A Comparative Study & Performance Evaluation of AI Based Hybrid Techniques for Seasonal Wind Speed Forecasting

Hemavathi M K¹, Neethi M², M S Sashikala³

1(Department of Electrical & Electronics, SJCE JSSSTU, Mysuru hemakuppan@gmail.com) 2 (Department of Electrical & Electronics, SJCE JSSSTU, Mysuru neethi@sjce.ac,.in) 3(Department of Electrical & Electronics, SJCE JSSSTU, Mysuru dr.mss1962@gmail.com)

Abstract:

Wind speed forecasting plays a vital role in wind system operations. Accurate assessment of wind data is essential for wind power dispatch. Analysis of literature on season wise forecasting of wind data shows that, most of models developed suffer with limited accuracy. This is due to variable quantified nature of wind, selection criterion & assumptions employed in models. The most commonly used forecasting method of wind speed is the Autoregressive Integrated Moving Average (ARIMA) model. Forecasting using ARIMA is quite tricky and requires more time for computation and also more assumptions and results in limited accuracy, hence developing a forecasting model which does not require assumptions is utmost scope in forecasting of wind speed.

Artificial Intelligence (AI)- fuzzy based forecasting method that does not require assumptions is employed in this study i.e., the Adaptive Neuro Fuzzy Inference System (ANFIS), which suits the requirement and also there are some difficulties in developing ANFIS model i.e., in constructing membership functions (MFs). The difficulty of using ANFIS in constructing membership functions lies in tuning the function to build the best model. Therefore, meta heuristic algorithms could be employed for constructing the membership functions for ANFIS controller. In view of this, the project work contributes to provide a solution to the above said problem by developing hybrid wind forecasting models employing ANFIS controller with three different meta heuristic algorithms namely Differential Evolution Algorithm, Particle Swarm Optimization Algorithm & Genetic Algorithm for constructing membership

I. INTRODUCTION

Season wise forecasting of wind speed gives a strong base for efficient extraction of power output from a wind turbine. The wind future is most necessary with greater concern in wind farm design, almost wind have a 10.3% [1] share on total installed capacity of electricity generation.

Further there is an incremental order in wind plant projects worldwide, in concern to this incremental order there is a requirement for data base of future availability of winds to construct the renewable electricity projects. Then the focus on wind speed forecasting is also towards the deregulation of electricity markets. From accurate forecast, one can definitely do the efficient management of electrical utility system in sustainable way. i.e., by providing the utmost accurate data base of wind speed the transmission system operators can have the efficient management over other non-renewable electrical sources, so that accuracy in forecasting matters a lot.

Regarding the forecasting techniques, such as physical & statistical and other series forecasting methods, they are suffering with limited accuracy, and years together research is carried out in improvement of physical & statistical approaches. And many research is carried out on Artificial Intelligent Techniques such as neuro fuzzy systems.

Again, on parameter construction of ANFIS, research is focused on using mathematical algorithm which is simpler and efficient is the key point. Hence the present work addresses to implement different population-based algorithms as an attempt on ANFIS for conducting a case study on wind speeds available in a place of Karnataka named Chitradurga.

II. WIND DATA REPRESENTATION

The aim of this study is to predict long-term (seasonal) wind speed of the place Chitradurga situated in the state of Karnataka location and description as shown in Table 1. For this purpose, wind speed data were collected from the wind farm in the respective location for a duration of a year 2018.

As presented in Table 1, the wind data is measured at a height of 50mtr above sea level by a rotating cuptype anemometer. It is important to mention that, if the wind data for different locations are recorded in different heights, then it needs to be adjusted to the similar height [3]. The wind speed values used here are based on 2 second samples. The 10min samples are converted to hourly average data, and are used for seasonal forecasting of wind speed. The data is divided into four seasons summer, monsoon, postmonsoon & winter, and for each season 70% data is used for identification of the model and the 30% data is used for measuring the forecasting accuracy. The month wise wind speed data samples are shown in fig1 to fig 12, the data samples used for training & testing the model is shown in below Table (2).

| TABLE I | |
|------------------------|-------------|
| LOCATION & DESCRIPTION | OF THE SITE |

| Location | State | Geographical coordinate of meteorological stations | | Measured height of |
|-------------|-----------|---|------------------|-----------------------|
| | | Latitude | Longitude | wind speed(mtr) |
| Chitradurga | Karnataka | 23°26'13.7" S | 23°26'13.7" N | 50mtr |

| Season | Total data samples | Data used for training | Data used for testing | |
|--------------|--------------------|------------------------|-----------------------|--|
| Summer | 2155 | 1508 | 647 | |
| Monsoon | 2625 | 1837 | 788 | |
| Post monsoon | 2144 | 1501 | 643 | |

1044

1492





Fig 1: Wind speed data samples for the month of January



Fig 2: Wind speed data samples for the month of February



Fig 3: Wind speed data samples for the month of March



Fig 4: Wind speed data samples for the month of April

Winter

448



Fig 5: Wind speed data samples for the month of May



Fig 6: Wind speed data samples for the month of June



Fig 7: Wind speed data samples for the month of July



Fig 8: Wind speed data samples for the month of August



Fig 9: Wind speed data samples for the month of September



Fig 10: Wind speed data samples for the month of October



Fig 11: Wind speed data samples for the month of November



Fig 12: Wind speed data samples for the month of December





Fig14: Frequency Distribution plot of Monsoon



Fig15: Frequency Distribution plot of post-Monsoon



Fig16: Frequency Distribution plot of Winter







Fig: 13-16 describes the wind frequency distribution plots and it is observed that near zero wind speed values are at higher level and indicate higher uncertainty level and some wind speed values are close to zero wind speed and range from 2m/s to 28m/s. It is observed that the wind speed shows more chaotic behaviour and it reveals that wind speeds has strong correlation with previous hour time lags. Hence the time series t, t-1, t-2 & t-3 are used as four inputs for developing the ANFIS model.

Existence of outliers in wind speed data affects the performance of models. Hence detection of outliers is necessary to improve efficiency of forecasting models. Box plot is used here to detect outliers for the selected sites as shown in Fig.17. Very few outliers are present in wind speed, that is in between wind speeds of 25m/s to 30m/s. And Wind rose plot for the site is given in Fig. 4. it indicates higher wind velocity is arriving from north direction of Chitradurga.

III. METHODOLOGY

To accomplish the study objective, 2018 wind speed data measured by the rotating cup-type anemometer is collected from the wind farm located in Chitradurga, Karnataka, India. Afterward, the hourly mean wind speed from measured data were applied on the developed hybrid ANFIS models. In this study, the data size used for the training and testing the prediction models are defined as P and Q respectively. The purpose of the training process in ANFIS model is to minimize the error between the actual target and the ANFIS output. Based on the literature on ANN, the percentage of training data must be higher than testing data for effective learning of the system before the system can produce a good result. The developed models were trained and validated with data segments such as P = 70%, Q = 30%. The percentage of data selected for training and testing has been carefully tested based on the minimal error obtained in the statistical indicator. It is important to mention that no specific rules are considered to choose the data size for training and testing the models.

A. Adaptive Neuro Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) was proposed by Jang in 1993[4]. ANFIS is a graphical network representation of Sugeno-type fuzzy systems with the neural learning capabilities, Developed ANFIS architecture is shown in Fig (19).



Fig19: ANFIS Architecture with four Inputs and one Output

This network consists of the nodes with specific functions collected in layers, all layers of ANFIS equations are given below,

$$\mu_{Ai}(w) = e^{\left(\frac{-(w-ci)^2}{2\sigma i^2}\right)}, \quad \dots \quad (1)[6]$$

$$\mu_{Bi-2}(x) = e^{\left(\frac{-(x-ci)^2}{2\sigma i^2}\right)}, \quad \dots \quad (2)[6]$$

$$\mu_{Ci-4}(y) = e^{\left(\frac{-(y-ci)^2}{2\sigma i^2}\right)}, \quad \dots \quad (3)[6]$$

$$\mu_{Di-6}(z) = e^{\left(\frac{-(z-ci)^2}{2\sigma i^2}\right)}, \quad \dots \quad (4)[6]$$

$$w_i = \mu_{Ai}(w)\mu_{Bi}(x)\mu_{Ci}(y)\mu_{Di}(z) \ i = 1,2,3,4 \dots \quad (5)[6]$$

$$\overline{w}i = \frac{wi}{\Sigma_i wi} \ i = 1,2 \dots \quad (6)[6]$$

$$f_i = p_i w + q_i x + r_i y + s_i z + t_i, \ i = 1,2,3,4 \dots \quad (7)[6]$$

$$\overline{w}_i f_i = \overline{w}_i(p_i w + q_i x + r_i y + s_i z + t_i) \ i = 1,2,3,4 \dots \quad (8)$$

$$[6]$$

$$Z = \sum_i \overline{w}i fi = \frac{\sum_i \overline{w}i fi}{\Sigma_i wi} \dots \quad (9)[6]$$

In Equation (1), (2) (3) & (4) of the first layer of ANFIS, ci and σ i show the antecedent parameters and μ membership function. Preliminary rule results in the second layer are shown in Equation (5). The average preliminary results (Wi) are calculated at the output of the third layer. Where the p, q, r, s, t in the Equation (5) shows the result parameters, fi shows the rules of the Sugeno type fuzzy system. The evaluation of the application and rule results are presented in the output of the last layer.

B. ANFIS-GA

Genetic Algorithm is global search heuristics technique used to find solutions for optimization and solve highly complex search problems, implementation followed by inheritance, mutation, selection, and recombination. The fitness with intervention of ANFIS fitness function is represented by

$$f1(x) = 1/m\sqrt{\sum_{i=0}^{m}(di - ai)^2} - (10)[7]$$

where m is a number of feature attributes, ai is output derived through ANFIS The next fitness function can be presented as:

$$f^{2}(x) = 1/(n-m)\sqrt{\sum_{i=n}^{m} di - ai}$$
 -----(11) [7]

The final equation is minimised f(x), which can be describe as,

$$f(x) = \frac{f_1(x) + f_2(x)}{2} \qquad -----(12) [7]$$

For this case study, we determined the specific parameters initialization for the GA. These include;

number of iterations, population size, mutation and crossover percentage. Selection of these parameters decides, to a great extent, the ability of the designed controller. The range of the tuning parameters is listed in table3.

| Populati | Numb | Cross | Mutatio | Mutati | Selecti | Selecti |
|----------|----------|----------|----------|---------|---------|--|
| on size | er of | over | n | on rate | on | on |
| | iteratio | percenta | percenta | | pressur | functio |
| | ns | ge | ge | | e | n |
| 100 | 1000 | 0.4% | 0.7% | 0.15 | 8 | Roulet te wheel selecti on |

 TABLE 3

 PARAMETER SELECTION FOR ANFIS-GA MODEL

C. ANFIS-PSO

Particle swarm optimization (PSO) is an approach for optimizing "continuous" and "discontinuous" decision-making functions as developed by Kennedy and Eberhart in 1995 [6]. In this method, the position of each particle is changed constantly in a search space until getting to the optimum solutions and computational limitations are reached.

 TABLE 4

 PARAMETER SELECTION FOR ANFIS-PSO HYBRID MODEL

| Weight | Ratio | coefficient | |
|--------|-------|-------------|----------|
| 18 | | coefficient | |
| | | | |
| | | Personnel | Global |
| | | | |
| | | | |
| 1 | 0.99 | 1 | 2 |
| | 1 | 1 0.99 | 1 0.99 1 |

In PSO, swarm starts with a group of random solutions, each of which is called a particle, and $\overline{s_i}$ represents the particle's position. Likewise, a particle swarm moves in the problem space, where $\overline{v_i}$ expresses the particle's velocity. A function f is evaluated at each time step through input $\overline{s_i}$. Every particle records its best position related to the best fitness gained to this point, in $\overline{p_i}$ vector. $\overline{p_i^g}$ tracks the most appropriate position identified by any neighbourhood member. In universal form of

PSO, $\overline{p_i^g}$ represents the best appropriate position in the entire population. where w represents the inertia weight and positive acceleration coefficients are represented by c_1 and c_2 , $\overline{\phi_1}$ and $\overline{\phi_2}$ represent uniformly distributed random vectors [0,1], in which a random value is tried for every dimension.

The position of every particle alters depending upon the velocities as:

$$\overrightarrow{s_i}(t+1) = \overrightarrow{s_i}(t) + \overrightarrow{v_i}(t+1) - \dots - (13)$$

For this case studies, the optimum values of these parameters are determined by trial-and-error procedure. The range of the tuning parameters is listed in table4.

D. Statistical indicator and model performance evaluation

The performance of the proposed system can be checked by computing several statistical parameters. The most popular statistical error indicator is Mean Square Error (MSE). It presents the accuracy of the model by comparing the deviation between predicted and measured wind speed. The value of RMSE is always positive and it is defined as:

$$MSE = 1/N \sum_{i=1}^{N} (V_{i,P} - V_{i,M})^2 - (14)[13]$$

In the Eqn (14), $V_{i,P}$ and $V_{i,M}$ are wind speed estimated from developed prediction models and measured wind speed respectively.

IV. METHODOLOGY

The simulation results of the developed ANFIS hybrid models (ANFIS-GA/ANFIS-PSO) for seasonal forecasting of wind speed for the case study of Chitradurga of the year 2018 is tabulated in Table.5 and the respective results of ANFIS-GA model are shown in fig (20-27) and the results of ANFIS-PSO model are shown in fig (28-35). The models were trained and tested with data size of 70:30 %. From the results obtained it is observed that the error in the post-monsoon is minimal compared to other three seasons in both the hybrid models and ANFIS-PSO model is giving the minimal error

compared to ANFIS-GA model. Therefore, ANFIS-PSO model can be ranked as 1st performer for season wise forecasting of wind speed.

| TABLE 5 RESULTS OF HYBRID ANFIS-GA/ANFIS-PSO MODEL | | | | | |
|---|---------------|--------|-------|---------------|--------------------|
| Seasons | Model | MSE | RMSE | Error Mean | Standard Deviation |
| Summer | ANFIS- GA | 0.022 | 0.150 | 0.022 | 0.148 |
| | ANFIS- PSO | 0.020 | 0.144 | 0.023 | 0.425 |
| Monsoon | ANFIS- GA | 0.008 | 0.090 | -0.018 | 0.088 |
| | ANFIS- PSO | 0.007 | 0.089 | -0.024 | 0.085 |
| Post Monsoon | ANFIS- GA | 0.003 | 0.058 | 0.003 | 0.058 |
| | ANFIS- PSO | 0.003 | 0.058 | 0.003 | 0.058 |
| Winter | ANFIS- GA | 0.0106 | 0.103 | 0.036 | 0.096 |
| | ANFIS- PSO | 0.009 | 0.097 | 0.026 | 0.093 |

A. **Results of ANFIS-GA**



Fig20: ANFIS-GA results of Summer season



Fig21: ANFIS-GA (MSE & RMSE distribution summer season)



Fig22: ANFIS-GA results of Monsoon season





Fig24: ANFIS-GA results of Post-Monsoon season



Fig25: ANFIS-GA (MSE & RMSE distribution post-Monsoon season)



Fig26: ANFIS-GA results of Winter season



Fig27: ANFIS-GA (MSE & RMSE distribution Winter season)

B. Results of ANFIS-PSO



Fig28: ANFIS-PSO results of Summer season



Fig29: ANFIS-PSO (MSE & RMSE distribution summer season)



Fig30: ANFIS-PSO results of Monsoon season



Fig31: ANFIS-PSO model (MSE & RMSE distribution Monsoon season)



Fig32: ANFIS-PSO results of Post-Monsoon season



Fig33: ANFIS-PSO (MSE & RMSE distribution post-Monsoon season)



Fig34: ANFIS-PSO results of Winter season



Fig35: ANFIS-PSO (MSE & RMSE distribution Winter season)

V. CONCLUSIONS

Seasonal- forecasting of wind speed by two ANFIS methods is presented in this study. Detailed analysis of wind speed is carried out for four seasons using two ANFIS hybrid models. The wind speed density is the key assessment parameter in wind power production potentiality analysis. Therefore, an efficient soft computing technique namely ANFIS-PSO & ANFIS-GA prediction models were developed in this work to predict the long-term (season-wise) wind speed density. Based on the results of all the developed hybrid model, it is clear that the ANFIS-PSO is outperformed the ANFIS-GA for all the seasons. And hence the ANFIS-PSO model could be suggested for seasonal wind speed forecasting.

Further, with regard to future scope, wind speed forecasting enhances the sustained operation of power system. This necessitates the need for R&D activities in wind power forecasting. Present work is limited to wind speed forecasting, if wind power and wind speed data of similar sites are available, this work can be extended to long term wind power and further research to improve the accuracy in forecasting i.e., the variables such as humidity, wind direction, wind gust etc., could be considered while developing the forecasting model, and also the proposed approach could be implemented for online wind power forecasting at Load Dispatch Centers & also other soft computing techniques applicable to wind speed and power density prediction for other parts of the world can be developed.

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