system and maintenance schedule by predicting the availability of the electric power in the future.

D. Long-term forecast

Long-term forecasting of the PV power generation is done from one month to one year. This type of PV power forecasting is helpful for the planning of the electricity generation, transmission, and distribution organization aside from energy bidding and securing operation. However, some of the researchers have divided the forecast horizon of PV power generation into four categories. The fourth category is called “very short-term forecast horizon”. Very short-term PV power forecasting is considered for the few seconds, one minute, or several minutes (< 1 h) of forecast. This type of forecast has been done for power smoothing, real-time electricity dispatch, and optimal reserves.

E. Classification of PV power forecasting based on historical data

The forecasting methods of PV power generation can be categorized into four types based on the use of historical data of PV power output and related meteorological variables. These models are (a) persistence, (b) statistical, (c) machine-learning, and (d) hybrid method, as shown in Fig.13 with subcategories.

In the persistence model, the forecasted PV power output is equal to the actual power output of the previous day at a similar time. In this method, only the historical PV power output data are required to forecast the PV power generation. Generally, this model is used as a benchmark model. In the statistical methods, the PV power generation is forecasted by the statistical analysis of the different input variables. Therefore, the past time-series data are used in these methods. Normally, these methods are adopted for the short-term forecasting of the PV power generation. The historical data at the recent time should be used in these methods for increasing model accuracy. The requirement of the input data series in this model is less compared to the machine-learning method. Conversely, in the machine-learning methods, a large data set is required to forecast the PV power generation accurately. The machine-learning model is an intelligent technique, and it can handle linear, non-linear, and non-stationary data patterns. The combination of two or more techniques is used to design a forecasting model known as the hybrid model. The hybrid model shows better results than a single model for different forecasting problems by combining the advantages of each individual technique

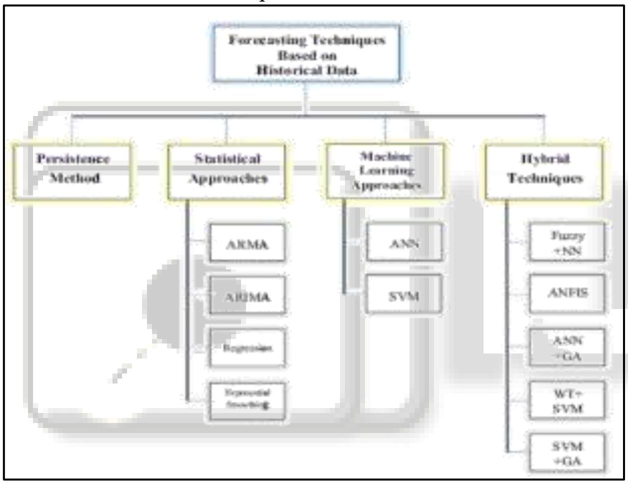

Fig. 13: Classification of PV power forecasting based on historical data.

XIII. THE PVPF TOOL

As described before, the PVPF tool is the application that implements our previous research into a real-time online forecasting system. A set of software interfaces have been developed to link and import data from the CLIMA DL16 Data logger and the SMA Sunny Web-box of the PV ASU09 (Faculty of Engineering) system, as depicted in Fig 14.

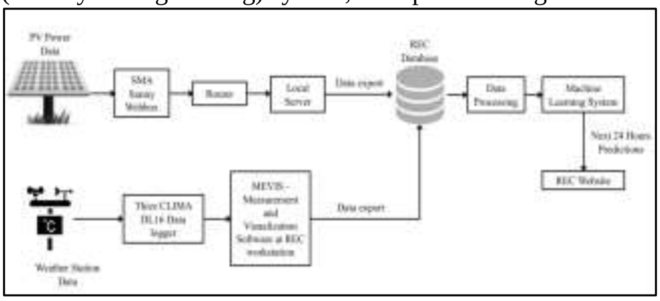

Fig. 14: The proposed PVPF tool

Data is stored at the REC database ready for the the data processing stage which includes: filtering extra data records, synchronizing timing stamps, normalization, and inserting correction values for missing records based on history data. Then, the processed data vectors are sorted in a proper way to be accepted by the machine learning system. This set of vectors represents the weather station data for the previous five days (24 hours per day) as depicted in Figure 15. Then, the predictions provided by the machine learning system are provided as a power/time curve which is published in real time online at the REC website. A sample result for the predicted power production on 12 June 2015 is shown in Figure 16 based on weather data of the previous five days. The system automatically provides the measured solar PV production on the same curve, once available from the SMA sunny web-box.

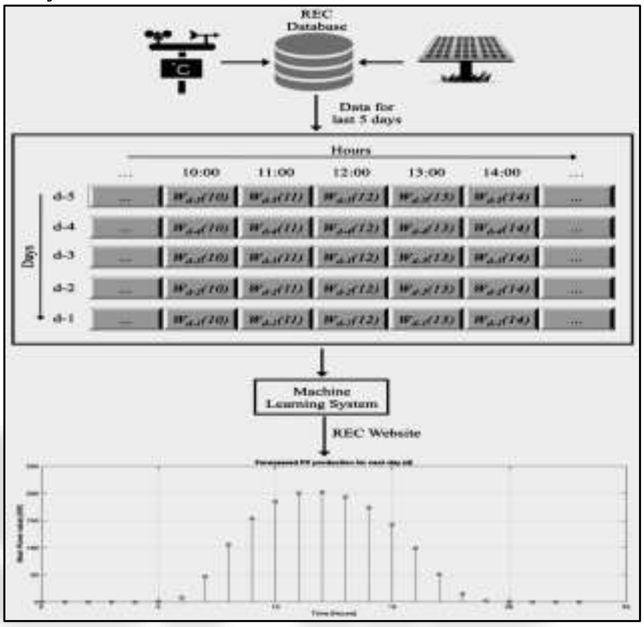

Fig. 15: Next-day PV forecasting based on the weather data of the previous five consecutive days

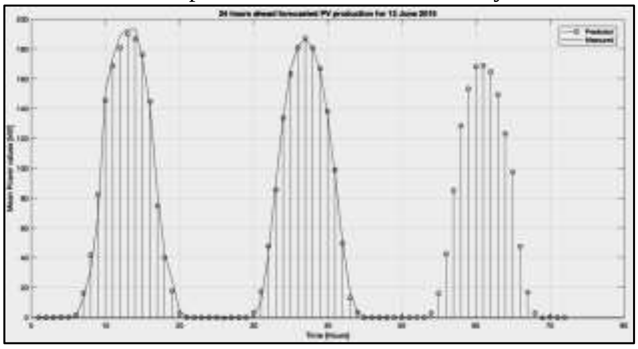

Fig. 16: Measured power production and automated forecasting results

XIV. CONCLUSION

An automated PV power forecasting system has been presented here that applies the Bayesian Regularization algorithm to neural networks to predict the next-day hourly power production based on weather data for the last five days. In a fully automated process, the system imports the weather station data from the Thies CLIMA DL16 Data logger and the solar PV power production data from the SMA Sunny Web-box. After running the sequence of data processing steps described here, the set of input vectors are passed into the machine learning system which provides the required forecasts in a publishable format. It is believed that this work can help researchers in the field of energy resource management and can be used as an assistive tool by the staff of the renewable energy center who are responsible for monitoring the current PV plants. The measured PV power production values can be used as a feedback input to the machine learning system to form an adaptable hybrid system that can improve the prediction accuracy with time.

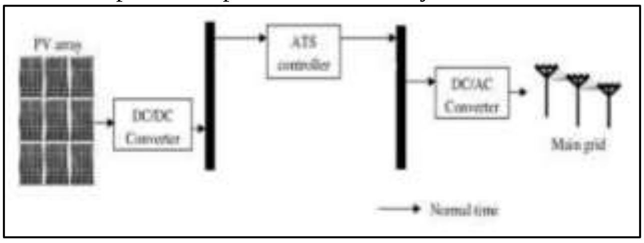

Fig. 17: Solar photovoltaic grid connected system

The proposed method is a part of a research on grid connected PV system (Fig. 17) and consequently the production of the PV system here is needed. This study proposed model predicts the output of grid connected PV system. The proposed model is based on implementation of artificial intelligent techniques. The SVM is used to classify and predict the future amount of production of the PV system.

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