Chapter 3 : Resources estimation and mapping – wind

Estimation and mapping of wind speed are essential requirements in locating and harvesting wind energy potential at any location. This chapter presents the estimation and mapping of wind energy potential in the Southern part of India: Andhra Pradesh (AP) and Telangana State (TS), whch lie between 12°41' and 22°N latitude and 77° and 84°40'E longitude. Prediction of wind speed is carried out using measured parameters and a parametric study is also carried out for accurate prediction. Data of meteorological parameters, such as pressure, temperature, relative humidity and wind speed are taken for each location. Generalized feed-forward with back-propagation neural networks were considered using MATLAB. This chapter begins with data analysis for a set of input parameters. Subsequently, a description of the overall modelling methodology with a brief discussion of ANN approach, training and testing of the model is presented. Then optimization of ANN model for accurate prediction is given, followed by an explanation for mapping of wind energy potential using GIS approach. Finally, land use and land cover analysis is presented to estimate ideal type of land available for wind farms within AP and TS.

3.1 Data analysis

In India, the meteorological parameters are being recorded and archived by a Government agency, India Meteorological Department (IMD), Pune. IMD, Pune has a few weather monitoring stations with an installed instrument to measure the wind speed. There are 28 base stations monitored by IMD, Pune, which have measured data of wind speed in AP and TS (for total area of 2,72,282 km^2). Other than these stations, accurate wind speed data is not available at local level within AP and TS. Thus, the main challenges for researchers and decision makers are the insufficient and inconsistent wind speed data to identify ideal locations for wind farm and to estimate the wind potential at local level. Present work is aimed to overcome these limitations by identifying the crucial parameter, which has high influence in predicting wind speed. Moreover, a model is developed using the available meteorological information to predict the wind speed at any given location, where measured data is not available.

In this study, four meteorological parameters have been considered which include; Temperature (T), station level Pressure (P), Relative Humidity (RH) and Wind Speed (WS). All four parameters taken here are monthly mean values. There are 28 locations within AP and TS at which meteorological parameter's data have been measured and archived by IMD, Pune for a period of 20 years (1995 - 2015). These data sets are procured from IMD, Pune for research purpose, as given in Appendix-I, Appendix-II and Appendix-III. It was found that there were some gaps in the data recorded. The parameters were not measured or they were measured with an error of more than 5%, such data was discarded. All the meteorological parameters were measured using measuring instrument at ground stations. The wind speed was measured at a height of 10 meters. Each parameter had monthly mean values for all 12-month over 20 years. Data of four parameters was obtained for 28 locations, which means there are 6,720 data points for each parameter and in total there are 26,880 data points. This data was then used to calculate monthly mean values for each parameter and further used to develop and evaluate ANN model.

The data of 28 weather monitoring stations was categorized into three sets: consisting of data for 20, 4 and 4 locations. The first data set of 20 locations was used for training of the ANN model, second data set of 4 locations was used to validate the model and finally third data set of 4 locations is kept aside to check the model for its accuracy. In order to evaluate prediction ability of the model at new locations, testing location was separated from training location to develop the model. The test location is selected randomly within AP and TS. Every input data set has mean meteorological data and geographical parameters along with its representative month during a year at each station. Hence, there are 12 data sets for each station, which includes input and output data. Therefore, 288 data sets are used to train and validate the model and 48 data sets are used to test the model in order to evaluate its prediction accuracy. The geographical map of AP and TS with the location of weather monitoring stations for which the measured data was obtained is shown in Figure 3.1. The geographical parameters of these ground stations are given in Table 3.1.

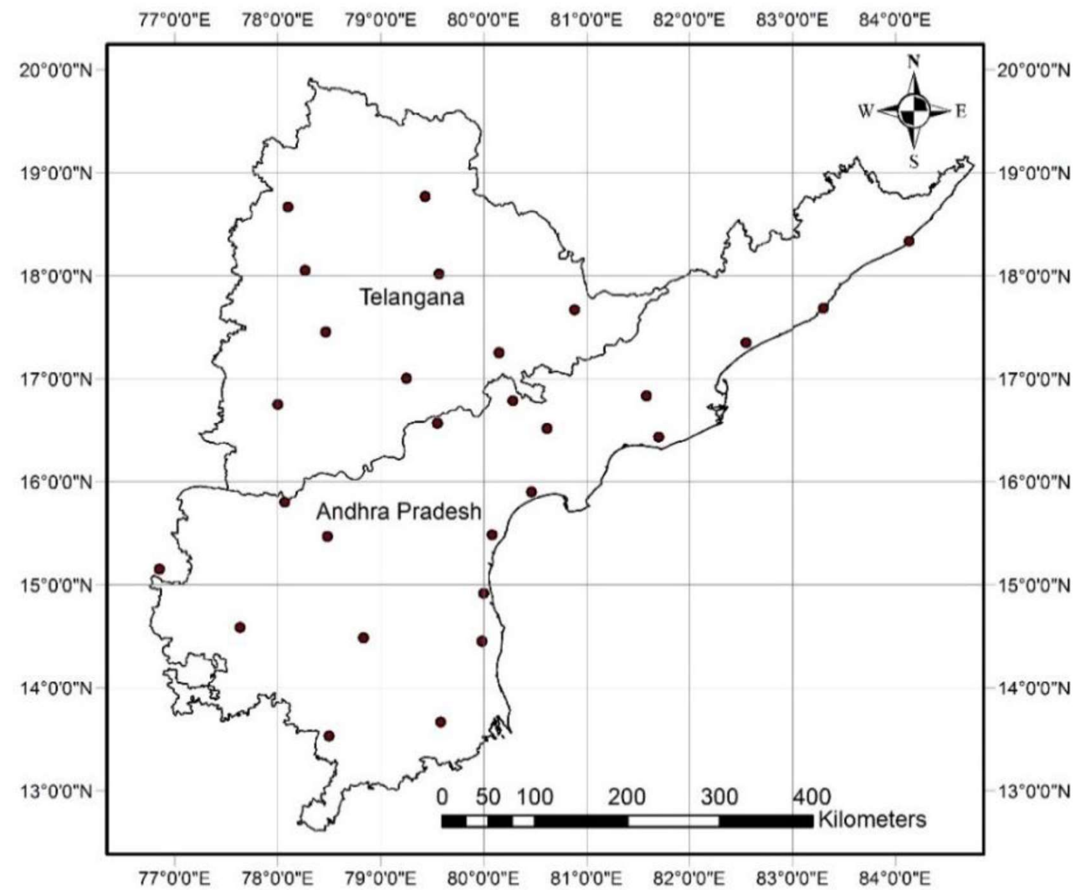

Figure 3.1. Location of data sites on AP and TS map used in model.

Table 3.1. Geographical parameters of data stations.

St.No.	Latitude (Degree)	Longitude (Degree)	Altitude (Meter)	St.No.	Latitude (Degree)	Longitude (Degree)	Altitude (Meter)
1	18.66	78.10	381	15	16.78	80.28	57
2	18.05	78.26	472	16	16.83	81.58	16
3	18.76	79.43	160	17	16.43	81.70	9
4	18.01	79.56	269	18	15.15	76.85	449
5	18.33	84.13	7	19	15.46	78.48	215
6	17.45	78.46	535	20	15.80	78.06	289
7	17.00	79.25	227	21	15.90	80.46	10
8	17.66	80.83	54	22	15.48	80.08	22
9	17.25	80.15	112	23	14.58	77.63	372
10	17.35	82.55	19	24	14.48	78.83	130
11	17.68	83.30	70	25	14.91	80.00	22
12	16.75	78.00	505	26	14.45	79.98	21
13	16.56	79.55	106	27	13.53	78.50	701
14	16.51	80.61	27	28	13.66	79.58	105

1- Nizamabad, 2-Medak, 3-Ramagundam, 4-Kishanpura, 5-Vomaravalli, 6-Hyderabad, 7-Charla Gouraram, 8-Morampalle, 9-Khammam, 10- Tuni, 11-Visakhapatnam, 12-Mahbubnagar, 13-Narasaraopet, 14- Vijayawada, 15-Nandigama, 16-Arugolanu, 17-Narsapur, 18-Ballari, 19-Nandyala, 20- Kurnool, 21- Bapatla, 22-Ongole, 23-Hindupur, 24- Kadapa, 25-Kavali, 26- Nellore, 27-Rajampet, 28Tirupati

It can be seen that all stations are distributed across the states. Three different ANN models are developed to identify the best ANN model. A parametric study has been carried out to find the most influencing parameter which can predict wind speed accurately. Each model has five data as input, which consists of three geographical parameters (latitude, longitude, and altitude of each location) along with the month of the year and one among three meteorological parameters (P, T, and RH). The output for all these three models is the wind speed. Therefore, each input data set has 5 data, which is associated with one output. The monthly mean meteorological parameters as input and output data set are given for one sample station in Table 3.2.

Table 3.2. Monthly mean meteorological parameters as input and output of the model for a representative station no. 1.

Five input to the model							One output
				One at a time for each model			
Month	**Lat.**	**Long.**	**Alt.**	**P (kPa)**	**T (ºC)**	**RH %**	**WS (m/s)**
1	18.66	78.10	381	970.63	23.53	57	3.35
2	18.66	78.10	381	968.92	26.6	48	3.60
3	18.66	78.10	381	966.88	30.72	40	4.09
4	18.66	78.10	381	964.4	34.27	34	4.94
5	18.66	78.10	381	961.65	35.78	34	6.85
6	18.66	78.10	381	959.67	31.11	57	9.00
7	18.66	78.10	381	960.13	27.88	72	8.08
8	18.66	78.10	381	961.34	27.08	76	7.35
9	18.66	78.10	381	963.56	27.75	73	5.38
10	18.66	78.10	381	967.50	26.98	68	4.09
11	18.66	78.10	381	969.90	24.55	63	3.17
12	18.66	78.10	381	971.43	22.55	60	2.64

* P- pressure, T- temperature, RH- relative humidity and WS- wind speed.

3.2 Methodology applied

The ANN model has been developed to predict the wind speed. Three different models are developed with different input parameters and optimized. Optimum and efficient model is then used to predict the wind speed within AP and TS. Predicted wind speed is then analyzed and mapped using GIS approach - to generate monthly plots.

3.2.1 ANN approach

The ANN is a computational model based on the structure and functions of biological neural networks. The model has the ability to train themselves, store for future calculation, and recall data for prediction based on the input dataset. One of the unique features of ANN models is to establish a relation among distinct input parameters, which helps to estimate the output parameter. Moreover, it provides weighting to each parameter based on its relation. The main components of a standard neural network are input units, junctions or nodes, and output units. All three components are arranged in a series of layers, starting from input to hidden to output layers. The connections between components are established by some number, which is known as weight. This weight could be either positive or negative. The component which has highest weight number is considered highly influencing in the relation to predict the output parameter.

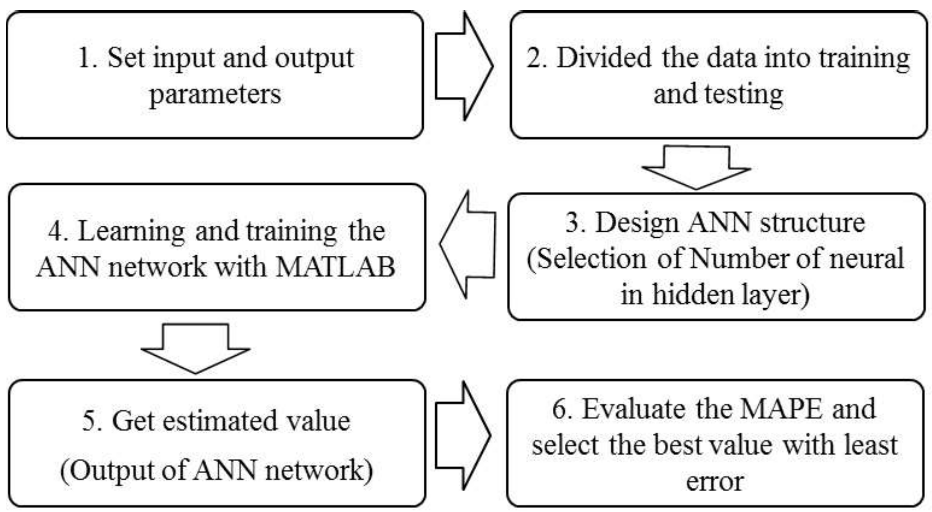

Figure 3.2. Steps taken to develop ANN model in the study.

In the present study, the multi-layer Feed-forward with Back-Propagation Neural Networks (FBPNN) model is used to predict the wind speed through geographical parameters and mean monthly meteorological data as inputs. The FBPNN model is reported the best for diverse data conditions, giving highest correlation coefficient values. Figure 3.2 shows six steps followed while developing the ANN model.

Design of ANN model

MATLAB version R2015a is used to develop the ANN model using multi-layer FBPNN. The neural network is composed of three layers - input, hidden and output layer. In Figure 3.3, architecture of present ANN model is presented. In this study, there are five input parameters to model and the output of model is wind speed, as discussed above. Three ANN models have been designed for three different input data sets. All the three models have five neurons in the input layer and one neuron in the output layer. Varying neurons in hidden layer is considered and simulated to optimized the model for its better accuracy. The number of neurons in hidden layer varies from 1 to 10 for each ANN model. Each neuron in the input layer takes one input parameter. One neuron in the output layer gives an estimated value of wind speed based on the relation established in hidden layer among input parameters.

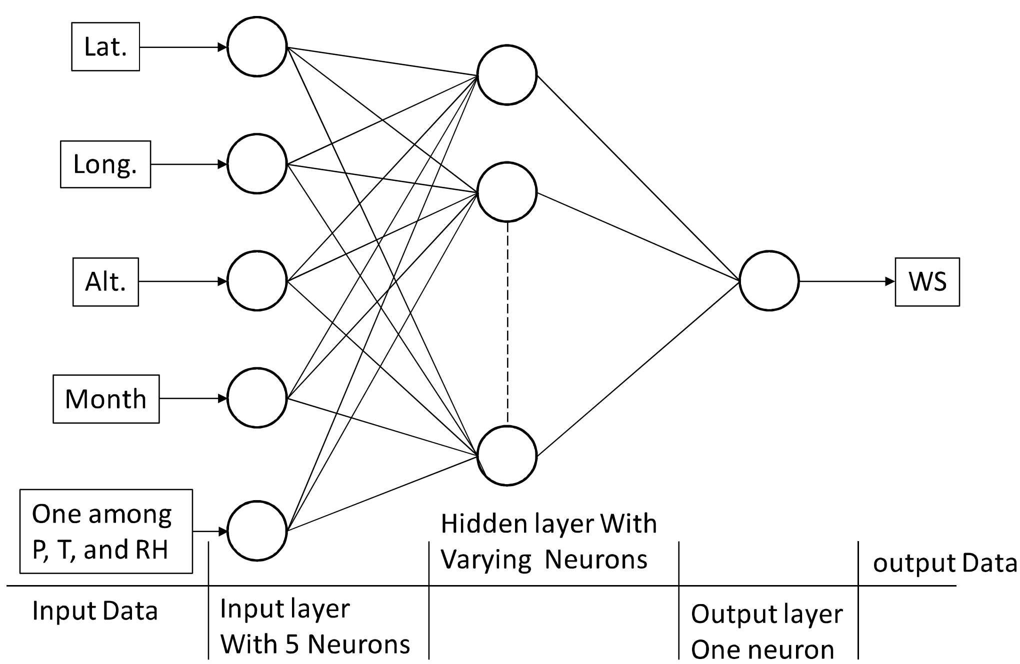

Figure 3.3. Architecture of ANN model for prediction of wind speed.

Training and testing of the model

Typically, in any ANN model information flows in both the directions. First information goes to model as input, to train the model. Once training is done, the model gives the information as output with an error range. The critical part of ANN model development is training with input data. Training of model is carried out on the basis of information received to update or adjust the baises in the network through various algorithms. These weights are updated until the ANN model restores the target output. There is a feedback mechanism in the model called backpropagation. Backpropagation matches the output generated by the model with actual or measured values. Initially, model was designed with multiple combinations of parameters, and different structures of network with single hidden layer. Multiple hidden layers were also tested, where the number of neurons in each hidden layer varied from 1 to 10. It is observed that the structure of ANN model with one hidden layer gives high accuracy. Therefore, network with one hidden layer is considered for study and results are presented for the same.

3.2.2 GIS approach

GIS is a geographic information system that helps to capture, analyze, and present useful information on a map. Predicted wind speed from the developed model was then used to create a map using ArcGIS 10.0. It is capable of handling geographical data, analyzing map information and creating map. GIS helps the decision maker to make a better decision using geographical information. In this case wind speed at different locations with latitude and longitude is represented using the GIS approach.

To develop a map for wind speed, a 3D surface plot is generated using scattered Z-value with X-Y co-ordinates. Wind speed is taken as Z-value and geographical coordinates (latitude and longitude) as X-Y coordinates. The wind speeds at all available locations with their geographical coordinates are imported in ArcGIS and converted into a shape-file. The Kriging method is used to interpolate and create the surface plot. Kriging is based on a geo-statistical analysis, which involves auto-correlation. It considers both distance and direction, and fits a relation to each surrounding point. The surface plot is then analyzed using spatial analyst to form a contour plot of wind speed. The steps used to create a map in this study are summarized in Figure 3.4.

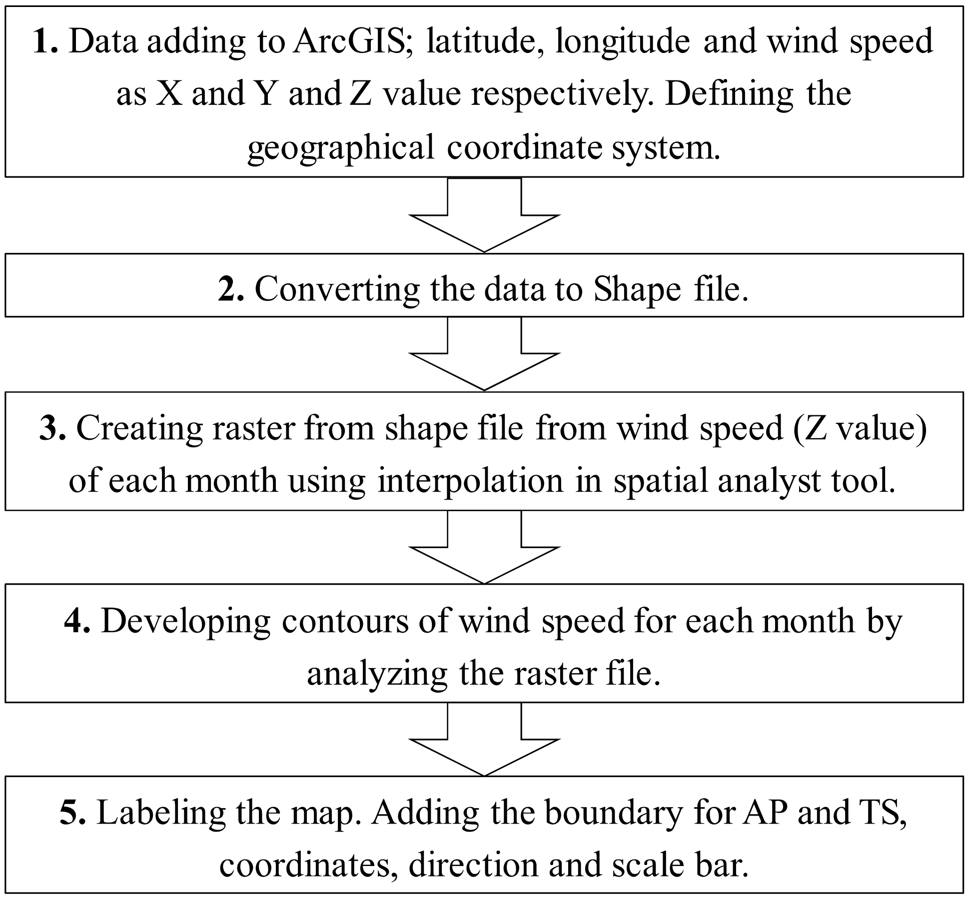

Figure 3.4. Steps involved in mapping of wind speed in GIS approach.

3.3 Estimation of wind speed

To analyze the effect of different parameters on the prediction of wind speed, three meteorological parameters have been taken into account (Temperature, Pressure and Relative Humidity). ANN model with three different sets of input data is designed, considering one meteorological parameter at a time as one of the five input parameters. Thus, there are three cases: Case 1 Pressure as input, Case 2 Relative Humidity as input and Case 3 Temperature as input. Each case is taken separately and analyzed for prediction of wind speed. Training and testing of data yield predicted values of wind speed and then these values are compared with measured values. This comparison is carried out for test location data, which was not used during training of the model. Mean Absolute Percentage Error (MAPE) and mean squared error (MSE) are calculated from predicted and measured values using the following equations:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{W_{mi}-W_{pi}}{W_{mi}}\right| \tag{3.1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(W_{mi} - W_{pi}\right)^2 \tag{3.2}$$

where,

W_{mi} = measured wind speed.

W_{pi} = predicted wind speed.

n = number of testing examples.

The MAPE and MSE evaluate the accuracy of a given forecasting method and expresses its accuracy as a percentage and neglects the signs of errors. All three ANN models were simulated and optimized for a varying number of neurons in the hidden layer. Neurons in the hidden layer varied from one to ten in each case. MAPE was calculated every time, each month for all the locations using Equation 3.1. MAPE for training locations would always be minimum since the training data is used for development of model, hence it is not reported here. The variation in MAPE with different number of neurons in hidden layer for all three cases at four test locations (T1, T2, T3, and T4) is represented in Table 3.3 to Table 3.5. The MAPE value in the first four columns (from T1 to T4) is average of twelve months for each station and in the last column is overall mean MAPE.

Table 3.3. The MAPE for predicted wind speed at test locations with different numbers of neurons in hidden layer for case-1 (pressure as input).

Numbers of neurons in hidden layers	MAPE				
	T1	**T2**	**T3**	**T4**	**Mean**
1	7.41	6.8	4.51	6.23	6.24
2	6.89	6.42	4.96	6.23	6.13
3	6.79	6.28	4.77	6.31	6.04
4	6.57	6.31	4.33	5.37	5.65
5	**6.24**	**5.93**	**3.67**	**5.38**	**5.31**
6	6.42	5.97	3.98	5.45	5.46
7	6.38	6.04	3.78	5.83	5.51
8	6.28	5.96	4.25	5.45	5.49
9	6.66	6.08	4.32	5.19	5.56
10	7.13	6.11	4.53	5.81	5.90

T1, T2, T3 and T4 are the four test locations.

Table 3.4. The MAPE for predicted wind speed at test locations with different numbers of neurons in hidden layer for case-2 (RH as input).

Numbers of neurons in hidden layers	**MAPE**				
	T1	**T2**	**T3**	**T4**	**Mean**
1	3.07	3.48	3.32	3.09	3.24
2	2.78	3.51	2.87	2.78	2.99
3	3.06	2.98	2.43	3	2.87
4	2.85	2.9	2.89	2.71	2.84
5	1.97	3.07	2.58	3.4	2.76
6	**2.02**	**2.19**	**2.42**	**2.01**	**2.16**
7	1.61	2.22	2.93	2.65	2.35
8	2.66	2.67	2.61	3.48	2.86
9	2.57	3.46	2.57	3.26	2.97
10	2.49	3.15	3.08	4.07	3.20

T1, T2, T3 and T4 are the four test locations.

Table 3.5. The MAPE for predicted wind speed at test locations with different numbers of neurons in hidden layer for case-3 (Temperature as input).

Numbers of neurons in hidden layers	MAPE				
	T1	**T2**	**T3**	**T4**	**Mean**
1	8.06	6.92	7.87	8.53	7.85
2	7.47	6.2	7.47	7.89	7.26
3	7.42	5.49	7.4	8.16	7.12
4	8.16	5.91	8.08	8.09	7.56
5	7.55	6.07	7.39	7.61	7.16
6	6.27	5.36	7.68	7.38	6.67
7	**6.62**	**5.5**	**6.59**	**6.8**	**6.38**
8	6.1	6.1	7.32	6.92	6.61
9	7.22	5.85	8.22	7.44	7.18
10	8.01	6.92	8.87	8.7	8.13

T1, T2, T3 and T4 are the four test locations.

It was found that the MAPE first decreases with increase in number of neurons in the hidden layer and then increases after a certain point. It can be observed from Table 3.3, for ANN model with pressure as one input parameter (case-1), that the overall mean MAPE is minimum for five neurons in the hidden layer and three out of four test location have least MAPE for this architecture of model. ANN model with relative humidity as one input parameter (case-2) gives minimum overall mean MAPE, when there are six neurons in the hidden layer (Table 3.4) and three out of four test location have least MAPE value with this architecture of model. Finally, for case-3, when the temperature is taken as input, the overall mean MAPE is minimum for a hidden layer having seven neurons and two out of four test locations have least MAPE value with this architecture of model (Table 3.5). Figure 3.5 shows the variation of mean MAPE for all three cases at four test locations. The comparison of optimized ANN model with respect to MAPE of test location for all three cases is presented in Figure 3.6. The overall mean MAPE of all three cases is 5.31, 2.16, and 6.38, respectively. The MAPE value is minimum for case-2. This indicates that relative humidity is a critical parameter among all the three parameters to predict the wind speed. For case-2, the error in predicted value for all test location is less than 2.5%. Hence, ANN model with six neurons in the hidden layer and relative humidity as one input parameter is considered the most accurate and is taken for further study.

The MSE is calculated for the best model as given in Table 3.6 using Equation 3.2. It can be noted that MSE is minimum for an optimum model with 6 neurons in the hidden layer. The mean MSE for all test locations is 0.0176, with a range from 0.0132 for T4 to 0.0226 for T3. Mean MSE for all training and all validation data sets are 0.00078972 and 0.013995033 respectively.

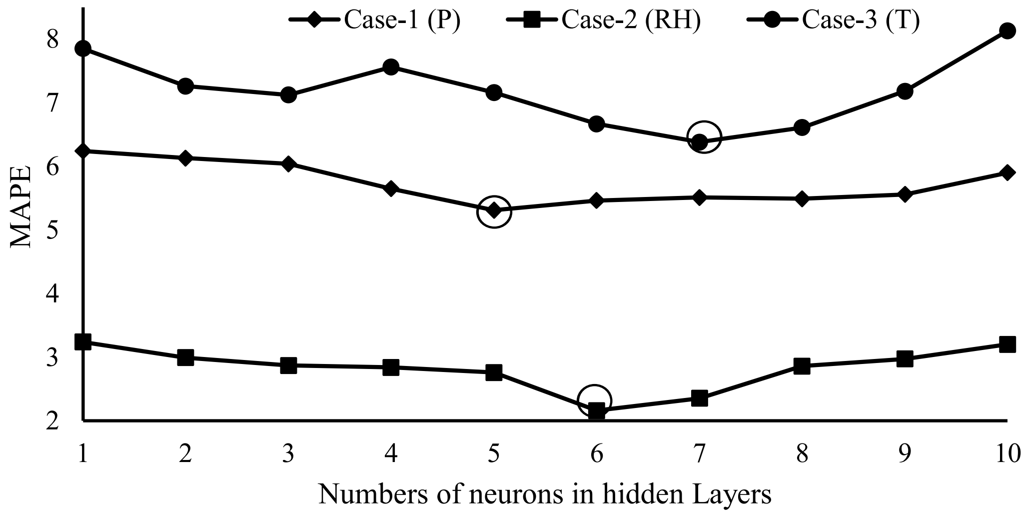

Figure 3.5. Performance evaluation of ANN model for different number of neurons in hidden (case-1, case-2 and case-3).

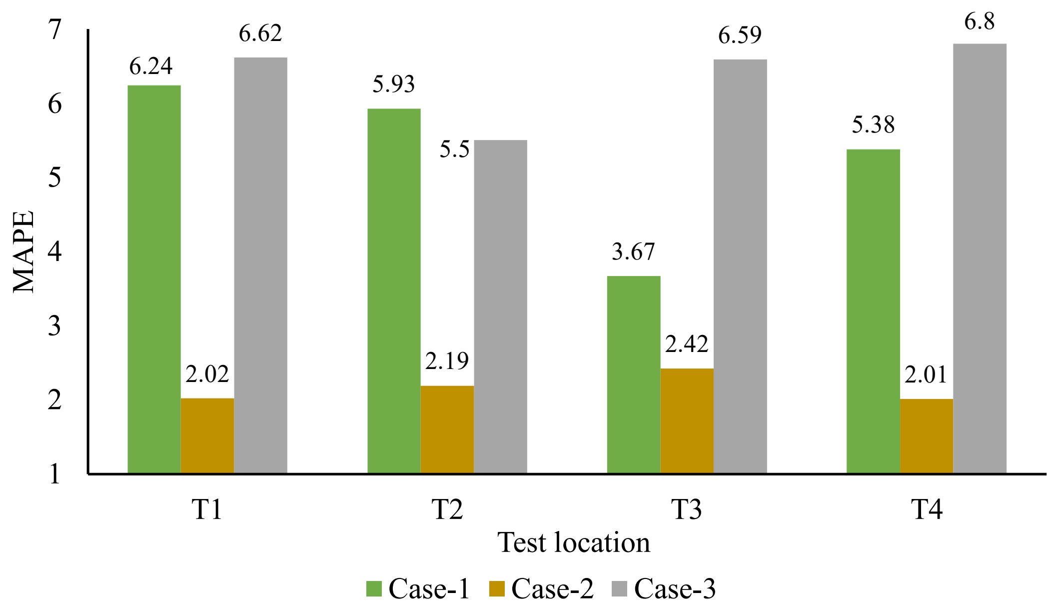

Figure 3.6. MAPE comparison of three optimal ANN model for case-1, case-2 and case-3 at test location (T1, T2, T3 and T4).

Table 3.6. The MSE for predicted wind speed at test locations with different numbers of neurons in the hidden layer for case-2 (RH as input).

Numbers of neurons in hidden layers	MSE				
	T1	T2	T3	T4	Mean
1	0.0390	0.0431	0.0437	0.0303	0.0390
2	0.0409	0.0425	0.0290	0.0314	0.0359
3	0.0385	0.0359	0.0288	0.0329	0.0340
4	0.0301	0.0293	0.0416	0.0325	0.0334
5	0.0189	0.0344	0.0421	0.0713	0.0417
6	**0.0164**	**0.0184**	**0.0226**	**0.0132**	**0.0176**
7	0.0123	0.0186	0.0262	0.0245	0.0204
8	0.0276	0.0257	0.0271	0.0446	0.0312
9	0.0336	0.0385	0.0221	0.0360	0.0325
10	0.0281	0.0523	0.0378	0.0782	0.0491

T1, T2, T3 and T4 are the four test locations.

The overall efficiency of an optimum neural network has been checked by calculating the R-value (coefficient of correlation). It can be seen from Figure 3.7 that optimum network of case-2 has R-values of 0.9974, 0.9577, 0.9611 and 0.9888 for training, validation, testing, and whole datasets, respectively. This shows that the predicted output of ANN model is very close to the measured values of wind speed.

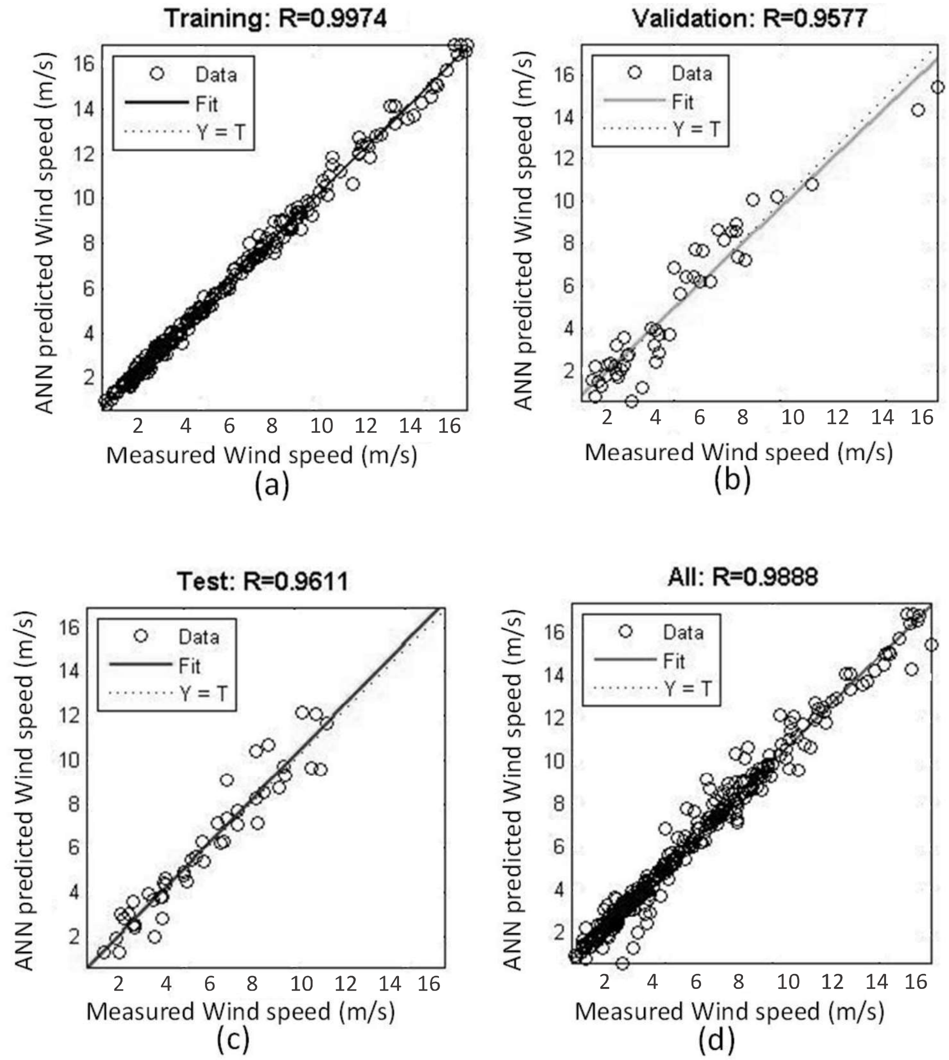

Figure 3.7. Performance of the best ANN model with RH as input parameter (R-value for training, validation, testing, and whole datasets).

Figure 3.8 and Figure 3.9 represented measured and predicted value of wind speed for four test locations (i.e. station number 25 to 28). The result shows a closer approximation between measured and predicted values of wind speed. As it can be seen in the Figure 3.8 and 3.9, the predicted values of wind speed follow the trend and are reasonably close to the measured values of wind speed. The MAPE calculated for the test locations falls in the range of zero to 5. Therefore, maximum error in the predicted value is less than 5%. The MSE for the predicted wind speed at test locations is varies from zero to 0.08, which means that the minimum and maximum difference between measured and predicted wind speed is zero and 0.28 m/s. This indicates the reliability of model, and average MAPE for four test locations are 2.02, 2.19, 2.42 and 2.01 from Table 3.4. This range of error is acceptable in weather data prediction studies, as it is below 6.0 (Celik and Kolhe, 2013). The performance of developed ANN model shows that it works accurately while predicting the wind speed within AP and TS, where the measured wind speed data is not available. Wind speed can be predicted in the form of monthly mean value for each month at any location within AP and TS. The developed model was then used to predict wind speed for 10 major cities in AP and TS.

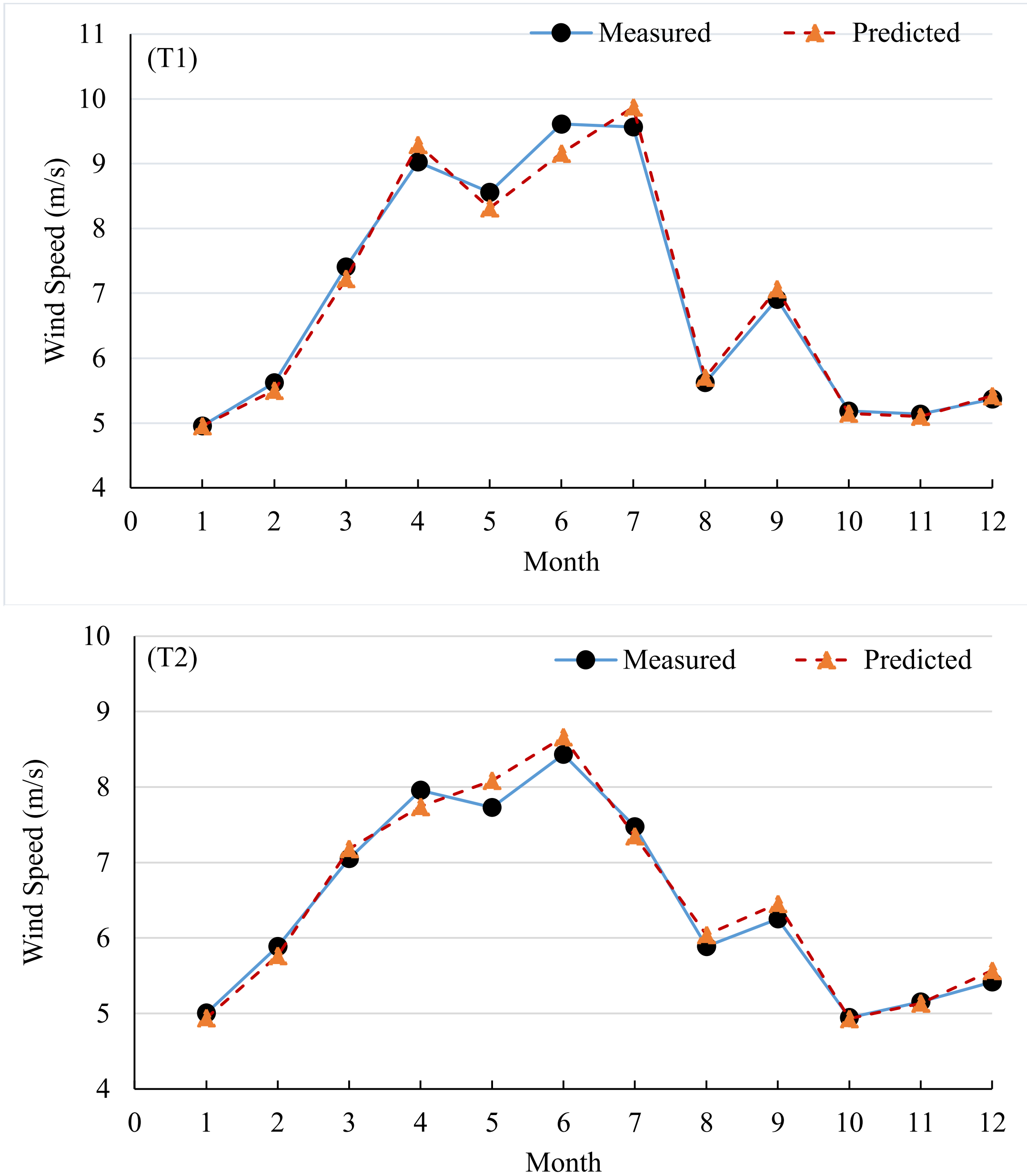

Figure 3.8. Comparison between measured values and predicted values of wind speed for two test locations (T1) station No. 25 and (T2) station No. 26.

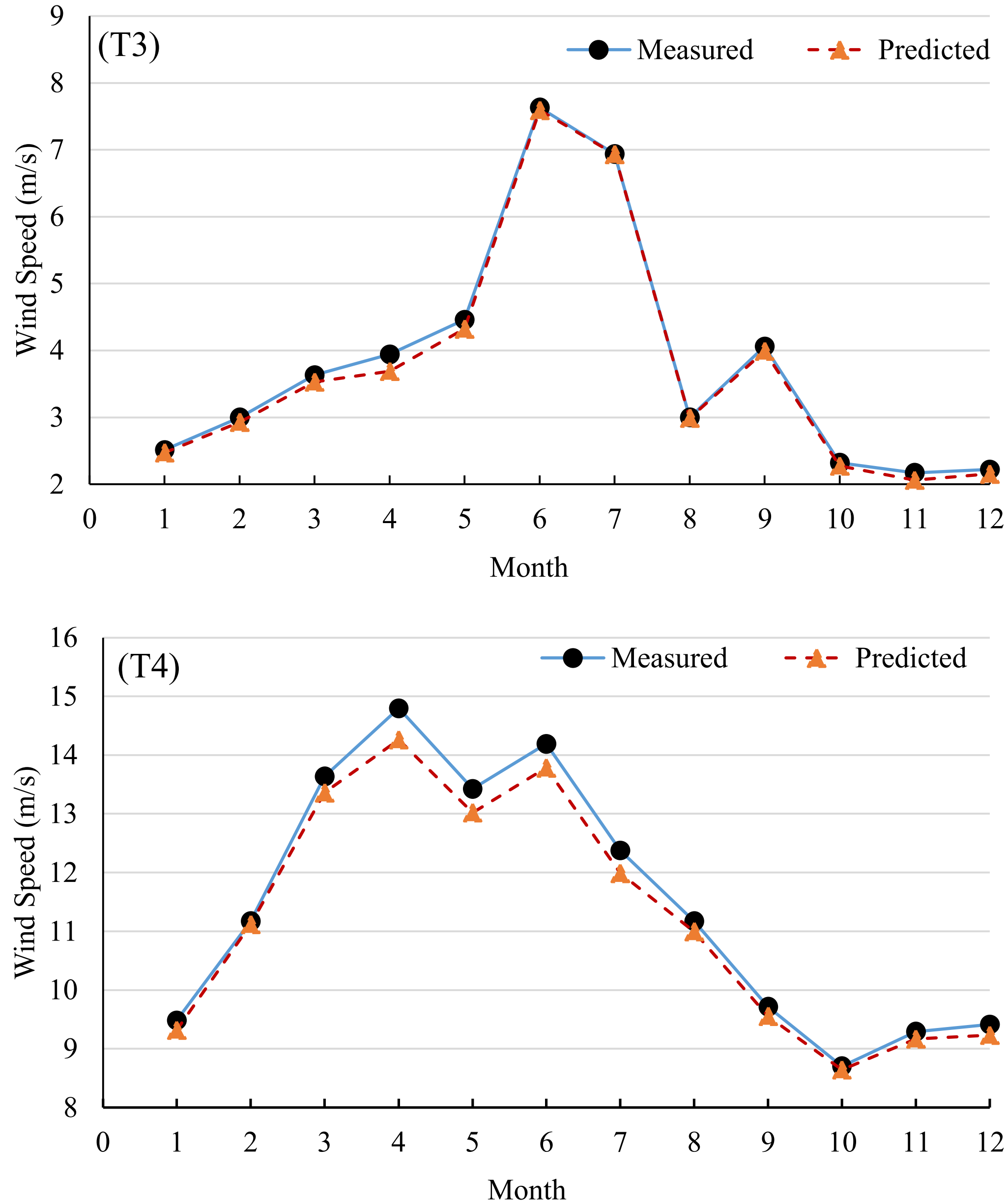

Figure 3.9. Comparison between measured values and predicted values of wind speed for two test locations (T3) station No. 27 and (T4) station No. 28.

Similar approach has been adopted to develop a new ANN model for predicting wind speed, where the measured data is not available. This ANN model requires historical data (minimum 10 years) to get trained. This approach is tested at a sample location (Anantapur district in AP), where monthly mean measured wind speed was available for 20 years (1995 – 2015). The ANN model is trained and optimized for different neurons in hidden layer with this historical data. It is observed that seven neurons in hidden layers gives better accuracy. The model is validated by comparing predicted wind speed with measured wind speed for 2009 and 2013. The MAPE value is calculated to evaluate the accuracy of the model. Table 3.7 presents the variation in MAPE value for the predicted wind speed in each month for the year 2009 and 2013. The average MAPE values for the years 2009 and 2013 are 3.91 and 4.29, respectively. Since the MAPE value is below 6.0, the model can be used to predict the wind speed in successive years (Celik and Kolhe, 2013).

Table 3.7. Performance of ANN model by MAPE calculation for validation years 2009 and 2013.

Month	**MAPE**	
	2009	**2013**
January	3.37	2.10
February	3.29	4.11
March	3.69	3.11
April	4.78	3.06
May	3.36	4.16
June	3.02	6.41
July	4.43	3.82
August	4.04	4.40
September	5.54	4.03
October	3.57	5.85
November	3.75	7.30
December	4.14	3.19

Table 3.8 shows the projected wind speed for the year 2016 and 2017. The projected wind speed for the year 2016 and 2017 is not validated with the measured wind speed, due to non-availability of data in public domain from IMD. IMD, Pune measures, processes and archives the meteorological parameters at various ground stations across the country. The entire process takes time. Then the data is made available for research purposes. The projected monthly mean wind speed using this approach can be used for checking the feasibility of wind farms at any location, where the measured data is not available.

Table 3.8. Projected monthly mean wind speed for the years 2016 and 2017.

Month	**Projected wind speed (m/s)**	
	2016	**2017**
January	5.32	4.87
February	4.93	4.42
March	4.51	4.02
April	4.29	3.85
May	4.95	4.32
June	9.08	7.75
July	13.50	12.60
August	13.48	13.20
September	9.18	9.30
October	5.63	5.80
November	4.794	4.93
December	4.48	4.53

3.4 Mapping of wind speed

The predicted wind speed from the model was analyzed and mapped as monthly mean value with the help of GIS approach. The yearly and monthly mean maps of wind speed in the form of contour were developed. Contour interval for mean wind speed was kept as 0.5 m/s. Wind speed is constant along the contour line in the map. Statistical analysis of wind speed is presented in Table 3.9 with maximum, minimum, average, and standard deviation of monthly mean wind speed.

Table 3.9. Statistical presentation of monthly mean wind speed within AP and TS.

	Monthly mean wind speed in m/s			
Month	**Min**	**Max**	**Mean**	**SD**
January	1.27	9.48	4.10	2.45
February	1.41	11.17	4.66	2.68
March	1.51	13.64	5.33	3.16
April	1.93	16.51	6.19	3.88
May	2.25	15.50	6.63	3.76
June	2.35	16.79	7.72	4.16
July	2.48	16.42	7.28	4.15
August	1.41	11.17	4.66	2.68
September	1.42	10.88	4.94	2.81
October	1.05	8.70	3.82	2.34
November	0.84	9.96	4.00	2.61
December	0.78	9.41	3.97	2.59

The maximum wind speed was found to be 16.79 m/s in the month of June. It can be observed that AP and TS have adequate wind energy potential for wind power systems, especially in

May, June, and July with an average wind speed of 6.63, 7.72, 7.28 m/s, respectively. It can also be noted that the wind speed varies from month to month and region to region. The wind speed is high in the North-East region for all months and low in the North-West region. It can be observed that the monthly mean wind speed ranged from 0.78 m/s in December to 16.79 m/s in June. The wind speed variation is less in October and high in June with a standard deviation of 2.34 and 4.16, respectively. The yearly average wind speed is mapped and shown in Figure 3.10.

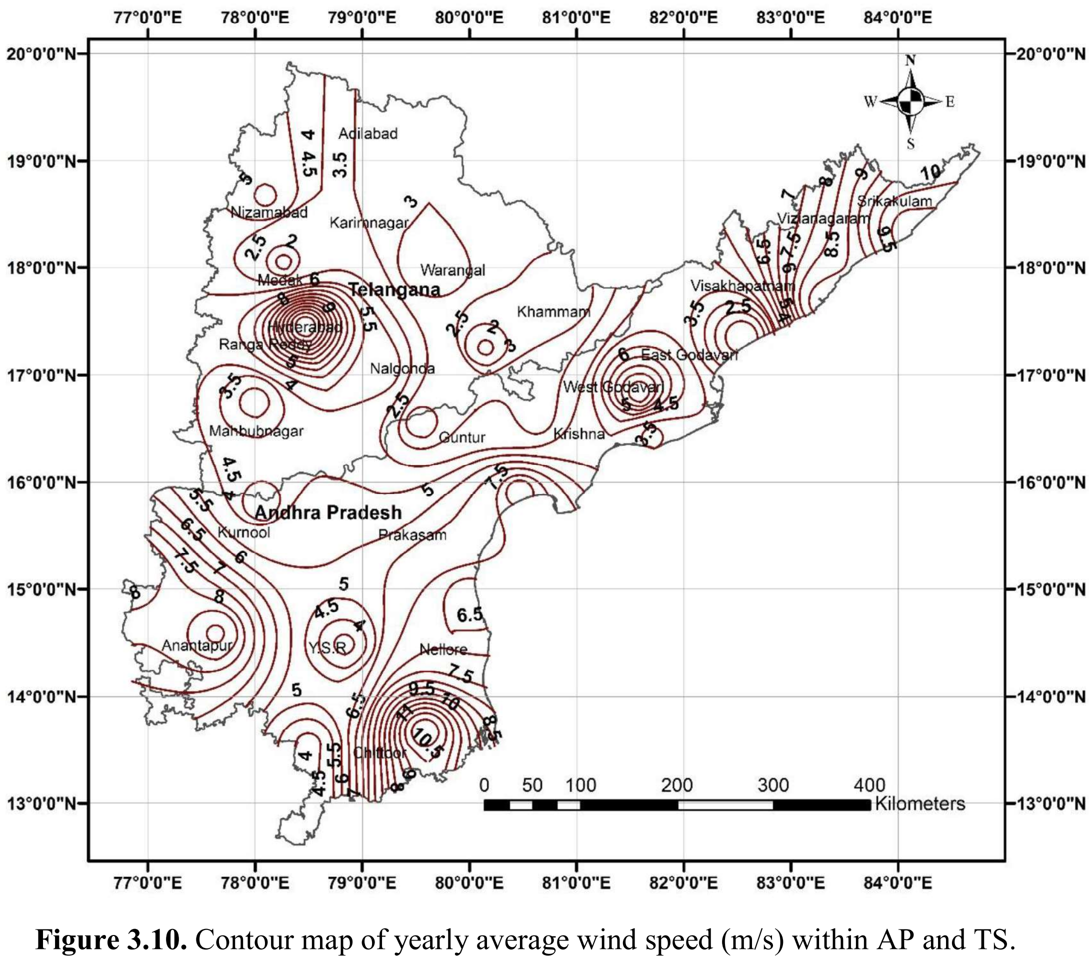

Figure 3.10. Contour map of yearly average wind speed (m/s) within AP and TS.

Variation in the wind speed for each month is also analyzed and mapped separately to visualize the monthly mean wind speed at local level. Figures 3.11 to Figure 3.16 shows the contour map of wind speed for each month from January to December, respectively. These maps can be zoomed-in to get the wind speed value at any location. These maps can be used to find the wind speed in all twelve months at local level within AP and TS. Better visualization and understanding the variation in wind potential in each month at local level can help the decision maker to locate the ideal locations for wind farm within the study region. The predicted wind speed *V,* in m/s at any given location is a key information to calculate the wind energy potential, P(*V*) in Watts. Theoretical wind energy potential can be calculated from:

$$P(V) = 0.5(\rho * A * V_m^3) \tag{3.3}$$

where,

A = sweep area of the rotor blade of the installed wind turbine in m^2.

ρ = present air density.

V_m = mean wind speed.

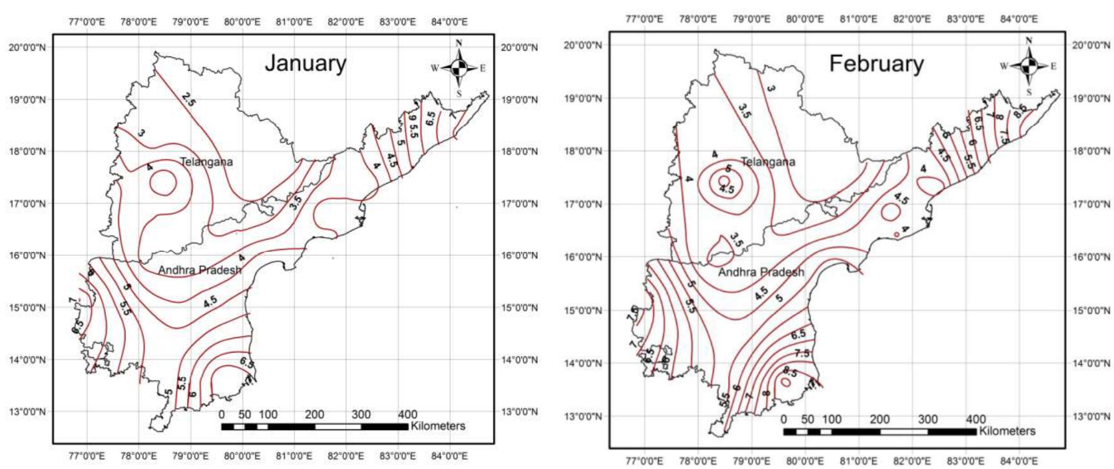

Figure 3.11. Contour map of predicted wind speed (m/s) within AP and TS (January and February).

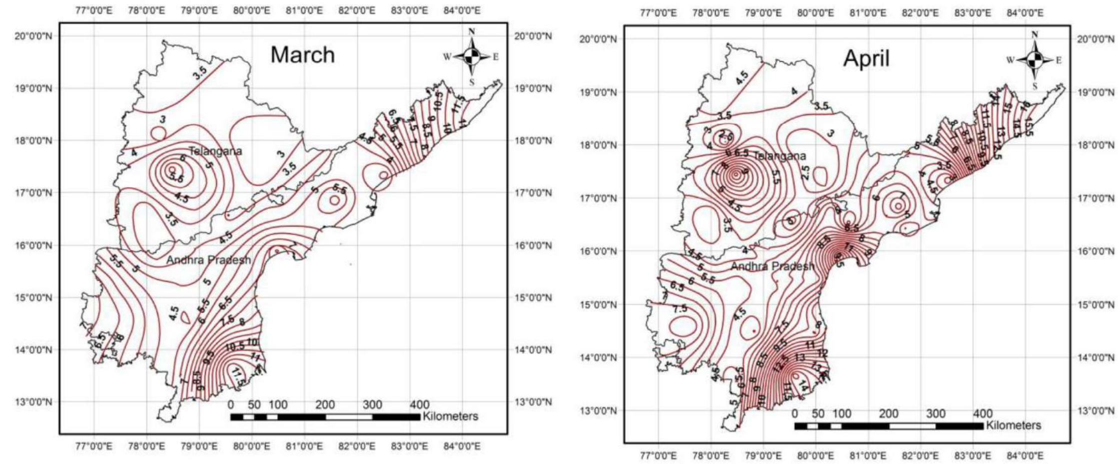

Figure 3.12. Contour map of predicted wind speed (m/s) within AP and TS (March and April).

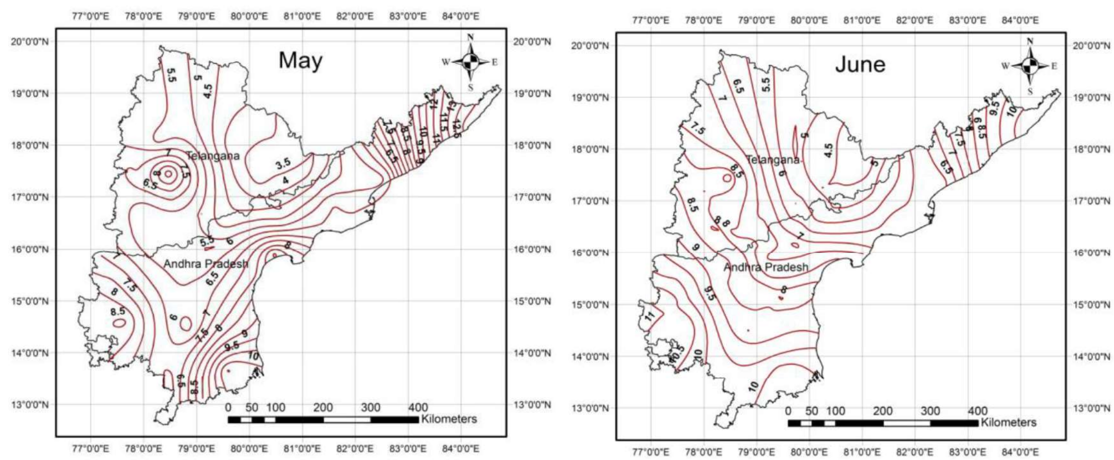

Figure 3.13. Contour map of predicted wind speed (m/s) within AP and TS (May and June).

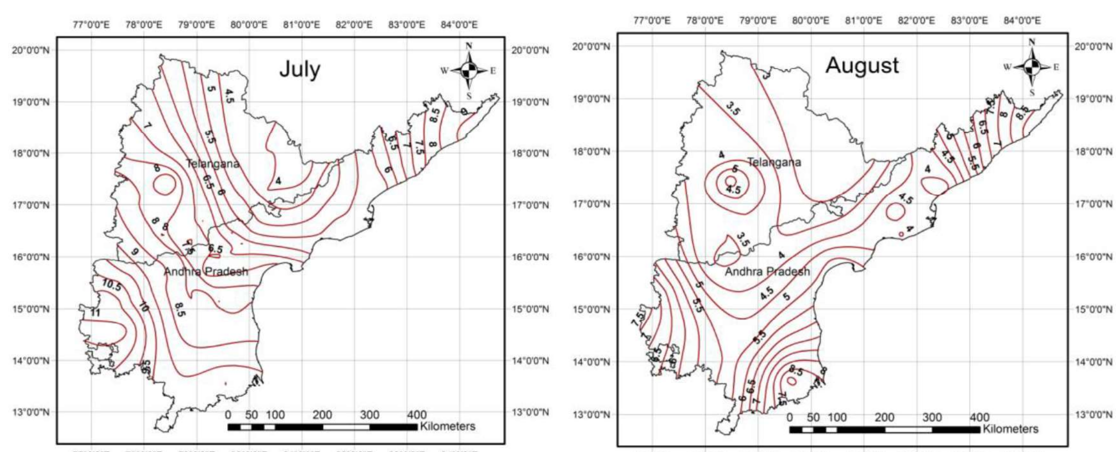

Figure 3.14. Contour map of predicted wind speed (m/s) within AP and TS (July and August).

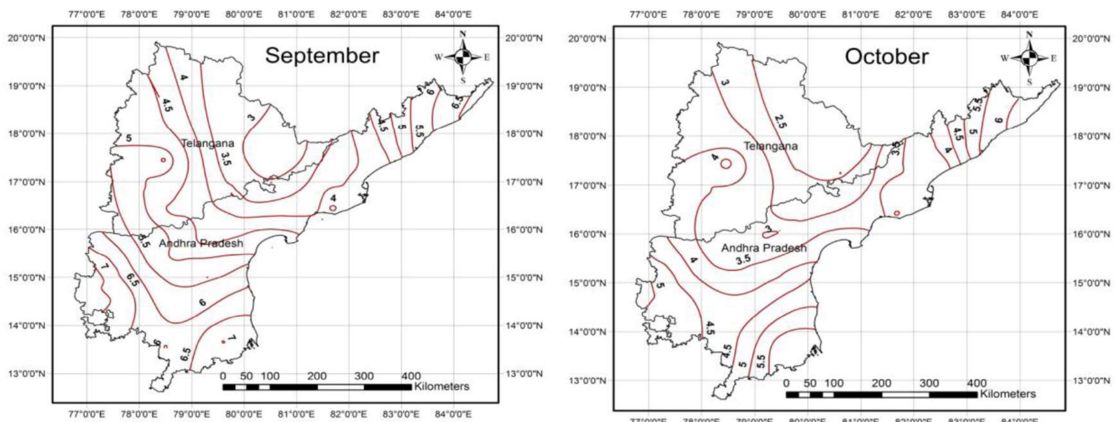

Figure 3.15. Contour map of predicted wind speed (m/s) within AP and TS (September to October).

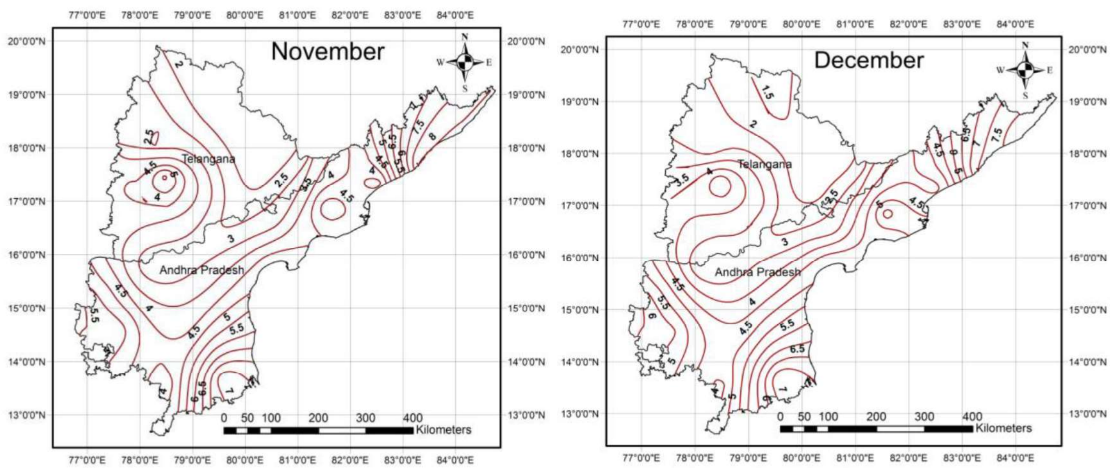

Figure 3.16. Contour map of predicted wind speed (m/s) within AP and TS (November and December).

3.5 Regions with high wind potential

Yearly and monthly wind potential maps are studied to locate the region with high wind potential within AP and TS. Three regions are identified, which have high wind potential as shown in Figure 3.17: North-East, South-West and West. There are three districts: Srikakulam, Vizianagaram and some portion of Visakhapatnam in the North-East region. This region has the highest wind speed for most of the months and the wind speed is in the range of 6 to 11 m/s, which is good and more than cut-in speed for most of the commercially available wind turbines. In spite of high wind speed, this region has large coastal area and uneven terrains, which are not favorable to set up a wind farm. Two districts (Anantapur and Kurnool) in South-West region have wind speeds is in the range of 5 to 11 m/s. These wind speeds are considered good and also have considerably flat terrains to install a wind farm. The West region with two districts, Medak and Ranga Reddy has the wind speed in the range of 4 to 8 m/s. This range of wind speed is more than the cut-in speed of most of the commercially available turbines. To analyze the different types of land classification, the land use and land cover analysis is carried out.

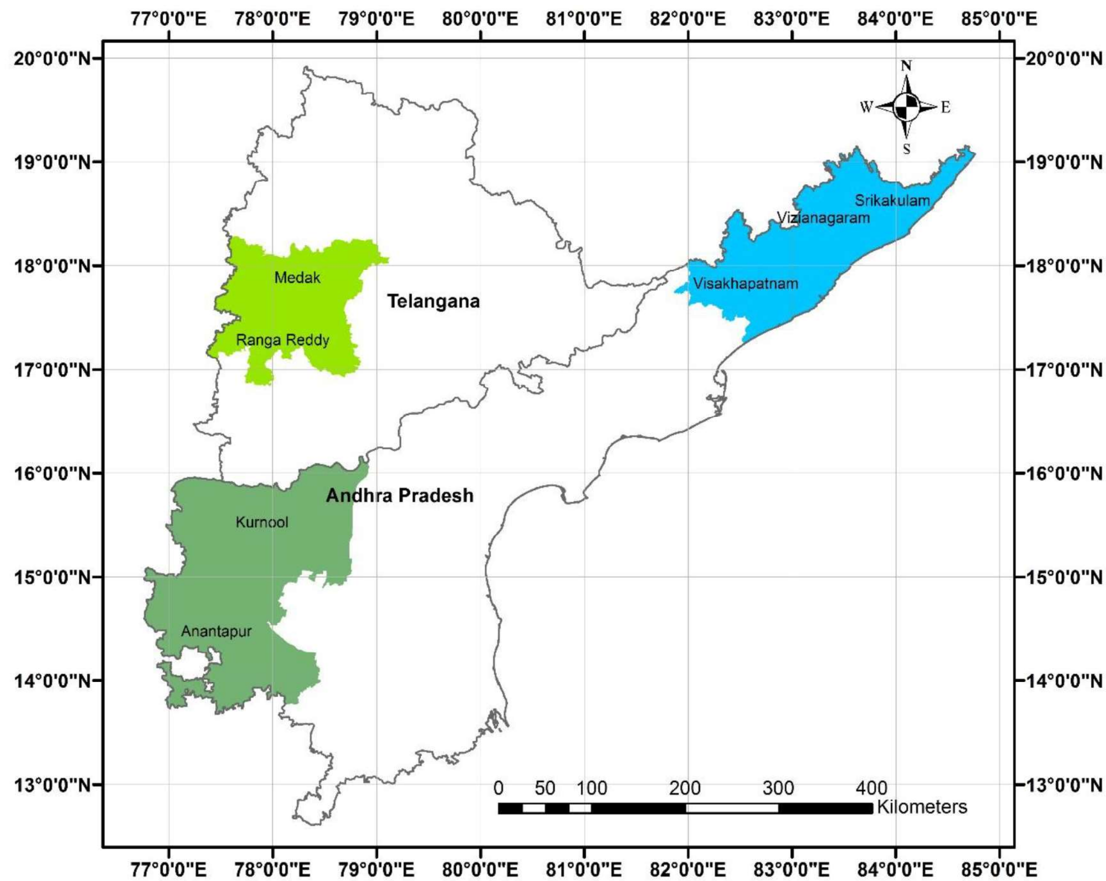

Figure 3.17. Districts in AP and TS with higher wind potential.

3.6 Land use and land cover analysis for wind farm

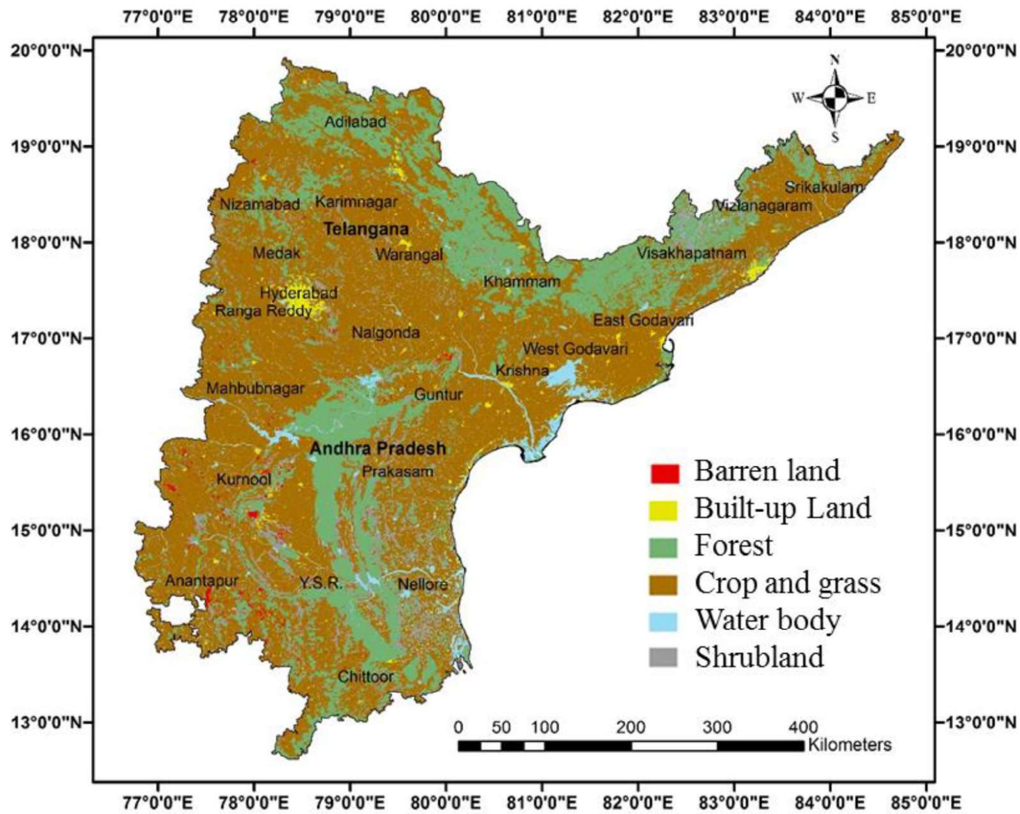

Figure 3.18. Land Use and Land Cover analysis for AP and TS.

Land Use and Land Cover (LULC) analysis is carried out to estimate the area of ideal locations for wind farm installation in the regions, which have higher wind speeds using GIS approach. Remote sensing data is taken from Distribute Active Archive center, Earth Data, NASA for LULC analysis. The data is obtained for India and analyzed to calculate district wise availability of different types of land within AP and TS. The remote sensing map shows the land distribution in sixteen different types, such as Barren land, Built-up Land, Mixed Forests, Mangrove Forest, Evergreen Broadleaf Forest, Deciduous Needleleaf Forest, Deciduous Broadleaf Forest, Cropland, Fallow land, Plantations, Grassland, Water bodies, Aquaculture, Permanent wetland, Shrubland and Wasteland. These types of land are further grouped into six categories as shown in Table 3.10 and the distribution of land categorization over AP and TS is shown in Figure 3.18.

Table 3.10. Classification of different types of land available within AP and TS.

Category	1	2	3	4	5	6
Classification	Barren land	Built-up land	Forest	Crop and grass	Water body	Shrubland
Land Type	Barren land	Built-up land	Mixed forests, Mangrove forest, Evergreen broadleaf forest, Deciduous needle-leaf forest, Deciduous broadleaf forest	Cropland, Fallow land, Plantations, Grassland	Water bodies, Aquaculture, Permanent wetland	Shrubland, Wasteland

Ideally, barren land can be used for installing wind farms. It can be observed from Table 3.11 that Anantapur district has maximum barren land (more than 500 km^2) and Kurnool district has approximately 338 km^2 of barren land. The other two districts, Ranga Reddy and Medak, have relatively less barren land, i.e., approximately 34 and 15 km^2, respectively. Another type of land which can be used for wind farm installation is crop and grass land. However, use of this type of land depends on cropping patterns, number of crops per year and road access for maintenance activities of wind turbines. The predicted wind speed maps and LULC map can be zoomed-in simultaneously to identify districts with high wind potential and to identify locations of barren land within the districts for wind farm installation.

Table 3.11. Area estimation of different types of land in four districts with higher wind potential in km^2.

S. No.	LULC	Anantapur	Kurnool	Ranga Reddy	Medak
1	Barren land	502.50	338.28	34.03	15.74
2	Crop land	13414.06	11377.13	4269.29	7401.96
3	Fallow land	1214.69	772.83	953.10	442.13
4	Wasteland	53.26	41.84	0.00	0.73
5	Shrubland	1357.14	1209.28	510.60	813.22
6	Water bodies	721.42	724.59	148.47	72.80
7	Built-up land	73.53	267.16	1179.92	101.86
8	Plantations	37.31	13.15	72.59	48.65
9	Broadleaf forest	424.78	2286.44	282.05	0.00
10	Mixed forests	1478.28	779.56	211.58	359.23
11	Needleleaf forest	0.00	0.00	42.97	511.63
12	Grassland	0.00	0.00	32.79	0.00

3.7 Summary

This chapter discussed the development and optimization of ANN model for prediction of wind speed within AP and TS, using measured meteorological parameters. A parametric study is carried out to find out the most influencing parameter amongst temperature, pressure and relative humidity to predict the wind speed. It is observed that the relative humidity has greater effect on the prediction of wind speed. The accuracy of model was validated using MAPE and MSE for four test locations. The optimum ANN model is used to predict wind speed within study region. Similar approach has been used to develop a new ANN model for predicting wind speed at a location using historical data, where the measured data is not available. The model is validated by comparing predicted wind speed with measured wind speed for 2009 and 2013 and used to project the wind speed for 2016 and 2017. The predicted wind speed is mapped in the form of contour using GIS approach. Developed contour maps have good visualization of wind energy potential at local level, which could enable decision maker to identify ideal locations for installing wind farms. Moreover, regions with high wind potential are identified based on yearly and monthly maps of wind speed. LULC analysis is carried out to estimate the ideal land area available to install wind farms in the regions of higher wind speeds.

Next chapter presents the estimation and mapping of solar energy potential.