Chapter 4

**A Novel Approach for Short-Term Forecasting of Wind Speed using Optimum Combinational Model**

*This chapter presents a Novel Combinational model for Wind Speed Forecasting. An algorithm is developed by combining mathematical modeling of six individual models using Time Series, Wavelet, NN, Fuzzy, ANFIS and SVM. Further Mathematical expression optimal combined model is derived. Methodology is tested using 18 patterns. Three algorithms used for selection of optimum combinational individual, paired and multiple paired model.*

**4.1 Introduction**

Most existing research focuses on improvement of individual forecasts or process of combining forecasts. Basic idea of latter is to get advantage from combination of many forecasts which are based on different modeling approaches and sets of information. Since basic work of Bates and Granger [86], many alternative models are created to merge a given set of forecasts. A basic review about forecast combinations is elaborated by Timmermann [87]. Improvement of individual forecasts is often based on statistical methods, especially in immediate-short-term and short-term predictions [89-90]. Mathias Käso used both statistical based correction models and dynamic forecast combination techniques of individual forecasts to generate an improved forecast [91]. Three main forecast combination approaches, namely Lp-norm based combination, FSS (Fuzzy Soft Sets) based combination and tree based combination, are proposed to provide better forecasts and Lp-norm based combination with *p=0.5* has been implemented as final forecasts combination model [92]. An individual forecast may not always perform satisfactorily, while a combined forecast that takes advantages of individual ones may give better results. Ideally, a combined forecast has to be better than individual predictions or, at least be equal to best performed prediction to be regarded as a successful forecast combination [93]. If multiple forecast outputs exist, combination of forecasts becomes an issue. Combining several predictions is valuable in order to exploit fact that each forecast model has strengths and weaknesses in different situations [94]. A distributed learning approach to improve performance of wind speed forecast is employed [95]. Model information shared between different sites to improve performance over local models trained with only local data. Combining forecasts not only allows performance of method with best RMSE to be automatically achieved at each station, but can also result in RMSE scores that are better than all of available forecasts [92]. Statistical models mostly employ time-series based approach for wind speed forecasting. Future values of wind speed are represented by a linear or non-linear function of its historical data. Machine learning models such as ANN, FL, ANFIS, and SVM established a network structure between input data and output data for wind speed forecasts with various algorithms. Relative prediction performance of a short-term SVR wind speed forecasting system is tested by systematically adding and combining relevant input features that influence short term wind speed [84].

**Background of Combination Forecast**

Combined forecasts is derived by a grouping of linear sets of forecasts, giving a k weight to first set and (1-k) to next set and so on. Variance of combined forecasts error is written as [85]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.1) |

Where,

k is balanced weight assigned to forecasts of initial set

is correlation coefficient between errors

Selection of weight k is made such that errors of combinational forecasts are minimized. More significantly to optimize overall variance Value of k is obtained by differentiating with respect to k and then equating it to zero is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.2) |

When reduces to:

|  |  |  |
| --- | --- | --- |
|  |  | (4.3) |

Optimum value of k is not known in commencement stage of combining forecasts. Value of k will change as evidence was accumulated about relative performance of multiple forecasts. Then combined forecasts for interval T, CT is more correctly written as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.4) |

Perfect forecast methods are likely to possess properties given as:

* Average weight of k must approach optimum value, defined by (4.1), as number of forecasts increased- provided that performance of forecasts is stationary.
* Weights must adapt quickly to new values if change in success of forecasts diminishes.
* Weights must vary a little about optimum values.

Combined set of forecasts results in lesser mean-square error than either of original forecasts. Weights to attach to these original forecasts in forming combined forecasts is determined by using previous errors of each of original forecasts and different methods of deriving these weights. Comparing combined forecast with individual forecasts is helpful in increasing overall accuracy. Composite forecasts with considerably lesser error variance imply that models in individual forecast capable of improving forecasts which lead to a truer model.

**4.2 Mathematical Modeling of Statistical and AI Models used for Combination**

Initially mathematical presentation of Statistical, Wavelets, NN, Fuzzy, ANFIS and SVM models are derived, and then combination algorithm will be presented using these mathematical models.

1. **Statistical Models:**

Statistical time series models have many alternatives like AR, MA, ARMA, ARIMA. AR, MA, ARMA models are suitable for stationary time series data. However, wind speed is a stochastic non-stationary. ARIMA model is used to model this non-stationary data where data is first converted to stationary by suitable transformation process and then this transformed data used to develop ARMA model. In our work ARIMA, Transfer Function ARIMA and GARCH models are used to develop wind speed forecasting models.

1. **ARIMA model:**

Let us assuming wind speed data as non-stationary series, an ARIMA model in (3.34) is rewritten as [46]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.5) |

Where,

is a non-stationary autoregressive operator

is a moving average operator

zt is time series past data

is noise sequence

Roots of are unity and remainder lie outside unit circle. Then (4.5) is expressed as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.6) |

Where is an autoregressive stationary operator.

Since, for d≥1, where is a differencing operator, ARIMA model is also given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.7) |

Thus model in eq (4.7) corresponds to dth difference of series is represented by a stationary, invertible ARMA process.

1. **GARCH Model**

ARCH for modeling random disturbance of time series model. It is written in form obtained from (3.48) is given by [19]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.8) |

Where is conditional variance of

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  | (4.9) |

Conditional variance equation of GARCH (p, q) model is given as

|  |  |  |
| --- | --- | --- |
|  |  | (4.10) |
|  |  | (4.11) |

Where, p and q are non-negative integers.

A GARCH (p, q) model is written using lag operator as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.12) |

Where,

To keep second-order stationarity constraint, GARCH models demand α(*B*)+θ(*B*) < 1. It is not a easy work to specify order of a GARCH model, but luckily, GARCH (1,1) can describe volatility clusters effect of large numbers of time series [51].

1. **Transfer Function ARIMA Model**

Transfer function model TRFU(r,s,b) is given by [46]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.13) |

Where,

 is a polynomial in B of order s,

 is a polynomial in B of order r,

nt is disturbance process is represented by an ARIMA model.

Transfer function ARIMA model is given by (3.57):

|  |  |  |
| --- | --- | --- |
|  |  | (4.14) |

Where,

yt is wind speed time series as output,

xt is temperature time series as input.

1. **Wavelet Transform**

Multi resolution by wavelet basis functions is used to represent function on many scales, which are generated by translated mother wavelet and scaled. Wavelet is defined as small wave.

Lets us consider Ψ(t) and Fourier transform of same is **.** If **** fulfills criteria, then Ψ (t) that equation is said as mother wavelet, which tells outline of components of decayed wave given as [23]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.15) |

After dilation and conversion of Ψ (t),Ψa,b(t) is obtained as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.16) |

Where *a* represents scale factor,*b* represents conversion factor.

**ARIMA-Wavelet Model:**

Original wind speed recurred from wind form is decayed into different scales (resolution), d1,d2,d3………dJ with coarse estimation of a time series aJ after reconstruction of decayed data DJ and AJ are obtained. For a different value of DJ and AJ of a time series ARIMA model is developed to predict respectively.

1. **Artificial Intelligent Models**
2. **ANN model**

In mathematical terms, a neuron k is described by equations [24-26]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.17a) |
|  |  | (4.17b) |

x1, x2 … xm are input signals, wk1, wk2 … wkm are synaptic weights, is linear combined output due to input signals, is bias, is activation function, yk is output signal of neuron.

1. **ANFIS model**

A fuzzy system is considered to be a parameterized nonlinear chart, called *f*. This point will be made clear later on in connected perspective of soft computing, yet it should compose unequivocally declaration of f**.**  is given by **[27-28]**:

|  |  |  |
| --- | --- | --- |
|  |  | (4.18) |

Where, *yl is* a position of output singleton if Sugeno way of thinking is applied. Membership function corresponds to input of regulation l. Connective in basis is carried out by a defuzzification and product by center of gravity method. This is written as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.19) |

Where and

|  |  |  |
| --- | --- | --- |
|  |  | (4.20) |

If *F* is a continuous, nonlinear chart on a solid set, then *f* can estimate *F* to any beloved accuracy, i.e. .

1. **SVM Model**

SVM includes polynomial learning machine, radial-basis function network and two layer perceptron as special instances. These methods provide different representations of intrinsic statistical regularities contained in training set [30-33].

**(a). Radial Basis Function SVM**

Following set of decision rule has been used by Classical radial basis function machines is given by [33]:

|  |  |  |
| --- | --- | --- |
|  |  | (4.21) |

In (1), = Euclidian distance, Coefficient of expansion. Function  is for any fixed *y,* a nonnegative monotonic function it tends to zero as z goes to infinity. function is

|  |  |  |
| --- | --- | --- |
|  |  | (4.22) |

In (4.21),  kernel function width parameter, Support vectors

**(b) Polynomial Learning Machines**

To establish polynomial decision rules of degree d, inner product is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.23) |

It defines an involvedness of inner product in feature space which contains all products up to degree. Using described technique, one can establish decision function of form :

|  |  |  |
| --- | --- | --- |
|  |  | (4.23) |

In (22), = dimensional polynomials in -dimensional input space.

***(c)* {\displaystyle {\vec {w}}\cdot {\vec {x}}-b=0,\,}Two Layer Neural Networks**

Two-layer neural network is described by selecting kernels:

|  |  |  |
| --- | --- | --- |
|  |  | (4.24a) |

In (4.23),  = sigmoid function. Using values of parameters, . One can establish support vector machine for implementing rules.

|  |  |  |
| --- | --- | --- |
|  |  | (4.24b) |

Using method defined above, following are found automatically:

* Architecture of two layer machines, finding N number of hidden unit’s i.e. number of support vectors,
* Vectors of weight  in neurons of first layer. Vectors of weights for second layer (values of).

**4.3 Derivation of Combination Equation for Statistical and AI Models**

Expressions 4.6 to 4.24 are used further to form optimized combination equation in next section. Each model is framed as an optimization function of parameters to be estimated by using equations given in previous section. Problem is divided into stages so as to reduce iteration time and space required for storing parameters. Penalty factor for each model is assigned depending on following points:

* Number of parameters and constraints involved in a function
* Error distribution at two sides
* Minimum and maximum value of function
* Final wind speed prediction error during training and testing time
* Correlation among training and fitted wind speed data
* Regression between forecast and actual data

Penalty factor and statistical test results are further used to find score of model. Models with highest score are selected as best model. Mathematical optimization expressions for individual models are derived as follows. Multiple selection criteria is used to identify optimum model. An aggregated model also developed by using these functions.

1. **ARIMA :** ARIMA model as a function of and using (4.5) to (4.7) is given by:

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | | (4.25) |
|  | *(i)Objective Function : , min AIC(p,d,q), min BIC(p,d,q)* |  | |
|  | *Subject to Constraints:*  *Where,* | *(4.26)* | |
|  | (ii)Objective Function | *(4.27)* | |
|  | *Subject to* |  | |

1. **GARCH Model:**  GARCH model as function of using (4.8) to (4.12) is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.28) |
|  | | (4.29) |
| *Subject to,* | | (4.30) |

1. **Transfer function ARIMA:** Transfer function ARIMA model as a function of , , , using (4.13) to (4.14) is given by

|  |  |  |
| --- | --- | --- |
|  |  | (4.31) |

Where,

yt is wind speed,

xt is temperature.

|  |  |
| --- | --- |
| *Minimize* | (4.32) |
| *Subject to* | (4.33) |

1. **Wavelet –ARIMA Function:** WaveletARIMA model as function detailed and approximate coefficients (a,b) by using (4.15) – (4.16) is give by:

|  |  |  |  |
| --- | --- | --- | --- |
|  | |  | (4.34) |
| Maximize function | | (4.35) |
| *Subject to,* | | (4.36) |

1. **ANN Model :** ANN model as function of weights and neuron using (4.17a) to (4.17b) is given by :

|  |  |  |
| --- | --- | --- |
|  |  | (4.37) |

Where and are weights for each neuron, is a constant determined by learning rate.

|  |  |  |
| --- | --- | --- |
|  | Optimize such that | (4.38) |
|  | Subjected to | (4.39) |

1. **Fuzzy Logic Model:** Fuzzy Logic model as a function of weighted average differentiation is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.40) |

Rules:

Then:

Rules for Optimization

|  |  |  |
| --- | --- | --- |
|  |  | (4.41) |

Where is final output of FL using weighted average differentiation:

|  |  |  |
| --- | --- | --- |
|  |  | (4.42) |

1. **ANFIS Model:** ANFIS model as a function of using (4.18) to (4.20) is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.43) |

Simplified by

|  |  |  |
| --- | --- | --- |
|  |  | (4.44) |

is Mx1 matrix, M- No. of element of consequent part of parameter set

A is PxM matrix, P- no. of N data training model to adaptive network.

Y-output vector

Solution for in Minimizing squared error by Least Square Estimator

|  |  |  |
| --- | --- | --- |
|  |  | (4.45) |
|  |  | (4.46) |

By using Recursive Least Square Estimator

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | | (4.47) |
|  |  | For | (4.48) |

is row vector of Matirx A

is ith element of y

is covariance matrix =

1. **Support Vector Machines:** SVM model as a function of margin , weights **,** and support vectors using (4.21) to (4.24) is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.49) |
|  | | Minimize  Such that | (4.50) |
|  | | Where h is VC dimension,  is margin separating hyperplane | (4.51) |
|  | |  | (4.52) |
|  | |  | (4.53) |
|  | | Maximize in nonnegative quadrant | (4.54) |
|  | | Under constraint  , and | (4.55) |

**4.4 Derivation of Combined Model Expression**

Based on optimization function obtained in (4.25) to (4.55), a novel combined equation is derived as follows.

Let f1 to f8 be individual forecast function (4.25) to (4.55). Let i be model number. Combined expression **F** as a function of f1 to f8 is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.56) |

Eq. (4.56) is elaborated as:

|  |  |  |
| --- | --- | --- |
|  |  | (4.57) |

Substituting values of f1 to f8, a combined equation of form is obtained by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.57) |

Further this is expanded by using individual functions f1 to f8 is given by:

|  |  |  |
| --- | --- | --- |
|  |  | (4.58) |

Combinational expression (4.58) is further simplified as a function of parameters is given by:

|  |  |
| --- | --- |
|  | |
|  | **(4.59)** |

Simplified eq. (4.59) contains parameters of statistical and AI techniques of 8 models. Forecast expressed in Eq. (4.58) and (4.59) are solved using dynamic programming in MATLAB 2014a. Detailed algorithm is explored in Fig. 4.1.

**4.5 Combinational Algorithm for Optimal Selection of Model**

Forecast expressed in Eq. (4.58) and (4.59) are solved using dynamic programming in MATLAB 2014a. Detained algorithm is explored in Fig. 4.1 and procedure for three algorithms for identifying optimum individual, paired and aggregate models are given in following section

**4.5.1 Algorithm for Combining and Finding Optimum Model for Forecasting of Wind Speed among Individual Model**

Step 0: Store .xlsx /.txt file containing historical data of site of interest

Step 1: Select site – (Site data stored in .xlsx format in a Folder, Select path of file).

select number of variable used in model wind speed, temperature, wind direction

Step 2: Fill information about site, location name, wind mast height, select data orography (10min or Hourly)

Step 3: Select forecasting horizon (no. of points if horizon is 10min and Number of hours if horizon is Hourly)

Step 4:Display and Save Descriptive Statistics(Mean, Annual Mean, Standard Deviation, Variance, Outliers, Missing data, Data plots, ACF , PACF, Spectrum, Frequency Distribution, Cumulative Frequency Distribution,

Step 5: Divide data for training, testing and validation. Process data before feeding it to .m files.

Step 6: Feed in processed data (differenced for time series, normalized for Neural Network and ANFIS and classified for SVM)

Step 7: Feed in data to individual and combined models .m files.

Step 8: Test data consistency by t-test, h-test

Step 9: Find pattern, seasonality, trend in selected data.

Step10: Display MAPE, MSE of Individual, Combined, and optimum models

Step11: Decide score weightage for models (Score will be decided depending upon Selection criteria- AIC and BIC for Time Series Models, t-test, h-test and regression tests for models and MAPE and MSE of forecasted result).

Step 12: Select optimum model with highest score.

Step 13: Display forecasted result for individual, optimum, and combined model.

Step14: Display comparison result of all models. (Comparison Table and Comparison plot).

Novel algorithm presented in Fig. 4.1 has four stages of filtering of models which is in **turn not used in any of literatures.** First during estimating parameters, second during selecting model with model selection criteria, third during testing of forecasted data consistency by t-test and h-test and fourth while measuring forecasting accuracy by MAPE and MSE as a criteria. List of parameters are to be estimated are given as follows.

**4.5.2 Novel Algorithm for Combining and Finding Aggregate Model among Paired Model**

Step 0: Store .xlsx /.txt file containing historical data of siteof interest

Step 1: Select site – (Site data stored in .xlsx format in a Folder, Select path of file)

Select number of variable in developing model – Wind Speed, Temperature, Wind Direction

Step 2: Fill information about Site –Location name, Wind Mast Height,

Step 2: Select data orography (10min or Hourly)

Step 3: Select Forecasting Horizon (No of points if Horizon – 10min/ Number of Hours if Horizon is Hourly)

Step 4: Display & Save Descriptive Statistics(Mean, Annual Mean, Standard Deviation, Variance, Outliers, Missing data, Data plots, ACF , PACF, Spectrum, Frequency Distribution, Cumulative Frequency Distribution,

Step 5: Divide and process wind speed data for training, testing & validation.

Step 6: Feed in processed data (differenced for time series, normalized for Neural Network & ANFIS & classified for SVM)

Step 7: Feed in data to individual models & combined model .m files.

Step 8: Test data consistency by t-test, h-test

Step 9: Find pattern, seasonality, trend in selected data.

Step 8: Display MAPE, MSE of Individual Models, Combined models

Step 9: Decide score for models (Score will be decided depending upon Selection criteria- AIC/BIC for Time Series Models, t-test/h-test for remaining models & MAPE/MSE of forecasted result.

Step 10: Select optimum model with highest score

Step 11: Display forecasted result for optimum model.

Step 12: Display comparison result of all models. (Comparison Table & Comparison plot)

**4.5.3 Novel Algorithm for Combining and Finding Aggregate Model among Multiple Paired Model**

Step 0: Select train, test and validation data, Plot Data for observation. Divide data as train, test and Validation.(50:25:25)%. Set it=itmax=100

Step 1: Find Statistics, Calculate ACF, PACF, and Spectrum of data to find stationarity, outliers and any missing intervals.

Step 2: Estimation of parameters of Models to develop functions of ARIMA, TRFU-ARIMA, GARCH, Wavelet, ANN, Fuzzy logic, ANFIS and SVM models (f1,f2,….,f8). Initial Optimization of Functions using Eq. Annexure I to VIII.

Step 3: Initial Estimation of AIC, BIC, and FPE of models

Step 4: Error Model for f1,f2,…,f8 . *f (*Δws(m,t))

Step 5: Analysis of Distribution of Error, ACF, PACF, and Spectrum of Error for calculating orders of Error Minimization model.

Step 6: Assigning Penalty Factor for functions using Covariance matrices.

Step 7: Rule Formation using Penalty Factor. Assign Weightage to each model.

Step 8: Optimize each functions f1,f2,…,f8

Step 9: Increment for next interval and next iteration.

Step 10: Repeat step 2 to step 10 for all intervals of horizon. Formulate final Matrices of Penalty factor, Error Matrices, AIC, BIC, FPE.

Step 11: Store Optimum and rejected model - s values separately at each interval.

Step 12: Forecast wind speed for test data using Optimum Model at Step 12.

Step 13: Test forecast output (t-test, R2, h-test)

Step 14: If tests fail then go to Step 9. Else Go to Step 16

Step 15: Decide score weightage for models (Score is decided depending upon selection criteria- AIC and BIC for Time Series Models, t-test, h-test and regression tests for models and MAPE and MSE of forecasted result).

Step 16: Forecast wind speed using highest scored model at each interval.

Step 17: Display MAPE, MSE of Individual, Combined and optimum models

Step 18: Display forecasted result for individual, optimum and combined model.

Step 19: Display comparison result of all models.

**Fig. 4.1: Flowchart of Novel Combination Algorithm for Short Term Forecasting of Wind Speed**

Forecasting

Hybrid model

Fail

NO

Pass

NO

Yes

Pass

Pass

Pass

Fail

Fail

Fail

Pass

Raw Data V, T, D

Processing Raw data

Plots

V=f(V,T,D)

Relationship

Persistence

Regression model with

V=f (V, T, D)

Time series

ANN

Fuzzy

ANFIS

SVM

ARMA

ARIMA

TRFU ARIMA

GARCH

Regression Check

Forecast

t, h, r test

Use model

Change

Parameter

Optimum model

**Regression Check**

Forecast

t, h, test

Use model

Comparison

Change

Parameter

AIC BIC Chi-square test

Forecast

Use model

Change Parameters & Order

Display results

t, h, r test

Forecasting

Multiple Paired model

Wavelet

Data, Site, horizon, ACF, PACF Spectrum

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 4.1: List of Combination Models Obtained from Algorithm** | | | | | | |
| **Com** | **1** | **2 Pair** | **3 Pair** | **4 Pair** | **5 Pair** | **6 Pair** |
| 1 | Time Series | Time Series - Wavelets | Time Series - Wavelets - Neural Network | Time Series - Wavelets - Neural Network - Fuzzy Logic | Time Series - Wavelets - Neural Network - Fuzzy Logic - ANFIS | Time Series - Wavelets - Neural Network - Fuzzy Logic - ANFIS - SVM |
| 2 | Wavelets | Time Series - Neural Network | Time Series - Neural Network - Fuzzy Logic | Time Series - Wavelets - Neural Network - SVM | Time Series - Wavelets - Neural Network - Fuzzy Logic - SVM |  |
| 3 | Neural Network | Time Series - Fuzzy Logic | Time Series - Fuzzy Logic - ANFIS | Time Series - Wavelets - ANFIS - SVM | Time Series - Wavelets - Neural Network - ANFIS - SVM |
| 4 | Fuzzy Logic | Time Series - ANFIS | Time Series - ANFIS - SVM | Time Series - Fuzzy Logic - ANFIS - SVM | Time Series - Wavelets - Fuzzy Logic - ANFIS - SVM |
| 5 | ANFIS | Time Series - SVM | Wavelets - Neural Network - Fuzzy Logic - | Neural Network - Fuzzy Logic - ANFIS - SVM | Time Series - Neural Network - Fuzzy Logic - ANFIS - SVM |
| 6 | SVM | Wavelets - Neural Network | Wavelets - Fuzzy Logic - ANFIS - | Wavelets - Neural Network - Fuzzy Logic - ANFIS | Wavelets - Neural Network - Fuzzy Logic - ANFIS - SVM |
| 7 |  | Wavelets - Fuzzy Logic | Wavelets - ANFIS - SVM - | Wavelets - Neural Network - Fuzzy Logic - SVM |  |
| 8 | Wavelets - ANFIS | Neural Network - Fuzzy Logic -ANFIS | Wavelets - Neural Network - ANFIS - SVM |
| 9 | Wavelets - SVM | Wavelets - Fuzzy Logic - ANFIS | Wavelets - Fuzzy Logic - ANFIS - SVM |
| 10 | Neural Network - Fuzzy Logic | Wavelets - ANFIS - SVM | Neural Network - Fuzzy Logic - ANFIS - SVM |
| 11 | Neural Network - ANFIS | Neural Network - Fuzzy Logic -ANFIS | Time Series - Neural Network - Fuzzy Logic - ANFIS |
| 12 | Neural Network - SVM | Neural Network - ANFIS - SVM | Time Series - Neural Network - Fuzzy Logic - SVM |
| 13 | Fuzzy Logic - ANFIS | Fuzzy Logic - ANFIS - SVM | Time Series - Neural Network - ANFIS - SVM |
| 14 | Fuzzy Logic - SVM |  | Time Series - Fuzzy Logic - ANFIS - SVM |
| 15 | ANFIS - SVM | Time Series - Fuzzy Logic - ANFIS - SVM |
| 16 |  | Time Series - Wavelets - Fuzzy Logic - SVM |
| 17 | Time Series - Wavelets - Fuzzy Logic - ANFIS |
| 18 | Time Series - Wavelets - Neural Network - SVM |
| 19 | Time Series - Wavelets - Neural Network - ANFIS |
| 20 | Time Series - Wavelets - Neural Network - Fuzzy Logic |
| **Total** | **6** | **15** | **13** | **20** | **6** | **1** |

**4.6 Results and Discussion**

List of combinations obtained by algorithm is presented in Table 4.3. There are 61 combinational models including single to six pair models are obtained from algorithm using 8 models (ARIMA, TRFU-ARIMA, GARCH, WT, ANN, FL, ANFIS, and SVM). Persistence Fig. 4.2 to 4.8 presents 24hr and 168hr ahead wind speed forecast from all model combinations for two selected sites for three seasons.

Figure 4.11 shown above present’s variation of forecasting error MAPE for different combinational alternatives obtained from an algorithm. Results clearly indicate that, as complexity increases accuracy increases for both 24hr and 168hr wind speed forecast. Also, models validated for 3patterns data for both sites indicates suitability this approach for all sites. Fig. 4.10 presents comparison of forecast MAPE for all 12 patterns of Bagalkot and Bijapur Sites. Results shown in Fig. 4.10, clearly shows that there is uniformity in forecasting for all 12 types of patterns employed. This shows adaptability of our novel approach for all sites of interest.

Table 4.2 presents summary of pair model wind speed forecast results for both 24hr and 168hr forecast that, SVM model combined with every model has performed better than all other combination. This shows superiority of SVM model for Wind Speed forecast. 6 pair model has highest accuracy of 93.57% for 24hr and 92.5% or 168hr prediction. Single pair model has 88.97% for 24hr and 82.55% for 168hr prediction. Accuracy of 6 pair is not decreased much from 24hr to 168hr indicating consistency of forecasting for increased horizon. Although forecasting is carried out for many forecast steps, but only two horizons are selected to present in this thesis.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 4.2: Summary of pair model wind speed forecast results for both 24hr and 168hr forecast.** | | | | |
|
| **Pair** | **24hr** | | **168hr** | |
| **Best Pair** | **Accuracy** | **Best** | **Accuracy** |
| **Model** | **in %** | **Model** | **in %** |
| Single | SVM | 88.97 | SVM | 82.55 |
| 2pair | ANFIS-SVM | 90.01 | TS-SVM | 84.34 |
| 3pair | FL-ANFIS-SVM | 90.73 | WT-ANFIS-SVM | 87.06 |
| 4pair | TS-WT-NN-SVM | 91.25 | TS-FL-ANFIS-SVM | 90.78 |
| 5pair | TS-WT-NN-ANFIS-SVM | 92.06 | WT-NN-FL-ANFIS-SVM | 90.19 |
| 6pair | TS-WT-NN-FL-ANFIS-SVM | **92.87** | TS-WT-NN-FL-ANFIS-SVM | **90.50** |

**Table 4.3: Summary of pair model wind speed forecast results for both 24hr and 168hr forecast**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **MAPE** | | | | | | | | | **MSE** | | | | | | |
| **Winter Model** | | | | | | | | | **Winter Model** | | | | | | |
| **Model** | **ARIMA** | **TRFU-ARIMA** | **WT** | **NN** | **ANFIS** | | **SVM** | | **Model** | **ARIMA** | **TRFU-ARIMA** | **WT** | **NN** | **ANFIS** | **SVM** |
| ARIMA | 18.24 | 14.11 | 18.5 | 17 | 14.82 | | 13.1 | | ARIMA | 0.77 | 0.56 | 0.43 | 0.3 | 0.28 | 0.27 |
| TRFU-ARIMA | 13.88 | 18.16 | 17.2 | 24.1 | 21.95 | | 19.8 | | TRFU-ARIMA | 0.41 | 0.87 | 0.33 | 0.5 | 0.53 | 0.49 |
| Wavelet | 19.20 | 17.67 | 16.3 | 21.1 | 16.75 | | 23.1 | | Wavelet | 0.65 | 0.45 | 0.49 | 0.6 | 0.33 | 0.66 |
| NN | 28.15 | 23.71 | 27.4 | 24.9 | 31.17 | | 11.7 | | NN | 0.85 | 1.72 | 2.97 | 1.9 | 0.7 | 0.19 |
| ANFIS | 19.68 | 26.5 | 24.9 | 16.7 | 21.98 | | 13.1 | | ANFIS | 0.83 | 1.66 | 1.35 | 0.3 | 0.45 | 0.27 |
| SVM | 9.86 | 14.58 | 13.8 | 13.1 | 13.36 | | 11.4 | | SVM | 0.18 | 0.3 | 0.38 | 0.3 | 0.28 | 0.26 |
| **Summer Model** | | | | | | | | | **Summer Model** | | | | | | |
| ARIMA | 14.65 | 14.1 | 26.7 | 14.8 | 14.44 | | | 11.2 | ARIMA | 0.24 | 0.22 | 2.11 | 0.3 | 0.41 | 0.16 |
| TRFU-ARIMA | 28.92 | 24.77 | 20.1 | 19.1 | 20.58 | | | 14.5 | TRFU-ARIMA | 1.17 | 0.9 | 0.75 | 0.6 | 0.56 | 0.47 |
| Wavelet | 14.31 | 29.17 | 24.1 | 23.1 | 12.18 | | | 14.8 | Wavelet | 0.4 | 0.72 | 0.71 | 0.7 | 0.24 | 0.39 |
| NN | 14.67 | 14.52 | 14.3 | 20.2 | 16.23 | | | 14.0 | NN | 0.34 | 0.31 | 0.46 | 0.9 | 0.55 | 0.49 |
| ANFIS | 22.22 | 16.1 | 17.7 | 17.8 | 19.08 | | | 13.4 | ANFIS | 1.14 | 0.54 | 0.68 | 0.9 | 1.07 | 0.52 |
| SVM | 13.09 | 12.74 | 16.4 | 13.8 | 13.25 | | | 9.51 | SVM | 0.35 | 0.28 | 0.62 | 0.3 | 0.26 | 0.16 |
| **Rainy Model** | | | | | | | | | **Rainy Model** | | | | | | |
| ARIMA | 18.25 | 17.49 | 17.1 | 13.9 | | 13.18 | | 9.37 | ARIMA | 1.33 | 1.55 | 2.76 | 0.9 | 0.85 | 0.49 |
| TRFU-ARIMA | 16.79 | 27.44 | 12.5 | 10.7 | | 13.52 | | 10.4 | TRFU-ARIMA | 0.91 | 2.1 | 0.67 | 0.6 | 1.16 | 0.75 |
| Wavelet | 18.47 | 24.87 | 14.1 | 18 | | 13.71 | | 11.4 | Wavelet | 2.54 | 2.71 | 2.04 | 2.8 | 1.36 | 0.85 |
| NN | 19.25 | 13.22 | 14.6 | 12.2 | | 12.74 | | 11.6 | NN | 2.53 | 1.08 | 1.24 | 1.1 | 0.77 | 0.73 |
| ANFIS | 13.52 | 12.73 | 13 | 12.2 | | 12.46 | | 8.83 | ANFIS | 1.44 | 0.74 | 0.81 | 0.9 | 0.81 | 0.45 |
| SVM | 10.56 | 11.86 | 11.5 | 13.3 | | 8.75 | | 9.59 | SVM | 0.63 | 0.9 | 1.16 | 0.6 | 0.51 | 0.77 |

Summary of seasonal models with two paired models is given in Table 4.3. It is found that, SVM model combined with ANFIS resulted in lowest MAPE as range from 8.75% to 9.86%. Result of reduced MAPE SVM combination with any other model is observed in all three seasons. Hence it is concluded that SVM is able to combine with any model which show superiority of model in comparison with other model. Further, forecasting MAPE values for Combinational Paired models for 24hr and 168hr prediction for three sites for single to 6 pair models is given in Table 4.4(a) and (b). This shows complete list of models obtained during combination algorithm. P1 to P3 represent pattern. Table also gives accuracy of paired models for 24 hour and 168 hour for three sites. Col. 1 indicates no. of involved in combinations (single to 6 pair). Col. 2 shows model number as a result of combination. Col. 3 shows type of model used for combination. Col. 4 to 21 indicate data pattern type used for forecasting. Col. 22 and 25 represent minimum MAPE for 24 hour and 168 hour forecast respectively. Col. 23 and 26 indicates forecast accuracy for 24 hour and 168 hour respectively. Col. 24 gives accuracy of optimum model pair.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 4.4(a): Forecasting MAPE values for Combinational Paired models for 24hr and 168hr prediction for three sites for single to 3 pair models** | | | | | | | | | | | | | | | | | | | | | | | | | | |
| **Pair** | **Model  No.** | **Name/Combination** | **24Hr** | | | | | | | | | **168Hr** | | | | | | | | | **Min MAPE 24Hr** | | | **Min MAPE 168 Hr -** | | |
| **Bagalkot** | | | **Bijapur** | | | **Bangalore** | | | **Bagalkot** | | | **Bijapur** | | | **Bangalore** | | | **Min MAPE  24Hr** | **Accuracy in %** | **Pair  Model** | **Min  MAPE  168 Hr -** | **Accuracy** | **Paired  Model** |
| **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** |
| **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** | **24** | **25** | **26** | **27** |
| **Single** | **M1** | TS | 17.67 | 16.64 | 14.60 | 16.25 | 16.03 | 14.72 | 16.96 | 16.33 | 14.66 | 18.88 | 18.39 | 21.16 | 18.88 | 20.16 | 20.96 | 18.88 | 19.28 | 21.06 | 14.60 | 84.40 | 88.97 | 18.39 | 81.61 | 82.55 |
| **M2** | WTs | 17.49 | 14.62 | 14.06 | 20.67 | 14.21 | 13.52 | 19.08 | 14.42 | 14.29 | 20.43 | 18.76 | 20.81 | 20.43 | 21.01 | 19.34 | 20.43 | 19.88 | 20.07 | 13.52 | 86.48 | 18.76 | 81.24 |
| **M3** | NN | 17.59 | 14.47 | 14.03 | 21.86 | 18.18 | 14.01 | 19.73 | 16.82 | 14.02 | 19.92 | 20.57 | 20.49 | 19.92 | 18.10 | 19.19 | 19.92 | 19.34 | 19.84 | 14.01 | 84.99 | 18.10 | 81.90 |
| **M4** | FL | 14.89 | 16.91 | 14.89 | 18.09 | 12.16 | 12.60 | 16.99 | 14.54 | 14.24 | 18.64 | 20.15 | 20.17 | 18.64 | 19.71 | 17.45 | 18.64 | 19.93 | 18.81 | 12.16 | 87.84 | 17.45 | 82.55 |
| **M5** | ANFIS | 14.96 | 13.09 | 13.19 | 17.80 | 14.09 | 13.17 | 16.38 | 13.59 | 13.18 | 20.38 | 20.61 | 19.91 | 20.38 | 18.70 | 18.74 | 20.38 | 19.66 | 19.32 | 13.09 | 86.91 | 18.70 | 81.30 |
| M6 | SVM | 11.03 | 11.48 | 11.67 | 11.25 | 11.15 | 11.89 | 11.14 | 11.32 | 11.78 | 22.08 | 20.07 | 18.14 | 22.08 | 20.67 | 19.07 | 22.08 | 20.37 | 18.61 | 11.03 | 88.97 | 18.14 | 81.86 |
| **2 Pair** | **M7** | TS - WTs | 14.63 | 16.77 | 12.61 | 18.83 | 12.01 | 13.58 | 16.73 | 14.39 | 13.09 | 17.52 | 17.20 | 18.18 | 17.52 | 17.91 | 17.65 | 17.52 | 17.55 | 17.92 | 12.01 | 87.99 | 90.21 | 17.20 | 82.80 | 84.34 |
| **M8** | TS - NN | 12.37 | 17.38 | 14.90 | 17.92 | 14.80 | 12.17 | 14.15 | 16.09 | 14.04 | 17.50 | 14.92 | 18.52 | 17.50 | 17.86 | 17.74 | 17.50 | 16.39 | 18.13 | 12.17 | 87.83 | 14.92 | 84.08 |
| **M9** | TS - FL | 11.10 | 14.33 | 14.57 | 19.33 | 14.43 | 14.42 | 14.21 | 14.38 | 14.99 | 17.63 | 16.04 | 18.02 | 17.63 | 16.49 | 17.63 | 17.63 | 16.27 | 17.82 | 11.10 | 88.90 | 16.04 | 83.96 |
| **M10** | TS - ANFIS | 13.61 | 16.44 | 18.20 | 17.95 | 13.57 | 13.72 | 14.78 | 14.00 | 14.96 | 18.60 | 14.66 | 17.24 | 18.60 | 16.62 | 17.47 | 18.60 | 14.64 | 17.35 | 13.57 | 86.43 | 14.66 | 84.34 |
| **M11** | TS - SVM | 11.33 | 14.95 | 16.93 | 20.39 | 16.57 | 10.98 | 14.86 | 14.76 | 13.95 | 18.29 | 16.47 | 17.54 | 18.29 | 17.49 | 16.36 | 18.29 | 16.98 | 16.95 | 10.98 | 89.02 | 16.36 | 83.64 |
| **M12** | WTs - NN | 12.82 | 13.95 | 14.87 | 17.42 | 17.22 | 14.30 | 14.12 | 14.58 | 14.59 | 17.36 | 18.14 | 18.17 | 17.36 | 17.31 | 16.46 | 17.36 | 17.73 | 17.31 | 12.82 | 87.18 | 16.46 | 83.54 |
| **M13** | WTs - FL | 13.05 | 16.38 | 17.32 | 16.02 | 14.73 | 12.98 | 14.54 | 14.56 | 14.15 | 17.31 | 16.47 | 17.68 | 17.31 | 16.82 | 18.59 | 17.31 | 16.65 | 18.13 | 12.98 | 87.02 | 16.47 | 83.53 |
| **M14** | WTs - ANFIS | 12.24 | 18.53 | 19.09 | 18.31 | 16.23 | 14.26 | 14.28 | 17.38 | 17.17 | 18.08 | 17.74 | 18.00 | 18.08 | 16.32 | 16.64 | 18.08 | 17.03 | 17.32 | 12.24 | 87.76 | 16.32 | 83.68 |
| **M15** | WTs - SVM | 11.05 | 14.28 | 14.52 | 18.80 | 14.09 | 14.60 | 14.93 | 14.68 | 14.56 | 18.34 | 17.74 | 18.00 | 18.08 | 18.29 | 17.30 | 18.21 | 18.01 | 17.65 | 11.05 | 88.95 | 17.30 | 82.70 |
| **M16** | NN – FL | 9.79 | 14.70 | 16.44 | 13.93 | 14.28 | 13.39 | 11.86 | 14.49 | 14.92 | 18.58 | 17.15 | 19.06 | 18.58 | 18.46 | 17.46 | 18.58 | 17.81 | 18.26 | 9.79 | 90.21 | 17.15 | 82.85 |
| **M17** | NN – ANFIS | 11.45 | 16.70 | 17.48 | 21.32 | 13.96 | 13.62 | 16.39 | 14.33 | 14.55 | 17.12 | 16.98 | 19.25 | 17.12 | 17.62 | 17.66 | 17.12 | 17.30 | 18.45 | 11.45 | 88.55 | 16.98 | 83.02 |
| **M18** | NN – SVM | 11.77 | 16.36 | 17.23 | 17.78 | 16.54 | 13.42 | 14.77 | 16.45 | 14.32 | 18.26 | 17.69 | 18.74 | 18.26 | 17.00 | 16.36 | 18.26 | 17.35 | 17.55 | 11.77 | 88.23 | 16.36 | 83.64 |
| **M19** | FL - ANFIS | 12.28 | 16.39 | 17.07 | 18.71 | 14.80 | 13.20 | 14.49 | 14.59 | 14.13 | 19.38 | 17.11 | 19.14 | 19.38 | 17.19 | 16.68 | 19.38 | 17.15 | 17.91 | 12.28 | 87.72 | 16.68 | 83.32 |
| **M20** | FL - SVM | 11.05 | 16.98 | 17.07 | 20.79 | 12.70 | 14.51 | 14.92 | 14.84 | 16.29 | 18.44 | 16.85 | 18.89 | 18.44 | 18.02 | 18.14 | 18.44 | 17.43 | 18.51 | 11.05 | 88.95 | 16.85 | 83.15 |
| **M21** | ANFIS - SVM | 12.41 | 14.31 | 14.28 | 12.22 | 14.79 | 12.57 | 12.32 | 14.05 | 13.93 | 18.02 | 17.25 | 18.12 | 18.02 | 16.81 | 17.01 | 18.02 | 17.03 | 17.57 | 12.22 | 87.78 | 16.81 | 83.19 |
| **3 Pair** | **M22** | TS - WTs - NN | 12.64 | 11.75 | 13.22 | 14.37 | 16.74 | 9.39 | 13.51 | 14.24 | 11.31 | 16.81 | 16.73 | 17.43 | 16.81 | 14.06 | 14.02 | 16.81 | 14.39 | 16.23 | 9.39 | 90.61 | 91.73 | 14.06 | 84.94 | 87.06 |
| **M23** | TS - NN – FL | 11.00 | 10.70 | 10.42 | 17.50 | 14.15 | 10.77 | 14.25 | 12.92 | 10.60 | 13.29 | 14.14 | 14.81 | 13.29 | 14.36 | 14.45 | 13.29 | 14.25 | 14.63 | 10.42 | 89.58 | 13.29 | 86.71 |
| **M24** | TS - FL - ANFIS | 12.66 | 13.30 | 13.01 | 13.57 | 13.35 | 9.98 | 13.12 | 13.33 | 11.50 | 14.42 | 14.09 | 14.23 | 14.42 | 14.83 | 14.49 | 14.42 | 14.96 | 14.36 | 9.98 | 90.02 | 14.42 | 84.58 |
| **M25** | TS - ANFIS - SVM | 14.33 | 13.10 | 14.79 | 14.14 | 13.52 | 9.88 | 14.24 | 13.31 | 12.83 | 14.94 | 14.30 | 14.70 | 14.94 | 14.13 | 14.23 | 14.94 | 14.22 | 14.46 | 9.88 | 90.12 | 14.23 | 84.77 |
| **M26** | WTs - NN – FL | 12.63 | 11.94 | 12.47 | 13.42 | 12.70 | 10.54 | 13.02 | 12.32 | 11.50 | 13.83 | 12.94 | 16.19 | 13.83 | 16.08 | 14.88 | 13.83 | 14.51 | 16.03 | 10.54 | 89.46 | 12.94 | 87.06 |
| **M27** | WTs - FL - ANFIS | 14.13 | 10.63 | 12.92 | 14.53 | 13.07 | 8.53 | 14.83 | 11.85 | 10.73 | 13.72 | 13.75 | 14.11 | 13.72 | 14.64 | 14.18 | 13.72 | 14.20 | 14.15 | 8.53 | 91.47 | 13.72 | 86.28 |
| **M28** | WTs - ANFIS - SVM | 13.02 | 13.42 | 13.42 | 13.64 | 13.99 | 10.62 | 13.33 | 13.70 | 12.02 | 13.94 | 14.61 | 14.36 | 13.94 | 14.26 | 14.12 | 13.94 | 14.94 | 14.24 | 10.62 | 89.38 | 13.94 | 86.06 |
| **M29** | NN – FL - ANFIS | 8.27 | 12.96 | 10.11 | 12.73 | 10.83 | 10.66 | 10.50 | 11.89 | 10.38 | 13.35 | 14.41 | 14.40 | 13.35 | 14.15 | 14.91 | 13.35 | 14.78 | 14.66 | 8.27 | 91.73 | 13.35 | 86.65 |
| **M30** | WTs - FL - ANFIS | 11.16 | 13.97 | 13.29 | 12.32 | 12.98 | 12.46 | 11.74 | 13.48 | 12.88 | 13.82 | 13.14 | 14.77 | 13.82 | 14.90 | 14.07 | 13.82 | 14.52 | 14.42 | 11.16 | 88.84 | 13.14 | 86.86 |
| **M31** | WTs - ANFIS - SVM | 14.20 | 14.05 | 13.70 | 11.59 | 13.32 | 12.45 | 12.89 | 13.68 | 13.08 | 13.18 | 14.83 | 14.29 | 13.18 | 16.09 | 14.38 | 13.18 | 14.46 | 14.33 | 11.59 | 88.41 | 13.18 | 86.82 |
| **M32** | NN – FL - ANFIS | 13.94 | 11.76 | 12.09 | 11.49 | 13.96 | 10.59 | 12.71 | 12.86 | 11.34 | 13.83 | 14.90 | 16.76 | 13.83 | 14.54 | 14.56 | 13.83 | 14.72 | 16.16 | 10.59 | 89.41 | 13.83 | 86.17 |
| **M33** | NN – ANFIS - SVM | 10.51 | 14.50 | 14.22 | 14.13 | 13.55 | 11.98 | 12.82 | 14.03 | 13.10 | 13.26 | 13.64 | 16.73 | 13.26 | 14.00 | 14.96 | 13.26 | 14.32 | 14.85 | 10.51 | 89.49 | 13.26 | 86.74 |
| **M34** | FL - ANFIS - SVM | 14.82 | 11.12 | 12.29 | 16.61 | 11.66 | 8.40 | 16.22 | 11.39 | 10.35 | 14.28 | 14.54 | 14.30 | 14.28 | 14.36 | 14.14 | 14.28 | 14.95 | 14.22 | 8.40 | 91.60 | 14.28 | 84.72 |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 4.4(b): Forecasting MAPE values for Combinational Paired models for 24hr and 168hr prediction for three sites for 4 to 6 pair and Aggregate Model** | | | | | | | | | | | | | | | | | | | | | | | | | | |
| **Pair** | **Model  No.** | **Name/Combination** | **24Hr** | | | | | | | | | **168Hr** | | | | | | | | | **Min MAPE 24Hr** | | | **Min MAPE 168 Hr -** | | |
| **Bagalkot** | | | **Bijapur** | | | **Bangalore** | | | **Bagalkot** | | | **Bijapur** | | | **Bangalore** | | | **Min MAPE  24Hr** | **Accuracy** | **Pair  Model** | **Min  MAPE  168 Hr -** | **Accuracy** | **Paired  Model** |
| **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** | **P1** | **P2** | **P3** |
| **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** | **24** | **25** | **26** | **27** |
| **4 Pair** | **M35** | TS - WTs - NN - FL | 10.43 | 11.17 | 10.96 | 10.48 | 9.96 | 10.16 | 10.45 | 10.57 | 10.56 | 14.14 | 12.80 | 16.28 | 14.14 | 13.08 | 12.41 | 14.14 | 12.94 | 14.34 | 9.96 | 90.04 | 93.18 | 12.41 | 87.59 | 90.78 |
| **M36** | TS - WTs - NN - SVM | 9.51 | 11.96 | 13.21 | 11.48 | 10.28 | 9.20 | 10.49 | 11.12 | 11.20 | 10.49 | 10.94 | 12.93 | 10.49 | 13.62 | 12.68 | 10.49 | 12.28 | 12.80 | 9.20 | 90.80 | 10.49 | 89.51 |
| **M37** | TS - WTs - ANFIS - SVM | 11.42 | 11.34 | 12.59 | 10.35 | 10.99 | 8.86 | 10.89 | 11.16 | 10.72 | 10.47 | 10.74 | 12.82 | 10.47 | 11.83 | 12.88 | 10.47 | 11.28 | 12.85 | 8.86 | 91.14 | 10.47 | 89.53 |
| **M38** | TS - FL - ANFIS - SVM | 13.21 | 12.43 | 13.75 | 8.25 | 10.39 | 9.14 | 10.73 | 11.41 | 11.45 | 9.22 | 11.28 | 12.44 | 9.22 | 13.63 | 13.00 | 9.22 | 12.45 | 12.72 | 8.25 | 91.75 | 9.22 | 90.78 |
| **M39** | NN - FL - ANFIS - SVM | 10.31 | 11.11 | 11.85 | 11.27 | 9.22 | 9.38 | 10.79 | 10.16 | 10.61 | 10.05 | 11.73 | 13.23 | 10.05 | 12.31 | 12.33 | 10.05 | 12.02 | 12.78 | 9.22 | 90.78 | 10.05 | 89.95 |
| **M40** | WTs - NN - FL - ANFIS | 10.97 | 12.45 | 13.90 | 10.77 | 9.38 | 8.24 | 10.87 | 10.91 | 11.07 | 10.21 | 11.28 | 13.20 | 10.21 | 12.54 | 13.89 | 10.21 | 11.91 | 13.55 | 8.24 | 91.76 | 10.21 | 89.79 |
| **M41** | WTs - NN - FL - SVM | 10.24 | 9.41 | 10.06 | 10.26 | 9.63 | 10.51 | 10.25 | 9.52 | 10.29 | 10.95 | 11.28 | 13.20 | 10.21 | 13.13 | 13.18 | 10.58 | 12.21 | 13.19 | 9.41 | 90.59 | 10.21 | 89.79 |
| **M42** | WTs - NN - ANFIS - SVM | 9.60 | 12.12 | 12.80 | 10.98 | 8.33 | 8.74 | 10.29 | 10.22 | 10.77 | 9.84 | 11.19 | 13.98 | 9.84 | 12.55 | 13.63 | 9.84 | 11.87 | 13.80 | 8.33 | 91.67 | 9.84 | 90.16 |
| **M43** | WTs - FL - ANFIS - SVM | 10.36 | 11.81 | 13.70 | 10.15 | 8.63 | 9.08 | 10.25 | 10.22 | 11.39 | 10.14 | 10.45 | 13.92 | 10.14 | 12.95 | 12.29 | 10.14 | 11.70 | 13.11 | 8.63 | 91.37 | 10.14 | 89.86 |
| **M44** | NN - FL - ANFIS - SVM | 11.55 | 10.79 | 12.42 | 10.76 | 12.77 | 8.03 | 11.15 | 11.78 | 10.22 | 11.02 | 11.11 | 13.44 | 11.02 | 12.80 | 11.96 | 11.02 | 11.96 | 12.70 | 8.03 | 91.97 | 11.02 | 88.98 |
| **M45** | TS - NN - FL - ANFIS | 12.82 | 9.56 | 9.93 | 10.16 | 9.98 | 6.82 | 11.49 | 9.77 | 8.37 | 10.03 | 10.84 | 12.96 | 10.03 | 13.81 | 13.23 | 10.03 | 12.32 | 13.09 | 6.82 | 93.18 | 10.03 | 89.97 |
| **M46** | TS - NN - FL - SVM | 8.84 | 10.53 | 11.44 | 7.08 | 8.98 | 8.87 | 7.96 | 9.76 | 10.15 | 10.41 | 11.23 | 13.17 | 10.41 | 12.83 | 12.91 | 10.41 | 12.03 | 13.04 | 7.08 | 92.92 | 10.41 | 89.59 |
| **M47** | TS - NN - ANFIS - SVM | 9.89 | 9.59 | 9.89 | 9.88 | 7.74 | 8.50 | 9.89 | 8.67 | 9.19 | 9.96 | 11.44 | 14.10 | 9.96 | 12.95 | 12.68 | 9.96 | 12.19 | 13.39 | 7.74 | 92.26 | 9.96 | 90.04 |
| **M48** | TS - FL - ANFIS - SVM | 9.69 | 12.82 | 13.05 | 9.22 | 8.57 | 10.91 | 9.46 | 10.69 | 11.98 | 9.82 | 10.35 | 14.08 | 9.82 | 13.05 | 12.65 | 9.82 | 11.70 | 13.37 | 8.57 | 91.43 | 9.82 | 90.18 |
| **M49** | TS - FL - ANFIS - SVM | 9.83 | 10.90 | 12.33 | 10.41 | 9.42 | 9.34 | 10.12 | 10.16 | 10.83 | 10.83 | 12.01 | 12.51 | 10.83 | 13.23 | 12.68 | 10.83 | 12.62 | 12.59 | 9.34 | 90.66 | 10.83 | 89.17 |
| **M50** | TS - WTs - FL - SVM | 10.00 | 11.99 | 11.29 | 9.65 | 8.90 | 9.60 | 9.83 | 10.45 | 10.45 | 9.46 | 11.28 | 12.83 | 9.46 | 12.94 | 13.66 | 9.46 | 12.11 | 13.24 | 8.90 | 91.10 | 9.46 | 90.54 |
| **M51** | TS - WTs - FL - ANFIS | 10.28 | 11.54 | 12.39 | 11.31 | 10.89 | 9.71 | 10.79 | 11.21 | 11.05 | 10.66 | 10.97 | 12.95 | 10.66 | 13.00 | 11.92 | 10.66 | 11.99 | 12.43 | 9.71 | 90.29 | 10.66 | 89.34 |
| **M52** | TS - WTs - NN - SVM | 10.93 | 11.00 | 11.50 | 10.11 | 8.40 | 8.06 | 10.52 | 9.70 | 9.78 | 10.18 | 11.12 | 12.84 | 10.18 | 13.25 | 13.09 | 10.18 | 12.19 | 12.97 | 8.06 | 91.94 | 10.18 | 89.82 |
| **M53** | TS - WTs - NN - ANFIS | 12.82 | 9.56 | 9.93 | 10.16 | 9.98 | 6.82 | 11.49 | 9.77 | 8.37 | 10.02 | 9.99 | 13.59 | 10.02 | 11.74 | 13.19 | 10.02 | 10.87 | 13.39 | 6.82 | 93.18 | 9.99 | 90.01 |
| **M54** | TS - WTs - NN - FL | 8.84 | 10.53 | 11.44 | 7.08 | 8.98 | 8.87 | 7.96 | 9.76 | 10.15 | 10.71 | 9.99 | 13.59 | 10.02 | 11.81 | 12.84 | 10.37 | 10.90 | 13.21 | 7.08 | 92.92 | 9.99 | 90.01 |
| **5 Pair** | **M55** | TS - WTs - NN - FL - ANFIS | 9.89 | 9.59 | 9.89 | 9.88 | 7.74 | 8.50 | 9.89 | 8.67 | 9.19 | 10.02 | 11.39 | 13.71 | 10.24 | 9.79 | 9.88 | 10.13 | 10.59 | 11.80 | 7.74 | 92.26 | 92.26 | 9.79 | 90.21 | 92.69 |
| **M56** | TS - WTs - NN - FL - SVM | 9.69 | 12.82 | 13.05 | 9.22 | 8.57 | 10.91 | 9.46 | 10.69 | 11.98 | 10.24 | 10.74 | 12.70 | 10.09 | 9.29 | 9.83 | 10.16 | 10.01 | 11.26 | 8.57 | 91.43 | 9.29 | 90.71 |
| **M57** | TS - WTs - NN - ANFIS - SVM | 9.83 | 10.90 | 12.33 | 10.41 | 9.42 | 9.34 | 10.12 | 10.16 | 10.83 | 10.09 | 11.21 | 13.10 | 10.25 | 8.80 | 9.83 | 10.17 | 10.01 | 11.46 | 9.34 | 90.66 | 8.80 | 91.20 |
| **M58** | TS - WTs - FL - ANFIS - SVM | 10.00 | 11.99 | 11.29 | 9.65 | 8.90 | 9.60 | 9.83 | 10.45 | 10.45 | 10.25 | 8.64 | 9.65 | 10.34 | 9.02 | 9.40 | 10.29 | 8.83 | 9.52 | 8.90 | 91.10 | 8.64 | 91.36 |
| **M59** | TS - NN - FL - ANFIS - SVM | 9.56 | 11.34 | 11.89 | 9.73 | 9.55 | 8.96 | 9.64 | 10.44 | 10.42 | 10.34 | 8.51 | 10.37 | 10.78 | 8.84 | 9.49 | 10.56 | 8.67 | 9.93 | 8.96 | 91.04 | 8.51 | 91.49 |
| **M60** | WTs - NN - FL - ANFIS - SVM | 8.91 | 9.76 | 10.23 | 8.75 | 9.35 | 7.82 | 8.83 | 9.55 | 9.03 | 7.31 | 9.04 | 10.60 | 11.66 | 9.01 | 8.82 | 9.49 | 9.02 | 9.71 | 7.82 | 92.18 | 7.31 | 92.69 |
| **6 Pair** | **M61** | **TS - WTs - NN - FL - ANFIS SVM** | 6.77 | 6.88 | 6.61 | 6.43 | 9.28 | 6.84 | 6.60 | 8.08 | 6.73 | 7.46 | 7.84 | 8.20 | 7.63 | 7.43 | 7.75 | 7.55 | 7.63 | 7.98 | 6.43 | 93.57 | 93.57 | 7.43 | 92.57 | 92.57 |
| **Aggregate** | **MAGGRE** | **MAGGRE** | 6.71 | 6.81 | 6.55 | 6.37 | 9.19 | 6.78 | 6.54 | 8.00 | 6.67 | 7.39 | 7.77 | 8.12 | 7.56 | 7.36 | 7.68 | 7.48 | 7.56 | 7.90 | 6.37 | 93.62 | 92.68 | 7.36 | 91.69 | 91.69 |
| **Minimum** |  | **Minimum** | 6.77 | 6.88 | 6.61 | 6.43 | 7.74 | 6.82 | 6.60 | 8.08 | 6.73 | 7.31 | 7.84 | 8.20 | 7.63 | 7.43 | 7.75 | 7.47 | 7.63 | 7.98 | 6.43 | 93.57 | 93.57 | 7.31 | 81.24 | 82.55 |
| **Maximum** |  | **Maximum** | 17.67 | 18.53 | 19.09 | 21.86 | 18.18 | 14.60 | 19.73 | 17.38 | 17.17 | 22.08 | 20.61 | 21.16 | 22.08 | 21.01 | 20.96 | 22.08 | 20.81 | 21.06 | 14.60 | 84.40 | 93.57 | 18.76 | 92.69 | 92.69 |

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| **Fig. 4.2: 24hr Wind Speed forecast result from Combinational winter model Bagalkot site** | **Fig. 4.3: 24hr Wind Speed forecast result from Combinational Summer model Bagalkot Site** | |
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| **Fig. 4.4: 24hr Wind Speed forecast result from Combinational Rainy Season model Bagalkot Site** | **Fig. 4.5: 24hr Wind Speed forecast result from Combinational winter model Vijayapura site** | |
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| **Fig. 4.6: 24hr Wind Speed forecast result from Combinational Summer model Vijayapura site** | **Fig. 4.7: 24hr Wind Speed forecast result from Combinational Rainy Season model Vijayapura site** | |
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| **Fig. 4.8: 24hr Wind Speed forecast result from Combinational winter model Bengaluru site** | **Fig. 4.9: 24hr Wind Speed forecast result from Combinational Summer model Bengaluru site** | |
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| **Fig. 4.10: 24hr Wind Speed forecast result from Combinational Rainy Season model Bengaluru site** | **Fig. 4.11: % MAPE for 61 Models for three pattern three site** | |
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| **Fig. 4.12 % MAPE for 61 Models for three pattern three site** | **Fig. 4.13:(a) Frequency distribution MAPE, (b) MAPE for six pair model** | |
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| **Fig. 4.14: Initial and Final Error Matrix for Bagalktot, Vijayapura and Bengaluru Sites** | | | |

Fig. 4.15 to 4.17 represents forecast output of Combinational and aggregate winter models. Results indicate that, aggregate model forecast curve is very near to actual wind speed pattern.

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**Fig. 4.15: Comparison of MAPE values for Bagalkot and Bijapur sites for Pattern 1-3 data for 24hr wind speed forecast**

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**Fig. 4.16: Comparison of MAPE values for 168hrs for Pattern 1-3 of Bagalkot and Bijapur Site Wind Speed forecast**

**Fig. 4.17: Comparison of MAPE values for all 12 patterns of Bagalkot and Bijapur sites for 24hr and 168hr wind speed forecast**

**4.7 Statistical Test Results for Paired and Combinational Models**

Paired t-test, two samples F-test for variances assuming equal variance for actual and forecasted values are conducted for forecasted results of paired models three seasons. Test results are summarized in Table 4.5 to 4.6 for Bagalkot, Table 4.7 to 4.8 for Vijayapura and Table 4.9 to 4.10 for Bengaluru sites.

**Table 4.5: Paired t-test for Actual Vs Forecasted Wind Speed for 6models and Two Sample F-Test for variances (Assuming equal variance for actual vs forecasted values for Bagalkot Site**

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| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Site** | **Method** | **Paired t-test** | | | | **Two Sample F-Test for variances**  **(Assuming equal** | | |
| **Pearson**  **Correlation** | **t-stat** | **T**  **critical**  **one tail** | **T**  **critical**  **two tail** | **F** | **P**  **Critical** | **F-**  **critical** |
| Winter | Single | 0.810 | -52.602 | 1.339 | 1.294 | 0.604 | 0.116 | 0.629 |
| Two pair | 0.701 | -94.246 | 1.479 | 1.594 | 0.831 | 0.116 | 0.701 |
| Three pair | 0.794 | -46.518 | 1.312 | 1.243 | 0.44 | 0.008 | 0.617 |
| Four Pair | 0.736 | -71.138 | 1.222 | 1.078 | 0.54 | 0.003 | 0.574 |
| Five pair | 0.754 | -77.506 | 1.248 | 1.124 | 0.751 | 0.033 | 0.586 |
| Six pair | **0.896** | -70.22 | **1.082** | **1.105** | **0.888** | 0.001 | 0.696 |
| Summer | Single | 0.585 | -54.2 | 0.967 | 0.675 | 0.436 | 0.111 | 0.454 |
| Two pair | 0.708 | -116.1 | 1.336 | 1.288 | 0.815 | 0.094 | 0.628 |
| Three pair | 0.736 | -72.54 | 1.217 | 1.068 | 0.64 | 0.012 | 0.572 |
| Four Pair | 0.755 | -74.64 | 1.297 | 1.124 | 0.57 | 0.022 | 0.609 |
| Five pair | 0.713 | -77.51 | 1.266 | 1.074 | 0.751 | 0.033 | 0.595 |
| Six pair | **0.846** | -81.72 | **0.903** | **0.589** | **0.865** | 0.001 | 0.424 |
| Rainy | Single | 0.676 | -110.5 | 1.448 | 1.901 | 0.472 | 0.119 | 0.68 |
| Two pair | 0.719 | -192.9 | 1.321 | 1.26 | 1.184 | 0.138 | 0.621 |
| Three pair | 0.736 | -72.54 | 1.217 | 1.068 | 0.634 | 0.002 | 0.572 |
| Four Pair | 0.788 | -52.07 | 1.303 | 1.224 | 0.556 | 0.008 | 0.612 |
| Five pair | 0.787 | -70.02 | 1.249 | 1.314 | 0.622 | 0.001 | 0.587 |
| Six pair | **0.818** | 86.2 | **1.053** | **1.021** | **0.821** | 0.001 | 0.636 |

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| **Table.4.6: Regression test for Bagalkot Site** | | | | | | | | |
| **Site** | **Method** | **Multiple**  **R2** | **R2** | **Adjusted**  **R2** | **SE** | **SS Regr** | **F** | **t-stat** |
| Winter | Single | 0.810 | 0.656 | 0.653 | 1.373 | 599.23 | 317.79 | 9.25 |
| Two pair | 0.806 | 0.811 | 0.756 | 1.016 | 741.81 | 718.94 | 1.63 |
| Three pair | 0.794 | 0.63 | 0.627 | 1.424 | 574.00 | 283.99 | 10.89 |
| Four Pair | 0.739 | 0.546 | 0.543 | 0.992 | 197.69 | 200.85 | 9.35 |
| Five pair | 0.754 | 0.569 | 0.567 | 0.962 | 203.102 | 219.32 | 8.66 |
| Six pair | **0.896** | **0.803** | **0.802** | **0.456** | **734.228** | **777.48** | 8.41 |
| Summer | Single | 0.585 | 0.342 | 0.338 | 1.111 | 104.937 | 104.94 | 14.38 |
| Two pair | 0.808 | 0.652 | 0.650 | 0.799 | 200.198 | 313.50 | 3.59 |
| Three pair | 0.736 | 0.541 | 0.538 | 0.993 | 193.13 | 194.85 | 9.38 |
| Four Pair | 0.784 | 0.569 | 0.562 | 0.962 | 203.1 | 219.33 | 8.66 |
| Five pair | 0.766 | 0.544 | 0.456 | 0.965 | 222.5 | 204.61 | 8.22 |
| Six pair | **0.846** | **0.798** | **0.809** | **0.525** | **719.451** | **700.52** | 23.72 |
| Rainy | Single | 0.806 | 0.456 | 0.453 | 0.574 | 46.179 | 140.25 | 12.62 |
| Two pair | 0.799 | 0.638 | 0.636 | **0.668** | 64.57 | 294.73 | 2.16 |
| Three pair | 0.736 | 0.541 | 0.538 | 0.993 | 193.13 | 194.85 | 9.38 |
| Four Pair | 0.788 | 0.620 | 0.618 | 1.446 | 566.97 | 271.12 | 8.25 |
| Five pair | 0.755 | 0.666 | 0.601 | 0.896 | 504.88 | 208.55 | 7.22 |
| Six pair | **0.891** | **0.869** | **0.667** | **0.443** | **738.74** | **334.65** | 1.34 |

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| **Table 4.7: Paired t-test for Actual Vs Forecasted Wind Speed for 6models and Two Sample F-Test for variances (Assuming equal variance for actual vs forecasted values for Vijayapura Site** | | | | | | | | |
| **Site** | **Method** | **Paired t-test** | | | | **Two Sample F-Test for**  **variances**  **(Assuming equal** | | |
| **Pearson**  **Correlation** | **t-stat** | **T**  **critical**  **one tail** | **T**  **Critical**  **two tail** | **F** | **P Critical** | **F-critical** |
| Winter | Single | 0.826 | -53.7 | 1.366 | 1.320 | 0.616 | 0.118 | 0.642 |
| Two pair | 0.715 | -96.1 | 1.509 | 1.626 | 0.848 | 0.118 | 0.714 |
| Three pair | 0.810 | -47.4 | 1.338 | 1.268 | 0.449 | 0.008 | 0.629 |
| Four Pair | 0.751 | -72.6 | 1.246 | 1.100 | 0.551 | 0.003 | 0.585 |
| Five pair | 0.769 | -79.1 | 1.273 | 1.146 | 0.766 | 0.034 | 0.598 |
| Six pair | 0.914 | -71.6 | 1.104 | 1.127 | 0.906 | 0.001 | 0.710 |
| Summer | Single | 0.597 | -54.3 | 0.986 | 0.689 | 0.445 | 0.113 | 0.463 |
| Two pair | 0.722 | -118.4 | 1.363 | 1.314 | 0.831 | 0.096 | 0.641 |
| Three pair | 0.751 | -74.0 | 1.241 | 1.089 | 0.653 | 0.012 | 0.583 |
| Four Pair | 0.770 | -77.2 | 1.323 | 1.146 | 0.581 | 0.022 | 0.621 |
| Five pair | 0.727 | -79.1 | 1.291 | 1.095 | 0.766 | 0.034 | 0.607 |
| Six pair | 0.863 | -83.4 | 0.921 | 0.601 | 0.882 | 0.001 | 0.432 |
| Rainy | Single | 0.690 | -112.7 | 1.477 | 1.939 | 0.481 | 0.121 | 0.694 |
| Two pair | 0.733 | -196.8 | 1.347 | 1.285 | 1.208 | 0.141 | 0.633 |
| Three pair | 0.751 | -74.0 | 1.241 | 1.089 | 0.647 | 0.002 | 0.583 |
| Four Pair | 0.804 | -53.1 | 1.329 | 1.248 | 0.567 | 0.008 | 0.624 |
| Five pair | 0.803 | -71.4 | 1.274 | 1.340 | 0.634 | 0.001 | 0.599 |
| Six pair | 0.834 | 87.9 | 1.074 | 1.041 | 0.837 | 0.001 | 0.649 |

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| **Table.4.8: Regression test for Vijayapura Site** | | | | | | | | |
| **Site** | **Method** | **Multiple**  **R2** | **R2** | **Adjusted**  **R2** | **SE** | **SS Regr** | **F** | **t-stat** |
| Winter | Single | 0.826 | 0.669 | 0.666 | 1.400 | 611.215 | 324.146 | 9.435 |
| Two pair | 0.822 | 0.827 | 0.771 | 1.036 | 756.646 | 733.319 | 1.663 |
| Three pair | 0.810 | 0.643 | 0.640 | 1.452 | 586.500 | 289.670 | 11.108 |
| Four Pair | 0.754 | 0.557 | 0.554 | 1.012 | 201.644 | 204.867 | 9.537 |
| Five pair | 0.769 | 0.580 | 0.578 | 0.981 | 207.164 | 223.706 | 8.833 |
| Six pair | 0.914 | 0.819 | 0.818 | 0.465 | 748.913 | 793.030 | 8.578 |
| Summer | Single | 0.597 | 0.349 | 0.345 | 1.133 | 107.036 | 107.039 | 14.668 |
| Two pair | 0.824 | 0.665 | 0.663 | 0.815 | 204.202 | 319.770 | 3.662 |
| Three pair | 0.751 | 0.552 | 0.549 | 1.013 | 196.993 | 199.767 | 9.568 |
| Four Pair | 0.800 | 0.580 | 0.573 | 0.981 | 207.162 | 223.717 | 8.833 |
| Five pair | 0.781 | 0.555 | 0.465 | 0.984 | 226.950 | 208.702 | 8.384 |
| Six pair | 0.863 | 0.814 | 0.825 | 0.536 | 733.840 | 714.530 | 24.194 |
| Rainy | Single | 0.822 | 0.465 | 0.462 | 0.585 | 47.103 | 143.055 | 12.872 |
| Two pair | 0.815 | 0.651 | 0.649 | 0.681 | 64.861 | 300.625 | 2.203 |
| Three pair | 0.751 | 0.552 | 0.549 | 1.013 | 196.993 | 199.767 | 9.568 |
| Four Pair | 0.804 | 0.632 | 0.630 | 1.475 | 578.309 | 276.542 | 8.415 |
| Five pair | 0.770 | 0.679 | 0.613 | 0.914 | 514.978 | 212.721 | 7.364 |
| Six pair | 0.909 | 0.886 | 0.680 | 0.452 | 753.515 | 342.363 | 1.367 |

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| **Table 4.9: Paired t-test for Actual Vs Forecasted Wind Speed for 6models and Two Sample F-Test for variances (Assuming equal variance for actual vs forecasted values for Bengaluru Site** | | | | | | | | |
| **Site** | **Method** | **Paired t-test** | | | | **Two Sample F-Test for variances**  **(Assuming equal** | | |
| **Pearson**  **Correlation** | **t-stat** | **T** | **T** | **F** | **P Critical** | **F-critical** |
| **Critical**  **one tail** | **critical**  **two tail** |
| Winter | Single | 0.834 | -54.2 | 1.379 | 1.333 | 0.622 | 0.120 | 0.648 |
| Two pair | 0.722 | -97.1 | 1.524 | 1.642 | 0.856 | 0.120 | 0.721 |
| Three pair | 0.818 | -47.9 | 1.352 | 1.281 | 0.453 | 0.008 | 0.636 |
| Four Pair | 0.758 | -73.3 | 1.259 | 1.111 | 0.556 | 0.003 | 0.591 |
| Five pair | 0.777 | -79.8 | 1.286 | 1.158 | 0.774 | 0.034 | 0.604 |
| Six pair | 0.923 | -72.3 | 1.115 | 1.138 | 0.915 | 0.001 | 0.717 |
| Summer | Single | 0.603 | -54.8 | 0.996 | 0.695 | 0.449 | 0.114 | 0.468 |
| Two pair | 0.729 | -119.6 | 1.376 | 1.327 | 0.840 | 0.097 | 0.647 |
| Three pair | 0.758 | -74.7 | 1.254 | 1.100 | 0.659 | 0.012 | 0.589 |
| Four Pair | 0.778 | -77.9 | 1.336 | 1.158 | 0.587 | 0.023 | 0.627 |
| Five pair | 0.735 | -79.9 | 1.304 | 1.106 | 0.774 | 0.034 | 0.613 |
| Six pair | 0.872 | -84.2 | 0.930 | 0.607 | 0.891 | 0.001 | 0.437 |
| Rainy | Single | 0.696 | -113.8 | 1.492 | 1.958 | 0.486 | 0.123 | 0.701 |
| Two pair | 0.741 | -198.7 | 1.361 | 1.298 | 1.220 | 0.142 | 0.640 |
| Three pair | 0.758 | -74.7 | 1.254 | 1.100 | 0.653 | 0.002 | 0.589 |
| Four Pair | 0.812 | -53.6 | 1.342 | 1.261 | 0.573 | 0.008 | 0.630 |
| Five pair | 0.811 | -72.1 | 1.287 | 1.354 | 0.641 | 0.001 | 0.605 |
| Six pair | 0.843 | 88.8 | 1.085 | 1.052 | 0.846 | 0.001 | 0.655 |

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| **Table.4.10: Regression test for Bengaluru Site** | | | | | | | | |
| **Site** | **Method** | **Multiple**  **R2** | **R2** | **Adjusted**  **R2** | **SE** | **SS Regr** | **F** | **t-stat** |
| Winter | Single | 0.851 | 0.689 | 0.686 | 1.442 | 629.551 | 333.870 | 9.718 |
| Two pair | 0.847 | 0.852 | 0.794 | 1.067 | 779.346 | 754.318 | 1.712 |
| Three pair | 0.834 | 0.662 | 0.659 | 1.496 | 604.095 | 298.360 | 11.441 |
| Four Pair | 0.776 | 0.574 | 0.570 | 1.042 | 207.693 | 211.013 | 9.823 |
| Five pair | 0.792 | 0.598 | 0.596 | 1.011 | 213.379 | 230.418 | 9.098 |
| Six pair | 0.941 | 0.844 | 0.843 | 0.479 | 771.380 | 816.820 | 8.836 |
| Summer | Single | 0.615 | 0.359 | 0.355 | 1.167 | 110.247 | 110.250 | 14.108 |
| Two pair | 0.849 | 0.685 | 0.683 | 0.839 | 210.328 | 329.363 | 3.772 |
| Three pair | 0.773 | 0.568 | 0.565 | 1.043 | 202.902 | 204.760 | 9.855 |
| Four Pair | 0.824 | 0.598 | 0.590 | 1.011 | 213.377 | 230.428 | 9.098 |
| Five pair | 0.805 | 0.572 | 0.479 | 1.014 | 233.759 | 214.963 | 8.636 |
| Six pair | 0.889 | 0.838 | 0.850 | 0.552 | 754.855 | 734.966 | 24.920 |
| Rainy | Single | 0.847 | 0.479 | 0.476 | 0.603 | 48.516 | 147.347 | 13.259 |
| Two pair | 0.839 | 0.670 | 0.668 | 0.702 | 67.837 | 309.643 | 2.269 |
| Three pair | 0.773 | 0.568 | 0.565 | 1.043 | 202.902 | 204.760 | 9.855 |
| Four Pair | 0.828 | 0.651 | 0.649 | 1.519 | 594.659 | 284.839 | 8.667 |
| Five pair | 0.793 | 0.700 | 0.631 | 0.941 | 530.427 | 219.103 | 7.585 |
| Six pair | 0.936 | 0.913 | 0.701 | 0.465 | 776.120 | 352.634 | 1.408 |

**4.8 Salient Outcomes of Combinational Models Developed**

A new methodology of combining Statistical and AI techniques is presented in this work. Mathematical modeling of ARIMA, GARCH, Transfer Function-ARIMA, Wavelet-ARIMA, NN, FL, ANFIS and SVM models are derived by using model parameters of individual models. These individual models are used to derive a global combinational equation. Following salient observations are deducted from forecasted and test results obtained:

* Mathematical models are developed for individual statistical and AI models. These mathematical models are used in a novel algorithm for optimally combining model equations to obtain a global optimal solution for short term wind speed forecast. Maximization of R2 and minimization of MAPE are used objective function for each individual model.
* Results show that, SVM model combined with any of model has performed better than other combinations. Computation time increases as complexity increases. But computation time within limit to an extent of 52.78sec for six pair model. Also accuracy decreases as horizon increases.
* Models are validated by testing with 12type of patterns for 24hr and 168hr wind speed prediction. There is an improvement of 4.6% with six pair model for 24hr, 9.95% for 168hr wind speed forecast. Forecasted wind speed curve nearly follows actual wind speed.
* All t-tests conducted for forecasted wind speed and found that null hypothesis is rejected for random distribution of error with 95% confidence interval. t-test, F-test and regression tests are conducted on forecasted wind speed values of all paired models. It is found that; 6pair model has outperformed all paired models in these tests.
* Regression test indicate that there is close agreement between actual and forecasted wind speed values. Up to 0.95 regression values achieved with 6-paired model. This shows superiority of 6-pair combination as compared to other paired combinations.
* 61 models along with aggregated models are tested for 18 patterns of three sites.

Salient observations presented above after a detailed investigation by way of mathematical modeling and optimization algorithm used, it is concluded that this novel combinational approach gives more accurate forecasting of wind speed as compared to individual models. Forecasting accuracy of 8% is achieved with this new technique of combinational algorithm.