DETERMINISTIC AND PROBABILISTIC FORECASTING FOR WIND AND SOLAR POWER USING ADVANCE DATA ANALYTICS AND MACHINE LEARNING TECHNIQUES.

by

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ABSTRACT

VINAYAK SHARMA. Deterministic and Probabilistic Forecasting for Wind and Solar Power Using Advance Data Analytics and Machine Learning Techniques. (Under the direction of DR UMIT CALI)

The world is moving towards renewable sources of energy for its energy needs and solar and wind power are one of the most promising sources of 'clean' energy. There is a high level of uncertainty and variability associated with these sources of energy due to their dependence on weather conditions. This makes it difficult to integrate them with the grid

The aim of this study is to develop wind and solar power forecasting models using advanced forecasting techniques. A model using a closed-loop non-linear autoregressive artificial neural networks (CL-NAR-ANN) has been implemented to forecast solar power without the use of numerical weather prediction (NWP) as input. This method is compared with its exogenous variant with solar irradiance as input as well as other data-driven models. The results suggest that the proposed model outperforms other models and can serve as a low-cost backup solution for situations when NWP data is not available. A probabilistic forecast is also implemented.

A neural network based one hour ahead to one day ahead wind power forecasting model using NWP data as input is presented. The inputs for the model are chosen after performing a sensitivity analysis of the variables. A multi-model ensemble forecast approach with NWP members is presented. A probabilistic wind power forecast is also presented using the multiple NWP members as input.

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Chapter 1: INTRODUCTION

The global population is projected to increase from 7.2 billion people in 2014 to 9.6 billion people by 2050 [1]. With this increase in population, the global demand for energy has also been increasing. This has led to a high jump in the production of electricity all around the world which is putting a burden on energy suppliers as they must bring more resources than they have in the past. Currently, this demand is met mostly by fossil fuels. The production of energy via fossil fuels like coal, oil, natural gas, etc. produces large volumes of greenhouse gasses which are a major reason for global warming [2]. Most of the current sources of energy are non-renewable in nature which means that they are finite and will soon deplete. The need of the hour is to develop cost-effective and sustainable energy for the future.

One way of doing this is by shifting to alternative sources such as wind and solar, which are considered cleaner and are available in abundance. Countries across the world have realized the energy problem and are in traducing energy policies to promote the use of renewable energy as well as reducing the energy consumption by increasing energy generation efficiency.

Energy as a commodity cannot be stored on a large scale and the demand must be instantaneously met with the supply. With the current energy sources, the supply of energy can be controlled in order to meet the demand [3]. Wind and solar energy generation are largely influenced by weather conditions. Change in weather conditions like temperature, solar irradiance, wind speed, etc. impacts the energy generated by wind and solar energy sources. The uncertain and uncontrollable nature of renewable energy production makes their integration into the grid complicated.

Since no forecast is perfect, there is always a scope for improving the current forecasting model to be more robust and more accurate. This Master's thesis work explores different methodologies to forecast wind and solar power. A model for forecasting day ahead solar power without the use of numerical weather prediction data has been developed and compared with other data-driven models. one hour to one day ahead wind power forecasting models have been developed.

Chapter 2: LITERATURE OVERVIEW

Utilities like California ISO, New York ISO, Midwest ISO, PJM, etc have been using wind and solar power forecasts to effectively manage the high penetration of renewables into the grid. Various forecasting models have been developed and applied for solar and wind power forecasting. Models can be categorized based on their approach to conducting the forecast as physical, statistical and machine learning models. Physical models use NWP data based on meteorological data such as barometric pressure, humidity, temperature, wind speed, wind direction, etc. These models use NWP data calculated using complex equations and initial conditions to calculate power. Statistical models such as time series models (ARIMA, ARMA, etc) form a relationship between the inputs (NWP data) and the power outputs. A mathematical/statistical equation or relationship is formulated between the inputs or the independent variables and the output or the dependent variables [4].

With the development of complex machine learning algorithms, which can not only learn linear but also learn non-linear relationship between the input and outputs, these models were used in renewable power forecasting. Machine learning models use artificial intelligence models such as ANN, support vector machine, etc. These models mimic the learning mechanism of the human brain to learn non-linear relationships [4].

2.1 STATE OF ART IN WIND POWER FORECASTING

2.1.1 WIND POWER FORECASTING USING STATISTICAL METHODS

Karakuş, Kuruoğlu et al. [5] use a polynomial autoregressive model to predict wind speed and wind power. The polynomial autoregressive model is then compared to complex models like ANN. The model uses historical wind power time series to predict future wind power using the dataset from Global Energy Forecasting Competition 2012. 1 hour ahead to 24 hours ahead forecasts are made. The performance of the proposed model is compared to other forecasting techniques such as Elman filter, MLP, etc. using NRMSE, NMAPE and model bias for different horizons. The proposed polynomial autoregressive model outperforms other models for wind power prediction which use the same dataset.

Cao, Liu et al. [6] develop two models to make 1-6 hour ahead wind power forecasts using the autoregressive moving average (ARMA). The first model uses a pattern matching based mechanism to forecast 0-24 hour ahead wind power based on previous days wind power. The second model using ARMA is used to make 1 hour ahead wind power forecasts. The outputs from the two models are then combined to produce 1-6-hour wind power forecast.

Renani, Elias et al [7] use data from an Iranian wind farm to develop a wind power forecasting model using statistical techniques and machine learning technique. ARMA is combined with multilayer perceptron (MLP) to predict wind speed. Subsequently, the wind speed predictions are used to calculate predicted wind power using wind power curve. The time horizon for the model is from 5 mins to 60 mins ahead.

Kavasseri and Seetharaman [8] use a fractional autoregressive moving average (f-ARIMA) to forecast wind power over 24 hours. And 48 hours horizons. Models were run on 4 different sites located in the Minnesota-North Dakota region. It is observed that wind speed follows a slow decaying autocorrelation manner which is used to make the model. The model proves to be about 40% better than the persistent model which is also applied for comparison.

Yatiyana, Rajakaruna et al. [9] explore the prediction of wind speed as well as wind direction to calculate predicted wind power. Wind power is calculated using wind speed, wind direction and air density. Data used is from an Australian wind farm with one-minute time step. Wind speed and wind direction are combined to get wind power using an ARIMA model.

Lijuan, Hongliang et al. [10] use an autoregressive integrated moving average technique to forecast wind power. Then, the residual of the difference between the predicted wind power and the actual wind power is calculated. The Chi-square matrix is calculated for the residual and a Markov chain method is used to correct the predicted next possible state. The Markov chain correction improves the quality of the forecast and reduces error.

Nayak, Sharma et al. [11] focuses on the ramps in weather data that intern cause ramps in wind power generation. A ramp in wind power occurs when the difference between two data points is more than the reference value or the power ramp rate. The suggested method uses a statistical ARIMA based approach to convert wind speed to wind power and identify ramps in wind power. Predicting wind power ramp is necessary for energy operators to maintain a balance in the electric grid. The model also differentiates between up and down ramps.

Zhou and Fang [12] explore the use of a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) technique to forecast wind power. GARCH is traditionally used in econometric forecasts like electric price forecast and stock market forecasts. Autocorrelation function and partial correlation function were plotted to compute the number of required lags for the GARCH model. ARIMA and ARCH models are also created and compared with the GARCH model. The results show that the GARCH model proved to be the best.

2.1.2 WIND POWER FORECASTING USING MACHINE LEARNING METHODS

Kariniotakis, Stavrakakis et al. [13] use wind speed and wind direction, etc. to predict wind power time series using advanced neural networks. The model first predicts wind speed and then uses the predicted wind speeds to predict wind power based on the characteristics of the wind turbine.

Abhinav, Pindoriya et al. [14] explore the use of wavelet transformation to predict wind power. Wind power is split into wavelets of different signals in time and frequency domain. Discrete wavelet transformation is used to decompose the signal using Daubechies wavelet transformation. After the decomposition of wind power signal into multiple wavelets, they are fed into different neural networks with backpropagation. The outputs of the neural networks are later combined to reproduce the predicted wind power signal. One day ahead forecasts are made using this technique. It is a good technique to create more robust models.

Barbounis, Theocharis et al. [15] deals with long-term wind power forecasting up to 72 hours. Recurrent neural networks (RNN) are used to predict wind power forecasting. 3 RNNs are created and compared to static models.

Bhaskar and Singh [16] explore the use of adaptive wavelet neural network in the first stage and feed-forward neural network in stage two to predict wind power without the use of numerical weather prediction data. The network is trained on four hours ahead prediction and used in a recurrent way to make 30 hours ahead wind power. In the second stage, a nonlinear autoregressive with exogenous inputs are used. Historical wind speed and wind power are used. The sigmoid activation function is used as the transfer function in this model.

Catalão, Pousinho et al. [17] combine the use of wavelet transformation and artificial neural networks to predict wind power. First, the wind power signal is broken down into several wavelets using wavelet transformation. These multiple wavelets are then predicted individually, and then inverse wavelet transformation is used to combine the wavelets. This approach yields wind power forecasts in the end. It is compared to the commonly used ARIMA model and the results show that the combination of neural network and wavelet transformation performs more efficiently than the ARIMA model.

Catalao, Pousinho et al. [18] explores multilayer perceptron-based artificial neural network to predict wind power. 24 hour ahead wind power is predicted using a feedforward ANN model. Random days in winter, spring, summer and fall are chosen and wind power is predicted to present a wide performance evaluation of the model. Mean absolute percentage error of 3.26% is achieved for Fall whereas MAPE for winter is around 9.5%. This shows the fluctuations in wind power generation over the year.

2.1.3 ENSEMBLE WIND POWER FORECASTING

Silva, Rosa et al. [19] explore ensemble wind power forecast. First deterministic forecasts are made using numerical weather prediction data and statistical methods. The model makes use of historical wind power data, most recent wind power data as well as NWP data to forecast wind power. Using these models the uncertainty is forecasted. These forecasts are combined to produce ensemble based wind power forecasts that are probabilistic.

Li, Wang et al [20] use an ensemble of neural network techniques to predict wind power. Frist a conditional mutual information model based on feature selection is proposed to forecast point wind power forecasts. A neural network-based wavelet method is also used to predict wind power. In this method, three layers of feedforward neural networks are designed to increase the accuracy of the model. The multiple frequencies in the wind power time series are captured using wavelet transformation. Then the wavelets are combined using an intelligent method to increase the accuracy further. Thirdly, a partial least squares regression method is developed. The methods are tested on data from National Renewable Energy Laboratory (NREL) for various look ahead times.

2.1.4 PROBABILISTIC WIND POWER FORECASTING

Gneiting and Katzfuss 2014 [21] define probabilistic forecasts as a prediction probability distribution of point forecasts or events. For energy forecasts, typically for hours to day ahead forecasts, probabilistic forecasts are very useful. Ensemble forecasts can be generated by using different input sets to generate multiple forecasts. Statistical post-processing of ensemble forecast is another way where quantiles of ensemble forecasts are generated and used to make probabilistic forecasts. The paper points out the trend of probabilistic forecasts from point forecasts and explores the use of the probability integral transform (PIT) histograms.

Wu, Su et al. [22] use NWP data from Taiwan to propose a probabilistic wind power forecasting method. The data is preprocessed in order to extract feature important for making a forecast. After preprocessing the data, a neural network was trained using this data to get lower-upper-bound-estimation. The final predictions were tested on three different test sets and compared with persistence methods to evaluate the performance of the model.

Gensler and Sick [23] explore probabilistic wind power forecasts using a multi-model approach. Data from 37 wind farms from EuropeWindFarm is used to make the multi-model forecasts. Then these forecasts are combined in a hierarchical manner based on weight factors termed as gradual cooperative soft gating.

2.2 STATE OF ART IN SOLAR POWER

2.2.1 SOLAR FORECASTING USING STATISTICAL METHODS

Bacher, Madsen et al. [24] propose a 2 stage approach to online forecasting of power production from PV systems. In the 1st stage, statistically normalized solar power is calculated using clear sky model. Then the solar power is calculated using adaptive linear time series models. 15 min observations from 21 PV systems located on rooftops across Denmark were used to train the models. Both AR and ARX models are compared. The ARX model, when fed with both solar observations and NWPs (Numerical weather Predictions), performs the best. Available observations of solar power are most important for the forecast of up to 2 hours ahead. For longer horizon, NWPs are the most important input. A 35% improvement of RMSE is observed with proposed reference.

Jiahui, Shutang et al. [25] explore statistical learning of historical solar power data to create ensemble forecasts. Using weather data and historical solar power data, three forecasting models are created: a linear regression model, a neural network model and a random forest model. The models are combined in a statistical manner to get maximum accuracy.

Darbali-Zamora, Gómez-Mendez et al. [26] use a Holt-Winters predict model to forecast solar irradiance. The data used is from Puerto Rico. The forecasts are then applied to different case studies to analyze the effect of the forecast accuracy and quality. Battery energy storage unit model and a PV system model are some of the models used to conduct the case studies. Energy management strategies are also analyzed and suggested in the work.

2.2.2 SOLAR POWER FORECASTING USING MACHINE LEARNING METHODS

Gairaa, Chellali et al. [27] use a non-autoregressive neural network to predict the clearness index, which is used to forecast solar radiations worldwide. The NAR model is compared to autoregressive moving average (ARMA) model. The model uses data of 3 years (2012-2014) global solar radiation time-series for Ghardaïa (dessert) site. (Before optimizing the NAR model, clear index approach was adopted in order to make the data stationary). The proposed model provides an improvement of 23.9% in terms of mean absolute error and a 15.50% decrease in terms of root mean square error value when compared to ARMA method. The NAR model can be used to predict daily global solar radiation with acceptable precisions.

Nazaripouya, Wang et al. [28] propose a discrete wave transformation with NARX to predict nonlinear patterns in solar power. An RNN is used with NARX to predict solar power time series with an exogenous input. The model performs well on all types of days. Later, wavelet transformation combined with ARMA is compared wavelet-ARMA-NARX.

İzgi, Öztopal et al. [29] use ANN to forecast solar power time series. They use past historical solar power data to train the ANN model. The predictions are performed from 30 mins to 300 mins with 30 min interval. The predicted values are compared with the actual values to calculate the error and performance of the model.

Behera, Majumder et al. [30] explore a new machine learning technique known as extreme learning machine (ELM) to predict solar power forecast. The models are trained in MATLAB based on a single layer feed-forward network (SLFN). Different time horizons are predicted. The performance of the ELM model is compared over 15 min, 30 min and 60 min time horizons. The ELM model performs better as compared to an ANN model in terms of RMSE, MAPE and MAE.

Huang, Huang et al. [31] build six sub-models based on the type of day: a sunny day, sunny and cloudy day, cloudy and sunny day, cloudy day, cloudy and rainy day and rainy day. To capture the recency of the weather information, past historical weather information is used in the model. The proposed model is compared with ANN and SVR model to evaluate the performance over different days in different seasons. Training the model based on different days gave better results than other models trained over continuous data.

2.2.3 PROBABILISTIC SOLAR POWER FORECASTING

Ordiano, Doneit et al [32] use regression to generate point forecasts using the present and historical information to make the next timestep ahead forecasts. Multiple point forecasts using data-driven forecasting models are modelled. The point forecasts are then converted to quantiles by combining them using a quantile regression model. The paper uses, k-nearest-neighbor based quantile regression model to generate the quantiles for probabilistic forecasts. They make use of a freely available dataset for PV power from an Australian energy provider.

Zhang and Wang [33] explore probabilistic solar power forecasts on the benchmark GEFCom 2014 solar data using k-nearest neighbour method combined with a kernel density estimator. the k-nearest neighbour method is used to predict point forecasts based on k-nearest points in the variable space. After predicting the point forecast, kernel density estimator is used to generate various quantiles required for the probabilistic forecast. An exploratory data analysis is conducted to achieve accurate point forecasts. RMSE is used to evaluate the point forecast and quantile scores are calculated for each of the 99 quantiles.

Silva, Lim et al. [34] aim to forecast solar irradiance using historical solar data and weather data. They produce point forecasts using linear regression, probabilistic forecasts, and Bayes models for one-day ahead forecasts. The effect of the size of the training set has also been explored. For the lesser amount of training set, Bayes models are recommended. For the probabilistic forecasts, k-means clustering is used based on historical solar irradiance data. By varying the training set, the robustness of each model is tested, and Bayes is concluded to be more robust.

Chapter 3: METHODOLOGY

3.1 FORECAST HORIZON

Wind and solar power forecasting models can be classified based on their forecasting horizon. The forecasting horizon can be defined as how many steps ahead in time is the model forecasting. Based on this forecasting horizon, models can be classified as very short-term forecasting, short-term forecasting, medium-term forecasting, and long-term forecasting.

In very short-term forecasting, the forecasting horizon is a few minutes. The forecasting model runs multiple times in an hour. In short-term forecasting, the forecasting horizon is from a few hours to day ahead. TSO uses short-term forecasting models to make energy trading decisions. Medium-term forecasting models have few days ahead as the forecasting horizon. Lastly, long-term forecasting models can have up to weeks ahead forecasting horizons. As the forecasting horizon increases, the prediction error also increases.

3.2 PERSISTENCE MODELS

Persistence models are the most basic and simplest forecasting models. As the name suggests, these models depend on the similarity in the predicting time series. In other words, persistence models assume forecasts to be same as previous actual values. In this research, three persistence models (Persis1-Persis3) are created in order to compare with the proposed models.

3.2.1 PERSISTENCE MODEL 1 (PERSIS 1):

The first persistence model assumes that there is no change in the power value. This model takes the value from the previous day and assumes it to be the forecast value. This model is explained by the equation:

$$\hat{P}[k + 24] = P[k]$$

3.2.2 PERSISTENCE MODEL 2 (PERSIS 2):

Unlike the first persistence model that assumes the forecast to be the same as that from the previous day, this persistence model considers the previous day and the day before that as well. This model averages the PV power values from the previous day and the day before the previous day. It is given by the equation:

$$\hat{P}[k + 24] = 0.5 * P[k] + 0.5 * P[k - 24]$$

3.2.3 PERSISTENCE MODEL 3 (PERSIS 3):

Similar to the first and second persistence models, this model goes a step ahead and considers the averages across the previous three days. It considers the average of previous day’s PV power,the day prior to the previous day and the day prior to that. The following equation can explain it:

$$\hat{P}[k + 24] = 0.33 * P[k] + 0.33 * P[k - 24] + 0.33 * P[k - 48]$$

3.3 POLYNOMIAL REGRESSION MODEL

A polynomial forecasting model is a regression-based approach where the dependent variable is regressed on powers of the independent variable. The equation can explain the polynomial model:

$$y_i = \beta_0 x_{i1} + \beta_1 x_{i2} + \cdots + \beta_k x_{ik} + e_i \; for \; i = 1,2,3, \ldots., n$$

Or

$$Y = X\beta + e$$

Where,

y_i is the i^{th} value of the dependent variable Y,

x_{ik} is the i^{th} value of the k^{th} independent variable,

β is the slope of the regression,

e_i is the error.

The least squares approach is used to minimize the error while performing the regression. The following equation can give an error:

$\mathrm{e} = Y - X\beta$

The aim is to minimize the sum of squares of error which is given by:

$$e^T e = (Y - X\beta)^T (Y - X\beta)$$

Where,

e^T is the transpose of the error matrix.

Poly'n' means that the model considers the value from P[k] to P[k-H1] and raises them to a degree 'n' and chooses the best four features through a least square approach.

3.4 ARTIFICIAL NEURAL NETWORK

The heart or the building block of a neural network is a perceptron. It takes inputs and produces the desired output. The following figure shows a perceptron.

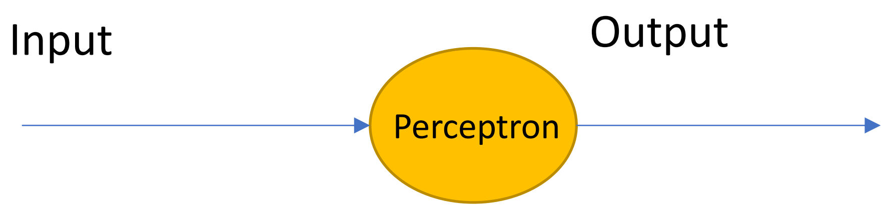

Figure 1 Perceptron of a neural network

A neural net consists of various perceptrons, and each perceptron is connected has multiple inputs and outputs. The following figure shows the connection:

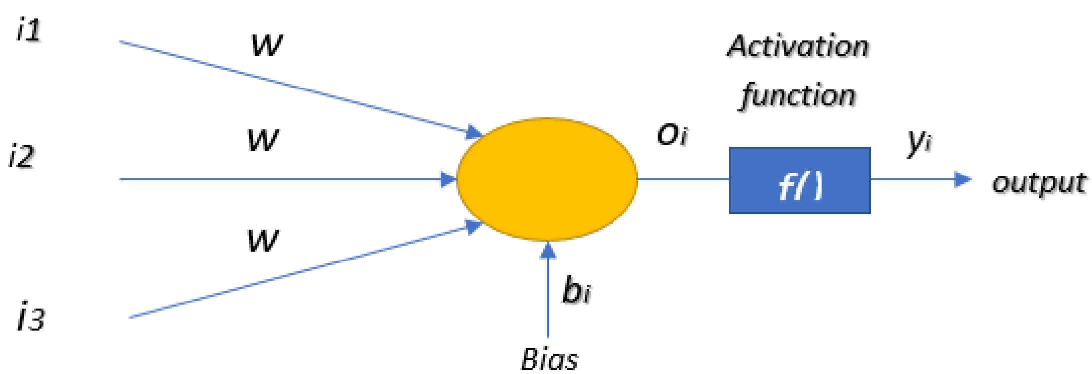

Figure 2 Input and output connections with perceptron along with bias and activation function.

Now, if a perceptron is connected to three inputs, i1, i2 and i3, each of these inputs contributes to deciding the output. These inputs are associated with weights to give reflect the significance of each input. So w1, w2 and w3 are the corresponding weights to i1, i2 and i3. Bias is added along with the weights. Bias is given by *b1*. The output is calculated based on an activation function.

Activation function: The activation function calculates the sum of inputs depending on their weights a calculates the output. In general, a nonlinear activation function is used in order to define a non-linear relationship [35] between the inputs and the output. can be given as:

$$\boldsymbol{O_i = f(\sum_{i=0}^{N} i_i w_i)}$$

The final output after adding bias would be:

$$\boldsymbol{y_i = O_i + b_i}$$

A simple piecewise-linear activation function can be given by:

$$f(\boldsymbol{i}) = \begin{cases} \boldsymbol{1\ if\ i > 0} \\ \boldsymbol{0\ if\ i = 0} \\ \boldsymbol{1\ if\ i < 0} \end{cases}$$

The most commonly used sigmoid function makes the value between 0 and 1.

The sigmoid function is given by:

$$\boldsymbol{f(i)\frac{i}{1 + e^{-i}}}$$

Sigmoid function when plotted can look like:

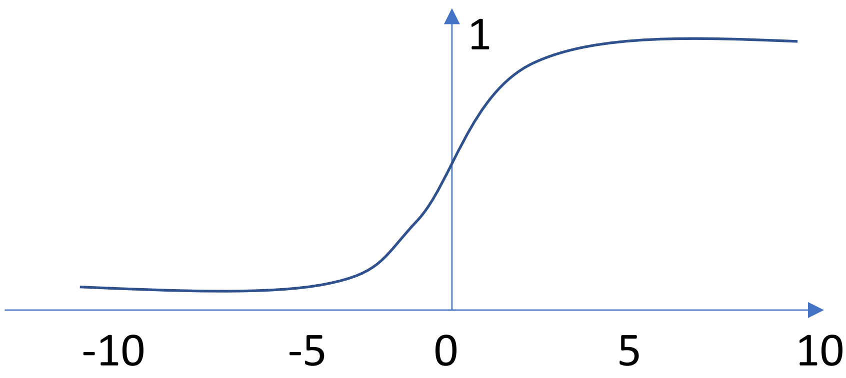

Figure 3 Sigmoid function plot

The following steps were followed to create a neural network model:

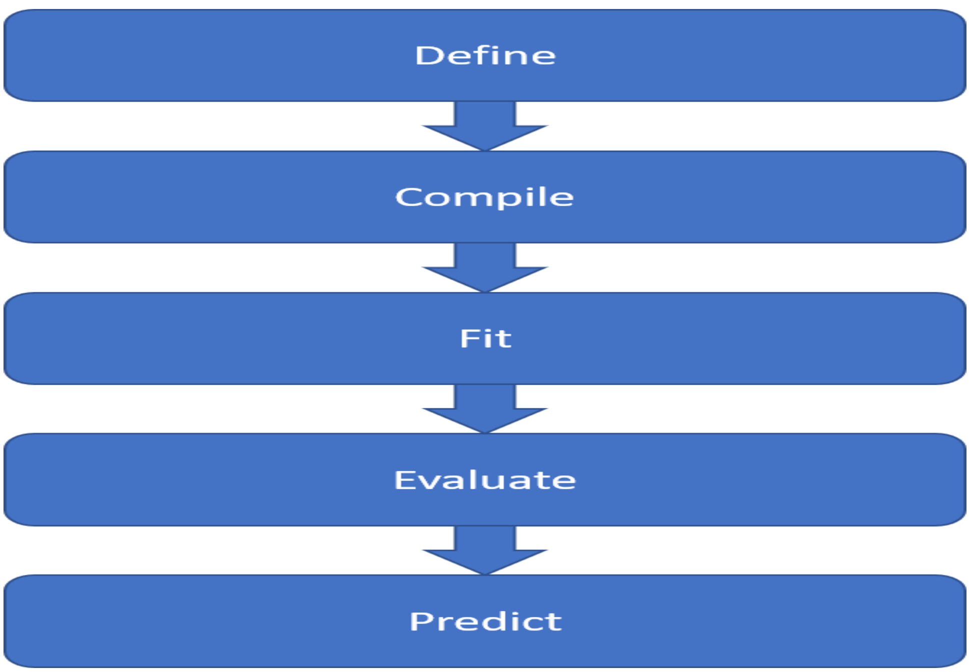

Figure 4 Process of creating a neural network model.

3.4.1.1 NETWORK DEFINITION

The very first step is to define a neural network. This is done in different layers as can be seen from the figure:

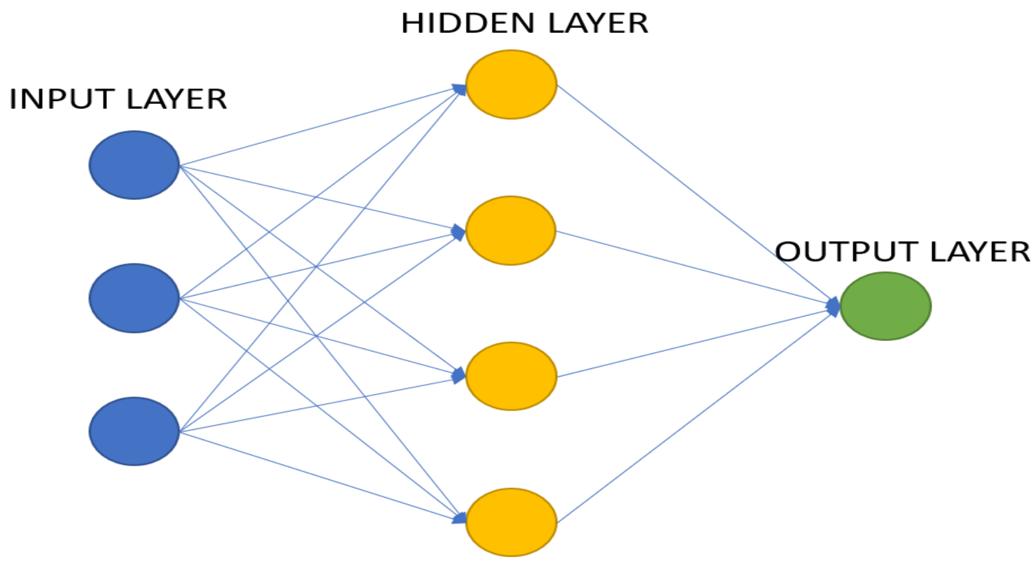

Figure 5 The various layers of a neural network and neurons in the layers.

- **Input layer:** This is the input layer of the neural network. It contains the inputs neurons corresponding to the inputs provided to the model.
- **Hidden layer:** It consists of nodes that are used to adjust the weight of each neuron [36]. A number of hidden neurons and the number of hidden layers can be adjusted to improve the model's performance.
- **Output layer:** It is the layer that consists of the output neurons. All the neurons from the hidden layer are connected to the output layer. One or more neurons can be in the output layer depends on the number of outputs.

3.4.1.2 COMPILE

The compilation is needed to make the network executable for the GPU or the CPU.

3.4.1.3 FIT

- Feed-forward neural network:

The most basic kind of neural network is a feed-forward neural network. In this model, the neural network is traversed from start to end and the values are predicted. There are no loops or feedback units, so the network runs in a feed forward manner and predicts the value.

- Back-propagation neural network:

Each neuron is further connected to other neurons. These connections have weights attached to them. So, more weight will make the connection strong and less weight will make the connection weak. Weights are connected randomly. In the first run, the output predicted by the first run is compared to the actual value. Since the weights were random, the predicted value and the output are very different. The error between the actual value and the predicted value from the first run is calculated. This error is fixed by a mechanism called as *backpropagation*. In this process, the neural network propagates back to each cell and tries to fix the error. The connection strength or the weights are changed accordingly. This process is run multiple times to adjust the weights perfectly.

3.4.1.4 EVALUATE

After the model is defined, compiled, and fit, it is important to evaluate the model on the known set. For this, we evaluate the model on the training set and check its performance. This gives an idea of the model's performance on unknown data or test set.

After evaluating the performance of the model, the model is tweaked if required to increase the performance. Hidden neurons, activation function, etc. can be adjusted to improve the performance of the model.

3.4.1.5 PREDICTION

The last step is to make the forecast. In this step, the created model is used to predict future values from the test set. The model is used to make out of sample forecast for single step or multi-step ahead.

3.5 NONLINEAR AUTOREGRESSIVE ARTIFICIAL NEURAL NETWORK MODELS

3.5.1 CLOSED LOOP NONLINEAR AUTOREGRESSIVE ARTIFICIAL NEURAL NETWORK (CL-NAR-ANN)

Solar power is periodic in nature, autoregression based forecasting models are more suitable for solar power. Thus, a nonlinear and autoregressive artificial neural network is chosen to forecast solar power[37].

A closed-loop nonlinear autoregressive artificial neural network (CL-NAR-ANN) is a neural network-based model used to forecast a time series using its previous values only. A CL-NAR-ANN model can be described as:

$$\hat{P}[k+H] = f(P[k], \dots\dots, P[k-H1])$$

Figure 6 describes the training topology of the CL-NAR-ANN. Time series P is the only input that goes into the CL-AR-ANN model. P[k], P[k-1], …., P[k-H1] is the feedback delays or in other words, it is how far in the past does the network look. The number of delay elements can be determined by observing the autocorrelation of the time series. The model is first trained in an open loop. The inputs are mapped to the output using a

Levenberg-Marquardt backpropagation training methodology. Once the model is trained, it is transformed into a closed loop, thus a closed loop nonlinear autoregressive artificial neural network. The closed loop configuration can be represented a figure 7.

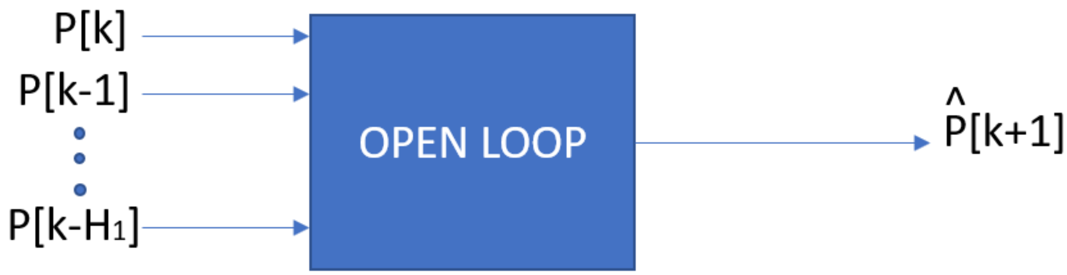

Figure 6 Open-loop training configuration of the CL-NAR-ANN model.

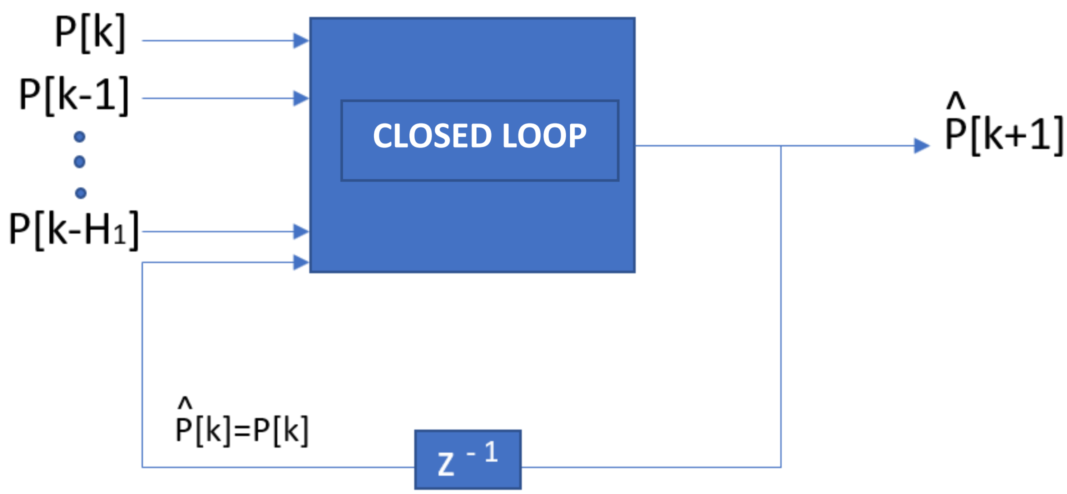

Figure 7 Closed- loop configuration of the CL-NAR-ANN model.

3.5.2 CLOSED LOOP NONLINEAR AUTOREGRESSIVE ARTIFICIAL NEURAL NETWORK WITH EXOGENEOUS INPUT (CL-NARX-ANN)

In general, the modelled time series is influenced by other external data as well as itself. Especially, renewable energy generation is highly influenced by weather conditions. Thus, the closed-loop nonlinear autoregressive artificial neural network with exogenous input (CL-NARX-ANN) model is a variant of the CL-NAR-ANN model with the addition of an exogenous time series as input.

A CL-NARX-ANN is a neural network-based model used to forecast a time series using its previous values and an exogenous time series as additional input. A CL-NARX-ANN model can be described as:

$$\hat{P}[k+H] = f(P[k], \dots \dots, P[k-H1], u[k], \dots \dots, u[k-H1])$$

Figure 8 describes the training topology of the CL-NARX-ANN. Time series P is the historical time series input that goes into the CL-NARX-ANN model. u is the exogenous time series input. P[k], P[k-1], …., P[k-H1] is the feedback delays or in other words, it is how far in the past does the network look. The number of delay elements can be determined by observing the autocorrelation and the correlation of the input time series. The model is first trained in an open loop. The inputs are mapped to the output using a Levenberg-Marquardt backpropagation training methodology. Once the model is trained, it is transformed into a closed loop, thus a closed loop nonlinear autoregressive artificial neural network with exogenous input. The closed loop configuration can be represented a figure 9.

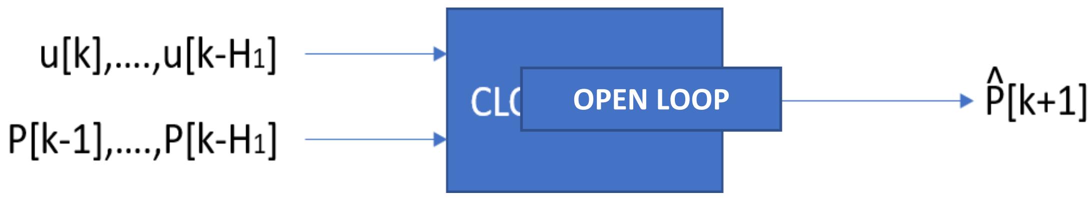

Figure 8 Open-loop training configuration of the CL-NARX-ANN model.

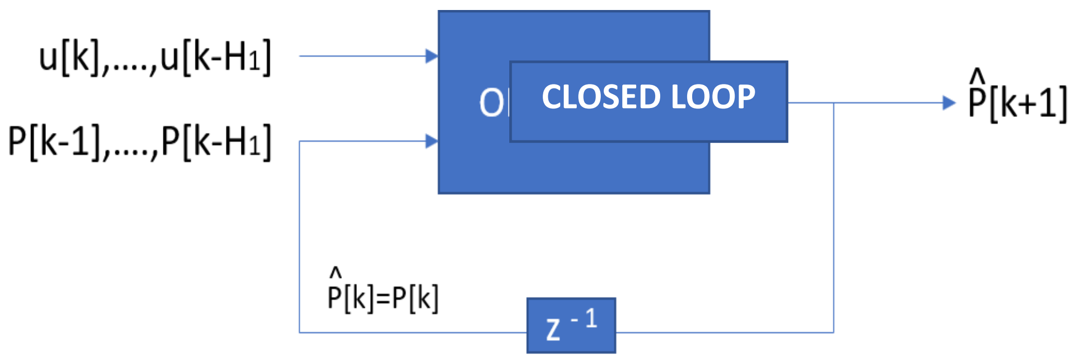

Figure 9 Closed- loop configuration of the CL-NARX-ANN model.

The CL-NAR-ANN and its exogenous variant, the CL-NARX-ANN models are first trained using an open loop configuration and then while applying or testing, the model is transformed into a closed loop. The CL-NAR-ANN and the CL-NARX-ANN models make a forecast one-time step in time i.e. they can predict one time step ahead. At the time ‘t’, the CL-NAR-ANN and the CL-NARX-ANN models can predict a value at a time ‘t+1’. For example, at midnight, the model makes the prediction one-time step in future, i.e. at 1 am using the past H1 values, again at 1 am it makes a forecast for 2 am and so on. This process is repeated ‘n’ number of times in order to get a complete forecast. The following figure describes the manner in which the CL-NAR-ANN and the CL-NARX-ANN models make a forecast one-time step in time.

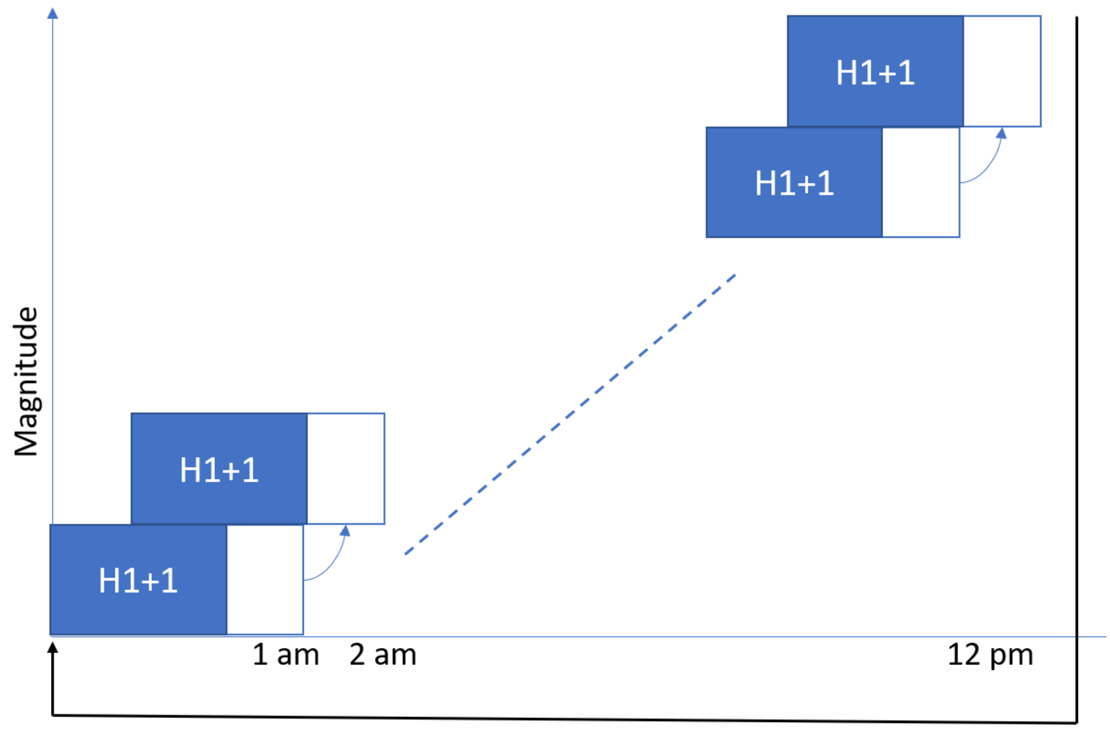

Figure 10 shows the forecasting mechanism of the CL-NAR-ANN and the CL-NARX-ANN model.

3.6 PROBABILISTIC FORECAST

The deterministic forecast provides point forecasts or a single value at each time step. Sometimes, this information is not enough. Probabilistic forecasts provide additional information about the uncertainty of the forecast value. Probabilistic forecasts provide an estimation of the future outcomes as well as the probabilities associated with them. Instead of providing a single forecast value, probabilistic forecasts provide a probability density function. A probabilistic forecast looks like:

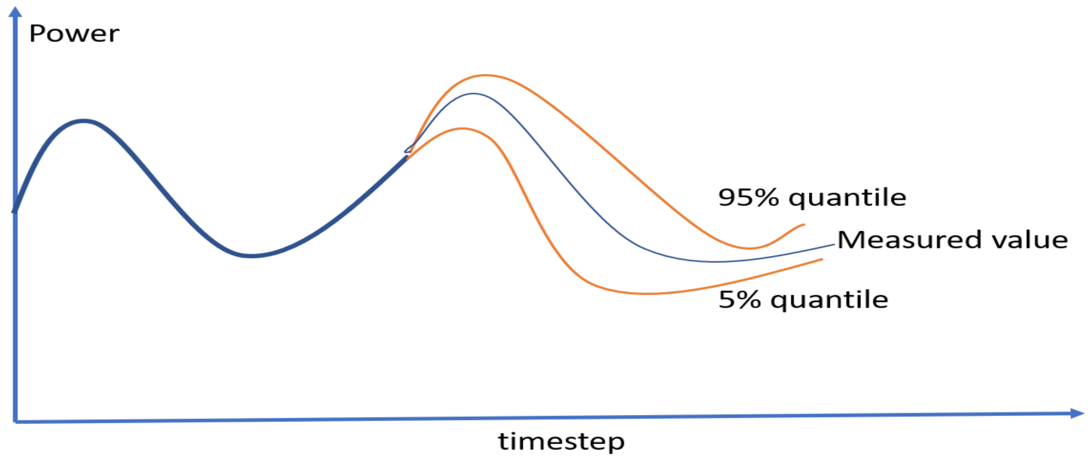

Figure 11 Shows time series probabilistic forecast.

First, multiple point forecasts are generated using different models by varying the input parameters. In the postprocessing stage, statistical methods are used to generate quantiles of multiple point forecasts. First, the percentile rank is calculated from the frequency domain. The values in the data set which are the multiple point forecasts are arranged from smallest to largest. Then, the qth quantile is multiplied by the number of point forecasts available. The value obtained, is where the qth quantile is when going from left to right. For example, if there are 10, point forecasts available. In order to calculate the 90th quantile, multiply 90% by 10, which gives 9. Thus the 9th value or the 9th point forecast when going from left to right is the 90% quantile. These quantiles are used to generate probabilistic forecasts. Quantiles are calculated using the following formula:

$$\boldsymbol{q = \frac{c_q + 0.5 f_q}{N}}$$

Where,

q is the quantile being calculated

c_q is the position of the value from left

f_q is the frequency of the qth quantile

N is the number of values

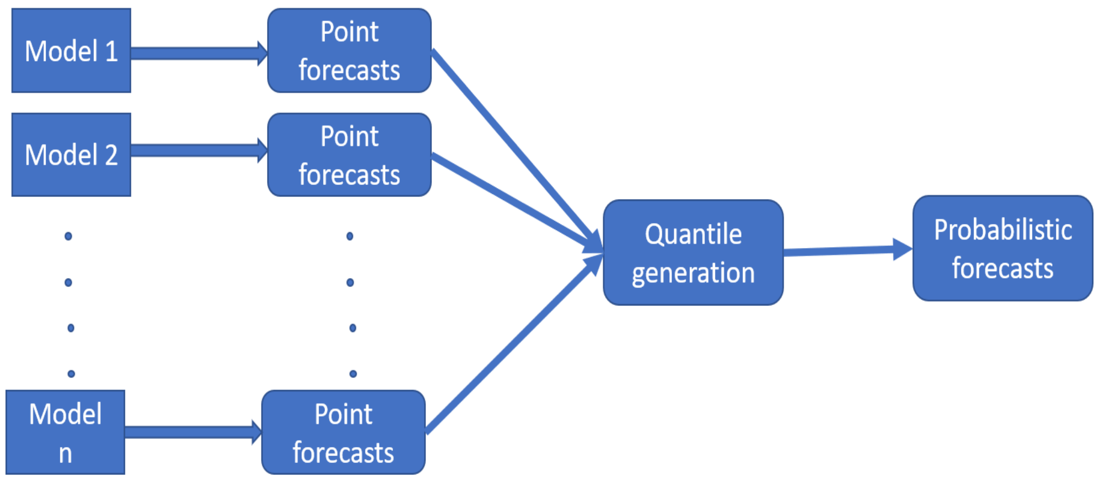

Figure 12 Shows the process of obtaining probabilistic forecasts.

3.7 MODEL PREDICTION ERROR

The main goal of a prediction model is to train on data in order to predict unseen or new data. Any model does well on the training data as it optimized for the training dataset. The main challenge is to select a model that performs well on new data. In the case of neural networks, gradient descent is used to find the most optimum result or minima. This is done by passing the data one by one through the model and updating the weights each time to better fit the model. The whole dataset is passed through the model forward and backwards, updating the weights, multiple times as gradient descent needs multiple passes to achieve optimum learning. The number of times this process is repeated is determined by the number of *epochs*. With each epoch, the model better fits the training set or better learns the training data by adjusting the weights. The number of epochs is a crucial factor in determining the performance of the model. Less number of epochs may lead to underfitting while more number of epochs may lead to overfitting [38].

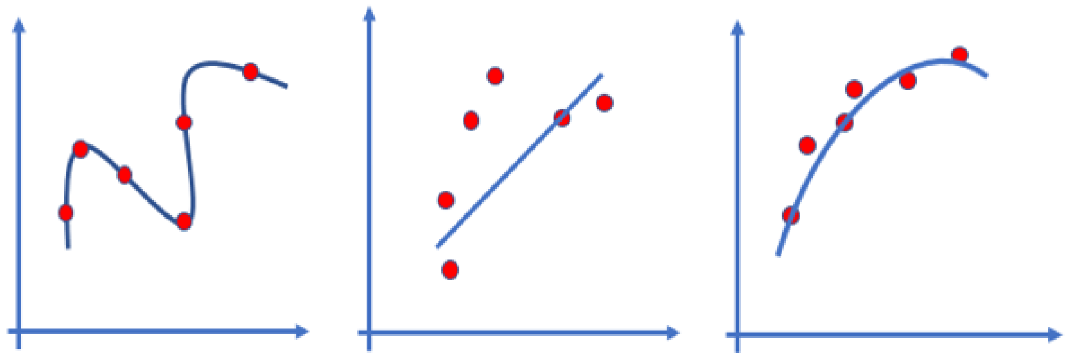

Figure 13 shows over training, under training and optimal training respectively.

Figure 13 shows a scenario when the model has been overfitted. This happens when the model learns the training set too well. The model even learns the sudden variation in the training data which might not be present in the unknown dataset. Figure 13 shows the scenario of underfitting. When the number of epochs is too less, the model is unable to learn the training data. Thus, the prediction will not the good for the test set and error will be large since the model has not learnt enough information about the available data to predict new data. Figure 13 shows the scenario when the model is fit in the most optimum manner. Here, the model learns the general trend of the data as well as some of the abnormalities. The error will be least when the model is trained with optimum fitting.

3.8 TRAINING AND TESTING SPLIT

The whole dataset is divided into training and testing sets. The total dataset contains one-year worth data. Out of this one year, nine months are used for training, which is about 75%. The rest of the three months which is about 25% of the data is used to test the model.

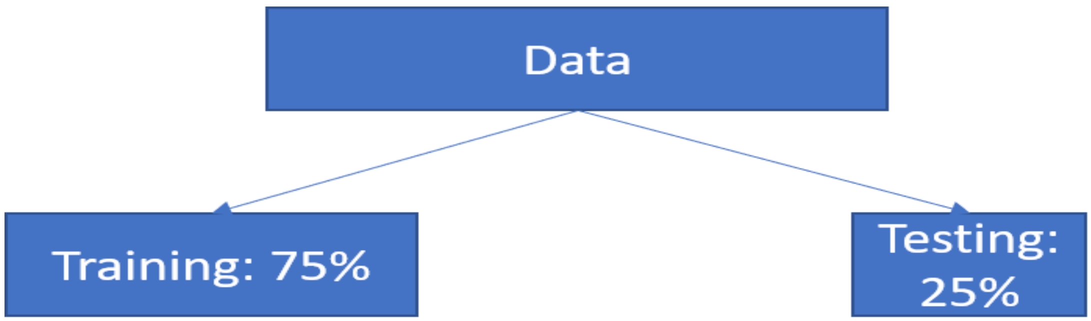

Figure 14 Shows the train and test split of the dataset.

3.9 TOOLS

MATLAB was used as the main platform to write the solar power forecast codes. MATLAB's neural network toolbox was used as the base to write the code.

For wind power forecasting, Python version 3.6.4 was used. The environment used to run the Python language was Spyder 3.2.8. The following libraries were used:

1. NumPy:

   NumPy was used to work with arrays and matrices in Python. It is one of the most essential libraries for scientific tasks in Python. NumPy arrays were used in the code to store and manipulate data.

2. Pandas:

A fundamental library for data science in Python is Pandas. Data manipulation and visualization can be done by using the functionalities of pandas. The ability of Pandas to convert data into data frames makes data manipulation tasks such as time shifts, data selection, etc. very easy to manage.

3. Matplotlib:

   Matplotlib is another core package offered in Python for data visualization. Line plots, scatter plots, pie charts, bar charts, etc. can be plotted using this library. Graphs can be customized to add labels, legends, etc. for more functionality.

4. SciKit-Learn:

   A free to use the library for basic machine learning tasks. Various machine learning algorithms can be implemented using SciKit-Learn. It is also used to calculate the error of the prediction.

5. Keras:

   The most important library used in the code is Keras. It is a freely available open source library for neural networks. Keras runs TensorFlow in the backend to prepare the data for the neural network layers. Keras is written in Python and is easy to implement. It can easily be customized to suit ones required task.

3.10 SYSTEM

The experiments were conducted on an Intel® Core™ i7-6700K CPU @ 4.00GHz with 8.00 GB installed RAM.

Chapter 4: DATA

4.1 SOLAR DATA

The data used is from the Global Energy Forecasting Competition held in 2014 [39]. The dataset contains three PV power time series, normalized to values between 0 and 1 and corresponding NWP data. Weather forecasts for the next 24 hours were issued at midnight of each day. The time series is given in an hourly resolution and contains measurements for a time-frame ranging from April 1st, 2012 to July 1st, 2014. The number of available measurements for each PV power time series is K=19704$. The total data-set has been divided into training (70%) and validation (30%) sets. The NWP data provided is as follows:

- Total cloud liquid water content unit (kg/m^2)
- Vertical integral of cloud ice water content (kg/m^2) -
- Surface pressure - Unit: Pa
- Relative humidity
- Total cloud cover
- 10-meter U wind component (m/ s)
- 10-meter V wind component (m/s)
- Temperature (K)
- Surface solar radiation down (J/m^2)
- Surface thermal radiation down (J/m^2)
- Top net solar radiation (J/m^2)

- Total precipitation (m)

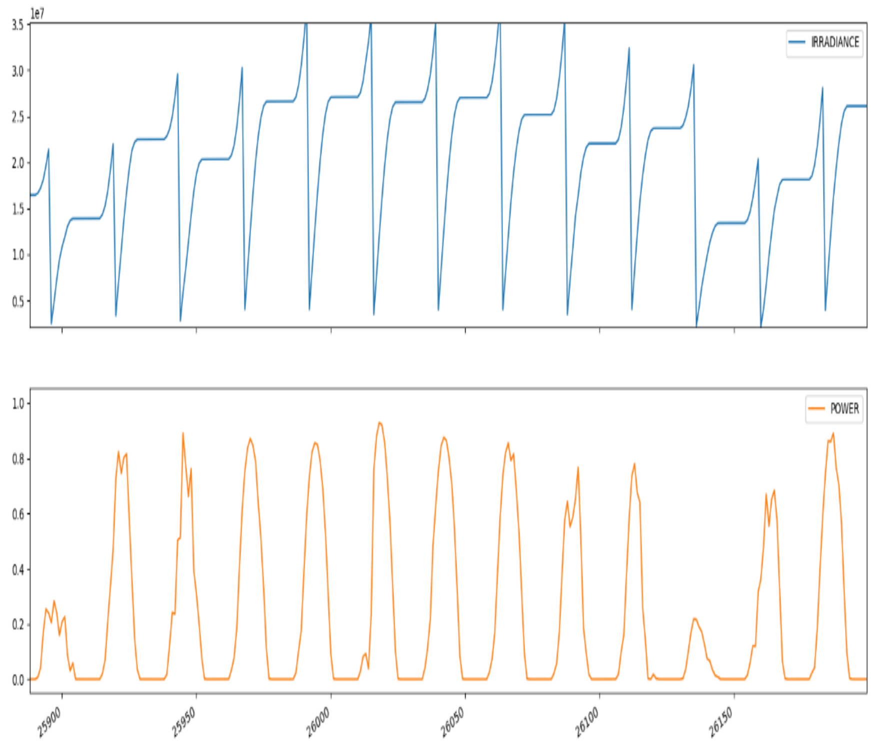

Figure 15 Shows the solar power and solar irradiance time series.

4.2 WIND DATA

The data used comes from a Spanish wind farm located in Galicia, Spain. It consists of 24 wind turbines. The power rating of the wind farm is 17.56 MW with an annual generation od 33,364 MWh. The average wind speed at the site is about 6.4 m/s [40]. The time series is given in an hourly resolution from 1st January 2016 to 31st December 2016. A total of 8757 data points are available in the time series. The NWP data for the wind farm is available in an overlapping format i.e. the NWP data is updated four times in a day with a horizon of 48 hours. Most recent six hours are used from each overlapping time series to create a new continuous time series. January to September months are used for training and October to December months are used for testing.

The NWP data contains the following variables:

- 75 wind speed members at 10 m height
- 75 wind speed members at 75 m height.
- 75 wind speed members at 100 m height
- 75 wind speed members at 170m height.
- Ensemble Prediction System (EPS) for 10 m, 75 m, 100 m, 170 m.
- Wind direction at 10 m and 170 m
- Average of all wind speed members
- 0 to 100 percentiles of wind speed
- Temperature (K)
- Momentum flux
- Sensible heat flux
- Latent heat flux
- Shortwave radiation
- Longwave radiation
- Surface pressure
- Large-scale precipitation
- Convective precipitation.
- Mean sea level pressure

- Cloud cover

Wind power forecast depends on the quality of NWP provided to the model. The most important factor in predicting wind power is wind speed. Figure 1 shows the scatter plot for wind power and wind speed. It can be inferred that wind power has a strong dependency on wind speed.

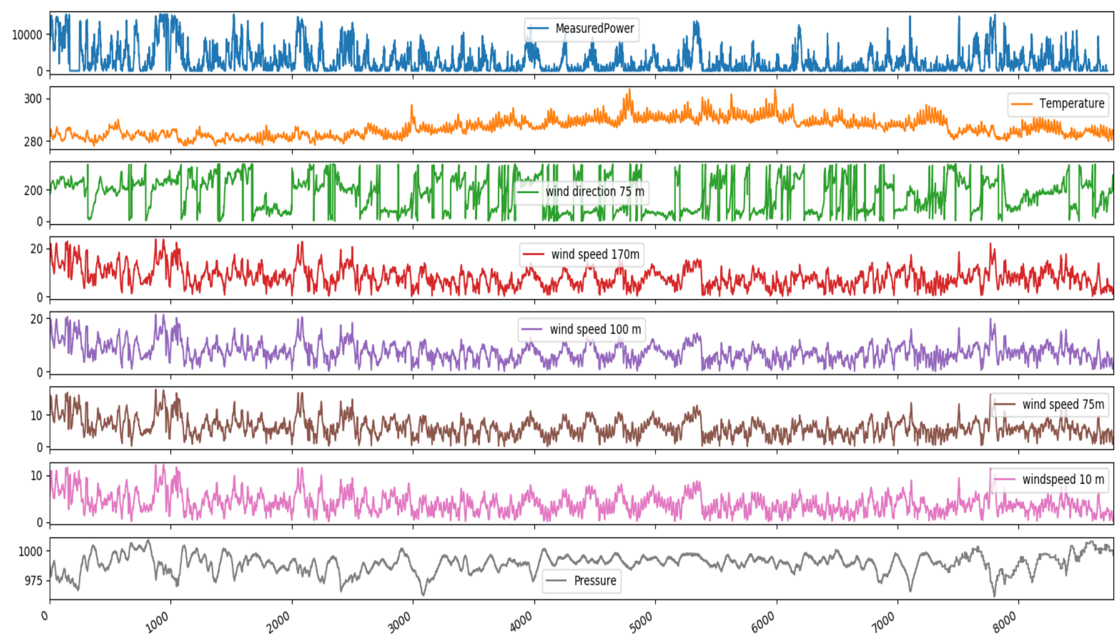

Figure 16 shows the various input variables times series.

NWP data, especially wind speed is the main factor for wind power prediction. The prediction error in wind speed and wind direction will cause a major error in the prediction of wind power. Figure 2 shows the comparison of measured wind speed and predicted wind speed for the wind farm. It can be inferred from the figure that there is some error in the predicted wind speed when compared to the measured wind speed. This error comes from a sudden change in temperature, pressure and other meteorological conditions that are difficult to predict.

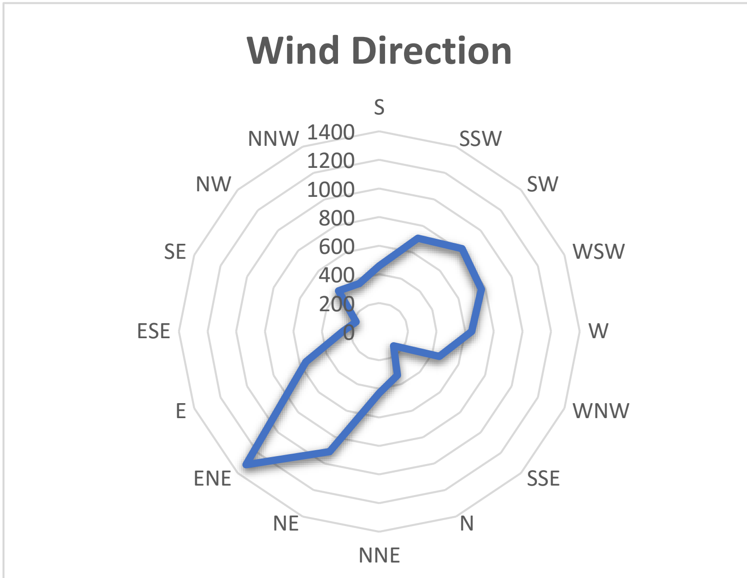

Figure 17 Shows wind direction map.

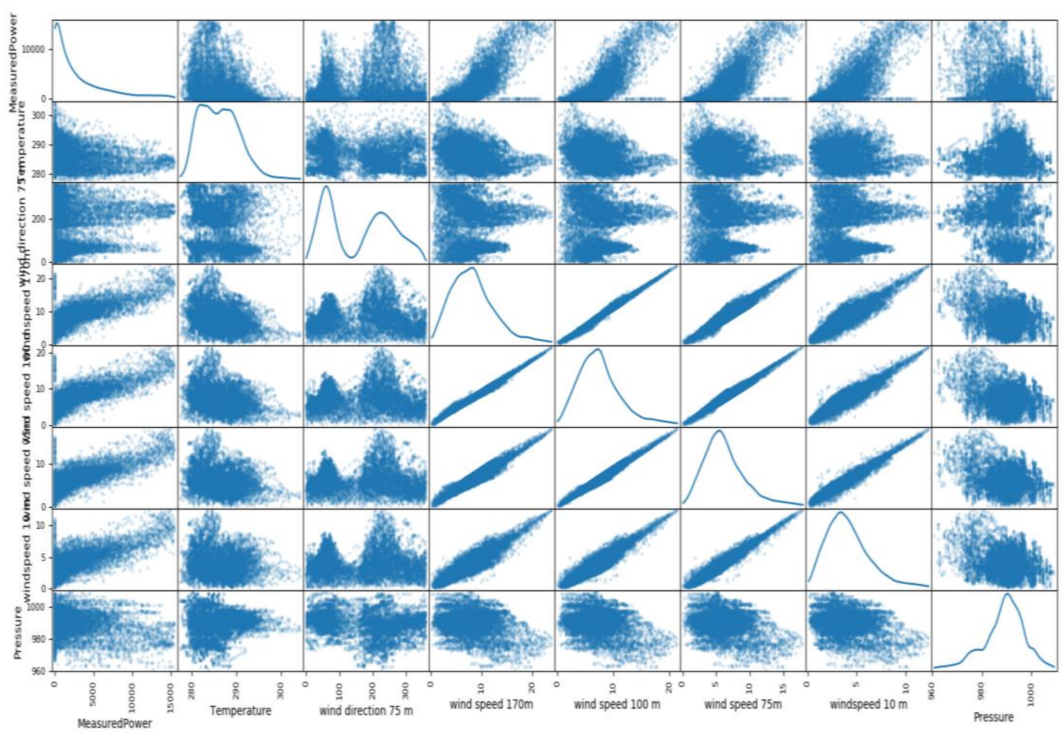

Figure 18 Shows the correlation between each variable.

Table 1 Correlation matrix for input-output variables

	Wind Power	direction 75	ws 170	ws 100	ws 75	ws10	direction 175	temperature	Pressure
Wind Power	1	0.150375	0.772347	0.776197	0.767624	0.73063	0.150528	-0.276921	-0.260434
direction 75	0.150375	1	0.0254456	0.023059	0.025491	0.038366	0.960616	-0.154929	-0.235837
ws 170	0.772347	0.0254456	1	0.993293	0.964432	0.900019	0.0299443	-0.309955	-0.318364
ws 100	0.776197	0.0230587	0.993293	1	0.98567	0.930395	0.0265878	-0.278542	-0.321016
ws 75	0.767624	0.0254906	0.964432	0.98567	1	0.966341	0.0242599	-0.218818	-0.320015
ws10	0.73063	0.0383656	0.900019	0.930395	0.966341	1	0.0360695	-0.145852	-0.292405
direction 175	0.150528	0.960616	0.0299443	0.026588	0.02426	0.03607	1	-0.161081	-0.234292
temperature	-0.276921	-0.154929	-0.309955	-0.27854	-0.21882	-0.14585	-0.161081	1	0.0982669
pressure	-0.260434	-0.235837	-0.318364	-0.32102	-0.32002	-0.29241	-0.234292	0.0982669	1

Table 1 shows the correlation matrix for an independent variable with each other as well as with the dependent variable. It can be observed that as expected, wind speed and wind direction have a high correlation with wind power.

Chapter 5: SOLAR POWER FORECASTING USING ADVANCE FORECASTING TECHNIQUES

Sun is the source of all life form on this planet. Solar cells use solar energy from sunlight to produce energy. Recent developments in photovoltaic (PV) panels have led to efficient and cost-effective solar power generation solutions. Solar energy will be responsible for more than 50% of the worlds electricity energy demand by the year 2050[41]. The amount of energy generated by PV panels depends on atmospheric variables like solar irradiance, temperature, cloud cover, humidity, etc. Dependency on these weather parameters makes PV power uncertain in nature. The amount of energy produced fluctuates, not only form day to day but even from hour to hour. Since it is weather dependent, which is not in our control it is not possible to reduce the inconsistency in the power produced by solar. But, it is possible to reduce the uncertainty about the inconsistent energy generation by using methods to forecast solar power.

A usual method to make the solar forecasts is the use of numerical weather prediction (NWP) data as an input. The NWP data contains information about weather conditions such as temperature, humidity, solar irradiance, etc. These weather parameters influence the amount of energy produced by the PV plant or panel. The NWP data is obtained by using mathematical equations that model the atmosphere. These mathematical models are based on meteorological parameters that predict the future weather scenarios. The future atmospheric conditions are predicted using equations for short term as well as long-term. Using the present weather observations and computer models, the future forecasts are made. Calculation of NWP data is a very sophisticated process and there are various NWP data providers such as (GDAS), Global Ensemble Forecast System (GEFS), Global Forecast System (GFS), North American Multi-Model Ensemble (NMME), North American Mesoscale (NAM), Rapid Refresh (RAP) and Navy Operational Global Atmospheric Prediction System (NOGAPS) that provide NWP data for various locations across the globe.

For a real-time forecasting model, NWP data must be obtained on a regular basis. To have a continuous input of NWP data, it must be purchased from an NWP data provider. It is generally done on a contractual basis for a period. This adds additional cost to the project. Additionally, there needs to be a well-established link between the NWP data provider and the forecasting site. This is generally done via the internet. The NWP data is sent by the provider and is updated multiple times a day to make the forecasts more accurate.

The obtainment of NWP data from the provider not only adds to the cost of the project but it also adds additional risk of system failure. In case of system failures, like loss of internet connectivity between the provider and the forecasting site, or in the case when it not secure to obtain NPW data, the reliability on NWP data to make forecast can be risky. Most of the current PV forecasting models solely rely on NWP data such that if this data becomes unavailable for some reason, the whole system runs the risk of shutting down. For that reason, this research attempts to solve this problem by exploring methods to make PV forecasts without the use of NWP data.

Persistence models:

Polynomials of degree one to four (Poly1-Poly4) are considered in this research. For example, in Poly4 the models take in the value from *P[k]* to *P[k-H1]* and raise them to the power of one, the power of two, the power of three and power of four. Then, the best four features are selected step-wise using a least squares approach. The polynomial models are created using weather in

5.1 ARTIFICIAL NEURAL NETWORK SOLAR POWER FORECASTING MODEL

ANN models for PV power forecasting is built using multilayer perceptrons (MLP) with one hidden layer. Two ANN models are created, one with NWP data and one without NWP data as input. The ANN models are trained using the Levenberg-Marquardt algorithm and contain one hidden layer with three hidden neurons. Figure 20 shows the ANN model for NWP data free forecasting and figure 19 shows the configuration for a model with NWP data as input.

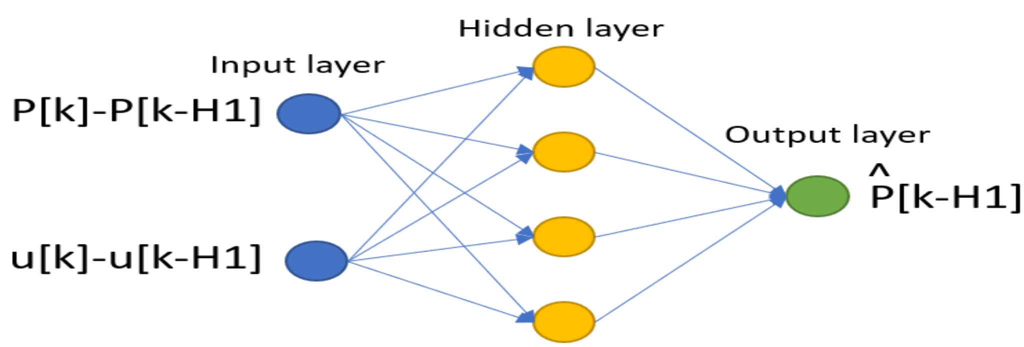

Figure 19 shows the ANN configuration without any NWP data.

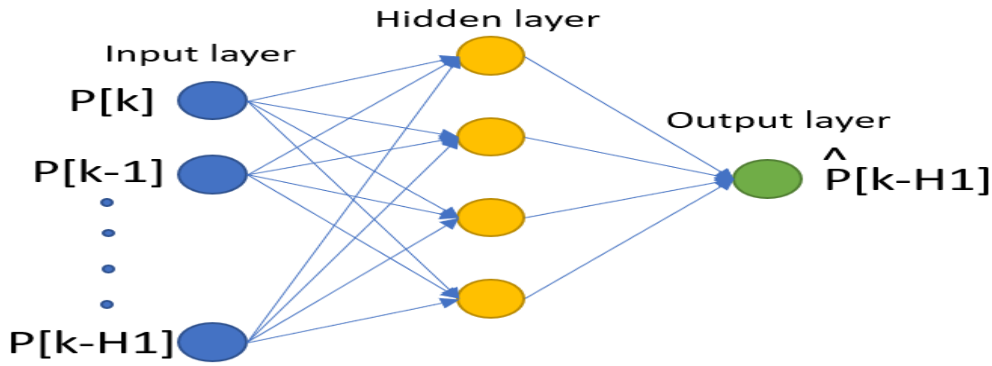

Figure 20 Shows the ANN configuration with NWP data.

5.2 CL-NAR-ANN AND CL-NARX-ANN MODEL FOR SOLAR POWER FORECASTING

CL-NAR-ANN and CL-NARX-ANN are modelled using one hidden layer containing three hidden neurons. For the Cl-NAR-ANN model, only historical PV power time series is given as input to forecast PV power. Thus, the CL-NAR-ANN model receives *P[k] to P[k-H1]* as the input time series and predicts a value at time-step *k+1*. For this experiment, the value of *H1* is set to 48. This implies that the model looks back 48 time-steps. This value of 48 was decided upon after observing the autocorrelation of the *P[k]* time-series, as well as the value of 48, gave the highest performance. Since the model can make a forecast only one time-step in time, this value is fed back into the model in a loopback fashion in order to forecast the next value. This process is repeated until 24 values are obtained in order to have one-day-ahead PV power forecast.

The exogenous variant of the CL-NAR-ANN, the CL-NARX-ANN model is built in a similar fashion, but with an exogenous input. Solar irradiance is taken as the exogenous input for the CL-NARX-ANN model. Thus, this model has *P[k] to P[k-H1]* and *u[k] to u[k-H1]* as the inputs. Since the model can make a forecast only one time-step in time, this value is fed back into the model in a loopback fashion in order to forecast the next value. This process is repeated until 24 values are obtained in order to have one-day-ahead PV power forecast.

5.2.1 RESULTS

Table 2 Results of the models without NWP data.

MODEL	**MAE (%)**	**RMSE (%)**
CL-NAR-ANN	5.85	11.43
Poly 1	6.39	12.41
Poly 2	6.34	12.41
Poly 3	6.34	12.41
Poly 4	6.34	12.451
ANN	6.58	12.85
Persis 1	6.15	14.17
Persis 2	6	13.16
Persis 3	6.09	13.1

Table 3 Results of the models with NWP data.

MODEL	**MAE (%)**	**RMSE (%)**
CL-NARX-ANN	4.01	8.04
Poly 1	4.57	9.01
Poly 2	4.4	8.81
Poly 3	4.55	8.93
Poly 4	4.53	8.92
ANN	5.41	10.49

The results of the NWP data free models are presented in table 1. It can be observed that the proposed CL-NAR-ANN model performs better than the ANN polynomial models. In terms of RMSE, the CL-NAR-ANN model is about 8% more accurate than the rest of the models. In terms of MAE, the CL-NAR-ANN model is about 9% better than the other models. It can be concluded that the CL-NAR-ANN model outperforms the other models. The NWP data free models perform considerably well, and the results are in an acceptable range. The persistence models perform comparably well in terms of MAE but not in terms of RMSE. This is because the deviations get averaged out in MAE but show up in RMSE. Also, for the given location, there is less fluctuation in PV power over time.

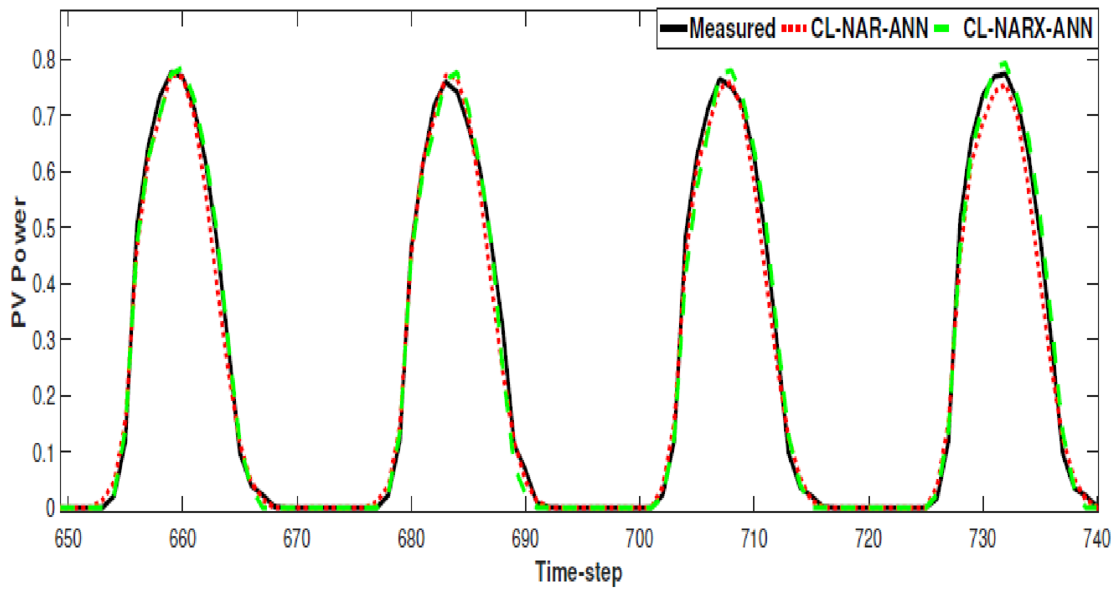

Figure 21 shows the performance of the models during consistent weather days.

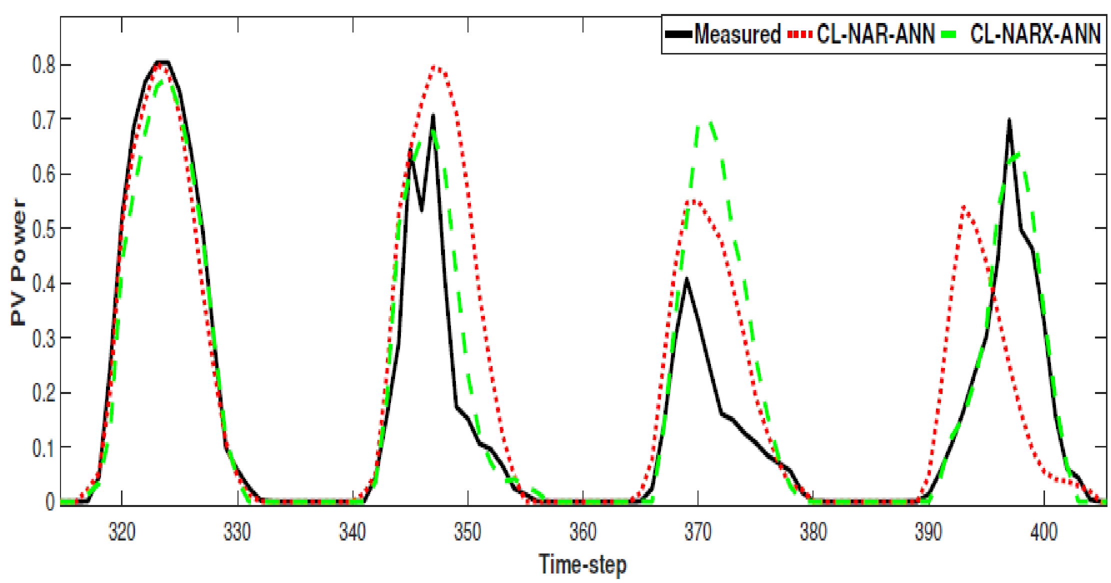

Figure 22 shows the performance of the models during inconsistent weather days.

The performance of models with NWP data as input is presented in table 2. The exogenous variant of the CL-NAR-ANN, the CL-NARX-ANN outperforms the ANN and the polynomial models. The CL-NARX-ANN outperforms the ANN and polynomial model by about 14% in terms of RMSE and about 13% in terms of MAE.

The loss of accuracy when comparing the models that contain NWP data to the models that do not contain NWP data is also evaluated. Results suggest that there is about 34% loss in terms of RMSE in the models that do not contain NWP data as compared to the models that have NWP data as input. The loss on MAE is about 37%. The main reason for the loss of accuracy is the lack of NWP data in the weather free models. The NWP data free models lack information regarding the sudden change in weather conditions and fluctuations in weather.

It is interesting to observe different types of days when comparing the performance of these models. In figure 21, it can be seen that for three similar days, weather-wise, the CL-NAR-ANN and the CL-NARX-ANN models perform very well. They are able to forecast the PV power very close to the actual measured PV power for that day. But, when the weather conditions change suddenly, as seen in figure 22, the CL-NARX-ANN model is still able to make comparably accurate forecasts than the CL-NAR-ANN model that lacks the information about the weather. The CL-NAR-ANN model doesn't perform very well for the days when there is a sudden change in the weather. If the weather conditions for the forecast day are very different from the weather conditions of the present and previous days, the CL-NAR-ANN model will forecast completely wrong.

Another interesting observation is the tradeoff between the complexity of models and the accuracy of models. The CL-NAR-ANN, CL-NARX-ANN and ANN models are very complex neural network-based models that require high computational power. These models take a longer time to run and have a complex code. On the other hand, polynomial models are very simple and basic mathematical models that do not require much processing time and computation. If computation power is of major concern and the loss of accuracy when comparing the more complex neural network-based models to the simple data-driven polynomial models is not very high, then polynomial models can also be implemented. If accuracy is of the highest priority, then neural network-based models can be implemented.

5.3 PROBABILISTIC SOLAR POWER FORECASTING

Probabilistic PV power forecasts are made using multiple point forecasts. In order to obtain, multiple point forecast, different scenarios are generated. This is done to obtain different possibilities of future weather. Lagging most influential variable (solar irradiance) by different days can be used to generate different scenarios. For example, considering lag by one day would mean that summer arrived a day early this year or two days sooner. Since probabilistic forecasting aims at explaining are a range of forecasts, thus irradiance data is used to generate four different scenarios. Irradiance is lagged by one day and two days to create two more models. Another two models are created by advancing irradiance by one and two days making a total of seven models. Using the different models, percentile intervals are generated from 0.01 to 0.99.

5.3.1 RESULTS

The pin-ball loss function is calculated for the quantiles and the pinball-loss score is 0.01298. The measured solar power values are close to the 50^{th} quantile. The probabilistic forecast gives a wide range of forecasts rather than a single point forecast. This range of forecasts can be used in making critical energy decisions with reduced risk.

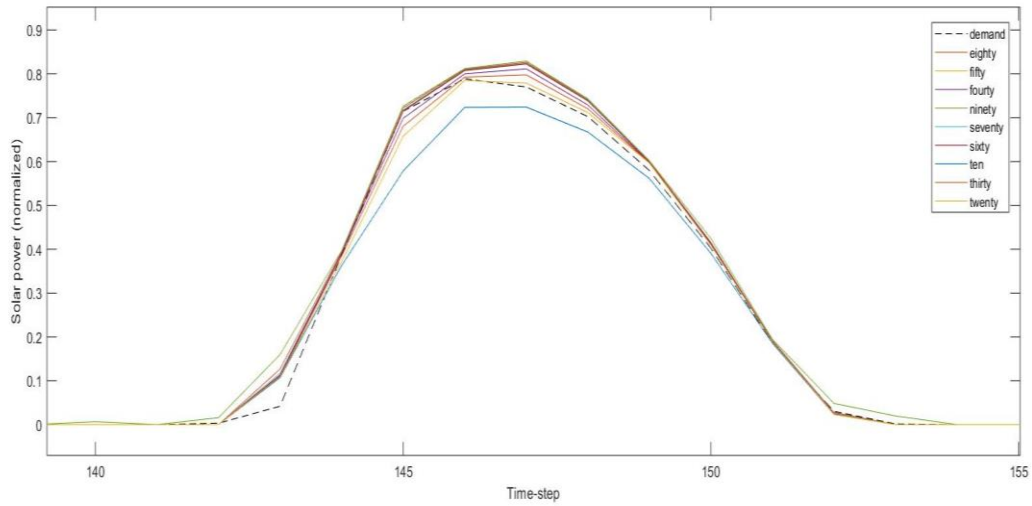

Figure 23 shows probabilistic forecast for solar power.

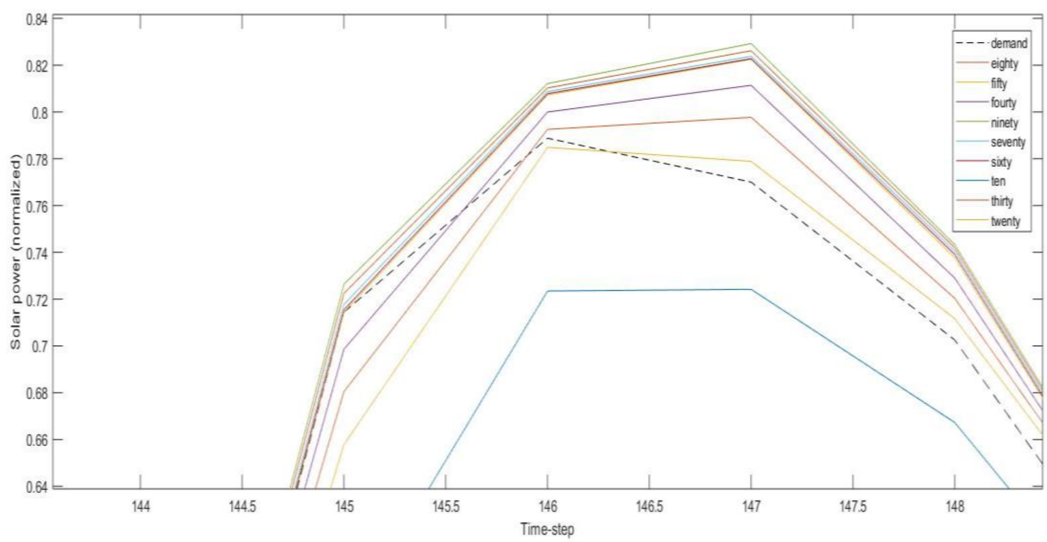

Figure 24 shows probabilistic solar power forecast

Chapter 6: WIND POWER FORECASTING USING ADVANCE FORECASTING TECHNIQUES

6.1 SENSITIVITY ANALYSIS FOR NWP VARIABLE SELECTION

Wind power prediction is highly influenced by the parameters in the NWP data. But, the NWP data contains a number of parameters and information that might not be useful for making the predictions. Some parameters can be highly influential while other unrelated parameters can cause a negative impact on the accuracy of the wind power predictions. For this reason, a sensitivity analysis is carried out, in order to assess the influence of various NWP parameters on wind power predictions. Artificial neural network model with one hidden layer and 20 hidden neurons has been used to predict day ahead wind power. This model was chosen by conducting a grid search to select the optimum number of hidden neurons from a range of 10 to 200 with an increment of 10 neurons. Using 20 hidden neurons gave the best result. The training set consisted of 9 months of data and the test set consisted of 3 months of data.

Figure 25 shows the wind power forecasting model.

Different sets and combinations of NWP parameters are used as input and each set is considered as a new experiment. From the values in Table 1, it can be seen that wind direction at 75m and 170m have very similar correlation values, but it was observed that using wind direction at 170m gave slightly better results than using wind direction at 75 m height. Thus, while selecting different combinations, wind direction at 170m was considered in all the models. For the first experiment titled F1, pressure, temperature, wind speeds at 10m, 35m, 100m and 170m are considered along with wind direction at 35 m and 170m. This is one of the most commonly found combinations of inputs in literature for wind power forecasting. In the second experiment (F2), the pressure is omitted out to observe its effect on the accuracy. For the third experiment (F3) pressure and temperature are both not included as inputs to the model. Since the wind speed at a higher height could be different from the wind speed at a lower height, the different wind speeds for different height are also considered individually. So, for the fourth model (F4), wind speed at 170 m height is omitted from the model to evaluate its effect on the accuracy of the predictions. For model F5, both the wind speeds at 170 m and 10m height are excluded from the model along with the pressure and temperature. For model F6, only the wind speed at 100 m height is considered along with the wind direction at 35 m and 170 m height. For experiment F7, the pressure is added to the inputs from F6. For experiment F8, temperature, wind speeds at 10 m,35 m, 100m and 170m height are considered along with the wind direction at 170 m height. A model containing all 323 inputs available in the NWP data was also created. This model was called FA.

Table 4 shows the different experiments for sensitivity analysis.

Parameters/Experiments	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**
P (Surface Pressure)	x							
T (Temperature)	x	x					x	x
Wind speed at 10m	x	x	x	x				x
Wind speed at 35 m	x	x	x	x	x			x
Wind speed at 100m	x	x	x	x	x	x	x	x
Wind speed at 170m	x	x	x					x
Wind direction at 35m	x	x	x	x	x	x	x	
Wind direction at 170 m	x	x	x	x	x	x	x	x

Table 3 shows the nRMSE, nMAE and correlation values for the experiments performed for

sensitivity analysis. Model F1, containing all possible 323 inputs has an nRMSE of 12.32%, nMAE of 8.22% and 83.5% correlation. The model F1 containing temperature, pressure, wind speeds at 10m, 35m, 100m and 170m as well as wind direction at 35m and 170m as inputs have a nRMSE of 10.88%, nMAE of 8.04% and 90.1% correlation. The model F2 containing temperature, wind speeds at 10m, 35m, 100m and 170m as well as wind direction at 35m and 170m as inputs have a nRMSE of 10.79%, nMAE of 7.65% and 92.5% correlation. The model F3, containing wind speeds at 10m, 35m, 100m and 170m as well as wind direction at 35m and 170m as inputs have a nRMSE of 11.12%, nMAE of 7.68% and 95% correlation. The removal of pressure decreases the nMAE. The model F2 is found to be the most accurate model. It is used in the subsequent experiments for wind power forecasting.

Table 5 shows the results of the sensitivity analysis.

Experiment name	**RMSE**	**MAE**
F1	10.88	8.08
F2	10.80	8.02
F3	11.12	7.68
F4	11.17	7.74
F5	11.08	7.67
F6	11.08	7.68
F7	10.94	8.08
F8	10.86	8.05

6.2 ONE HOUR TO ONE-DAY-AHEAD WIND POWER FORECASTS

The accuracy of the wind power forecasts is highly dependent on the forecast horizon. It is observed that there exists a short-term correlation or temporal dependency in weather variables as well as wind power. Due to these temporal dependencies, it is easier to predict the wind power more accurately for few hours ahead and less accurate to predict wind power for several hours ahead. The forecasts for the first hour are based on the actual power from the previous hour. But, for the subsequent hours, the actual value of the previous hour is absent, so the forecast value of the previous hour is used. The forecast value has some error associated to it, for several hour-ahead forecasts, this error gets accumulated and the accuracy decreases. The hours ahead or the forecast horizon is a crucial aspect of wind power forecasting as different countries have their energy market operating at different horizons. Artificial neural network model with one hidden layer and 20 hidden neurons has been used to predict wind power. The training set consisted of 9 months of data and the test set consisted of 3 months of data.

In order to create a comparison of the different models and to present a benchmark result for comparison, three persistence models have been used to conduct 24 hours ahead wind power forecast. The first model (Persis 1) assumes the forecast wind power of the next hour to be the same as the wind power 24 hours or a day ago. The second persistence model (Persis 2) assumes the average of previous two days to be the forecast days power and the third persistence model (Persis 3) assumes the forecast value to be same as that of the average of the previous three days.

Table 6 shows the results of the persistence models.

	nRMSE (%)	**nMAE (%)**
Persis 1	20.4108	14.89025
Persis 2	18.9442	17.56549
Persis 3	18.1495	16.90546

In this research, one hour ahead to one-day-ahead forecasts are made and the accuracy is compared using model F2. Fig 26 shows the structure of the model and the inputs used to make the short-term forecasts.

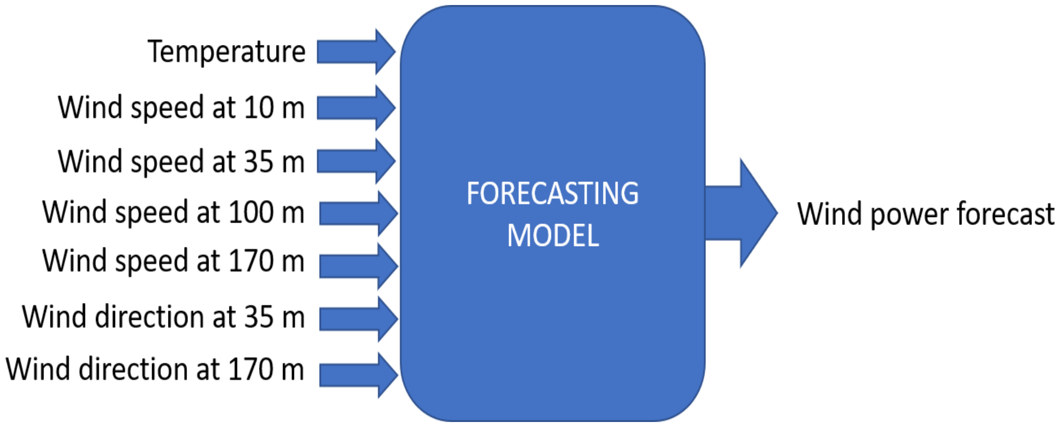

Figure 26 shows the structure of the model and the inputs used to make the short-term forecasts.

Forecasts were made from one hour ahead to 24 hour-ahead. Table 6 shows the results obtained from the experiments. It can be observed that the accuracy for one hour ahead wind power forecasts is the highest. As the forecast horizon increases, the accuracy decreases, and the root means square error increase. Figure 27 shows the increase in root means square error with an increase in the forecast horizon. The Figure 28 shows the increase in the mean square error with the increase in the forecast horizon.

Table 7 shows the results for 1 hour to 24 hour ahead time horizons.

Hours-ahead	**nRMSE (%)**	**nMAE (%)**
1	4.23	3.01
2	4.93	3.74
3	5.46	4.16
4	5.59	4.25
5	5.97	4.41
6	6.35	4.75
7	6.65	5.06
8	7.19	5.53
9	7.48	5.58
10	7.64	5.76
11	7.99	5.83
12	8.32	6.08
15	9.18	6.77
20	9.96	7.51
24	10.43	7.65

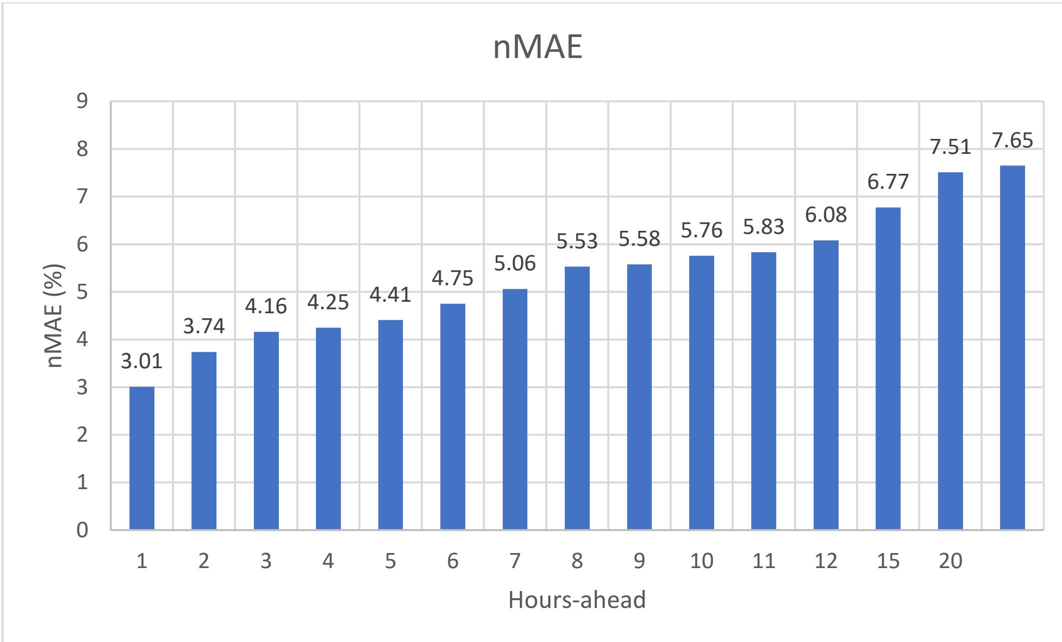

Figure 27 nMAE results for 1 to 24 hour ahead forecast.

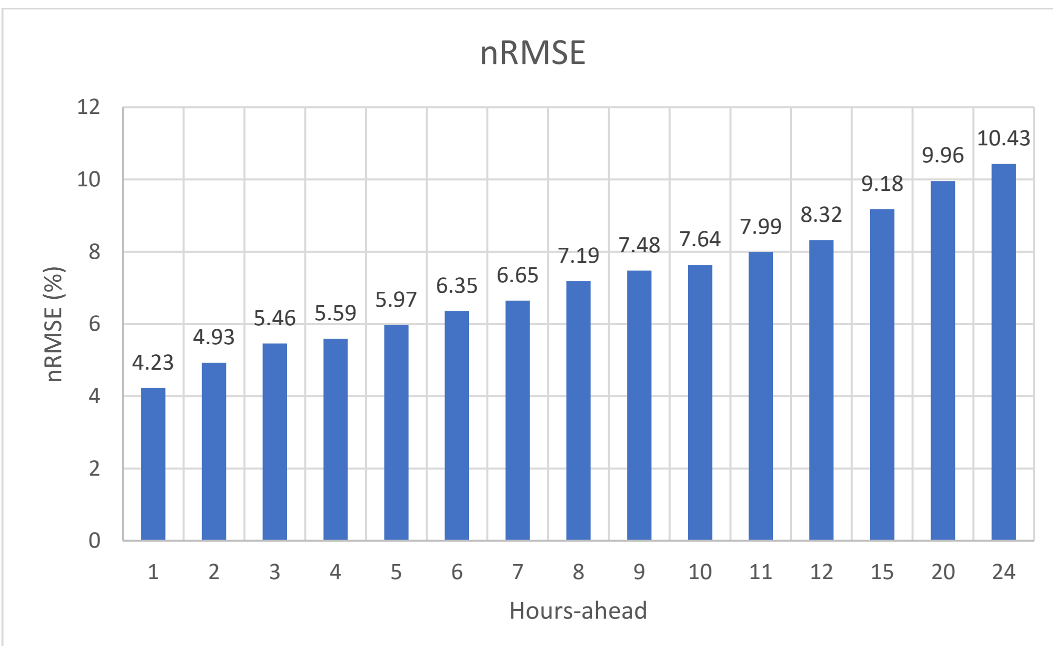

Figure 28 nRMSE results for 1 to 24 hours ahead forecast

6.3 ENSEMBLE WIND POWER FORECAST

Numerical weather prediction data uses multiple equations and techniques to make weather predictions. This is done to provide a more accurate prediction or representation of the atmosphere as well as cover a range of values to reduce the uncertainty. In the used NWP data, some values remain constant as there is no observable change in these atmospheric variables like temperature, humidity, etc. But, for wind speed, there are 75 different wind speeds for each height. These are predicted using different initial conditions and they provide a band of possible outcomes.

In this technique, each of the 75 members is trained separately and used to make predictions. The model is constructed with one hidden layer consisting of 10 hidden neurons. The training set consisted of 9 months of data and the test set consisted of 3 months of data. The inputs considered to build the model are shown in table 7. Temperature, Pressure, wind direction at 35 m and 170m and the wind speed members at 100m height.

Table 8 shows the inputs used to build the model

Input parameter	**Description**
T	Temperature
P	Pressure
Direction32	Wind direction at 35 m height
direction30	Wind direction at 170 m height
ws1-75	Wind speed members 1-75 at 100m height

The neural network-based model was applied on all 75 members of the NWP data. The following structure was used to build the ensemble models:

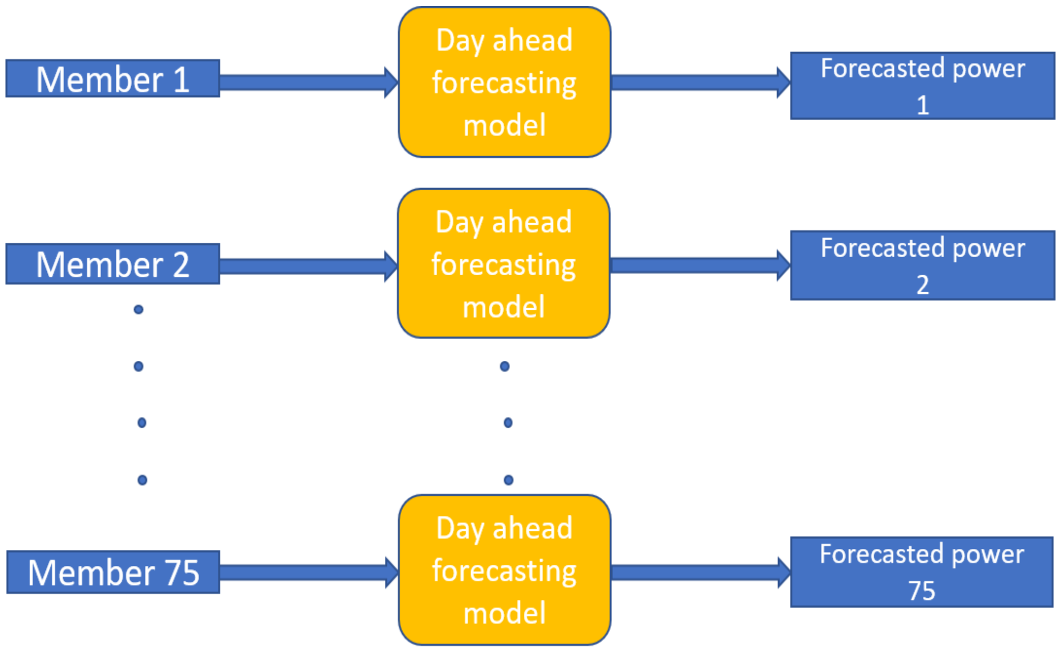

Figure 29 shows the models for 75 members.

For this experiment, the wind speed members at 100 m are considered and the model forecast error is calculated for each member. The results of the wind power forecasting models containing 75 members are plotted in figure 29. The root means square error lies between 10.58 % to about 11%. The results show that there is considerable variation in the wind power forecast accuracy using 75 ensemble NWP members.

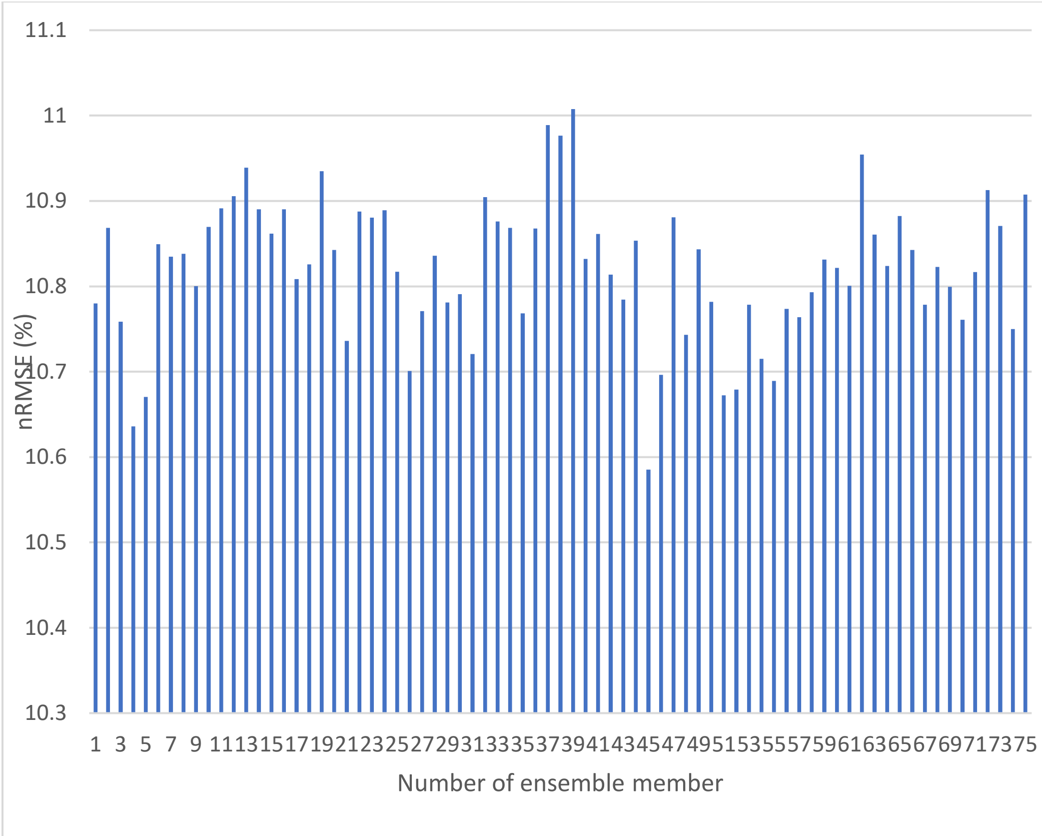

Figure 30 Results of 75-member forecasts

6.3.1 AVERAGING OF WIND POWER FORECASTS USING ENSEMBLE MEMBERS

After obtaining the results for each and every ensemble member, a simple averaging of the results obtained from the 75 members were calculated. The averaging was conducted without consideration of any weights. Secondly, a simple average of the 75 input parameters was calculated and the forecast was made using that as inputs. Thirdly,

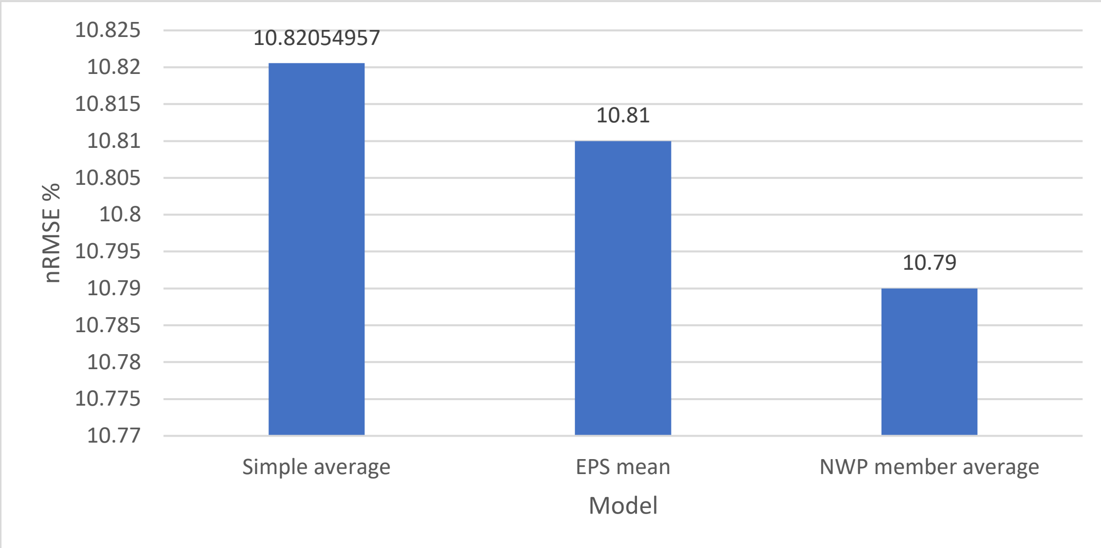

Figure 31 results from a combination of ensemble members.

the EPS mean was used as input to calculate the forecast. The results are plotted in figure 31. The results show that different methods of combining the NWP ensemble data can lead to different accuracy. This depends on the quality of the NWP data. The use of averaging reduces the forecast error and increases the accuracy.

6.4 PROBABILISTIC WIND POWER FORECASTING WITH MULTI NWP MODELS

Point forecasts or deterministic forecasts provide information about the next step in time. This value is an estimate of the next possible value. The amount of information about the future values could be improved upon by conducting a probabilistic forecast. Compared to point forecasts, probabilistic wind power forecasts provide information related to the uncertainty and the probability of the uncertainty of the forecast.

To find the probabilistic forecasts, the outputs or the forecasted wind power from the experiments conducted in sensitivity analysis are used. The models (F1-F8) use different sets of NWP data and hence have different outputs coming from the same forecasting methodology. Using the point forecasts from multiple NWP models, quantile forecasts were made. Quantiles are derived from 0.01 to 0.99 using the point forecasts.

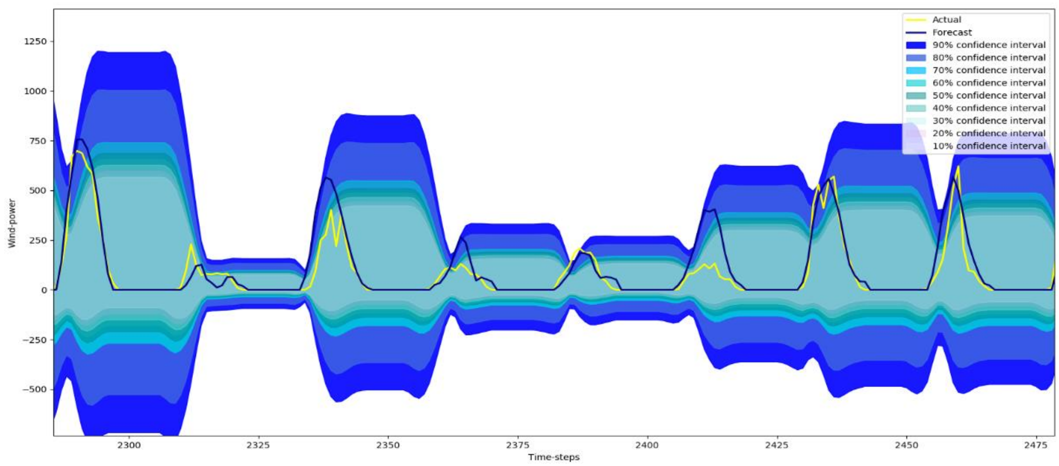

Figure 32 shows the wind power probabilistic forecast

In fig 32, a sample of the probabilistic forecast is shown. Quantiles at 10,20, 30, 30, 40, 50, 60, 70, 80 and 90 are plotted with different colors along with the measured wind power values plotted using the blue line. The actual value lies in the 50 percentile which means that is the most probable outcome.

Chapter 7: VALIDATION/ERROR MEASUREMENT

The performance of the models used to predict wind power forecasts is evaluated in order to understand the quality of the predictions. Determining the accuracy of the model is a way to test the performance of the model. Forecast error can be defined as the difference between the actual value and the predicted value at a time step. It is given by:

$$\boldsymbol{e_t = P_m - P_p}$$

Where,

Pm: is the measured wind power

Pp: is the predicted wind power

This is done by using the following statistical methods:

- Normalized Root Mean Squared Error (nRMSE)
- Normalized Mean Absolute Error (nMAE)
- Correlation

7.1 NORMALIZED ROOT MEAN SQUARED ERROR

To calculate the root mean square error, the first step is to calculate the error at each time step. This is done by calculating the difference between the measured wind power and predicted wind power at each time step. Next, the error at each point is raised to the power of two or in other words, the error is squared to give us a squared error. Now the squared error is added together and divided by the number of time steps, to get the mean of the squared error. This gives us mean squared error. The root mean squared of this value will give us the root mean square error. For the given wind farm, the wind farm capacity is 17560 MW. This value of 17560, is used to calculate the normalized root mean square error. The obtained root mean square error is divided by the value to get normalized root mean square error. nRMSE is given by:

RMSE = $\sqrt{\frac{\sum_{i=n}^{1}(Pm-Pp)^2}{n}}$

nRMSE = $\frac{RMSE}{Wc}$

Where,

N: is the number of time steps.

Wc =Wind farm capacity.

7.2 NORMALIZED MEAN ABSOLUTE ERROR

Mean absolute error is one of the most common statistical method used to calculate the error. To calculate the mean absolute error, the absolute error between the measured wind power and the predicted wind power is calculated at each time step. The next step is to take the sum of the absolute errors at each time step and then divide the sum by the number of time steps to get the mean of the absolute error values. MAE is given by:

MAE = $\frac{\sum_{i=n}^{1}|Pm-Pp|}{n}$

nMAE= $\frac{MAE}{Wc}$

7.3 PINBALL-LOSS FUNCTION FOR PROBABILISTIC FORECASTS:

The pinball-loss function is used to evaluate the quality of quantiles produced for the probabilistic forecast. The pinball loss function is used to evaluate the quantiles and not the forecasts, thus it's an evaluation of the quantiles generated from the forecasts. The pinball-loss function is evaluated for each quantile using:

$$\boldsymbol{L_{(y,q)} = (y - q)\hat{q} \qquad if\ y \geq q}$$

$$\boldsymbol{= (y - q)(\hat{q} - 1) \qquad if\ y < q}$$

Where,

$L_{(y,q)}$ is the Pinball loss

y is the measured value

q is the evaluated quantile value for the forecast

$\hat{q}$ is the actual quantile value

Thus $L_{(y,q)}$ is the accuracy of the evaluated value of the quantile.

In the pinball-loss function, the magnitude of each error deviation and weights are calculated depending on the evaluated quantile. A lower value means less error and that the evaluated regression is good.

Chapter 8: CONCLUSION

With the high penetration of wind and solar power into the grid, their smooth integration is a very crucial issue that needs to be looked into. An important step in the integration of these sources with the grid is to achieve accurate wind and solar power forecasts in order to efficiently plan for the uncertainty and variability in these sources. In this thesis, advanced machine learning and data analytical methods like ANN, CL-NAR-ANN, CL-NARX-ANN, ensemble and probabilistic forecasting models are explored to conduct wind and solar power forecasts.

For solar power forecasting, a scenario is explored where NWP data is not available due to a hindrance in the communication channel or purchasing NWP data on a regular basis is not possible due to economic reasons. A novel CL-NAR-ANN model is developed for one day ahead solar power forecast using only historical solar power time series as input. To evaluate the proposed model, it compared with three polynomial models and an ANN model. An exogenous variant of the CL-NAR-ANN, the CL-NARX-ANN with solar irradiance as the input, is also developed and compared with ANN and three polynomial models. The CL-NAR-ANN model outperforms other NWP data free models by about 9% in terms of RMSE. The CL-NARX-ANN model outperforms a Least Square Support Vector Regression (LS-SVR) model developed by Fentis, Bahatti et al. [42]. The NWP data free models lose about 30% in accuracy by their exogeneous variants. Thus, the CL-NAR-ANN model can act as a good back up model for solar power forecasting, for emergency situations when the more accurate NWP data-driven models fail. A probabilistic forecast for solar power is also presented.

For wind power forecasting, an ANN model with 20 hidden neurons in one hidden layer is modelled. First, a selective analysis of the input variables is conducted. Different combinations of input variables are selected, and their performance is evaluated. Then the most accurate model is selected as the base model for all other experiments. This model is then used to make one hour ahead to one day ahead forecasts. The change in accuracy of the models with a change in forecast horizon is plotted. With the increase in the forecast horizon, a decrease in the accuracy is observed. Then, a multi-modal approach based on 75 wind speed members is applied. A multi-model ensemble wind power forecast is developed with 75 different models for 75 wind speed members. It is observed that NWP data average gives the model with the highest accuracy when compared with simple averaging. These multi-model forecasts are then used to develop a probabilistic wind power forecast.

The presented solar and wind power forecasting models and methods provide a more robust and accurate forecasting solution for stakeholders in energy and power systems. Accurate wind and solar forecasts help grid operators manage the system better, utilities plan and allocate resources efficiently and plan expensive operating resources more efficiently. Accurate forecasts can save millions of dollars by planning better and avoiding penalties and outages.

8.1 FUTURE WORK

In future, more advanced machine learning and deep learning algorithms can be explored for wind and solar power forecasting. Also, the developed models can be applied and tested for load forecast and other power system forecast such as operational reserve forecasts.

An interesting point in solar power forecasts is the amount of accuracy of less complex regression models as compared to highly complicated neural network models. If accuracy is of utmost requirement, then complex neural network models can be used but if a little loss in accuracy can be tolerated over less complexity, then simpler models can be used.

NWP free models can also be implemented in decentralized agents where NWP data is not accessible due to contractual difficulties. The decentralized agents can run the NWP models as have some knowledge of the future power scenarios.

In future works, the effect of wind power forecasts and solar power forecasts on the energy market and the economic feasibility of maintaining and operating these resources can also be analyzed.

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