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Estimation of Wind Power Ramp Event

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ABSTRACT: Smart grid technology induces intelligence in the conventional power grid and comprises many different elements, both at supplier and consumer sides. The expansion of renewable resources, especially weather-based resources such as wind, creates more uncertainty and variability in the operation of the power grid**.** Time-series prediction of wind power production become important and challenging task. This proposed workis essential in weather forecast information to predict the possible fault events and make an early warning to improve the operational reliability of power system. This project introduces a method of short term wind power prediction and estimation of wind power ramp rate for a wind power plant based on historical data of wind speed, wind direction, temperature and pressure. For this purpose, Hidden Markov Model based approaches and artificial neural network algorithm are programmed in MATLAB software. In this proposed work Hidden Markov Model is assessed with the wind ramp rate classification based on K-NN classification.Neural networks are capable of handling non-linear data, Neural Networks model train the data, so that a particular input leads to a specific target output.Neural network have the ability to Learn from data, Recognize hidden patterns in chronological Observations, and use these relationships to predict wind ramp rate. In this project finally forecasting performance of proposal models are compared, where its result states that NN produce high accuracy and minimum MSE value when compared to HMM.

KEYWORDS: Hidden Markov Model, hidden layer, Neural Network, accuracy,MSE.

I.INTRODUCTION

Estimation of wind power ramp is defined as sudden raise or fall in the wind power within the short period of time. From the energy angle, predicting the speed of wind that blow in next moment and its duration became essential with an enlarging of renewable energy sector that totally dependent on nature and was largely sporadic. In case of wind energy, it was particularly significant to predict the wind resource in advance, which is due to rapidly increasing diffusion of wind power into the electricity grids compared to other renewable energy sources. Traditionally, the grid operators are habituated with the supply side of the load, the source of electricity, dispatch-ability, reserves, and balancing the whole system. However, with the approach of wind energy and other renewable source of energy a form of dispersed generation due to their intermittency, has mystified the grid operation during power planning like scheduling, dispatching and distribution of the power, which are amongst a variety of other problem. Wind resource although is highly uncertain due to its stochastic nature, but it can be predicted, however with a significant error. Yet with evolving methodologies and models, wind forecasting can be produced up to satisfactory accuracy, out to several days ahead by massive supercomputers which are fed by weather data from array of weather stations, satellite data (like NECP/NCAR) and online wind data sent out by advancing SCADA systems. Wind Power Forecasting InIndia have the total installed capacity of wind energy in India is 17352 MW (as of March 2012); making India the 5th largest wind energy producer in the world. The annual capacity addition is growing at a rate of around 20%.In 2012, according to the Central Electricity Authority, 8% of India's power capacity is supplied by wind energy. The growing wind power is brining prosperity to the country and serving towards energy security, but at a cost of technical challenges.Indian electricity grid condition wasn't really good until Electricity Act 2003 was enacted for development and betterment of this sector.Objective Of This Studyis to implement wind power forecasting **and t**o develop a probabilistic forecast model.

II.LITERATURE SURVEY

NWP models are very complex and can take minutes to hours to complete. The more sophisticated models require a large computing infrastructure and are typically run by large governmental agencies such as the Global

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Forecast System (GFS) at the National Center for Atmospheric Research (NCEP).[10] provided a focus upon forecasting electricity prices in the medium term (from a few weeks to several months ahead) in which accurate estimates of tail risks, e.g., at the 1%, 5%, 95%, and 99%, are important. Medium term forecasting and risk analysis are important for operational scheduling, fuel purchasing, trading, and profit management. A real application of the proposed methodology is successfully tested on the Spanish electric power system, in which the high penetration of intermittent wind generation creates extreme price risks.[9] developed a technique to deal with the wind ramp dynamics, a support vector machine (SVM)-enhanced Markov model for short-term wind power forecast, based on one key observation from the measurement data that wind ramps often occur with specific patterns. Specifically, using the historical data of the wind turbine power outputs recorded at an actual wind farm, data analytics-based finite-state, the forecast by the SVM is integrated cohesively into the finite-state Markov models.

III.PROPOSED METHODOLOGY AND DISCUSSION

In this proposed system, Hidden Markov Model based approaches and artificial neural network algorithm are programmed in MATLAB software.In Hidden Markov Model AlgorithmKNN-enhanced Markov model that incorporates the modelling of wind power ramps and both distributional and point forecasts are then derived accordingly. Specifically, using the statistical information of wind farm generation extracted from historical data, data analytics-based finite-state Markov models are developed to model the “normal” fluctuations of wind generation, while taking into account the diurnal non-stationary and the seasonality of wind generation. KNNs are then employed to capture the wind power ramp dynamics, based on one key observation from the measurement data that wind ramps often occur with specific patterns.

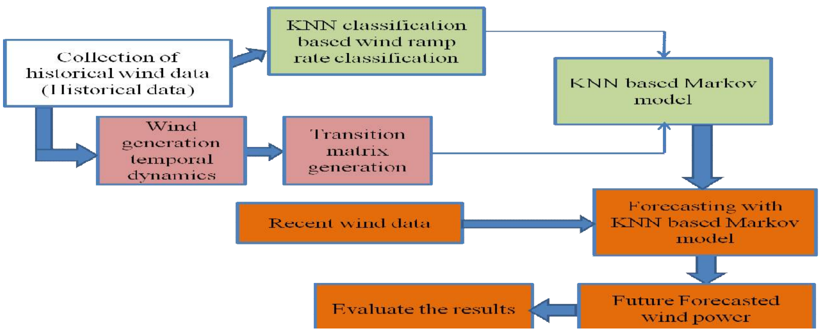

Figure 1 .Block diagram of HMM

A Neural Network is a system that consist of many simple processing elements operating in parallel which can achieve, store, and use experimental knowledge. Wind exhibits non-linear behaviour.Neural networks are capable of handling non-linear data.A simple approach for solving various problems that are otherwise difficult to be modelled by conventional methodsNeural network have the ability to Learn from data,Recognize conspicuous and hidden patterns in chronological observations,Use these relationships to predict forthcoming data. Motivation of Neural Networks is due to its Pattern Recognition, Optimization, Power Systems, Control Systems, Manufacturing, Signal Processing, Psychology, and Forecasting. Also applicable in Forecasting of Weather and market trends**,** Predicting mineral exploration sites Electrical & Thermal load predictions.

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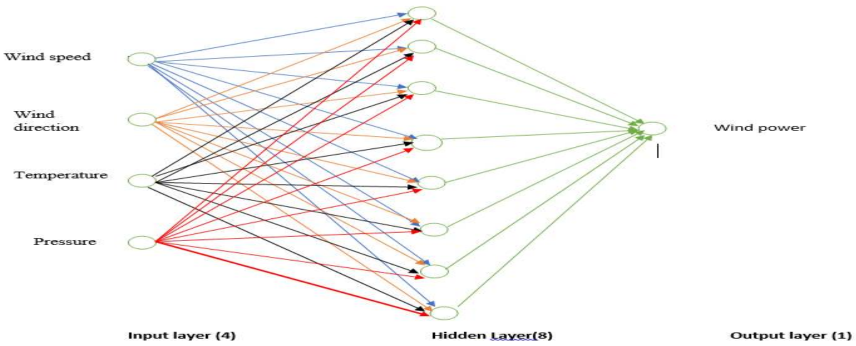

Figure 2. NN for Wind Power Estimation.

IV.EXPERIMENTAL RESULTS

The wind power forecast is mainly depending upon the previous historical collection of data. The data are collected within one hour time interval and the weather data like wind speed, direction, temperature and pressure are collected.

DATE	TIME	WindSpeed (m/s)	Wind Direction (deg)	Temperature (C)	Pressure (mb)	Gen (MW)	Energy (kWh)
08-08-16	21:30	12.1	289	27.0	978.1	47	46896
08-08-16	21:45	12.2	289	26.9	978.1	47	47136
08-08-16	22:00	12.3	289	26.9	978.2	47	47377
08-08-16	22:15	12.4	289	26.8	978.2	48	47617
08-08-16	22:30	12.5	289	26.7	978.2	48	47858
08-08-16	22:45	12.5	289	26.6	978.3	48	47942
08-08-16	23:00	12.5	290	26.5	978.3	48	48025
08-08-16	23:15	12.6	290	26.4	978.3	48	48109
08-08-16	23:30	12.6	290	26.3	978.4	48	48192
08-08-16	23:45	12.6	289	26.3	978.2	48	48110
09-08-16	0:00	12.5	289	26.2	978.1	48	48027
09-08-16	0:15	12.5	289	26.1	978.0	48	47945
09-08-16	0:30	12.5	288	26.1	977.9	48	47863
09-08-16	0:45	12.4	288	26.0	977.7	48	47658
09-08-16	1:00	12.3	287	25.9	977.6	47	47453

Table 1 wind power plant data

Temporal dynamics are called as $P_{ag}(t)$ *[aggregated power]*.This provides changes in power generation
The overall data is divided into samples.The Minimum and maximum values of each sample is calculated.
P_{ag}^{max} – maximum values within a sample.P_{ag}^{min} – minimum values within a sample.

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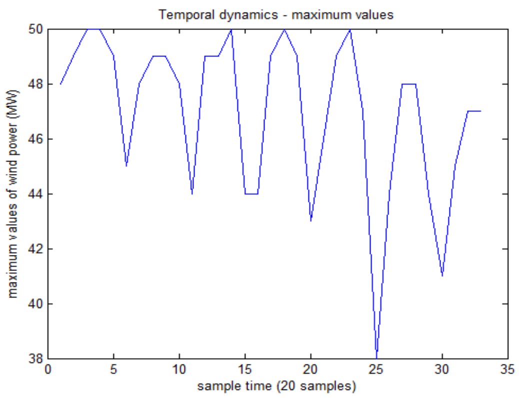

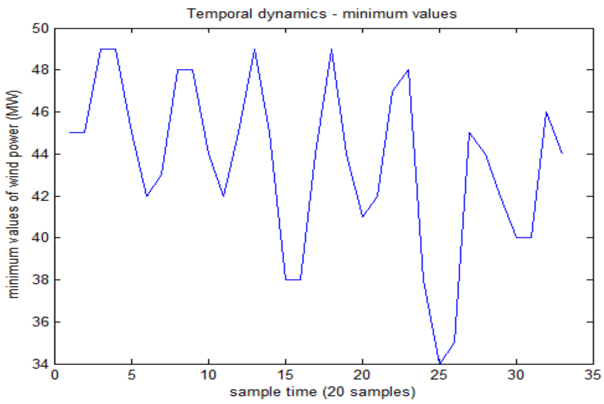

Figure 3 temporal dynamic response maximum values Figure 4 temporal dynamic response minimum values

From the figure 3 &4.The maximum and minimum values of temporal dynamics are 38 & 50MW power generation respectively

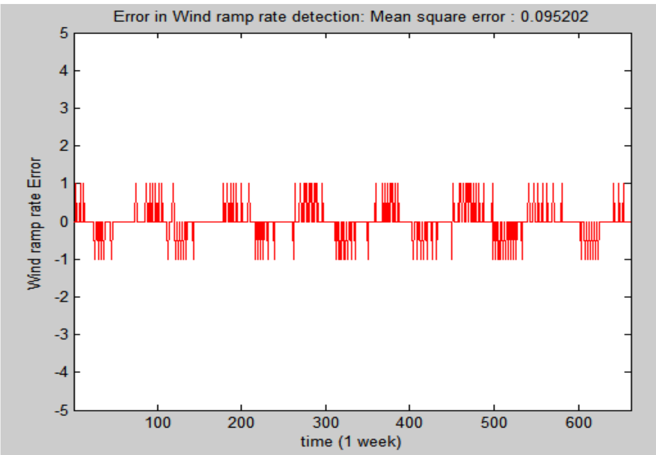

Figure 5.wind ramp rate error (K=1)

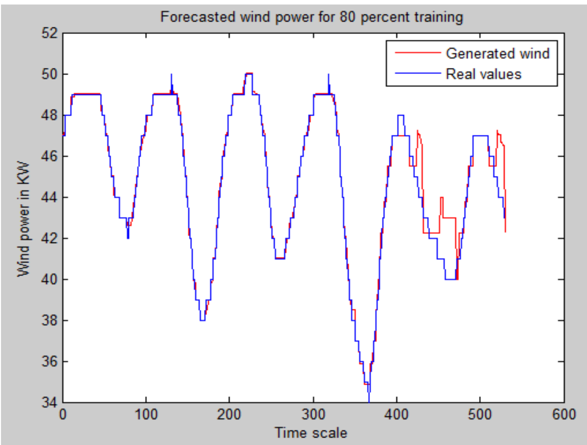

Figure 6.wind power forecast for 80% training

The forecast plot for the 80% training case is shown in the figure6 where the error is minimum due to the higher number of training samples.In KNN, the past observations are called features, and the wind power ramp rate is called as class.By considering value of K=1, the error in wind ramp rate detection mean square error value is calculated as 0.095202.

In figure 7 NN training tool Neural Network training stoppedwhen the validation error increased for six iterations, which occurred at iteration 26. By selecting Performance in the training window, a plot of the training errors, validation errors, and test errors appear.The final mean-square error is small. The test set error and the validation set error have similar characteristics.

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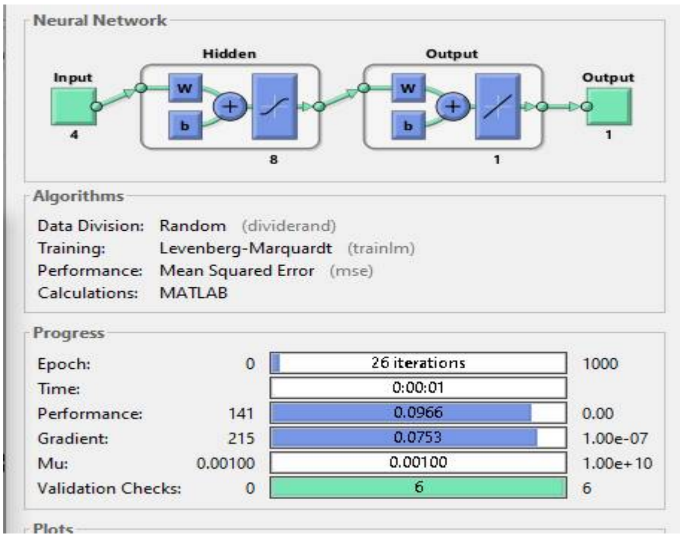

Figure 7 Neural Network Training Tool

Plot training state values (tr) plots the training state from a training record tr returned by train.In training state graph between mu, gradient and val fail are plotted.where mu is controling the parameter which control the weight of the neuron and updating the process.Gradient having linear approximate function compares near by point with actual value Validation defines the number of successive iteration.The property best epoch indicates the iteration at which the validation performance reached a minimum.

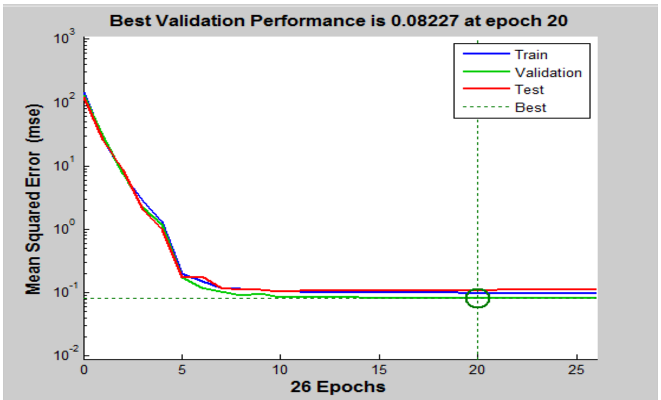

Figure 8 Neural Network Training Performance

In the figure 8 the best validation performance occur at epoch 20 and its MSE value is 0.08227. The training continued for 6 more iterations before the training stopped. This figure does not indicate any major problems with the training. The validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some over fitting might have occurred.

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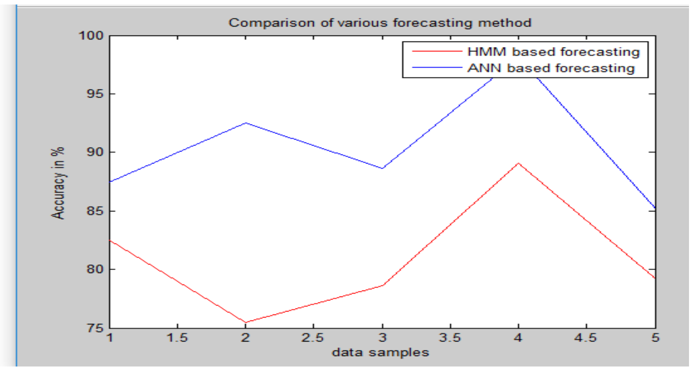

Figure 9 Neural Network Training State

The above figure shows the Comparison between HMM and ANN where the accuracy of ANN is high when compared to HMM. The MSE of HMM is 0.095202 and MSE of ANN is 0.08227. It shows that MSE of ANN is small when compared to HMM.

V.CONCLUSION

The real-time data were collected from the wind power generating companies. The proposed work is based on HMM chain which is a probabilistic model to forecast the wind power ramp rate from the past data. In HMM temporal dynamics values of wind power, transition matrix are simulated and the histogram of each states are observed. The KNN classification for the wind ramp rate was done with the past features. Artificial neural networks are a reliable method for prediction of wind ramp rate. In the ANN, Neural Network tool (nntool) is used for training the network. The neural network training is based on the real time data, where input and target output data are also required. By using NN performance, training state, error histogram, and regression were plotted and its output power values are calculated. Both, HMM and ANN neural networks predicted the time series fairly well. The Neural Network predicts the accuracy in high degree of precision. The proposed topology ANN is predicting the wind power with minimum error in MSE value and which is most suitable for the future implementation.

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