International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 03 | March - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

"Implementation of AI for forecasting of wind speed and solar irradiation using different Machine Learning techniques"

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ABSTRACT:

High penetration of solar and wind power in the electricity system provides a number of challenges to the grid such as grid stability and security, system operation, and market economics. Ones of the considerable problems of solar and wind systems, they depend on the weather, as compared to the conventional generation. As we know, the balance in managing load and generated power in energy system is very import ant. If the power which is supplied from solar and wind perfectly predictable, the extra cost of operating power system with a large penetration of renewable energy will be reduced. Since, the accurate and reliable forecasting system for renewable sources represents an important topic as a major contribution for increasing non-programmable renewable on over the world. The target of this research is to describe the advanced hybrid evolutionary techniques of computational intelligence applied for PV as well as wind power forecast. The evaluation of this investigation is obtained by comparing different definitions of the forecasting error. Moreover, the meaning of NWP (numerical weather prediction) values based on meteorological information on solar and wind power forecasting at Indore has been highlighted in this research.

1. INTRODUCTION:

Integration of REs to the power system has gained major interest in recent years due to the lack of carbon emission during their power generation cycles [1]. Being non-polluting, renewable and available in most sites and requiring no fuel, PV and wind have been the most significant parts of REs incorporated in the bulk power system [2]. To improve the economic sustainability and technical characteristics, the hybrid energy plants including different types of REs and energy storage systems are connected to the power system. The hybrid PV-wind power plant has been investigated as an economically and technically efficient scheme [3].

The wind and PV generated power has high variability, therefore the power system operation and control becomes more complex by increasing their penetration either in the form of hybrid renewable power plants or separate RE resource operations [4]. In line with this statement, forecasting the PV/wind energy production on regional scale would be crucial for the transmission system operators and managers [5] when making the medium-term control and long-term planning of the transmission system, especially regarding the cross-border power flows [6] or the power system with low marginal risk index [7]. This explains why much recent research has been devoted to the PV/wind generated power forecast [8]. Two approaches have been proposed in the PV/wind output power forecast. Some research studies have attempted to forecast the solar irradiance and wind speed and convert them to the power generated by PV/wind units by using the predefined mathematical models [9]. In this approach, some issues are not considered, e.g. tilt angle, and control actions of the solar tracking system, shadow effect of trees, buildings and other generation units and nonlinear control actions of wind turbines. The other approach directly models the output power of REs [10]. Compared to the indirect PV/wind power prediction, this method leads to a higher level of accuracy because the nonlinear behavior of different elements in the RE site are modeled as the generated power is measured at the connecting point to the power system. Therefore, the direct RE power forecast is studied in this paper.

In this study, due to the random nature of meteorological conditions, we use artificial neural networks (ANNs) to develop a prediction tool that forecast the short term solar and wind power. The advantage of the ANNs is to learn the relationship between inputs and outputs by nonlinear and complex. The ANNs are very efficient to solve many sorts of problems, because does not require previous knowledge on the system to be predicted.

If same or similar patterns are met, ANNs come up with a result with minimum errors.

2. Artificial Neural Network (ANN)

ANN are computing systems or technique that mimic the learning processes of the brain to discover the relations between the variables of a system. They process input data information to learn and obtain knowledge for forecasting or classifying patterns etc. type of work. ANN consists of number of simple processing elements called neurons. All information processing is done within this neuron only. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it [8]. Signals (Input data) are passed between neurons over connection links and Each connection link has an associated weight, which in a neural network, multiplies the signal transmitted. The weights represent information being used by the network to solve a problem. Then the weighted sum is operated upon by an activation function (usually nonlinear), and output data are conveyed to other neurons. The weights are continuously altered while training to improve accuracy and generalize abilities.

3. Resilient back propagation Algorithm

Resilient propagation, in short, RPROP is one ofthe fastest training algorithms available. The RPROP algorithm just refers to the direction of the gradient. It is a supervised learning method. It works similarly to back propagation, except that the weight updates is done in a different manner. In back propagation the change in weight is calculated with the magnitude of the partial derivative:

$$\Delta\omega_{ij}(t) = \alpha * x_i(t) * \delta_j(t)$$

where α is the learning rate, $x_i(t)$ represents the inputs propagating back to the ith neuron at time step t, and δ is the corresponding error gradient. Resilient propagation, on the other hand, calculates an individual delta Δ_{ij}, for each connection, which determines the size of the weight update. The following learning rule is applied to calculate delta:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} * \Delta_{ij}^{(t-1)}, & if\ \frac{\partial E^{(t-1)}}{\partial w_{ij}} \times \frac{\partial E^{(t)}}{\partial w_{ij}} > 0 \\ \eta^{-} * \Delta_{ij}^{(t-1)}, & if\ \frac{\partial E^{(t-1)}}{\partial w_{ij}} \times \frac{\partial E^{(t)}}{\partial w_{ij}} < 0 \\ \Delta_{ij}^{(t-1)}, & else \end{cases}$$

Where $0 < \eta^{-} < 1 < \eta^{+}$

The update-value Δ_{ij} evolves during the learning process based on the sign of the error gradient of the previous iteration, $\frac{\partial E^{(t-1)}}{\partial w_{ij}}$ and the error gradient of the current iteration, $\frac{\partial E^{(t)}}{\partial w_{ij}}$ Every time the partial derivative (error gradient) of the corresponding weight w_{ij} changes its sign, which indicates that the last update was too big and the algorithm has jumped over a local minimum, the update-value Δ_{ij} is decreased by the factor η- , which is a constant usually with a value of 0.5. If the derivative retains its sign, the updatevalue is slightly increased by the factor η+ in order to accelerate convergence in shallow regions. η+ , is a constant usually with a value of 1.2. If the derivative is 0 then we do not change the update-value. Once the update-value is calculated for each weight, the weight-update is then calculated. There are two rules to follow to calculate the weight-update. The first rule is that if the current derivative and the previous derivative retain their signs then Equation below is used to calculate the weight-update

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, & if\ \frac{\partial E^{(t)}}{\partial w_{ij}} > 0 \\ +\Delta_{ij}^{(t)}, & if\ \frac{\partial E^{(t)}}{\partial w_{ij}} < 0 \\ 0, & else \end{cases}$$

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}$$

If the current derivative is a positive value meaning the previous value was also a positive value (increasing error), then the weight is decreased by the update value. If the current derivative is negative value meaning the previous value was also a negative value (decreasing error) then the weight is increased by the update value. The second rule is that if the current derivative and the previous derivative have changed their signs i.e. there was a big step taken then chances are that a minimum was missed. To avoid such big jumps, the weights need to be reverted to the previous state.

$$\Delta w_{ij}^{(t)} = -\Delta w_{ij}^{(t-1)}, if \ \frac{\partial E^{(t-1)}}{\partial w_{ij}} \times \frac{\partial E^{(t)}}{\partial w_{ij}} < 0$$

If the weight was reverted then the previous derivative needs to also be changed, otherwise when the weight is updated again then it will reapply the same changes, repeating thisscenario. Therefore, the previous derivative $\frac{\partial E^{(t-1)}}{\partial w_{ij}}$ is set to 0.

Both back propagation and resilient propagation technique work in similar manner. There are three distinct steps:

1. Perform a regular feed forward pass

2. Process the levels backwards and determine the error gradients at each level

3. Apply the changes to the weights First, a regular feed forward pass is performed.

The output from each level is kept so that the error for each level can be evaluated independently. Second, the errors are calculated at each level, and the derivatives of each of the activation functions are used to calculate gradient descents. These gradients will be used in the third step. The third step is where the two algorithms vary. Back propagation simply takes the gradient descents and scales them by a learning rate. The scaled gradient descents are then directly applied to the weights and thresholds. RPROP keeps an individual delta value for every weight and only uses the sign of the gradient descent to increase or decrease the delta amounts. The delta amounts are then applied to the weights.

4. ANFIS system

The word "fuzzy" usually used for cases in which there is no clear answer or boundary like there is a vague situation. Fuzzy logic resembles the human decision taking methodology and deals with vague and imprecise information unlike classical set where precise and clear information is used for decision making. Fuzzy unlike Boolean logic where things can be either 0 or 1 i.e. true or false represent value with the degree of truth. This fuzzy logic is applicable to all real-world problems because in none of them the boundary is clear. The value in fuzzy logic comprises of value between 0 & 1 Including two.

Fuzzy logic was proposed in the USA by Prof L. A. Zadeh, in the early 1960s. FL is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth-truth values between "completely true" and "completely false". Lofti A. Zadeh, who is considered as father of fuzzy logic introduced fuzzy logic in 1965 in his research paper" fuzzy Sets" Fuzzy logic is a way to make machines more intelligent, enabling them to reason in a fuzzy manner like humans. Fuzzy models "think" the way humans do and include verbal expressions instead of numbers. This method mimics the way operation of expert's opinion over any decision making.

The structure of neural network both biological and artificial is such that each neuron is connected with other neuron through a link. This link holds an information in the form of what we call weights based upon the relationship between input and output data provided to model. Now we will discuss in this section how fuzzy logic can be beneficial to be used in Neural network:

Fuzzy logic is used mainly to optimize weights based on fuzzy set theory. Fuzzy is used when conventional set theory can't be used. Training validation and learning help neural networks do well in unpredicted circumstances. In those cases, fuzzy values would be more applicable than convention binary values.

5. Results and Discussion

Results obtained by training model using both algorithms discussed are summaries below.

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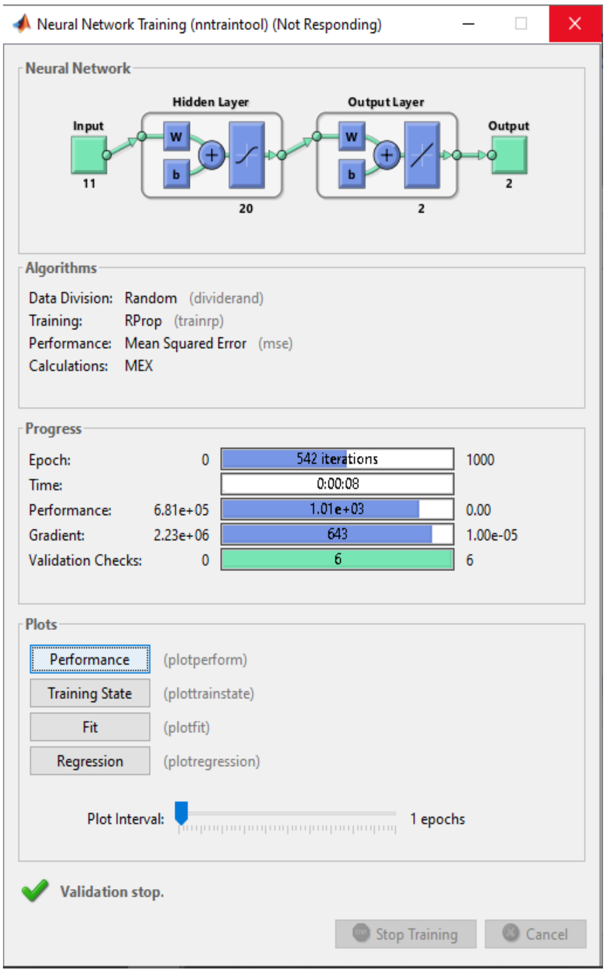

Figure 1: ANN GUI

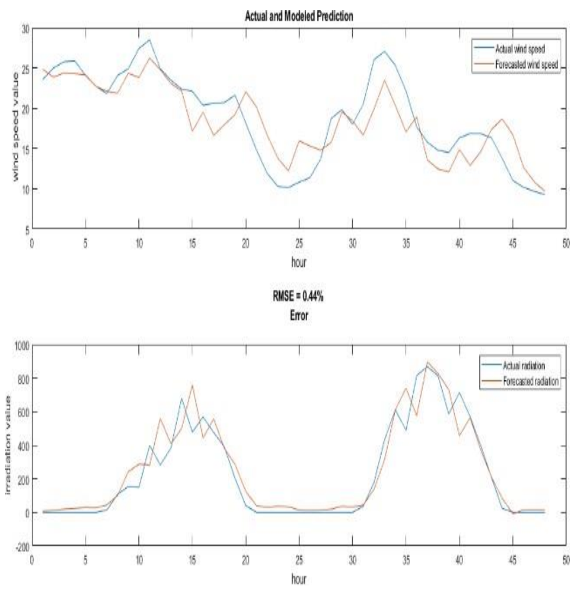

Figure 2: Comparison between the predicted and actual solar radiation and wind speed employing the proposed model using resilient prop training.

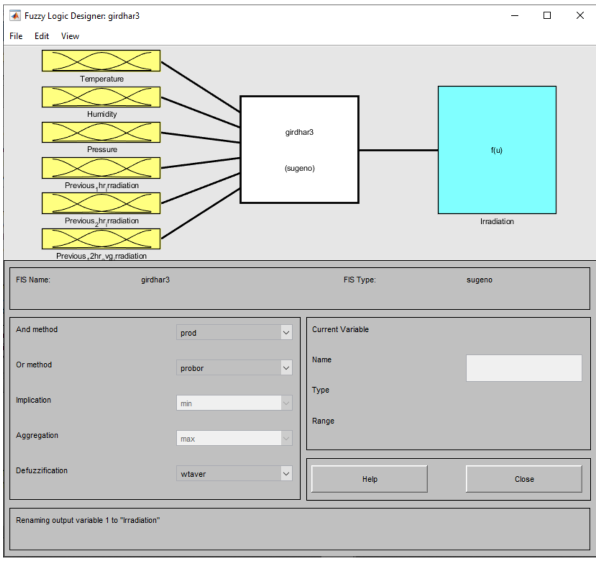

Figure 3 Fuzzy logic designer

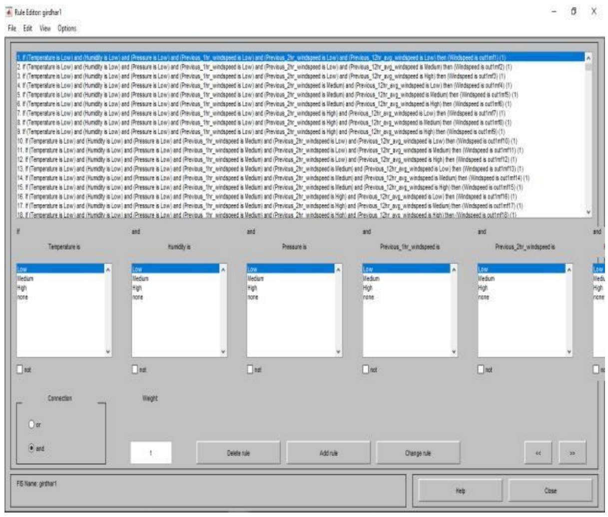

Figure 4 Rule viewer

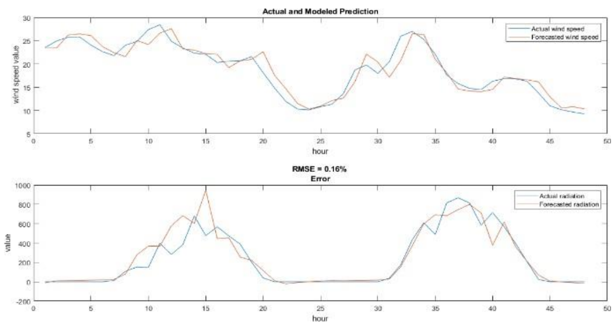

Figure 5: Comparison between the predicted and actual solar radiation and wind speed employing the proposed model ANFIS training.

6. CONCLUSION

In the present WORK, an attempt is made to forecast wind speed and soar irradiation using two models by utilizing historical weather data to train ANN model and Fuzzy logic model. The model developed is able to predict for next 48-time steps.

Obtained results are summarized below:

The developed RProp model with the configuration of 11-20-2 gives the best result with RMSE = 0.44 % after 542nd epochs.

The developed ANFIS model with the configuration of 6-(no. of rules)-1 gives the best result with RMSE = 0.16 % and after 3 epochs.

Out of the two techniques ANFIS has least error hence it will give the most accurate prediction also it has good convergence speed. After analyzing the results, it has been found that predicted data is very similar to actual measured data with a RMSE of 0.16%, which is a great improvement.

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