FORECASTING OF WIND AND SOLAR POWER GENERATIONS FOR ENHANCING THEIR PENETRATIONS IN SMART GRID

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Certificate

This is to certify that the thesis entitled "Forecasting of Wind and Solar Power Generations for enhancing their Penetrations in Smart Grid" is being submitted by **Ms. Jyothi Varanasi (2K14/PHD/EE/04)** for the award of degree of Doctor of Philosophy to the Delhi Technological University is based on the original research work carried out by her. She has worked under the supervision of **Prof. M. M. Tripathi** and has fulfilled the requirements, which to; our knowledge has reached the requisite standard for the submission of this thesis. It is further certified that the work embodied in this thesis has neither partially nor fully submitted to any other university or institution for the award of any degree or diploma.

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Abstract

The vanishing conventional energy sources and global warming drive the world for the power generation from renewable energy sources. The main renewable sources namely solar power and wind power are uncertain and intermittent in nature. Wind & solar photo voltaic (PV) power forecasting with good accuracy promise the power sector for large scale integrations of wind & solar PV power generations into the grid. In the context of smart grid and deregulated electricity market, price forecasting is a challenging job for researchers.

A rigorous literature review of wind power forecasting, solar PV power forecasting and price forecasting is conducted with focus on various statistical & learning forecasting methods. The data is collected from Belgium wind farms, US wind farms and Indian wind farms and Indian photo voltaic plants. The dependency of wind power generation and solar power generation is analyzed with the computation of correlation factors.

Nonlinear autoregressive with external input (NARX) model is implemented to forecast wind power generation of Belgium wind farms by using historical data of wind speed and wind power. Further, NARX model is also used to forecast wind speed for US wind farms from the input data of wind direction, temperature and air density. Wind speed is predicted with good accuracy and minimum MAPE is 2.3%.

The research work is continued to improve short term wind power forecasting accuracy by designing generalized regression neural network (GRNN) and radial basis function neural network (RBFN). A hybrid network of GRNN &RBFN is designed with parallel topology to forecast wind power for improved accuracy. Reliability of forecasting models is analyzed with the computation of confidence intervals on MAPE.

As support vector machine (SVM) is very good at classification and regression analysis, in this work the support vector regression (SVR) model with tuned parameters is used to

forecast wind power generation and solar PV power generation. To achieve better accuracy and to retain the benefits of individual models, a hybrid approach K-means clustering based artificial neural network- particle swarm optimization (ANN-PSO) model is designed and proposed for solar PV power forecasting.

In the context of smart grid, the uncertainty in wind & solar PV power generations increases the volatility of electricity price. A hybrid approach of K-means clustering based long short term memory (LSTM) network is proposed for short term electricity price forecasting of Austria by considering wind power generation in the market. The proposed model shows highest accuracy in prediction when compared against feed forward neural network-particle swarm optimization (FNN-PSO) and SVR models. In hour ahead price forecasting with the consideration of wind & solar PV power generations, bootstrap aggregation of ensemble model (proposed model) has outperformed with significant reduction in error.

As renewable energy integration to the power grid is enhancing day by day, it becomes pertinent to introduce new market models to operate the renewable energy (RE) enabled restructured electricity market. For such an RE enabled Indian electricity market, seven various market models are developed and proposed along with their salient features. An operating mechanism for future RE enabled Indian electricity market is also proposed based upon the developed models.

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Acronyms

WPF	Wind Power Forecasting
PV	Photo Voltaic
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
SVM	Support Vector Machine
ANN	Artificial Neural Network
NARX	Nonlinear Autoregressive with External (Exogenous) Input
SVR	Support Vector Regression
EHS	Enhanced Search Algorithm
MHNN	Modified Hybrid Neural Network
LSSVM	Least Square Support Vector Machine
RBFN	Radial Basis Function Neural Network
GRNN	Generalized Regression Neural Network
PSO	Particle Swarm Optimization
MLP	Multilayer Perceptron
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
NWP	Numerical Weather Prediction
RE	Renewable Energy
PGCIL	Power Grid Corporation India Limited
ISO	Independent System Operator
SLDC	State Load Dispatch Centre
MNRE	Ministry of New Renewable Energy
SEB	State Electricity Board
NLDC	National Load Dispatch Centre
RLDC	Regional Load Dispatch Centre
CTU	Central Transmission Utility
CERC	Central Electricity Regulatory Commission

SERC	State Electricity Regulatory Commission
PX	Power Exchange
SC	Scheduling Coordinator
UI	Unscheduled Interchange Mechanism
PPA	Power Purchase Agreements
REMC	Renewable Energy Management Centre
NTP	National Tariff Policy
RPO	Renewable Purchase Obligation
FITs	Feed In Tariffs
REC	Renewable Energy Certificate
NAPCC	National Action Plan for Climate Change
CEA	Central Electricity Authority
MCP	Market Clearing Price
DISCOM	Distribution Company
SDU	State Distribution Utility
IPP	Independent Power Producer
SGU	State Generating Utility
CGU	Central Generating Utility
BRP	Balance Responsible Parties
ADR	Alternative Dispute Resolution
CFD	Contract For Differences
FERC	Federal Energy Regulation Commission

Chapter 1

INTRODUCTION

1.1 Overview of renewable energy

Limited availability of conventional energy resources and their adverse impact on environment such as global warming are two important motivating factors to utilize renewable energy resources for meeting the increasing energy demand of our society. Most of the air pollution is generated by thermal power plants, hence currently the world is moving towards the clean energy with low carbon emissions. Development of the smart grid technology is also encouraging the integration of wind and solar power into the grid. Intelligent grid is often referred to as a digitized electricity network that treats electricity unconventionally; not as a commodity but as a value-added service. Its important features are deregulation, distributed generation, enhanced participation of consumers, generation and storage options, power quality, optimized asset utilization with high operational efficiency, self-healing and resiliency against attack & natural disaster. Integration of micro grids, electric vehicles and other utilities are another dimension added to the smart grid. The restructuring or deregulation of electricity market has demanded the control and analysis of large set of data being generated from smart power grid.

It is expected that global wind power capacity to reach 1,000 GW and global solar photo voltaic (PV) power capacity to reach 969 GW by the end of 2025. While solar photovoltaic capacity is currently several times smaller than wind power, it is expected to rise at a faster pace than wind in the coming decades. In India, the target for renewable energy capacity is set to 175 GW by 2022. In which, solar capacity comprises of 100GW and wind capacity comprises of 60 GW [1].

The wide and growing supply-demand gap in India and its high power losses have fuelled the government and other stakeholder's interest in the smart grid. India's power sector is one of the world's largest and globally, it ranks fourth in installed capacity, and sixth in energy consumption. Although the installed capacity in India is 369 GW approximately as of February 2020, its rising population and growing economy mean that the power demand could rise to 800 GW to as much as 900 GW by 2030. There is a need of gradual increase of power generation from renewable sources. The energy demand, by 2030 is estimated to be as high as 900 GW in India, out of which the renewable energy potential that can be exploited till 2030 is around 450 GW.

Both wind and solar generation experience intermittency, a combination of uncontrollable variability and partial unpredictability, and rely on location-dependent resources. These three distinct aspects each pose distinct challenges for wind and solar power generation owners and grid operators to incorporate.

To overcome the uncertainty of promising resources such as wind power and solar power, wind power forecasting (WPF) and solar photo voltaic (PV) power forecasting are greatly being carried worldwide in various power grids in order to maintain the stability and reliability of the grids. With growing penetrations of wind and solar power penetrations, it is necessary to examine their impact on the variations of electricity market price.

1.2 Literature Survey

1.2.1 Wind power forecasting

In a grid, balancing power generation and load demand is essential for its stable and reliable operation. Amid wind and solar power generations, the grid stability is a major issue to the power sector world-wide. One of the solutions includes forecasting wind power and solar power generations. The wind power forecasting methods are in turn categorized into four sub-categories based on the time horizon of forecasting as given below [2].

Very short term: It ranges from few seconds to 30 minutes and used in wind turbine control, electricity market clearing etc.

Short term: It ranges from 30 minutes to 72 hrs and useful in economic load dispatch, load increment or decrement decisions.

Medium term: It ranges from 72 hrs to one week ahead and used for maintenance related decisions/unit commitment.

Long term: It ranges from one week to one year ahead and applied in design of the wind farms.

Secondly, wind power forecasting can be classified as physical approach and statistical approach. The physical approach needs the detailed physical description to model the on-site conditions by using numerical weather prediction (NWP) data [3]. The physical approach does not require training input from historical data. The implementation of physical approach in short term wind power forecasting is beneficial for the financial gains in Electricity Market [4].

The other main forecasting method is statistical approach. It uses previous historical data to build statistical model. The statistical methods are appropriate for short term, medium term, long term forecasting. However, in case of very short term and short term horizon where NWP data plays a vital role to achieve accuracy, physical approaches are also essential. Most of the researchers aimed at short term forecasting using statistical methods [5]. As per forecasting data, WPF can also be classified into wind speed forecasting (indirect method) and wind power forecasting (direct method) [6].

Some other additional forecasts as per the requirements are (i) Regional forecasting, (ii) Spatial correlation forecasting and (iii) Probabilistic forecasting.

Regional or grid forecasting provides enough information to improve reliability of the grid. There are two ways the grid connected wind power can be predicted. For each farm wind power is forecasted individually and then grid power can be estimated by adding all wind farm power forecasts is one approach. On the other hand in Ref [7] the author proposed determination of weight coefficient of each farm by using correlation matrix of output power and forecast accuracy coefficient.

The weight coefficient is computed as below in eq.1.

$$\mathrm{Q}_i = \frac{Cap_i(1-RMSE_i)}{\sum_{i=1}^{F}[Cap_i(1-RMSE_i)]} \qquad (1)$$

In the above equation Q_i represents weight coefficient of i-th wind farm, Cap_i represents the installed capacity of i-th wind farm and $RMSE_i$ is RMSE of the i-th wind farm, where F indicates the total number of representative wind farms.

Grid power forecasting could be assessed by the following eq.2.

$$P_G = \frac{\sum_{i=1}^{F} P_i Q_i}{\sum_{i=1}^{F} Cap_i Q_i} Cap_T \qquad (2)$$

Where, P_G represents the forecasted grid scale power, P_i is the power forecast of i-th wind farm and Cap_T is indicating the maximum of running wind power capacity in the grid.

Spatial correlation forecasting is typically applied to forecast the wind speed and power at a wind farm if enough information is not available. The most commonly used approach is measure correlate predict method. This model is mainly used to predict the uncertainty of the total wind energy potential prior to the development of wind farms [8].

Unlike, conventional WPF the probabilistic forecasts could provide quantitative information on the uncertainty of wind power generation. With the help of probability density function (PDF) the uncertainty could be evaluated [9]-[10]. The proposed methods are kernel density estimation (KDE) and Quintile Regression [11].

Some of the conventional statistical methods are simplistic persistence model, autoregressive model, moving average model, ARMA, ARIMA etc. Some of the learning statistical methods are artificial neural network, particle swarm optimization, enhanced PSO, modified hybrid neural network and genetic algorithm etc.

Some of the researchers used combinational approach with ANN and PSO or ANN is combined with fuzzy logic. ANNs are simple and flexible tools for forecasting. Large input, output samples are required along with proper number of hidden layers. Three layered feed forward ANNs are used for forecasting.

WPF with ANNs mainly requires NWP data like wind speed, wind direction and temperature etc. and historical wind power data. The optimal structure of a neural network can be selected by applying an optimization technique like PSO, GA. There has been a clear comparison of various neural networks with the input parameters used in Ref. [12] for very short term forecasting and short term forecasting of wind power. ANN approach has been used for short term wind power forecasting in Portugal and forecasted data is computed by historical data with MAPE of 9.51% for winter [13].

Both ANN and markov chain are applied for short term forecast [14]. All models of the markov chain are based on transitional probability matrices of different time stages. It is a random process, undergoing transitions on a state space from one state to another. Markov chains have extensive applications as statistical methods of the processes in the real world.

This paper shows improved results in comparison to ANN application alone with MAPE for ANN-Markov approach is 4.025 and 4.055 for ANN approach.

Multi-layer neural network has been used to forecast wind power at Mia liao wind farm, Taiwan, utilizing five years of data obtained from 2002 to 2007. Enhanced simplified swarm optimization (iSSO) is also suggested to demonstrate better results from GA, PSO and BP. In Ref [15] input variables for MLP are selected by using autocorrelation function (ACF) and partial auto correlation function (PACF). Out of fifty three variables, two variables namely, last wind power and previous last wind speed are observed as most relevant variables under the confidence level 95%. It is also observed that MSE is greatly affected by number of training years. In WPF suitable parameter selection and data decomposition are observed to be crucial steps [16].

Persistence model is very much familiar and less costly. However, this method needs improvement for wind power forecasting technology. This method uses previous hour wind speed or wind power to forecast next hour wind power [17]. One another notable conventional forecasting method is auto regressive time series models ARMA and ARIMA. ARMA model is mainly used to forecast wind speed and its direction. The general form is shown in eq.3.

$$X_t = C + \varepsilon_t + \Sigma_{i=1}^{p} \varphi_i X_{t-i} + \Sigma_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (3)$$

Where C is the constant term of the ARMA model, φ_i is the i-th auto regressive coefficient, θ_j is the j-th moving average coefficient, ε_t is the error term at time period t and X_t represents the value of wind speed observed or forecasted at time period t.

There has been a comparison of four statistical methods component model, traditional linked ARMA, vector auto regression (VAR) and restricted VAR for short term wind speed and direction forecasting in [18]. To forecast wind speed, traditional linked ARMA has shown better performance and VAR based methods are performing better in forecasting wind direction. Among all the proposed models, the performance is evaluated in terms of mean absolute error (MAE). ARMA model is well suited for WPF because of good correlation in wind power generations. For very short term forecasting of wind energy, ARMA models are widely used [19]-[20].

In [21], the author proposed a new forecast engine composed of modified hybrid neural network (MHNN) and enhanced particle swarm optimization (EPSO). HNN is efficient in price forecasting for Electricity Market with good accuracy. Due to complexity of wind power in case of wind power forecasting the combinational approach (HNN& EPSO) is proved to be effective. RMSE is evaluated as 6.71 for HNN alone and RMSE for the combination is 4.18.

In [22], indexed semi-Markov chains forecasting (ISMC) has been proposed and compared with persistence and auto regressive models for RMSE values. To reproduce the statistical behaviour of wind speed, ISMC is best suitable model .Since, the model doesn't need any assumption for wind speed distribution, ISMC model is considered for wind speed forecast in a specific site.

Ref. [23] has successfully presented the data mining approach for predicting future wind power values over short time horizons. Data mining is an observational method intended to analyze vast volumes of data in order to determine the hierarchical association between variables. It has been already proven to be effective approach in marketing business and manufacturing industry.

1.2.2 Uncertainty in prediction

WPF mainly aims at the demand side management, maintenance of operating reserves and generating units scheduling. Absolutely, the accurate prediction leads to the proper estimation of storage capacity and provides correct information to energy trading. Thus, WPF must be reliable and provides right information to power sector. To check the uncertainty in WPF, estimation of confidence interval for the errors is required. Evaluation of confidence interval promises reliability in the forecast. As error distribution of WPF is not the normal distribution due to non-linearity in the power curve, confidence intervals can be estimated using regression models and fuzzy interference [24]. Confidence interval is a range of values so defined that there is specific probability for the parameter value to fall in the range. The confidence interval is also used to express the degree of uncertainty. Confidence level is the probability that the value of the parameter falls within a specified range of values.

A proper comparison has been carried among three methods for WPF i.e. ANN, wavelet decomposition (WD) and least squares support vector machine (LS-SVM) in terms of error range probabilities in [25]. The hybrid model with ANN&WD has performed better with 82.84% probability in the confidence interval of -10% to 10% for Mean Absolute Error (MAE). An analysis on uncertainties associated with wind speed forecasts has been carried using a Hybrid model established by cuckoo search optimization (CSO) based back propagation neural network (BPNN) for different wind speed intervals [26].

1.2.3 Solar PV power forecasting

Due to its availability and flexible technology, solar PV power generation is gaining prominence worldwide at a fast rate**.** Solar PV power forecasting techniques have been developed and evaluated for accuracy for many years now. Statistical methods, research, and functional strategies are utilized mainly. Statistical methods incorporate several models of mathematics such as ARMA, ARIMA, and SVM etc. [27]-[28]. Solar PV power is highly dependent on to solar irradiation [29]. This approach mainly establishes the relationship between meteorological variables such as solar irradiation, ambient temperature with generation of solar PV power utilizing historical data from time series. Physical approaches are using data from numerical weather forecast (NWP).

Further learning methods are used in forecasting, such as artificial neural networks (ANNs), genetic algorithms (GA), and fuzzy systems etc. In addition to the above mentioned image processing techniques, optimal linear filters are also implemented. To evaluate their efficiency, the results are compared with specific feed forward neural networks [30]. The hybrid method with different combinations of ANN, PSO and fuzzy logic is built to increase precision in solar PV power forecasting. An optimized hybrid forecasting model GA, PSO and ANFIS for PV power prediction in micro grids is suggested and evaluated effectively [31]. The impact of solar PV power prediction through back propagation neural network on load forecasting is observed and understood [32]. Recently, data mining strategies such as support vector machine and relevance vector machine for PV capacity forecasting are being applied in order to achieve greater accuracy [33]. Categorizing historical data based on highly influenced parameters such as solar irradiation and ambient temperature is derived from the different operating conditions of PV systems. Further probability distribution function (PDF) of PV output power is forecasted by implementing higher order Markov chains [34]. In addition to meteorological parameters such as solar irradiance, temperature, humidity and wind speed, BPNN finds the aerosol index as an input vector for PV power forecasts [35]. Six simple forecasting models such as grey box model, neural network model, quantile random forest, k-nearest neighbours, ensemble averaging and support vector regression are compared for their performance to forecast PV power in 32 different Photo Voltaic plants [36]. Support vector machine (SVM) models are developed based on the weather classification to predict the generation of PV power at a PV station in China [37]. EMS is designed to forecast PV power to optimize the power flows between PV systems, grid and battery electric vehicles (BEVs) at the work place [38].

Gradually research is continuing to build hybrid models of ANN, GA, Fuzzy systems, and PSO to improve the accuracy of solar PV power forecasting. Therefore, a hybrid model for forecasting PV power is being developed. The neural networks are well trained with the output power data of fuzzy systems and weather data [39].

1.2.4 Electricity price forecasting

With the restructuring and deregulation of the electric power industry, electricity price forecasting has been the key to operate a power market. Electricity is a non-storable commodity and its supply and demand must be matched at all times. Otherwise, maintaining the steady state frequency would become a serious problem. Since supply and demand dynamics are forced to play out constantly, price is often determined for short time periods.

Electricity price is highly dependent on many factors which include power demand, day or night time, day of the week, weather conditions, climatic conditions, fuel price, power generation, emission allowances and transmission capacity etc. The volatility of electricity price is high unlike other commodities mainly due to two important factors; one is its non-storability and short time users of electricity. Restructured and deregulated electricity market introduces competition to supply reliable energy with good quality to consumers at low cost.

Especially, the dealings of electricity market are of two types one is pool trading and the other is bilateral contracts. In pool, both producers and consumers submit bids and then a particular market operator announces market clearing price for next day with the intersection of supply and demand curves, whereas in bilateral contracts, buyer and seller reaches to certain agreement on price and the amount of power to be transferred. Restructured and deregulated market is being dynamic and competitive; the price volatility is a major concern for market participants. However, electricity price forecasts provide crucial information to producers and consumers in trading and bidding activities of the market. An accurate prediction of price could assist a generating company in bidding and power exchange in trading. Efficient price forecasting could also help in setting up highly precise bilateral contracts. Hourly price forecasts assist a generating company in managing its prices and generating schedule.

Many methods are used for short term price forecasting by implementing various statistical, learning and hybrid models. Wavelet neural networks with data filtering are proposed for price forecasting in deregulated electricity market. Wavelet decomposition is used to partition loads at different frequencies. For decomposed loads at different frequencies, separate neural networks are applied and results are combined finally to get the complete error [40]. A hybrid approach of relevance vector machine and extreme gradient boost is proposed and proved to be the best one among various models like multilayer perceptron(MLP), recurrent neural network (RNN), relevance vector machine (RVM), random forest, support vector machine (SVM) and LASSO with the computation of confidence interval [41]. Extreme learning machine-bootstrap method is employed for probabilistic forecasting of electricity price. Reliability and sharpness are considered in the evaluation of the hybrid approach. The forecasting uncertainty is evaluated with model uncertainty and the data noise [42]. Input-output hidden markov model (IOHMM) is proposed to forecast electricity price with good accuracy and to provide dynamic information of the market [43].

ANNs are used for non-linear modelling and famous for short term load forecasts. One hour ahead load forecast is performed using ANNs with the concept of similar data [44]. ANNs are also simple to implement in electricity price forecasting [45]. Proposed ANN model has come to be more robust than autoregressive models and ANN predicts with good accuracy irrespective of length of time horizon considered for forecast [46]. Global warming being a major concern to the world, solar energy and wind energy are most promising renewable energy sources to produce clean & green electricity. But, large integration of solar energy and wind energy sources into the grid makes much volatile due to their intermittent nature. In process of smart grid deployment, price forecasting in a day ahead deregulated market is crucial [47]. Price forecasting is essential in assisting trading and bidding activities of electricity market. Producers and consumers could set up bilateral contracts based on price forecasts [48]. In deregulated electricity market, electricity prices and loads are forecasted for one hour ahead and six hours ahead. It is identified with the increase of time horizon of forecast the error increases in terms of MAPE [49]. Elman network (Recurrent neural network model) has been proposed to forecast price in a day ahead deregulated electricity market of New York [50]. A rigorous analysis on electricity price forecasting is carried with the RNN-Elman network and various models like ARIMA, wavelet ARIMA, fuzzy neural network, radial basis function neural network, adaptive wavelet neural network and hybrid intelligent system.

The deregulated electricity price forecasting could be analysed based on time horizon, input variables, output variables, data points used for analysis, pre-processing technique employed, and architecture of the model [51]. Identification of various features which impact price is significant for one hour ahead and a day ahead forecasting in deregulated electricity market with classification and regression trees, bagging and random forests [52]. Extreme gradient boosting based ensemble model of relevance vector machine using radial basis function and polynomial kernels has outperformed among many models such as relevant vector machine, recurrent neural network, support vector regression, multi-layer perceptron and random forest regression [53]. An hour ahead price forecasts provide crucial information to market participants in order to decide the strategy for bidding an hour before. A hybrid approach of least square support vector regression and bacterial foraging optimization algorithm was developed in forecasting electricity price one hour ahead [54]. A hybrid approach of relevance vector machine with various kernels such as gaussian, polynomial and spline and genetic algorithm has been proposed for price forecasts with higher accuracy than autoregressive moving average and naïve forecasting techniques [55]. A stacked denoising auto encoder (SDA) model is implemented in a day ahead price forecasting using the data collected US electricity markets, and compared to conventional neural networks(NN), support vector machine(SVM) and multivariate adaptive regression splines (MARS) [56]. A Rigorous literature review on electricity price forecasting based on various single models, hybrid models and time horizon in the past fifteen years is carried to explore the strengths and the weaknesses of the models and to suggest right directions in electricity price forecasting for future [57]. The real time electricity market works to balance the differences between day ahead production/demand and actual production/demand and establishes real time local marginal price (LMP). Thus one hour ahead forecasting of price plays a vital role in spot market. Real-time forecasting of electricity price has been carried using extreme learning machine algorithm in dynamic electricity market by considering the impact of unexpected changes [58]. As integration of electricity markets is gaining importance worldwide, a day ahead electricity prices are predicted with deep neural networks in Europe [59]. Short term electricity prices are forecasted in Australian electricity market with generalized neuron model tuned by environment method adaptation method algorithm after pre-processing the data through wavelet transform [60].

1.3 Research gaps

With above literature survey, the research gaps found listed below.

- Many authors analyzed the performance of the models of wind power forecasting either by calculating MAPE or RMSE, but not with both the evaluation factors.
- As renewable power forecasting has a great role in the operation of a smart grid, the reliability of a forecasting model has to be checked with the analysis of uncertainty in the prediction.

- In Smart grid scenario, the effect of renewable energy on electricity market price could be investigated.
- The uncertainty in wind speed forecasting and wind power forecasting could be analysed using a developed hybrid model.
- The work shall be done to improve the convergence rate.
- Many authors tested and validated the forecasting models developed using the data of one location. Further, the location dependency of the model requires verification using the data from more than one location.
- Most of the research on wind power forecasting shows models developed for short term forecasting, but not much for long term forecasting.
- In case of grid integration of large capacity renewable energy sources, more work can be carried towards wind power forecasting at grid level.
- To know the reliability of a forecasting tool, a comparison study can be carried between physical model and statistical model in forecasting.
- The effect of wind direction on the prediction of wind power can be evaluated.

1.4 Main objectives of the research proposal

After rigorous literature review in the relevant areas above research gaps are identified. To proceed with the research work the following objectives are defined.

- To design a suitable model for wind power forecasting.
- To design a suitable model for solar photo voltaic (PV) power forecasting.
- To develop a suitable market model for enhancing the wind and solar power penetrations in smart grid.
- To investigate the impact of wind and solar power generations on electricity prices.

- To analyse the uncertainty in the prediction of renewable power generation.

1.5 Key research outcomes

The outcomes of the research work are listed below.

- NARX model is consistent in short term wind power forecasting irrespective of the location.
- A Hybrid network of GRNN and RBFN with parallel topology is developed to incorporate the benefits of individual networks.
- Data clustering by K-means improves the accuracy in solar PV power forecasting.
- Season wise dependency of solar power on either diffuse radiation or direct radiation is investigated.
- A hybrid GRNN-RBFN is developed to reduce uncertainty in prediction analyzed in wind power forecasting.
- Seven market models and operating mechanism are proposed for renewable energy (RE) enabled Indian electricity market.
- Load clustering improves the accuracy in short term electricity price forecasting.
- Electricity price forecasting is significantly influenced by wind power generation.
- Bootstrap aggregation of ensemble model has been developed for an hour ahead accurate electricity price forecasting in RE enabled electricity market.

1.6 Organization of thesis

One of the objectives is to design a suitable model for wind power forecasting. Chapter 2 explains the work carried in order to achieve this objective. The work implements models like NARX, GRNN, RBFN and SVR for wind power forecasting with the data acquired from Belgium wind farms, US wind farms and Indian wind farms. NARX neural network is used to predict wind speed and wind power. This method of prediction is showing good accuracy in wind speed forecasting and consistency in wind power forecasting. In one day ahead WPF, the SVR approach is more consistent and reliable. The GRNN model is also performing consistently with accuracy similar to SVR model.

Chapter 3 explores analysis of uncertainty in prediction of wind power. The work implements GRNN, RBFN and a hybrid GRNN-RBFN. Confidence intervals are calculated on MAPE for all the models to analyse the uncertainty in prediction. GRNN has performed consistently in all months of 2014 with significant reliability. Further a hybrid GRNN-RBFN is designed to forecast wind power, which emphasizes proper assignment of weights to each neural network in parallel topology. The hybrid neural network provides better accuracy in forecasting, if a single neural network is not reliable in forecasting.

In chapter 4, the work carried for solar PV power forecasting is explained. This work mainly implements SVR model, a hybrid model ANN-PSO and a hybrid approach of K-means based ANN-PSO. The results indicate improvement in forecasting accuracy of ANN-PSO model with clustering. The selection of input parameters for season wise forecasting between direct irradiation and diffuse irradiation is investigated.

Chapter 5 & chapter 6 provide price forecasting in electricity market influenced by renewable energy sources. This work is carried by SVR model, a hybrid model of ANN-PSO and a hybrid approach of K-means clustering based LSTM network. The impact of wind power on price forecasting is investigated. In price forecasting an hour ahead, Bootstrap Aggregation of Ensemble model (proposed model) is developed and best accuracy is achieved in comparison of many other models.

In chapter 7, various market models and operating mechanism is suggested for renewable energy enabled electricity market. Considering various aspects like the growth of RE generation, MNRE policies, state wise targets of RE generation, competition in the market and reliable power supply to the consumers, this paper has proposed seven different market models. The operating mechanism is proposed to operate such a market has many new components.

Chapter 8 concludes the work.

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Chapter 2

WIND POWER FORECASTING

2.1 Introduction

About 75 to 80 percent of thermal pollution is generated by power plants which is primarily responsible for global warming. As the conventional energy sources are vanishing, renewable energy sources are the promising alternative to the conventional sources. Currently the world is moving towards clean energy with low carbon emissions. Smart grid technology development also encourages more wind power and solar power integration to the grid. The energy demand, by 2030 is estimated to be as high as 900 GW in India, out of which the renewable energy potential that can be exploited till 2030 is around 450 GW [1]. Wind power is growing rapidly all over the world especially in European countries, America and China. India also has sufficient potential for wind energy.

The Global Cumulative installed wind capacity by 2019 is 597 GW. Globally installed wind power capacity is increasing at a rate of 19%. It is also estimated that wind power contribution will be increased to 12% of the Global power generation by 2020. Worldwide, India has 5th largest wind installed capacity. Fig.2.1 shows 47 percent contribution of wind energy in India by 2018.

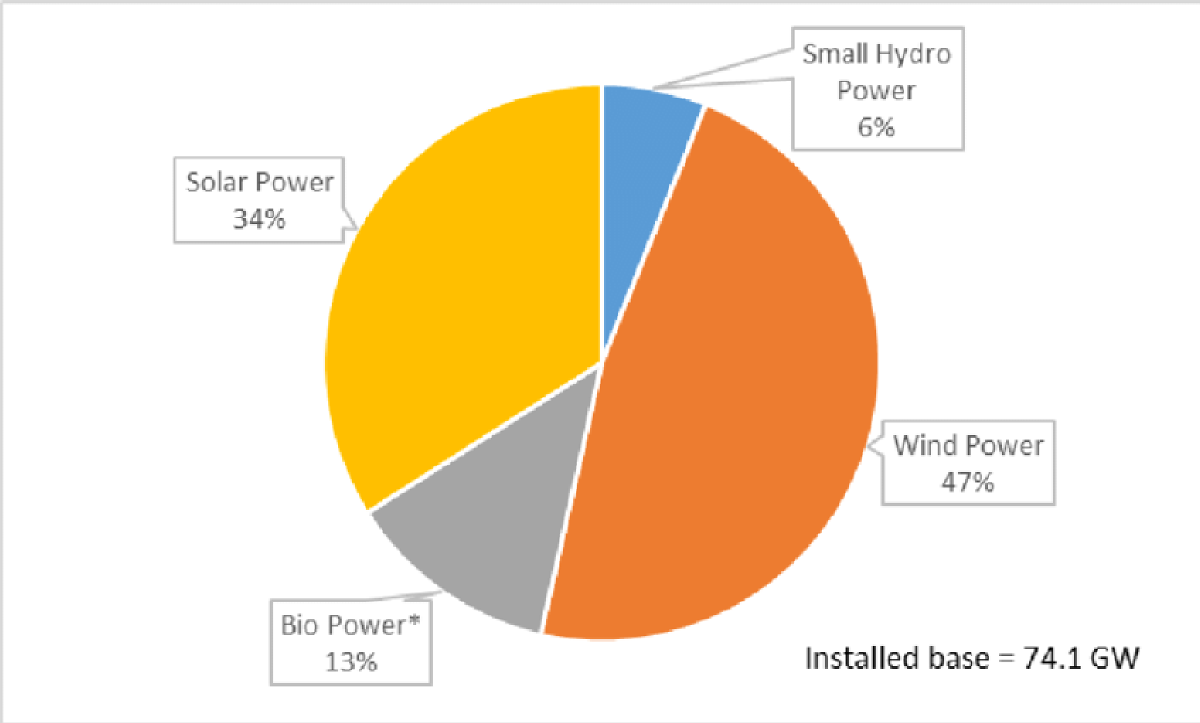

Fig.2.1: Renewable energy in India

The variant nature of wind poses a few challenges to the power sector. Being uncertain and intermittent, the wind power integration leads to the unbalance between generation and load in the power grid. WPF is identified as an important task in the proper operation of power systems with large wind power penetrations. Wind speed and power forecasting plays a prominent role for maintaining balance of generation and load. Accurate wind power forecasting can provide a proper technical support for wind power trading in electricity market to achieve the significant economic benefit. To decide the operating reserves, the wind power forecasts are very much essential. Wind power forecasts are also required in selecting the site & location of new wind farms. Accurate prediction of renewable energy is very much required, where the power system operators would be fined with the penalty cost for imbalance between predicted and actual generation. Since wind power is a non-linear function of wind speed, air density and turbulent kinetic energy and turbine characteristics, a lot of research is carried in the area of forecasting techniques of wind speed & wind power [2].

Wind power & speed forecasts are able to produce information about the wind speed & power in next few minutes, hours and days. Accordingly WPF is categorized into short term, medium term and long term as per the power system operational requirements. Short term forecasting is important for turbine control and also to balance with the load. Medium term forecasting is essential for managing power system and energy trading, whereas long term forecasting is focused for maintenance of wind farms. To plan the installation of new wind turbines and farms the technical assistance is obtained from long term wind speed and power forecasting. WPF is also a part of energy management system (EMS) implemented for micro grid operation & control. EMS provides significant information for scheduling generating units and provides signals towards demand side management [3]. Researchers developed many forecasting techniques with the increase of accuracy. Fig.2.2 presents classification of wind power forecasting based on technique.

The wind power forecasting methods basically can be categorized into 4 types based on the time horizon of forecasting as given below.

Very short term: It ranges from few seconds to 30 minutes and used in wind turbine control, electricity market clearing etc.

Short term: It ranges from 30 minutes to 72 hrs and useful in economic load dispatch, load increment or decrement decisions.

Medium term: It ranges from 72 hrs to one week ahead and used for maintenance related decisions/unit commitment.

Long term: It ranges from one week to one year ahead and applied in design of the wind farms.

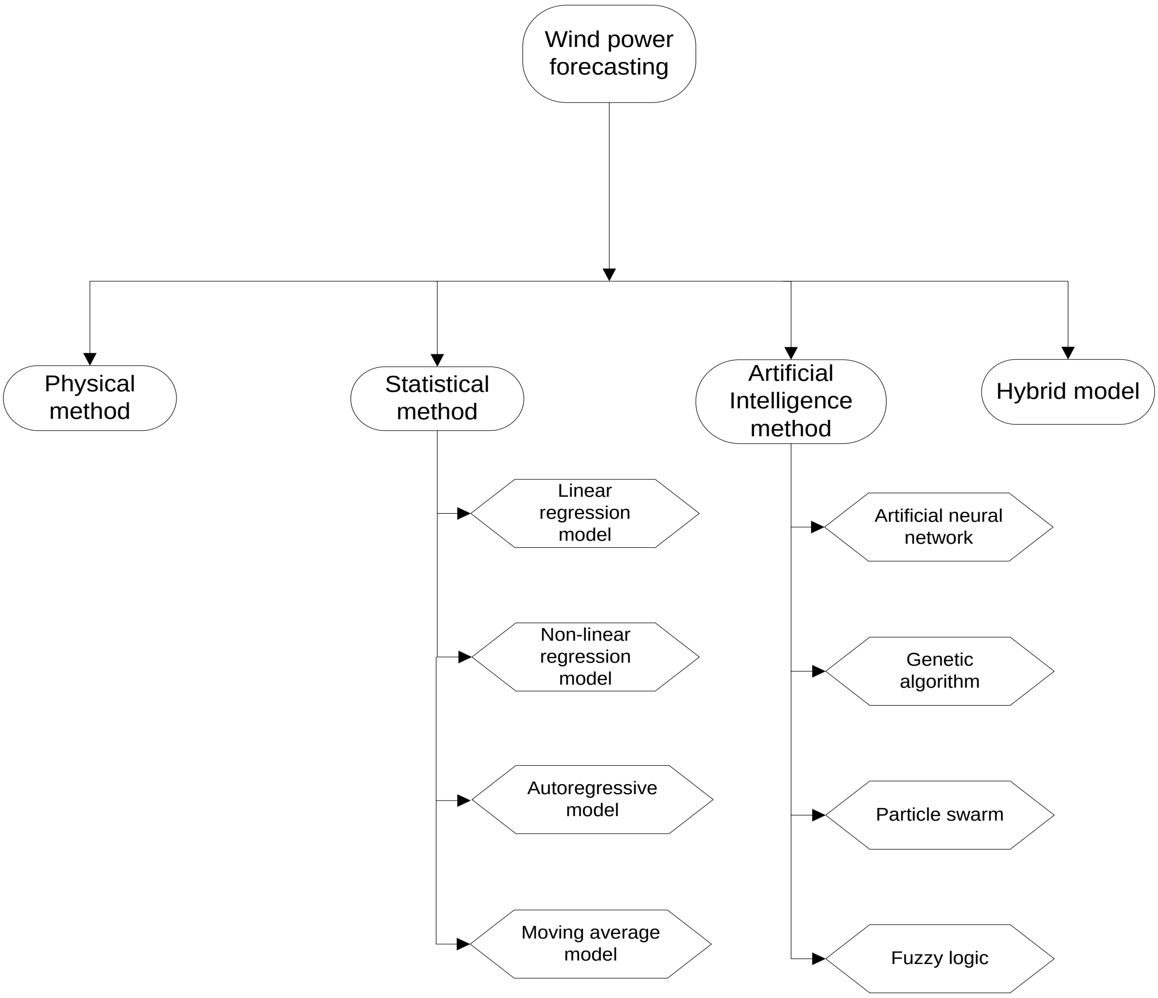

Fig.2.2: Wind power forecasting methods

2.2 Wind speed & wind power forecasting using NARX model

2.2.1 Data collection & pre-processing

Data has been acquired from Belgium wind farms for the years of 2013 & 2014 from its official website. In wind power forecasting, the data set of wind speed, historical wind power with the frequency of 15 min. is utilized.

Data also has been acquired from US wind farms for the years of 2011 & 2012. Using the data set of five parameters wind speed, wind direction, temperature, air density & wind power with the frequency of 5 min., wind power and wind speed have been forecasted in US wind farms.

Poor and missing data from the collected sample data can affect forecast accuracy. Data normalization improves the pace of convergence and the precision of neural network training. The acquired data is normalized to organize the data

2.2.2 Nonlinear autoregressive with external input (NARX) model

Neural networks comprise neurons inspired by biological nervous systems. The neural network of the appropriate function is well trained with data from the real world. The trained neural network can perform the function required. Fig.2.3 shows a neural network with multilayers.

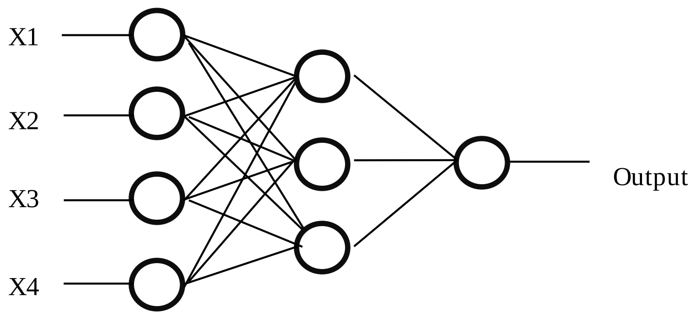

Fig.2.3: A multilayer neural network

The standard NARX network is a feed forward network which is of three layers. In the hidden layer a sigmoid transfer method is applied in this network, and a linear transfer mechanism is used for the output layer. This network often incorporates tapped delay lines to store previous x (t) and y (t) series values. The NARX network output y (t) is fed back to the network input (by delays). A nonlinear autoregressive with exogenous (external) input (NARX) predicts future values of a time series y(t) from past values of that time series and past values of a second time series x(t). It can be written as per eq.2.1.

$$y(t) = f(y(t-1), ..., y(t-d), x(t-1), ..., x(t-d)) \qquad (2.1)$$

This model is widely being used for time series prediction in finance sector, manufacturing systems, robotics, aerospace vehicle and chemical processes etc.

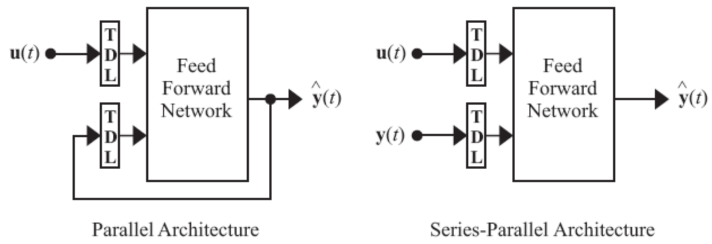

Fig.2.4: Parallel and series parallel architectures of NARX networks

These networks, as shown in fig.2.4, are again classified as parallel and series-parallel architecture. The NARX network with series-parallel architecture uses the past values of the actual time series to be predicted and past values of other inputs to predict the future value of the target series. In the parallel architecture, the NARX network predicts future value of target series by using past predicted values of time the time series y(t) and the past values of other inputs [4].

2.2.3 Design of neural network

Neural network design requires a three layer design. The three layers are neurons in the input layer, hidden layer, and output layer. There are connections from each input layer neuron to everyone in the hidden layer, and in turn, from each hidden layer neuron to each output layer neuron for feed forward activity. Thus activation of hidden neurons and output neurons requires two sets of weights [5].

Using Levenberg-Marquardt back propagation method, the weights are adjusted to reduce the mean squared error (MSE) between the predicted value of the network and the real goal value in each training range. These modifications are rendered in the reverse direction, from the output layer, via each hidden layer down to the first hidden layer, before the state of termination is reached. The below steps are followed in the proposed algorithm.

- Initialization of the weights
- Transmission of the inputs in forward direction

- Back propagation of the error
- Terminating condition

2.2.4 Training & testing of the network

The neural network is properly trained to predict future wind power with the selected input parameters such as historical wind power, and wind speed. The data used in training is 70% and the remaining input values are used for testing and validation. The minimum error is achieved by varying the number of hidden layers in the network, the number of test epochs, the tolerance of errors and the number of neurons in hidden layer etc. [6]. The selection of various parameters of NARX model is depicted in table 2.1.

Table 2.1: Various parameters of designed NARX model

Parameters	**Selection**
Number of hidden layers	1
Neurons in hidden layer	10
Delays	2
Training parameters	Error: MSE Learning algorithm: Levenberg-Marquardt

2.2.5 Simulations & results

a) Results of wind power forecasting in Belgium wind farms

This work implements artificial neural network using NARX model. Forecasting is carried in MATLAB. A three layer ANN is used. The optimum number of hidden neurons of hidden layer of the network is identified while minimizing the forecasting error in terms of mean squared error (MSE) and improving regression. MSE is calculated between the predicted value and the actual value. Regression signifies the correlation between the predicted and actual values. Input data used are wind speed and historical wind power to forecast wind power as specified in table 2.2.

The accuracy of this forecasting is assessed with the MAPE calculation. MAPE represents mean absolute percentage error. The wind power forecast was carried out from Belgium's wind farms by using 6 months of historical power data and wind speed of every 15 minutes. The assessment factor MAPE is set out in eq.2.2. All the calculated MAPE values for wind power forecasting are depicted in table 2.2.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \qquad (2.2)$$

Where, Ai and Fi are actual and forecasted values respectively.

Table 2.2: **Forecasting accuracy in terms of MAPE in Belgium wind farms**

Input Data Used	**Predicted parameter**	**% MAPE**
Historical wind power of Jan 2013	Wind power of Jan 2014	3.3
Historical wind power of Feb 2013	Wind power of Feb 2014	3.19
Historical wind power of Mar 2013	Wind power of Mar 2014	8.3
Historical wind power of Apr 2013	Wind power of Apr 2014	9.6
Historical wind power of May 2013	Wind power of May 2014	9.3
Historical wind power of June 2013	Wind power of June 2014	10.1
6 months wind speed of Jan 2014 to June 2014	Wind power of Jan 2014 to June 2014	7.4

In fig.2.5, the MAPE plot is shown for wind power forecasting of Jan’14. The error in terms of MAPE is 3.3 % as mentioned in table 2.2. The MAPE plot depicts lower errors indicating good accuracy in forecasting. The MAPE plot for the wind power forecasting of

Feb'14 is also shown in fig.2.6. This plot indicates few samples with high errors. The MAPE plot in fig.2.7 for wind power forecasting in Mar'14 clearly indicate higher error in terms of MAPE. Wind power forecasting for the month Mar'14 is less accurate. For the months of Apr'14, May'14 and June'14, the MAPE plots are shown in fig.2.8, fig.2.9 & fig.2.10 respectively. In Belgium, wind speeds are high in the months January and February. The results in table 2.2 are clearly depicting with good accuracy in forecasting in Jan'14 and Feb'14 as the wind speed patterns are similar in the consecutive years 2013 and 2014.

In the regression plot seen in fig.2.11, x-axis quantity is actual wind power and y-axis quantity is predicted wind power. The plot clearly illustrates the usage of strongly correlated data in Jan 2014 wind power prediction. Whereas in fig.2.12 the regression map indicates the usage of reasonably linked data for the June 2014 wind power forecasting. Fig.2.13 displays MAPE plot using wind speed as input data for wind power forecasting. The MAPE error is obtained to be 7.4%.

It is understood that NARX artificial neural network, using historical power data or wind speed data used in this work, performs with proper reliability in the wind power forecasting. Wind power forecasting error is increasing in the Apr'14, May'14 & June'14 monthly wind power forecast.

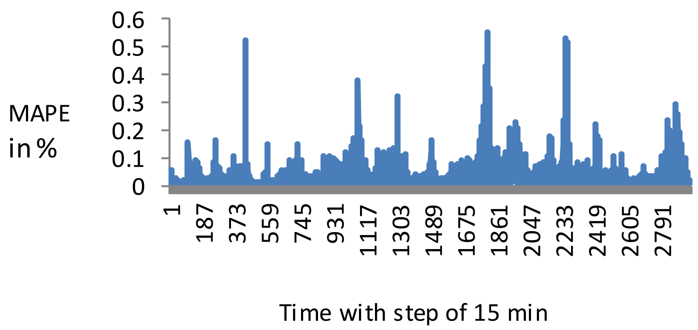

Fig.2.5: MAPE plot as a function of time for wind power forecasting in Jan'14

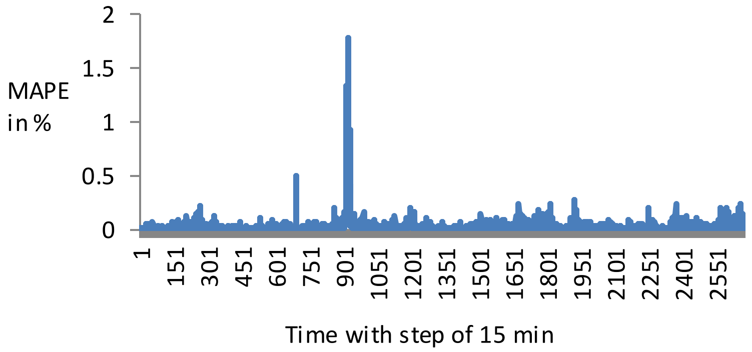

Fig.2.6: MAPE plot as a function of time for wind power forecasting in Feb'14

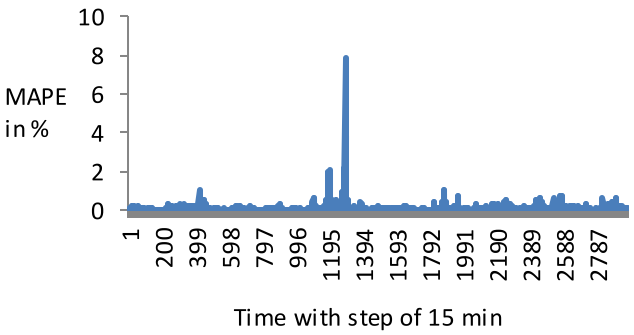

Fig.2.7: MAPE plot obtained for wind power forecasting in Mar'14

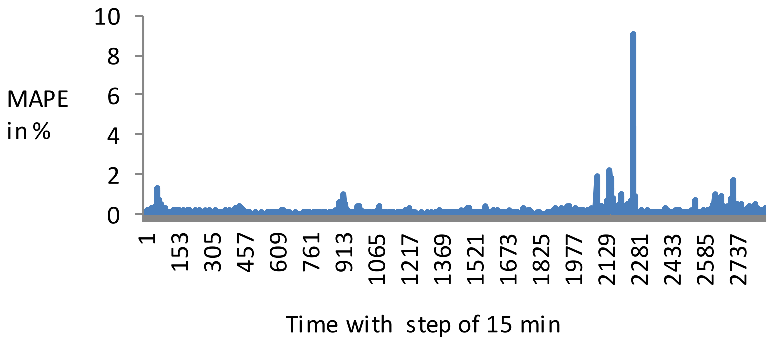

Fig.2.8: MAPE plot obtained for wind power forecasting in Apr'14

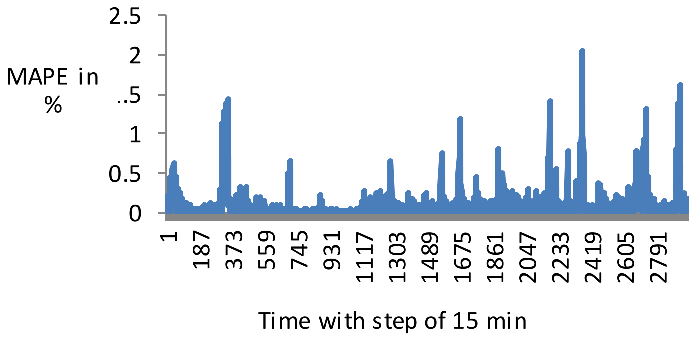

Fig.2.9: MAPE plot obtained for wind power forecast of May'14 using historical wind power as input data

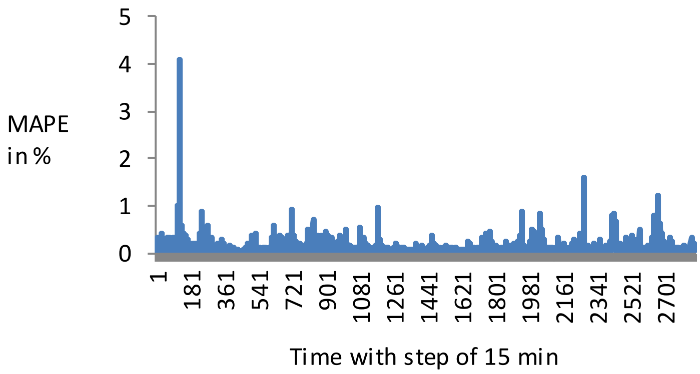

Fig.2.10: MAPE plot obtained for wind power forecast of June'14 using historical wind power as input data

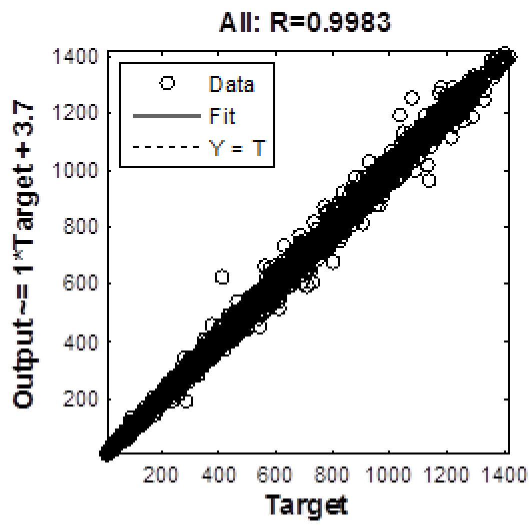

Fig.2.11: Regression plot obtained for wind power forecast for Jan '14 using historical wind power as input data

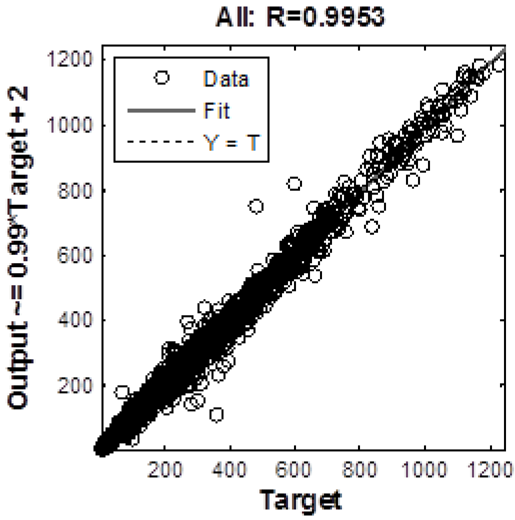

Fig.2.12: MAPE plot obtained for wind power forecast for June'14 using historical wind power as input data

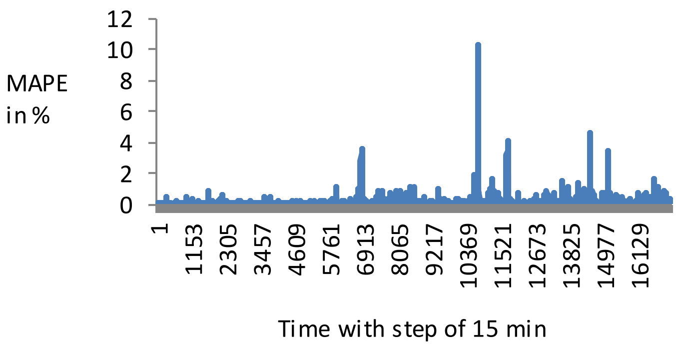

Fig.2.13: MAPE plot obtained for wind power forecast using wind speed as input data

b) Results of wind speed & wind power forecasting in US wind farms

I. Wind speed forecasting

In this work, forecasting is mainly carried in MATLAB using the NARX model with artificial neural network. Using A three-layer ANN, repeated simulations are done to provide the optimal number of hidden neurons to reduce the statistical error and boost regression. Input parameters used for forecasting wind speed are wind direction, air density & temperature.

With MAPE's evaluation the accuracy of this forecast is estimated. MAPE reflects mean absolute percentage error, specified in eq.2.2. The wind speed forecast was carried out from US wind farms using one month data of every 5 minutes. In the regression plot in fig. 2.14, actual wind speed is indicated on x- axis and predicted wind speed is specified on y-axis. The regression plot depicts high accuracy in wind speed forecast. Fig.2.15 shows evaluation factor MAPE plot. All the calculated MAPE values for wind speed & wind power forecasting are depicted in table 2.3.

Table 2.3: **Forecasting accuracy in terms of MAPE for US wind farms**

Wind Speed & wind power forecasting		
Input Data Used	**Predicted parameter**	**% MAPE**
Air density, wind direction and temperature of Jan 2011	Wind speed of 2011	2.3
Wind speed, wind direction & temperature of Jan 2011	Wind power of Jan 2011	20
Historical wind power of Jan 2011	Wind power of Jan 2012	22.3
Historical wind power of Feb 2011	Wind power of Feb 2012	22.7
Historical wind power & wind speed of Jan 2011	Wind power of Jan 2012	19.7
Historical one day wind speed & wind power	One day ahead Forecast of wind power	17

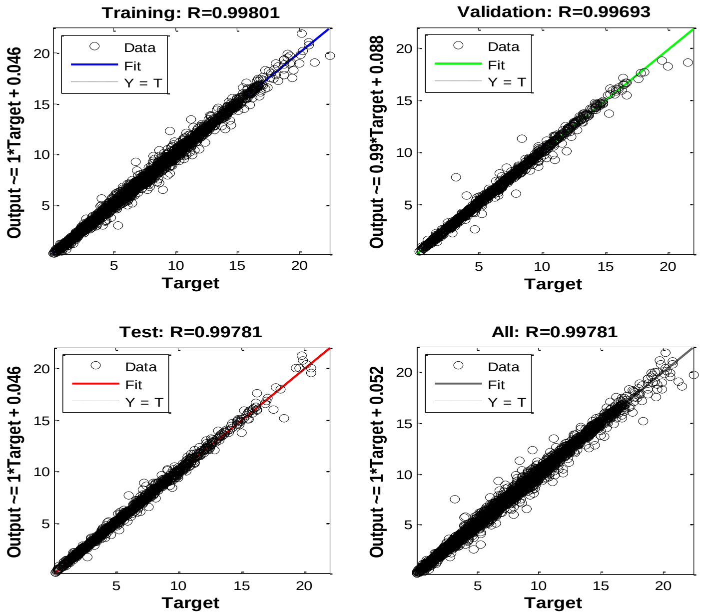

Fig.2.14: Regression plot obtained for wind speed forecast

As shown in fig.2.14, the regression plots clearly indicate the use of highly correlated data in the wind speed forecast. MAPE plot in fig.2.15 is depicting good accuracy of the wind speed forecast.

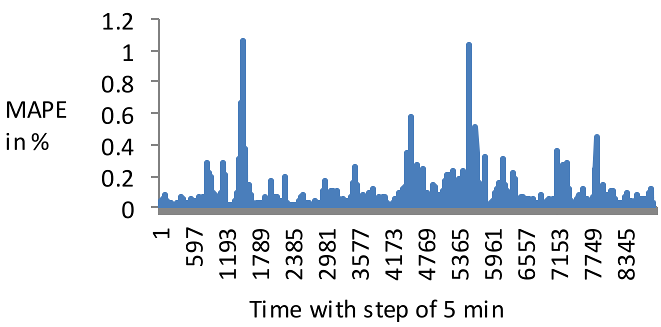

Fig.2.15: MAPE plot as a function of time for wind speed forecast

II. Wind power forecasting

By using the data sets of wind speed, wind direction, temperature & historical wind power as input data future wind power is forecasted. The data of 2011 & 2012 of US wind farm is used in this work. The wind power forecasting is carried by artificial neural network using NARX model in MATLAB. In this work, the forecasting accuracy is evaluated in terms of the error calculation MAPE.

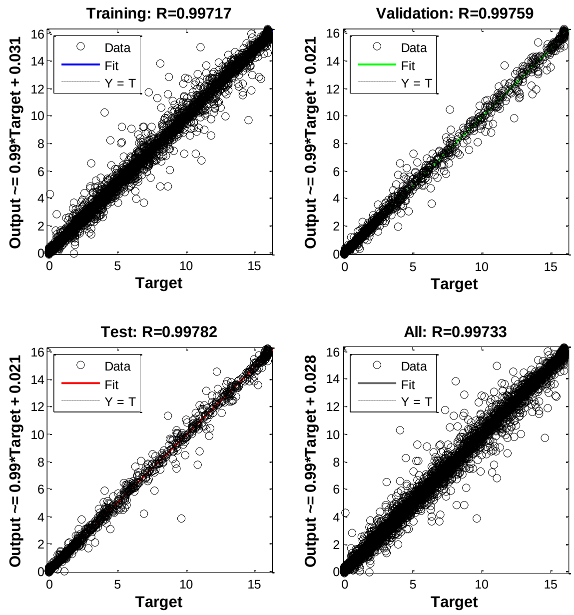

Fig.2.16: Regression plot obtained for wind power forecast based on meteorological information

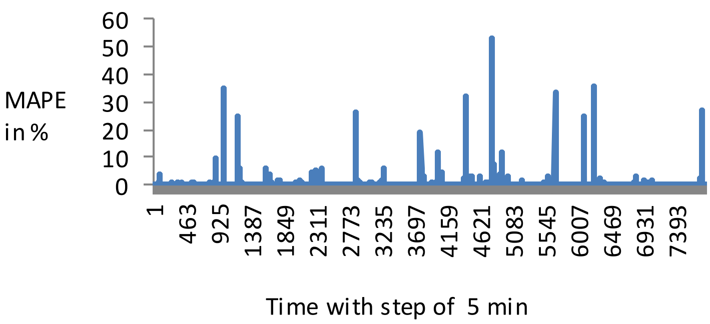

Fig.2.17: MAPE plot as a function of time in wind power forecast

Here fig.2.16 & fig.2.17 show regression plots and MAPE plot respectively in the wind power forecast using meteorological data. The regression plot of wind power forecast suggests the utilization of moderately correlated data. From MAPE plot, it is understood the MAPE value is much larger for some samples which increases the error of prediction up to 20%.

It is clear that NARX network performs with good reliability in wind power forecasting either by using meteorological data or historical power as the input data used in this work. The error of wind power forecasting is reduced to some extent when historical wind power & wind speed data is used as input as shown in MAPE plot in fig.2.22.

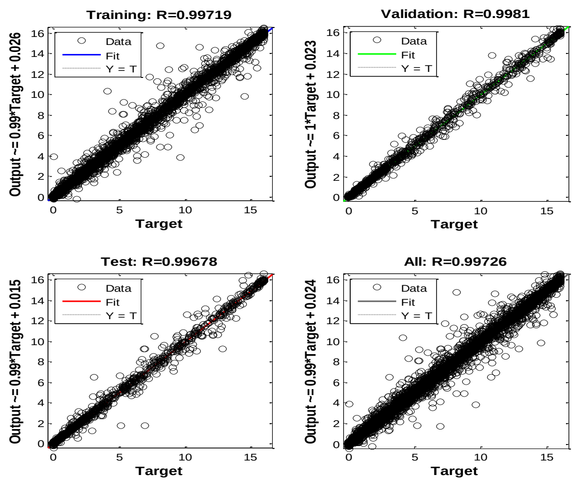

Fig.2.18: Regression plot obtained for wind power forecast for Jan'12

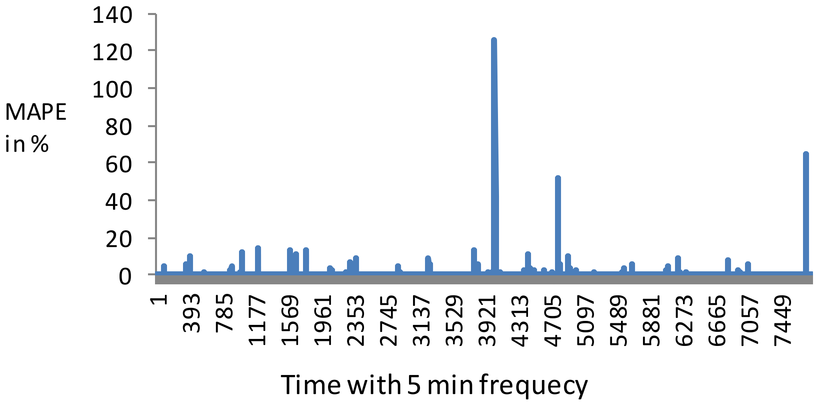

Fig.2.19: MAPE plot obtained for wind power forecast for Jan'12

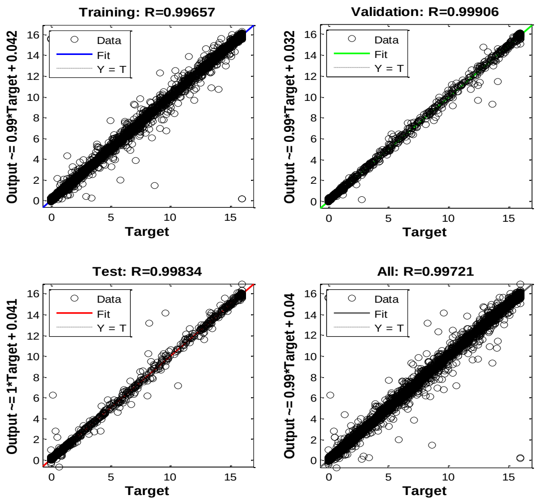

Fig.2.20: Regression plot obtained for wind power forecast for Feb'12

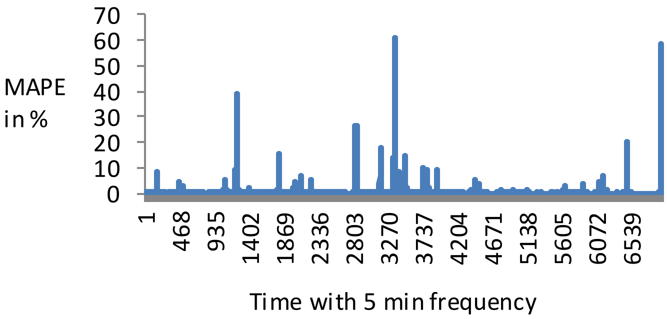

Fig.2.21: MAPE plot obtained for wind power forecast for Feb'12

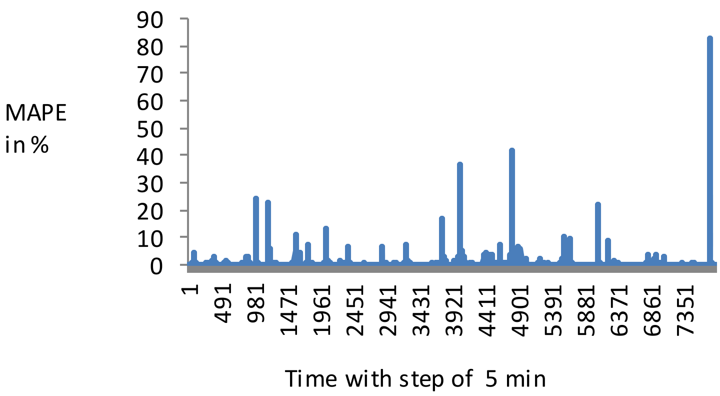

Fig.2.22: MAPE plot obtained for wind power forecast for Jan'12 using historical wind power & wind speed as input data

2.3 One day ahead wind power forecasting

This section proposes radial basis function neural network (RBFN), generalized regression neural network (GRNN) and support vector regression (SVR) approach towards effective & efficient wind power forecasting using less historical wind power data in the training.

2.3.1. Data collection & pre-processing

Data has been acquired from Indian wind farms for the year 2014. In wind power forecasting, the data set of hourly wind speed, historical wind power is utilized.

Poor and missing data from the collected sample data can affect forecast accuracy. Data normalization improves the pace of convergence and the precision of neural network training. The acquired data is normalized to organize the data [7]. The formula is implemented to normalize the available data is given by eq.2.4. This normalization technique is implemented when the data is normally distributed.

$$x_{new} = \frac{(x-\mu)}{\sigma} \qquad (2.4)$$

Where, μ is the mean of data set and σ is the standard deviation.

2.3.2 Methods

The methods implemented in the work described below.

a) Radial basis function neural network

Radial basis function neural network (RBFN) is a specific type of neural network resembling to K-nearest neighbour model. Generally, artificial neural networks are referred to be multilayer perceptron (MLP).In MLP; each neuron receives the sum of product of input value and its connection weight. This describes linear classification [8]-[9]. But the combination of these neurons leads to a complex non-linear classification technique. Unlike MLP, RBFN a three layer neural network performs classification by analysing the input's similarity to training set. Each neuron stores a prototype from the examples of the training set while RBFN gets trained. The new input is classified by computing the Euclidean distance between the input and its prototype. The weight of each neuron can be computed by applying a radial basis function to the Euclidean distance. Further, the choice of the receptor is crucial in the weight's calculation in RBFN [10]-[11]. Fig. 2.23 presents the structure of RBFN.

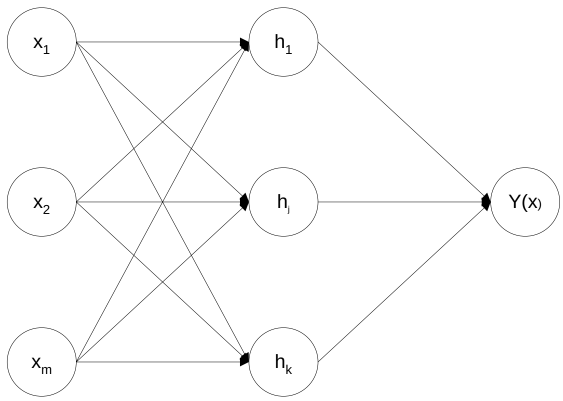

Fig.2.23: Structure of RBF neural network

As depicted in fig.2.23 the inputs to the neural network are denoted as x_1, x_2 up to x_m. Whereas the hidden layer h_j takes a radial basis function. The most commonly used radial basis function in neural networks is Gaussian function as described in eq.2.5. Finally, the network's output is calculated as per the eq.2.6, where w_j indicates the weight of the connections.

Gaussian Function: $\emptyset(r) = \exp[\frac{-r^2}{2\sigma^2}]$ (2.5)

Where, r indicates Euclidean distance and σ is standard deviation.

Output: $y(x) = \sum_{j=1}^{k} w_j h_j(x)$ (2.6)

b) Generalized regression neural network

Generalized regression neural network (GRNN) is a type of probabilistic neural networks. It is based on the function approximation one pass learning algorithm. GRNN applies the probability density function following normal distribution. This neural network needs only a fraction of training data that is required by any neural network follows backpropagation. Training data maps input to output. Once the network is trained, testing data set is used to predict the result [12].

In case of GRNN, output is estimated using weighted average of the outputs of training dataset, where the weight is calculated using the Euclidean distance between the training data and testing data. If the distance is large then the weight will be very less and if the distance is small, it will put more weight to the output. This neural network mainly consists of four layers named input layer, pattern layer, summation layer and output layer. The input layer passes the input to next layer. In pattern layer, a Gaussian probability distribution function RADBAS is applied which needs the calculation of Euclidean distance. Further every training sample will represent a mean to a radial basis neuron.

In summation layer, two sub parts, numerator and denominator of the function as described in eq.2.7 are computed. Numerator part computes the summation of multiplication of training output data and activation function. Denominator part calculates the summation of activation function. The output layer finally calculates the output by taking the ratio of numerator part to denominator part as per eq.2.7.

$$Y(x) = \frac{\sum_{i=1}^{n} Y_i \exp(-\frac{Di^2}{2\sigma^2})}{\sum_{i=1}^{n} \exp(-\frac{Di^2}{2\sigma^2})} \quad (2.7)$$

Where D_i is the distance between the training sample and point of prediction, Y_i is the training sample and the parameter σ is defined as the standard deviation or spread**.**

c) Support vector regression

For classification and regression analysis the algorithms of supervised learning models are used in support vector machines. In a linear classifier the feature vectors in non-linear classifier are effectively translated into high-dimensional space. Implicitly, this mapping can be done with the Kernel functions. For a given training data $\{(x_1, y_1),.....,(x_l, y_l)\} \subset X \times R$, where X denotes the space of input patterns. In ε support vector regression, our goal is to find a function f(x) that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time, is flat as possible. As long as the errors are less than ε, it is accepted otherwise the errors will be taken care [13]-[15]. Ultimately Support vector regression finds a regression function as in eq.2.8.

$$y = f(x) = w^T \varphi(x) + b \qquad (2.8)$$

Where, $\varphi(x)$ is a function that can map data x from low dimension to high dimensional space, w is a weight vector and b represents bias that is either increased or decreased. Standard support vector regression adopts ε-insensitive function. It is assumed that all the training data is fitted with a linear function in the accuracy of ε.The problem is translated into an objective function to optimize its minimization as given in eq.2.9.

$$\text{Minimize} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \qquad (2.9)$$

Subject to

$$w^T \varphi(x) + b - y_i \le \varepsilon + \xi_i$$

$$y_i - w^T \varphi(x) - b \leq \varepsilon + \xi_i^*$$

$$\xi_i , \xi_i^* \qquad \geq 0$$

Where, ξ_i , ξ_i^* are known as the relaxation factors.

When there is an error in fitting, ξ_i , ξ_i^* are greater than 0.If not, ξ_i , ξ_i^* are all equal to zero. For the fitting method the first term of the optimization function more smoothen to boost generalization. The second term is that of reducing the error. The next important parameter is the error penalty parameter C which greatly affects support vector regression performance C is a trade-off between the difficulty of the algorithm and the degree of samples wrongly classified. Smaller C values indicate lower punishment for the original data's empirical error, and higher risk of experience. If the value of C is larger, the empirical error penalty is larger and experience risk is smaller. The greater C value also results in high computational complexity. The selection of appropriate penalty factor C thus has a major impact on the convergence of the model and its performance in prediction. Another critical element is kernel function, which is known to be the origin of support vector regression. It has an impact on support vector regression results. Significant steps in the performance of support vector regression are the determination of the appropriate kernel function and the appropriate values for the various relevant kernel parameters.

Mostly four types of kernel functions, linear kernel, polynomial kernel, RBF kernel and sigmoid kernel are implemented in support vector regression. As construction of RBF kernel (Gauss kernel) is relatively easy, this is widely used at present. The function is as follows in eq.2.10.

$$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / \sigma^2) \qquad (2.10)$$

Where σ is the standard deviation, $\sigma > 0$.

2.3.3 Training & testing of the models

After normalization, the multilayer neural network RBFN which is a three-layer neural network has been developed for wind power forecasting. The three layers of the RBFN are described as input, output and hidden layers. The hidden layer incorporates radial basis function RADBAS .The neurons of hidden layer are increased for a radial basis network until it reaches specified mean squared error. The connections are made for feed forward. In RBFN the weights are adjusted according to the receptor and spread unlike conventional neural network. So, proper receptor selection rapidly converges with the network. GRNN is also a kind of radial basis network and used for approximation of functions. The GRNN applies Gaussian distribution function RADBAS. Similarly, for the GRNN, spread is selected as per random search method to approach minimum error in forecasting. Smaller spread ensures to fit the data closely.

Further the SVR model is designed with RBF kernel function. In SVR model kernel plays a key role because with kernel trick only nonlinear regression is performed by implicitly mapping their inputs into high dimensional feature spaces. The effectiveness of SVR depends on the selection of kernel, kernel parameters and regularization parameter C. Most widely used kernel is RBF, since it is simple in construction with only one parameter γ. It is the inverse of the standard deviation of RBF kernel (Gaussian kernel) which is used as similarity measure between two points. The appropriate values of the parameters C& γ are required to achieve higher cross validation accuracy. Fig.2.24 describes the methodology of the work carried out for WPF in this paper. The work presented in this section is initiated with data collection from an official website of Indian wind farms. The data includes historical data of meteorological parameters wind speed, temperature and wind power. After proper data acquisition, relevant excel files have been prepared to pre-process the data. To ensure continuity of the data, and to improve the convergence rate of neural networks, normalization is carried as mentioned in the above section. Then three different forecasting models GRNN, RBFN and SVR have been designed. With the data wind speed and wind power of 27 days from every month in the year 2014 is utilized in training of the models .Once the models are well trained and ready to forecast, the hourly wind power on 28th day of every month for the year 2014 is forecasted. Then, rigorous evaluation is carried to assess the performance of all the forecasting models. Finally, the work concludes with the comparison of the model's performance.

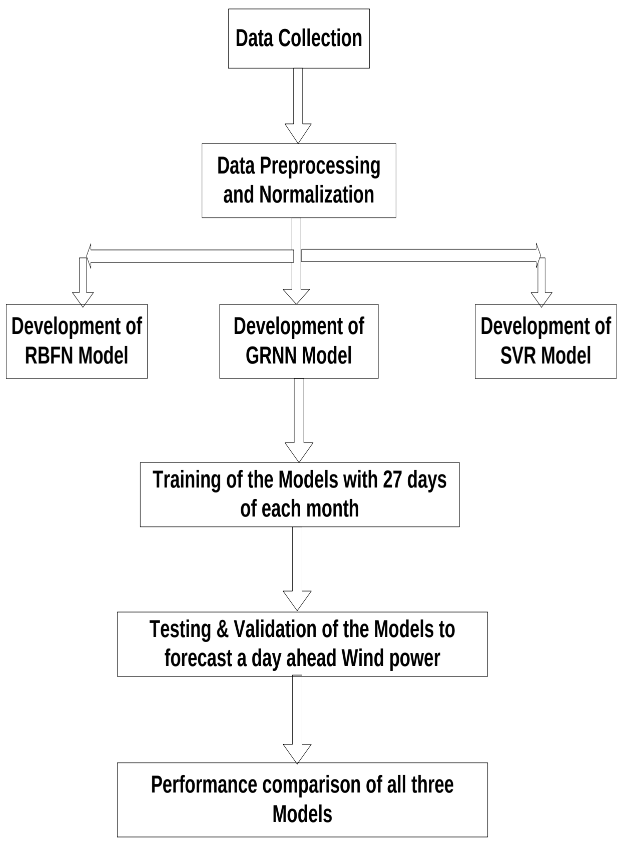

Fig.2.24: Flow chart of the proposed methodology

2.3.4 Simulations & results

This work mainly proposes wind power forecasting with two different neural networks RBFN, GRNN and SVR model. The WPF uses the data of the year 2014 from the Indian region Kolkata. It is availed from the official website consists NWP data of hourly wind speed and wind power for the year 2014. The data is divided into two sets for training and testing. In each month, 27 days hourly data is used in training the neural networks GRNN and RBFN and the SVR model. For the GRNN and the RBFN suitable spread values are chosen. The spread value is optimized to 0.005 with random search method for GRNN and it is 1 for RBFN. The SVR model establishes a suitable kernel which evolves with the selection of suitable values for regularization parameter C and γ.To handle misclassification of training sample, the regularization parameter C must be optimized. If the value of γ is small, variance is large. Further, it is well understood that large gamma indicates high bias and small variance .In this work, RBF kernel is chosen. Using grid search method, the values of C and γ are optimized to 100 and 1 respectively.

In each month the historical data of wind speed and wind power is used to train the neural network models and the SVR model effectively for 648 epochs. A day ahead hourly wind power generation is forecasted by using all three models. The forecasting accuracy of these models is analyzed by calculating the two errors such as mean absolute percentage error (MAPE) and root mean squared error (RMSE) as given by eq.2.11 and eq.2.12 respectively.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \qquad (2.11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2} \qquad (2.12)$$

Where, A_i and F_i are actual and forecasted values of the parameter (to be predicted) respectively.

The MAPE values are presented in table 2.4. It is observed that the SVR model shows consistent performance though the errors in terms of MAPE in a day ahead WPF of the months of Oct'14 and Nov'14 are higher than usual. Fig.2.25 presents bar graph of MAPE values of all three models.

Table 2.4: Comparison of forecasting accuracy in terms of MAPE values

MAPE values for Wind power forecasting one day ahead			
Day of prediction	**RBFN**	**SVR**	**GRNN**
28th Jan'14	0.24	0.2	0.32
28th Feb'14	7.33	7.93	3.6
28th Mar'14	0.24	0.26	0.37
28th Apr '14	0.56	0.55	0.67
28th May'14	42.70	1.33	0.51
28th June'14	0.24	0.16	0.46
28th July '14	0.12	0.14	0.17
28th Aug'14	0.18	0.12	0.18
28th Sep'14	0.64	0.65	0.77
28th Oct'014	15.4	9.4	13.07
28th Nov '14	7.2	11	12.92
28th Dec'14	0.23	0.22	0.47
Maximum	42.70	11	13.07
Minimum	0.12	0.12	0.17

Table 2.5: Comparison of forecasting accuracy in terms of RMSE values

RMSE values in kW for Wind power forecasting one day ahead			
Day of prediction	**RBFN**	**SVR**	**GRNN**
28th Jan'14	0.03	0.03	0.068
28th Feb'14	0.007	0.007	0.0095
28th Mar'14	0.04	0.041	0.155

28th Apr ‘14	0.04	0.036	0.38
28th May’14	125	2.8	0.62
28th June’14	0.028	0.028	0.055
28th July ‘14	0.04	0.046	0.09
28th Aug’14	0.029	0.031	0.034
28th Sep’14	0.026	0.03	0.022
28th Oct’014	0.02	0.018	0.02
28th Nov ‘14	0.02	0.02	0.053
28th Dec’14	0.033	0.036	0.223
Maximum	125	2.8	0.62
Minimum	0.007	0.007	0.0095

Support vector regression is mainly influenced by kernel function and the proper selection of its parameters. Though the RBFN model forecasted has wind power with similar accuracy of the SVR model in some months, it got failed to predict wind power on 28th May’14 with very poor MAPE of 42.7% as range of wind speed is higher side on that day. In RBFN model when the samples of larger variance dominate the objective function, the model will not be able to predict accurately. But, unlike the RBFN model, other two models the SVR model and the GRNN model are successful in forecasting with good accuracy. Fig.2.26 & fig.2.27 depict the comparison of the forecasted power and the actual power for the forecasted day 28th May’14. Except in one or two months, the SVR model provides higher accuracy in a day head forecasting. Though MAPE values of WPF with the GRNN model are little bit higher than the SVR model, being improved version of neural networks based on non-parametric regression, GRNN model is reliable in short term WPF. In the months of October and November all three models suffer with less accuracy because of lower values of wind speed for many samples and high volatility in wind speed of the forecasted day. Fig. 2.28 clearly indicates MAPE values are at the higher range for SVR model when wind speeds are very much lower. The lower wind speeds lead to higher MAPE for the SVR model in WPF on 28th Nov’14. Fig.2.29 shows highly variant wind speed on the forecasted day 28th Nov’14. For WPF through SVR model , MAPE value ranges from 11% to 0.12 %.The maximum MAPE for WPF with GRNN model is 13.07% and minimum MAPE is 0.17%.Similarly maximum MAPE, minimum MAPE are 42.7% and 0.12% for WPF using the RBFN model respectively. To emphasize the performance of all three models RMSE values are computed in KW and presented in table 2.4.While analysing RMSE values also, the SVR model is considered to be the best model for short term WPF. The maximum RMSE for WPF through the RBFN model is abnormal value as shown in table 2.5, indicating the inability of the model for a day ahead WPF of the day in the month of May’14 i.e.28th May’14.

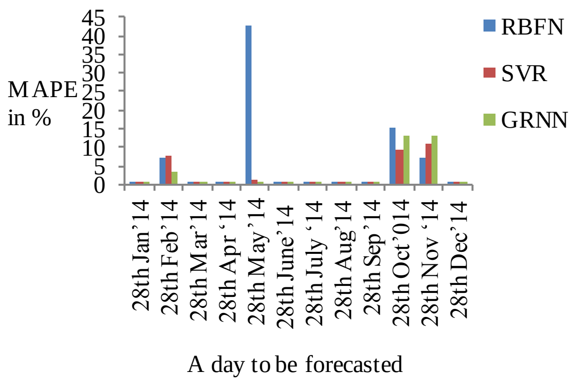

Fig.2.25: Comparison of RBFN, SVR and GRNN performances in terms of MAPE

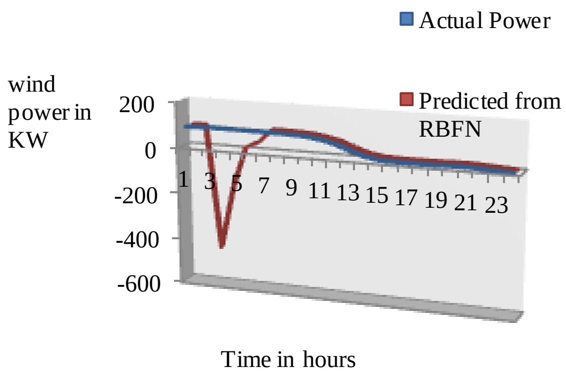

Fig.2.26: Comparison of forecasted power of RBFN to actual power of 28th May’14

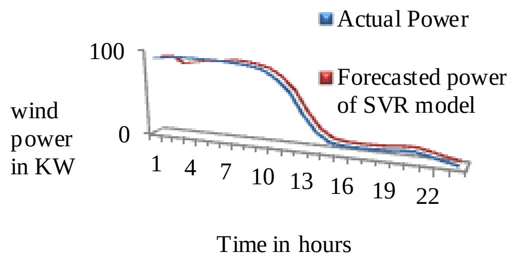

Fig.2.27: Comparison of forecasted power of SVR to Actual power of 28th May'14

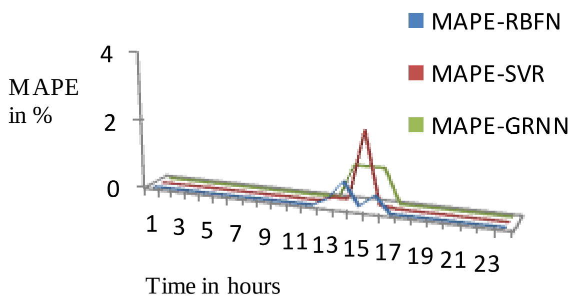

Fig.2.28: Comparison of MAPE plots of 28th Nov'14

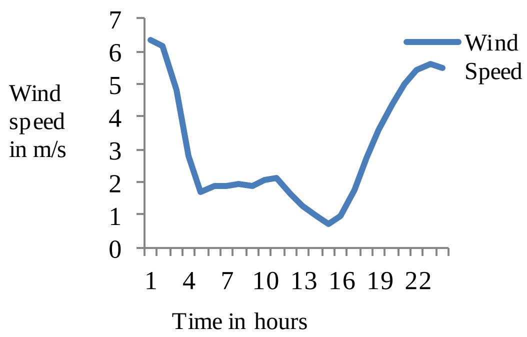

Fig.2.29: Variation of wind speed on 28th Nov'14

2.4 Summary

This work effectively describes the performance of NARX Neural Network in wind power forecasting and wind speed forecasting. The optimization of number of hidden layer's neurons is significant. In this work, the number of neurons in hidden layer is set by repeated simulations. NARX model is consistent in short term wind power forecasting irrespective of the location. Further to understand the performance of various models like GRNN, RBFN and SVR, one day ahead forecasting of wind power is carried, and the tuning of parameters is done using grid search method. The SVR model is identified to be more consistent and reliable one. The GRNN model is also performing consistently with good accuracy.

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Chapter 3

UNCERTAINTY IN PREDICTION OF WIND POWER

3.1. Introduction

Renewable energy supply is slowly replacing traditional sources of energy. Wind energy is a big stakeholder in clean energy production, but wind power supply instability is the main issue regarding its power grid penetration. Wind power's uncertainty and intermittent nature leads to the unbalance between load and generation. Scientists have been trying to overcome this challenge over the past one decade to bring on more and more wind energy production. Wind power forecasting assists in managing the balance between power generation and demand. Wind power forecasting (WPF) also assists the market in electricity trading.

Apart from conventional neural networks, generalized regression neural network can be implemented in wind power forecasting by using less training data that overcomes drawbacks like requirement of large sets of data and slow learning of neural networks in order to improve accuracy in forecasting [1]-[4]. Composite neural network with parallel topology may improve accuracy in wind power forecasting [5].

The effectiveness of any forecasting technique or model is evaluated by knowing its reliability. In this chapter generalized regression neural network (GRNN), radial basis function neural network (RBFN) are used and a hybrid GRNN-RBFN model has been developed with parallel topology for wind power forecasting. Forecasting accuracy is evaluated in terms of mean absolute percentage error (MAPE). To evaluate uncertainty in prediction with the above mentioned methods, the confidence intervals are computed on MAPE. Among all three methods confidence intervals are narrower for GRNN. In case individual methods may not show good accuracy in forecasting, the hybrid GRNN-RBFN is much reliable with narrower confidence intervals. This chapter presents three models GRNN, RBFN and hybrid GRNN-RBFN for forecasting hourly wind power a week ahead in Indian wind farms.

3.2 Methods applied for wind power forecasting

This work implements RBFN, GRNN and a hybrid GRNN-RBFN. This section describes the above mentioned models.

3.2.1 Radial basis function neural network

Radial basis function neural network (RBFN) is conceptually close to neighbour type K-nearest. RBFN is a neural network comprising three layers formed of an input layer, a hidden layer and an output layer. It is usually used for approximation of functions. Every hidden-layer neuron consists of a component on a radial basis. The output layer calculates weighted sum of outputs to form network output. An RBFN locates one or more neurons inside the predictor variables defined in the space. The space would be multi-dimensional as per the number of predictor variables. Each neuron's weight is computed by applying a radial basis function to the Euclidean distance computed between each neuron's input and centre. Unlike in traditional neural networks, where back propagation algorithm is implemented, receptor selection has a major impact on weight calculation [6]-[10]. The structure of RBFN is shown in fig.3.1.

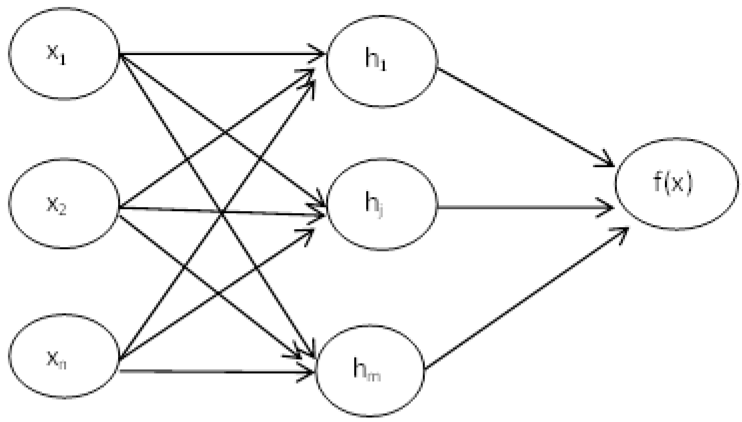

Fig.3.1: Structure of RBF neural network

As shown in fig.3.1, x_1, x_2 up to x_n are the inputs to the neural network. For hidden layer h_x takes a radial basis function. The radial basis functions used in neural networks may be represented by eq.3.1, eq.3.2 or eq.3.3. Most commonly used radial basis function is Gaussian function. The output of the network is calculated as per the eq.3.4, where w_j specifies the weight of the connections.

Multiquadri : $\emptyset(r) = (r^2 + c^2)^{\frac{1}{2}}$ (3.1)

Inverse Multiquadrics : $\emptyset(r) = \frac{1}{(r^2 + c^2)^{1/2}}$ (3.2)

Gaussian Function : $\emptyset(r) = \exp[\frac{-r^2}{2\sigma^2}]$ (3.3)

In eq.3.1, eq.3.2 and eq.3.3, r indicates Euclidian distance and c is shape parameter and σ represents standard deviation.

Output: $f(x) = \sum_{j=1}^{m} w_j h_j(x)$ (3.4)

3.2.2 Generalized regression neural network

Generalized regression neural network (GRNN) is basically a probabilistic neural network. It is function approximation based one pass learning algorithm. Following normal distribution GRNN applies probability density function. This neural network needs to train itself with a training data. The training data should include mapping of input-outputs. After the network is trained with the training data set, the results are predicted using a new test data set.

Depending on Euclidean distance, the weights of the connections are determined in GRNN. The Euclidean distance is measured between the training data and evaluation data. The wide distance means less weight, so with a limited distance weight is greater. This neural network basically contains four layers labelled to be input layer, pattern layer, summation layer, and output layer [11]. Input layer works when input data is transferred to next layer. Whereas Gaussian probability distribution function is implemented in pattern layer.

The summation layer, as presented in eq.3.5, consists of two sub-parts, the function numerator and denominator. In the numerator the sum of the product of the training output data and activation function is calculated, and the sum of the activation function is calculated as a denominator part. Ultimately, the output is computed with the ratio of numerator part to denominator.

$$f(x) = \frac{\sum_{i=1}^{n} f_i \exp(-\frac{Di^2}{2\sigma^2})}{\sum_{i=1}^{n} \exp(-\frac{Di^2}{2\sigma^2})} \qquad (3.5)$$

Where D_i is the distance between the training sample and point of prediction, f_i is the training sample and the parameter σ is defined as the standard deviation or spread**.**

3.2.3 Hybrid GRNN-RBFN

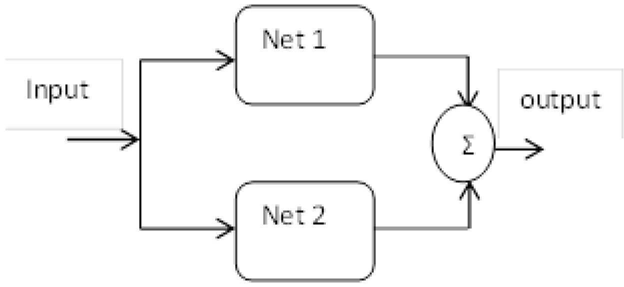

Fig.3.2: Parallel topology of Hybrid GRNN-RBFN

As illustrated in fig.3.2, two neural networks are connected in parallel and trained for prescribed target with the same input data [5]. The neural trained networks predict future wind power. The wind power output shall be calculated according to the weights assigned to each network. According to Mean Squared Error measured in network training, the weight is allocated to each network. The output is calculated as per eq.3.6.

$$Output= W_1*OUTPUT_{GRNN}+W_2*OUTPUT_{RBFN} \qquad (3.6)$$

W_1&W_2 are the weights assigned to GRNN and RBFN respectively, such that the sum of W_1 and W_2 equal to 1.

The flow chart for methodology of wind power forecasting using hybrid neural network is shown in fig.3.3 which is self-explanatory.

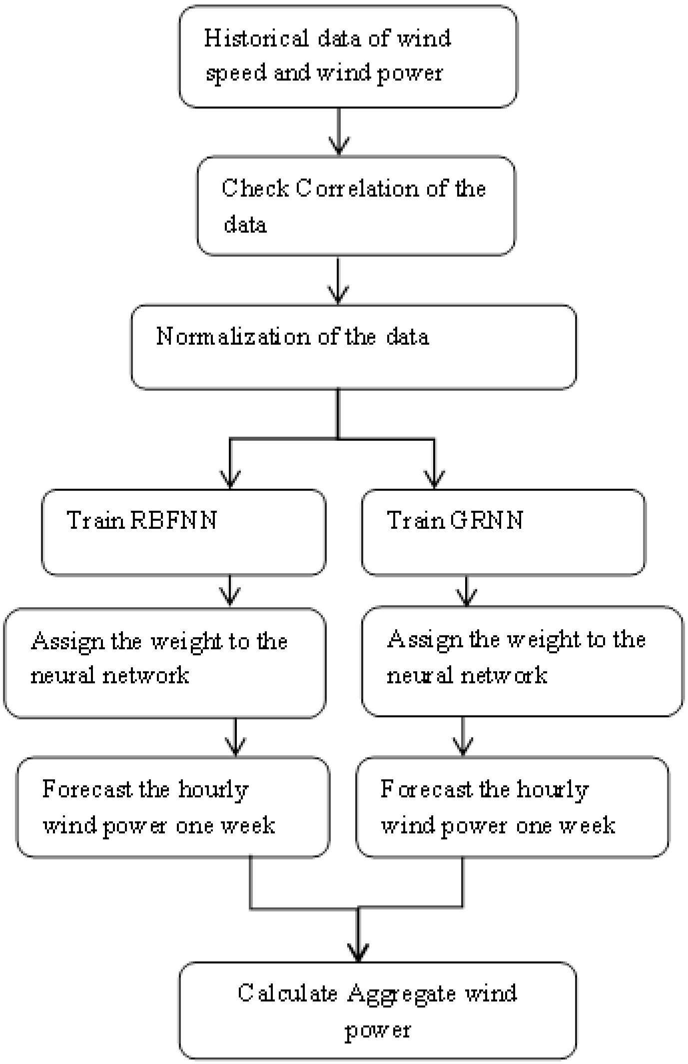

Fig.3.3: Flow chart of WPF for Hybrid GRNN-RBFN

3.3 Data collection & pre-processing

3.3.1 Data acquisition & statistical analysis

Data has been acquired from Indian wind farms for the year of 2014 towards prediction of wind power. The forecast of wind power has been done for one week in every month using the historical data of wind speed and wind power. To decrease the computational complexity in wind power forecasting, it is necessary to select suitable input parameters. Initially, correlation factors are computed among the historical wind power, wind speed and temperature. Then, the highly correlated data of historical wind power and wind speed is used in the training of neural networks. The correlation factors of the data for the months Jan’14 and Feb’14 are closer. For the months Apr’14 and June’14, correlation factors are higher reflecting the accuracy of forecasting. Further in months Oct’14 and Nov’14, the correlation factors are lower, which decreases the forecasting accuracy in the respective months.

3.3.2 Normalization of the data

Improper and missing data of the acquired data affects accuracy in WPF. In order to address this issue, the data is normalized, hence improves accuracy and convergence in training of the neural networks. In order to organize the data, the acquired data is normalized with two formulas initially; more effective formula for the sample data is chosen according to the accuracy of the forecasting. As per eq.3.7, the available data is normalized in the present work. This leads to the standardization of the data [12].

$$x_{new} = \frac{(x-\mu)}{\sigma} \tag{3.7}$$

Where, μ is the mean of data set and σ is the standard deviation.

Another normalization method is shown in eq.3.8. It is feature scaling used to fix the data set in a particular range.

$$x_{new} = \frac{(x-x_{min})}{(x_{max}-x_{min})} \tag{3.8}$$

After normalization, the multilayer neural network RBFN implemented for wind power forecasting is a three-layer neural network. They are described as input, output and hidden layers. The hidden layer uses radial basis function RADBAS. The neurons of hidden are increased for a radial basis network until it reached specified mean squared error. The feed forward connections are done. In RBF neural network, unlike conventional neural network, the weights are adjusted according to the receptor and spread. Hence proper choice of receptor gets the network converge fast. A GRNN is also a kind of radial basis network and used for function approximation. The GRNN applies Gaussian distribution function RADBAS. Similarly, for the GRNN, spread is selected as per random search method to approach minimum error in forecasting. Smaller spread ensures to fit data closely.

3.4 Simulations & results

This work essentially offers wind power forecasting with three different neural networks such as GRNN, RBFN and Hybrid GRNN-RBFN. The WPF consumes the data of the year 2014 from Indian wind farms obtained from its official website. The data comprises meteorological data of hourly wind speed and historical wind power of the year 2014. The data is divided into two sets for training and testing. In each month, three weeks hourly data is used in training the neural network with the selection of suitable spread value for GRNN and RBFN. The spread value is optimized to 0.005 with random search method for GRNN and it is 1 for RBFN.

Using each month data of wind speed and wind power, the neural network models are effectively trained for 504 epochs to forecast a week ahead hourly wind power generation. The forecasting accuracy of these networks are analysed by calculating the various errors such as mean absolute percentage error (MAPE) and root mean squared error (RMSE) as given by eq.3.9 and eq.3.10 respectively.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \qquad (3.9)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2} \qquad (3.10)$$

Where, A_i and F_i are actual and forecasted values respectively.

All the calculated MAPE values for wind power forecasting are listed in table 3.1. From table 3.1, it is evident that GRNN forecasts wind power with MAPE range of 0.48 % to 10.53 % for all months of the year. Whereas the samples of negligible wind power generations increase error in forecasting with RBFN and affect the performance of RBFN. If the wind power variations are regular enough in any month RBFN is also performing well. The performance of GRNN is analysed thoroughly by forecasting wind power one day ahead even. A day head forecasting is done for a month in each season. The results are tabulated in tables 3.2, 3.3 & 3.4. Fig.3.4 shows the variations of MAPE values for 24 hours in wind power forecasting one day ahead of 27^{th} June 2014. Fig.3.5 compares the accuracy of the neural network models in wind power forecasting in terms of MAPE for every month of the year 2014. In the year 2014, for all the months GRNN has shown consistency in forecasting wind power effectively with lower errors irrespective to the large variations in the data for the months Feb'14 and Mar'14. The forecasting analysis in this paper suggests GRNN can do better for dynamical systems like WPF.

To support the performance of GRNN, evaluation is also done by calculating RMSE values as depicted in table 3.5. From Table 3.5 of RMSE values, it is found that in forecasting wind power a week ahead for the month of Mar'14, GRNN forecasted with RMSE of 3.31kW, whereas RBFN has shown poor performance with RMSE of 11.61kW. Irrespective of the higher uncertainty in wind speed, the wind power is forecasted accurately in the month of May'14 using GRNN with MAPE of 7.5 % and RMSE 0.76 kW. The plot in fig.3.6 shows the predicted wind power vs. actual wind power of the month Jan'14. It depicts the accuracy in forecasting wind power one week ahead with GRNN. The plot also indicates the inefficiency of GRNN in the prediction of some peak values. The plot in fig.3.7 compares the forecasted wind power to actual one in the month Mar'14 with GRNN. The forecasted wind power is matching the actual one except for some peak samples.

3.5 Uncertainty analysis in prediction

In this work, uncertainty involved in wind power forecasts is investigated effectively with the computation of confidence intervals (CI) [13]-[14]. In further evaluation of performance of the above mentioned neural network models, confidence intervals on MAPE vector for all the models are computed. For the calculation of the confidence interval of a vector, first the standard deviation (σ) of the vector is calculated and then standard error (SE) is computed using eq.3.11. In the next step margin of error is calculated using eq. 3.12 for the desired confidence level. The value of variable t in eq.3.12 is found from standard normal distribution for desired confidence level. In this work, the confidence level considered is 95%, for which the value of t is 1.96. Finally, CI is calculated using eq.3.13 [15].

$$SE = \sigma/\sqrt{n} \qquad (3.11)$$

Where n is the sample size.

$$\text{Margin of error } E = t * SE \qquad (3.12)$$

$$CI = \text{Mean}(X) \pm E \qquad (3.13)$$

The computed confidence intervals for confidence level 95% are presented in table 3.6. As shown in table 3.6, the GRNN model has narrow confidence interval with respect to higher accuracy in every month in week ahead forecasting. For some months the confidence interval of the RBFN model is so wider like in the month May’14 with lower boundary of 11.5 % and upper boundary 39.7 %. But, the GRNN model has narrower confidence interval comparatively with lower boundary of 4.9 % and upper boundary of 10.1%. Compared to RBFN and hybrid GRNN-RBFN, GRNN can provide good prediction in wind power because it is an improved technique in neural networks based on nonparametric regression.

Table 3.1: Forecasting accuracy of various models in terms of MAPE for one week ahead

MAPE in Wind power forecasting one week ahead				
Input Data Used	**Month of forecasted week**	**RBFN**	**GRNN**	**Hybrid GRNN-RBFN**
Wind speed	Jan 2014	7.70	3.50	4.50
Wind speed	Feb 2014	16.90	7.50	9.50
Wind speed	Mar 2014	17.40	2.60	8.30
Wind speed	Apr 2014	2.10	0.90	1.10
Wind speed	May 2014	25.60	7.50	11.40
Wind speed	June 2014	2.00	0.68	1.00
Wind speed	July 2014	9.70	3.20	5.10
Wind speed	Aug 2014	0.31	0.70	0.51
Wind speed	Sept 2014	0.44	0.73	0.52
Wind speed	Octo 2014	11.88	10.53	10.84
Wind speed	Nov 2014	13.90	10.08	9.77
Wind speed	Dec 2014	0.25	0.48	0.25

Table 3.2: A day ahead forecasting accuracy in terms of MAPE in the month Apr’14

MAPE in Wind power forecasting one day ahead			
Day for the week of	**RBFN**	**GRNN**	**Hybrid GRNN -**
22^{nd} Apr’14	5.30	0.80	2.50
23^{rd} Apr’14	0.40	0.39	0.30
24^{th} Apr’14	1.60	0.37	0.80
25^{th} Apr’14	0.47	0.43	0.37
26^{th} Apr’14	1.54	0.18	0.69
27^{th} Apr’14	5.57	0.14	2.05
28^{th} Apr’14	0.42	0.96	0.63

Table 3.3: A day ahead forecasting accuracy in terms of MAPE in the month Aug’14

MAPE in Wind power forecasting one day ahead			
Day for the week of Aug’14	**RBFN**	**GRNN**	**Hybrid GRNN-RBFN**

22nd Aug'14	0.18	0.56	0.42
23rd Aug'14	0.30	0.87	0.63
24th Aug'14	0.24	0.40	0.29
25th Aug'14	0.27	0.55	0.41
26th Aug'14	0.32	0.63	0.47
27th Aug'14	0.64	1.60	1.15
28th Aug'14	0.25	0.25	0.19

Table 3.4: A day ahead forecasting accuracy in terms of MAPE in the month Dec'14

MAPE in Wind power forecasting one day ahead			
Day for the week of Dec'14	**RBFN**	**GRNN**	**Hybrid GRNN-RBFN**
22nd Dec'14	0.28	0.45	0.30
23rd Dec'14	0.38	0.88	0.66
24th Dec'14	0.22	0.54	0.41
25th Dec'14	0.14	0.31	0.22
26th Dec'14	0.27	0.27	0.19
27th Dec'14	0.20	0.35	0.27
28th Dec'14	0.22	0.59	0.42

Table 3.5: Table for RMSE values in KW

RMSE values in kW for Wind power forecasting one week ahead			
Month	**RBFN**	**GRNN**	**Hybrid GRNN-RBFN**
Jan. 2014	0.17	0.65	1.00
Feb. 2014	0.01	0.01	0.009
March 2014	11.61	3.31	6.44
April 2014	0.02	0.23	0.14
May 2014	1.25	0.76	0.22
June 2014	0.03	0.08	0.05
July 2014	0.02	0.07	0.05
August 2014	0.02	0.04	0.03
Sept. 2014	0.02	0.03	0.02
October 2014	0.01	0.05	0.04
Nov. 2014	0.03	0.06	0.04

Dec. 2014	0.03	0.14	0.10

Table 3.6: Comparison of Confidence Intervals

Confidence intervals of MAPE values in Wind power forecasting month wise			
Month of forecasted week	**RBFN**	**GRNN**	**Hybrid GRNN-RBFN**
Jan'14	[-0.6 16]	[1.3 5.7]	[0.3 8.7]
Feb'14	[2.9 30.9]	[4.2 10.8]	[2.9 16.1]
Mar'14	[8.5 26.35]	[1.6 3.6]	[4.6 12]
Apr'14	[0.9 1.2]	[0.53 1.25]	[0.54 1.4]
May'14	[11.5 39.7]	[4.9 10.1]	[6.9 15.9]
Jun'14	[0.5 3.5]	[0.43 0.93]	[0.46 1.54]
July''14	[-1.7 21.19]	[1.2 5.2]	[0.5 9.7]
Aug'14	[0.25 0.36]	[0.48 0.92]	[0.37 0.65]
Sep'14	[0.37 0.5]	[0.57 0.89]	[0.4 0.64]
Oct'14	[6.7 16.9]	[6.3 14.7]	[6.4 15.2]
Nov'14	[7.1 20.7]	[5.81 14.35]	[5.5 14.04]
Dec'14	[0.21 0.28]	[0.37 0.59]	[0.27 0.43]

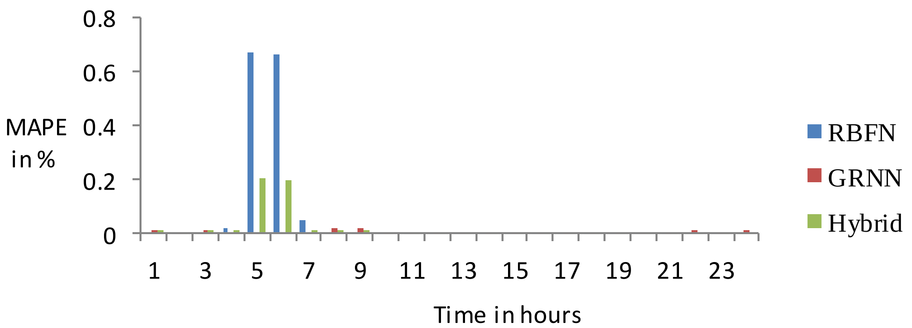

Fig.3.4: Comparison of RBFN,GRNN and Hybrid GRNN-RBFN performance in terms of MAPE of a day ahead wind power forecasting for 27th June'14

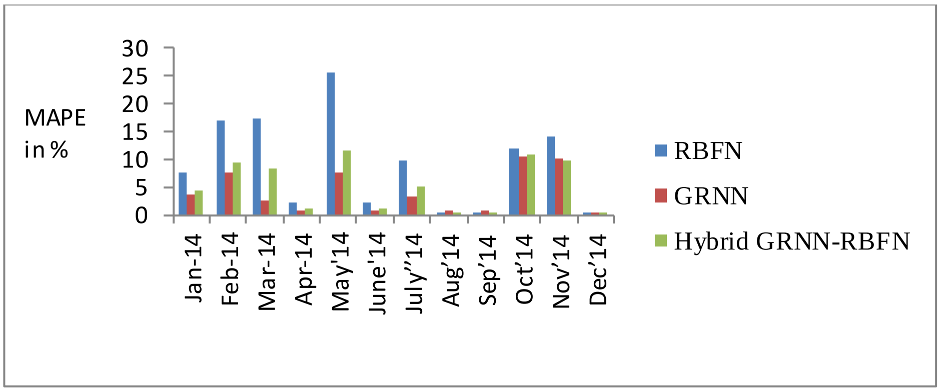

Fig.3.5: Comparison of RBFN,GRNN and Hybrid GRNN-RBFN performance in terms of MAPE

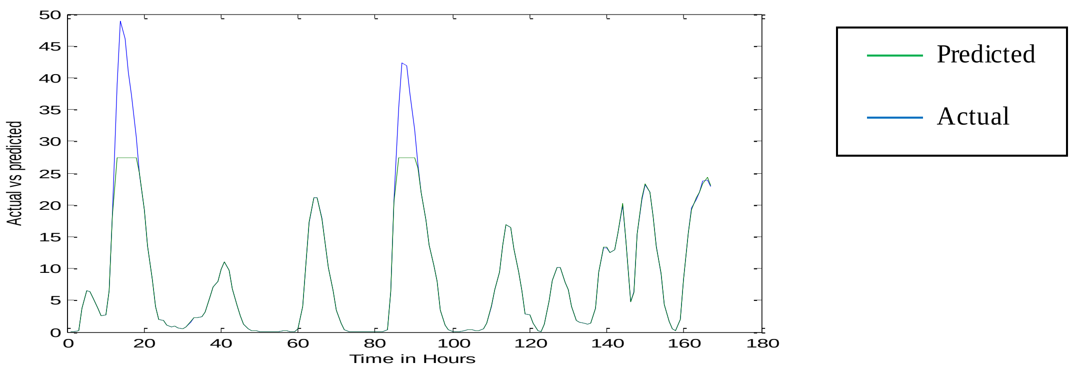

Fig.3.6: Predicted wind power one week ahead of Jan'14 with the actual wind power

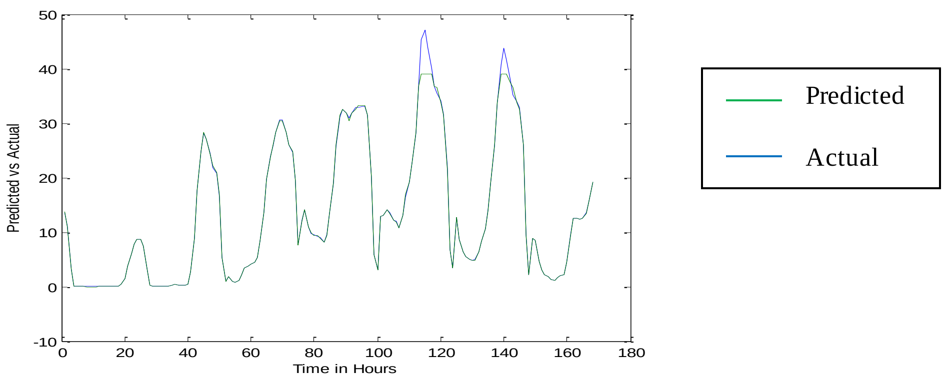

Fig.3.7: Predicted wind power one week ahead of Mar'14 with the actual wind power

3.6 Summary

The randomness of wind power poses safety concerns to the power grid to increase wind power penetration. Forecasting wind power using GRNN, RBFN and Hybrid GRNN-RBFN is carried out in this paper to address this issue. The GRNN model has performed consistently in all months of 2014 with significant reliability, which is ensured with the narrowest confidence interval of MAPE values in WPF for all months. The cases where there is highly correlated data, the RBFN model improves its performance. Further a hybrid GRNN-RBFN model is designed to forecast wind power, which emphasizes proper assignment of weights to each neural network in parallel topology. The hybrid neural network provides better accuracy in forecasting, if a single neural network is not reliable in forecasting. Various topologies like series, parallel and series parallel connections can be designed to increase the accuracy in wind power forecasting.

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Chapter 4

SOLAR PHOTO VOLTAIC POWER FORECASTING

4.1 Introduction

Reliable electric power supply is crucial in the sustainable development for any country in recent years. The growing demand for power worldwide, the disappearance of conventional energy sources and the free generation of pollution-free power insist on the necessity of generating power from renewable sources. A major motivating force for sustainable power production is also the enhanced output from renewable energy sources. Solar photo voltaic (PV) power promises a clean and renewable resource that generates electricity with low pollution. Solar energy plays a key role in future electricity generation as sun is the powerful source. Solar energy is actually the fast-growing solar technology for producing electricity with an annual growth of 48 percent [1]. The power grids face stability and efficiency issues because of the volatility and irregularity of solar PV power production. Solar PV power production is very much decided by solar irradiation. Its intermittent nature causes uncertain and volatile solar power generation. Solar PV power generation is susceptible to meteorological parameters such as solar irradiance and temperature, as seen in eq.4.1 [2]. The characteristics of the PV system are highly nonlinear [3]. Solar PV power forecasting is evolved as the right solution to overcome this variability in solar PV power generation for the power grid operators.

$$P_{pv} = n_p\, V_{pv}\, (I_{ph} - I_{sat}\left(\exp\left(\frac{q}{nkT} \cdot \frac{V_{pv}}{n_s}\right) - 1\right)) \tag{4.1}$$

$$I_{ph} = \left(I_{scr} + \frac{K_r}{1000}(T - T_r)\right)S_r \tag{4.2}$$

Where, P_{pv} represents PV array's output power. n_p Indicates the number of PV arrays connected in parallel. When PV arrays connected in series, n_s shows the number, the output voltage of a PV array is represented by V_{pv}. I_{ph} describes the output current of a PV array, I_{sat} describes the dark saturation current of PV array, the charge of an electron is given by q, n represents the identity factor, k is the Boltzmann constant, the absolute temperature is given by T, the reference temperature in kelvin is given by T_r, I_{scr} indicates the short circuit current at 1KW/m^2 of solar irradiance and reference temperature, K_r is the temperature coefficient of the short circuit current and S_r is the solar irradiance (KW/m^2) .

Solar PV power production has been witnessing a substantial increase over the past decade. Power grid operators rely mostly on solar PV power forecasting in order to penetrate PV power stably into the power grid and towards efficient planning for distributed generation. Precise solar PV power forecasting is important for power grid operators to sustain a safe and effective power network in an efficient load control. Solar PV power forecasting is also very helpful in trading of electricity to achieve economic benefits.

Solar PV power is predicted in two ways, i.e. the direct and the indirect. PV output is predicted in direct method, while solar irradiation is calculated in advance to determine PV capacity by indirect process. According to time-based grouping, three approaches are used by several researchers worldwide for the short, medium and long term [4].

This chapter explains the implementation and significance of K-means clustering technique with a hybrid model of artificial neural network-particle swarm optimization (ANN-PSO) to improve forecasting accuracy. The forecasting results are validated in comparison with support vector regression (SVR) model.

4.2 Methods implemented in solar PV power forecasting

The various methods applied for solar PV power forecasting are described in this section.

4.2.1 Particle swarm optimization

Particle swarm optimization (PSO) is triggered by the birds and fish collecting and moving patterns. PSO was invented by Russel Eberhart and James Kennedy in 1995. Since two decades, researchers are implementing PSO in various optimization problems like training of neural networks and optimization of power distribution networks [5].

This algorithm's understanding is simple, and easy. After a few iterations, the values of a community of variables are changed according to the participant whose value at any given moment is nearest to the target which is equivalent to a grouping of birds taking rounds around a secret food supply. The one that is closest to the sounds of the food, and other birds are swinging in its direction. If some of the other birds around come near to the target than the first one, it will tweet to encourage everyone to join them. Finally one of the birds enters the target i.e. the position of the food, the cycle continues until then. The steps to be followed are given below in the algorithm. Fig.4.1 describes PSO Algorithm steps.

a) PSO algorithm

x_j^i : Position of the particle

v_j^i : Velocity of the particle

p_j^i : Best position of the individual particle

p_j^g : Best position of the swarm

m_1, m_2 : Cognitive and social parameters

r_1, r_2 : Random numbers between 0 and 1

Position of individual position updated as follows

$$x_{j+1}^{i} = x_{j}^{i} + v_{j+1}^{i} \tag{4.3}$$

With the velocity calculated as follows

$$v_{j+1}^{i} = v_{j}^{i} + m_1 r_1 (p_j^i - x_j^i) + m_2 r_2 (p_j^g - x_j^i) \tag{4.4}$$

b) Steps to be followed

1. Initialize

Set constants $j_{\max}, m_1, m_2$

Randomly initialize particle positions $x_0^i \in D$ in IR^n for $i = 1, ..., p$

Randomly initialize particle velocities $0 \le v_0^i \le v_0^{\max}$ for $i = 1, ..., p$

Set $j = 1$

2. Optimize

Evaluate function value f_j^i using design space coordinates x_j^i

a) If $f_j^i \le f_{best}^i$ then $f_{best}^i = f_j^i$, $p_j^i = x_j^i$.

b) If $f_j^i \le f_{best}^g$ then $f_{best}^g = f_j^i$, $p_j^g = x_j^i$

If stopping condition is met then go to 3

Update all particle velocities v_j^i for $i = 1, ..., p$

Update all particle positions x_j^i for $i = 1, ..., p$

Increment j

Go to 2(a)

3. Terminate

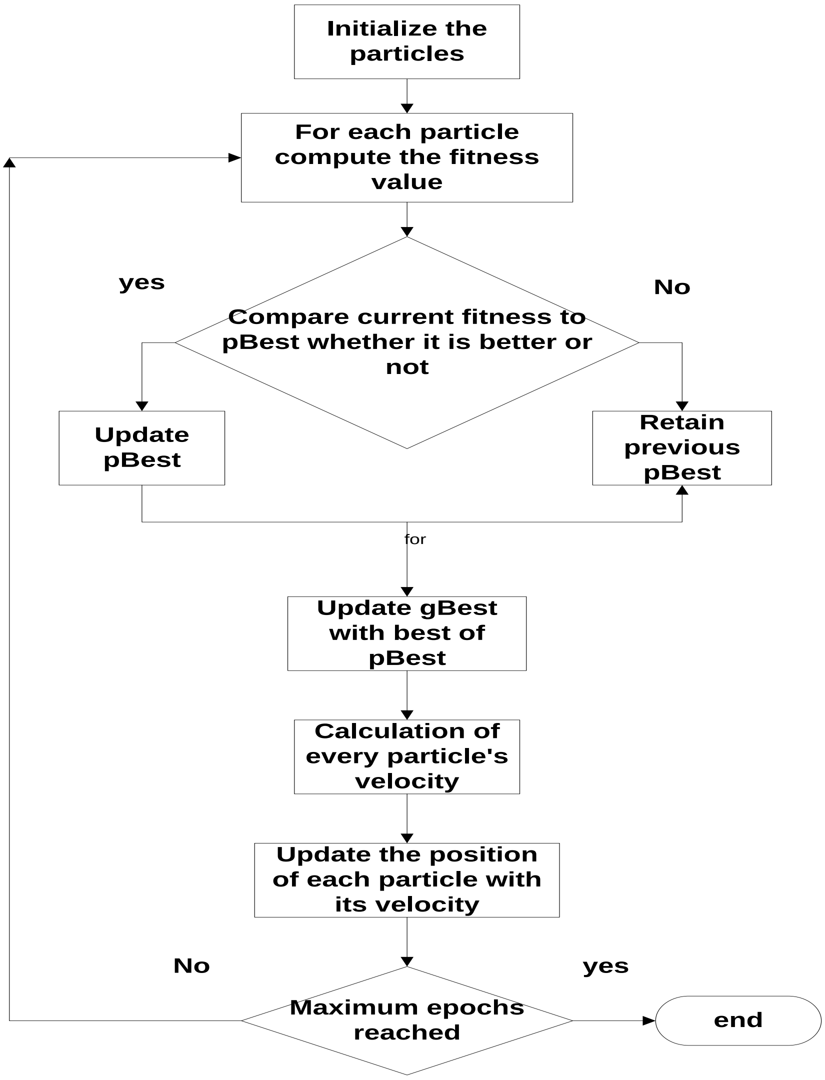

Fig.4.1: PSO flow chart

4.2.2 Feed forward neural networks

The artificial neural network (ANN) is a simulation of the human brain in order to accommodate human intellect and the capacity to learn from experience. ANN’s structures imply nonlinearity. Without prior information on the relationships between input variables and output variables, the ANNs can model nonlinear problems. Hence, they are simple and powerful models for forecasting solar PV power generation which is a nonlinear problem. Therefore, they are simple and powerful models that are a nonlinear problem for forecasting soar PV power generation. Feed forward neural networks are one of the types of ANN [6]-[8]. Feed forward neural networks are the simplest among all neural artificial networks. The information flows in these networks in just one way, i.e. from the input layer to hidden layers and hidden layers to the output layer. In its training ANN implements both supervised learning and unsupervised learning. Forecasting Models focused on ANN often adopt supervised learning. Fig.4.2 shows a multilayer artificial neural network composed of the layer of input, the hidden layer and the layer of output. In the fig.4.2, x1, x2 denote network inputs, w, v are connection weights, input layer to hidden layer, and hidden layer to output layer. Whereas b represents the bias and y is the network output.

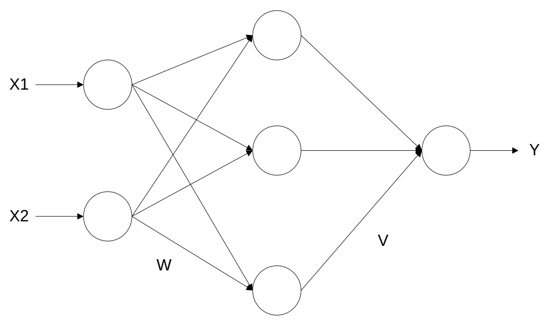

Fig.4.2: Structure of a three layer artificial neural network

Hidden layer neuron's output o_j is calculated as shown by eq.4.5. Here f denotes the activation function such as step, ramp, sigmoid and Gaussian etc.

$$o_j = f(\sum_{i=1}^{m} w_{ij}x_i + b_j) \quad (4.5)$$

Similarly the output of multilayer neural network is obtained as shown in eq.4.6.

$$y = f(\sum_{i=1}^{n} v_i o_i + b) \quad (4.6)$$

4.2.3 K-means clustering

In normal operation PV device provides a huge number of details. Conventionally, statistical approaches such as auto-regressive approaches are used to predict solar PV power treating the data as time series [9]. Nevertheless, the volatility of solar irradiation will lead to training sample inconsistencies. Then, unsuitable training can greatly affect predictive accuracy. The key features of any predictive approach are accuracy, consistency, and reliability. Therefore it is important to choose similar days such as rainy day, cloudy day and sunny day to classify them into the same category as the training samples. This can be deemed a good approach for enhancing the predictability.

a) Cluster formation

The generation of solar PV power mostly depends on meteorological parameters such as solar irradiation and temperature [10]-[11]. The days are to be chosen from historical data, which have the most similar irradiation and temperature to the day of prediction. A data set of maximum solar irradiation, minimum solar irradiation, average solar irradiation, maximum temperature, minimum temperature and average temperature is used in the clustering technique, which is built as in eq.4.7.

$$S = [\mathrm{IRmax},\ \mathrm{IRmin},\ \mathrm{IRmean},\ T\mathrm{max},\ T\mathrm{min},\ T\mathrm{mean}] \quad (4.7)$$

Where, IRmax, IRmin, IRmean, Tmax, Tmin, and Tmean represent the maximum, minimum, and average values of solar irradiation and temperature respectively. Solar PV power production is primarily affected by meteorological factors such as solar irradiation and temperature according to the various research and empirical tests. A cluster from S is picked which has most similarity to the day of prediction. The days belonging to the respective cluster are gathered as forecast model training samples.

b) Clustering algorithm

Clustering is an unsupervised learning method. There are several effective clustering techniques. One among is the K-means clustering technique. In this chapter, the K-means clustering is used as the clustering technique for the reason that *K*-means algorithm can take care of large amount of data sets effectively. K-means algorithm, which is based on partitioning mainly, computes the distance to know the similarity. In K-means technique, randomly the data is partitioned and k centre points are selected. The partitioning is revised according to the distance between k-centre points and the remaining data. The Euclidean distance is computed, the clustering technique allocates each data to its nearest centre point P_k, which is calculated as per eq.4.8.

$$P_k = \frac{1}{N}\sum_{i=1}^{N} x_i^k \qquad (4.8)$$

Where x_i^k is the *i*th data in the cluster k, and N is the number of data points of the respective cluster. Then calculate the average value of every cluster to update the centre of the cluster. The above process is continued till the value does not change any more. Hence, k clusters are derived from the original data set. The data of each cluster is highly similar .The process of clustering is as follows.

1st step) There will be K objects as the initial centres of the clusters from the data set of M objects.

2nd step) Compute the distance between the data objects and centre of the cluster is to classify them to the closest cluster.

3rd step) Calculate the average value of the each cluster, which is utilized in the updating of the centre of the cluster.

4^{th} step) The iterative method is repeated as per 2^{nd} and 3^{rd} steps until no more change in the clustering centre. If not, the process continues [12].

It is not compulsory that K-means provides global optimal solution. In contrary to that, fuzzy based K-means assigns a degree of membership to each data vector, which can lead to better solution. This work implements normal K-means clustering to classify the weather data into three different types as cloudy day, rainy day and sunny day.

4.2.4 Support vector regression

For classification and regression analysis the algorithms of supervised learning models are used in supporting vector machines. In a linear classifier the feature vectors in non-linear classifier are effectively transformed into high-dimensional space. Implicitly, this mapping can be done with the kernel functions.

Let a training data is given by $\{(x_1, y_1),.....,(x_l, y_l)\} \subset X \times R$, where X represents the space of input patterns. Especially, ε support vector regression aims to get a function f(x) that has a maximum ε deviance from the originally obtained targets y_j for all the training samples, and at the same time, is flat as possible. As long as the errors are less than ε, it is accepted otherwise the errors will be taken care [13]**.** Ultimately Support vector regression finds a regression function as in eq.4.9.

$$y = f(x) = w^T \varphi(x) + b \tag{4.9}$$

Here $\varphi(x)$ is a function used to map data x from low dimension to high dimensional space, w represents a weight vector and b represents bias, which can be increased or decreased. Standard SVR implements ε-insensitive function. As per assumption, all the samples of training are fixed with a linear function in the accuracy of ε. The problem is converted into an objective function to adjust the objective function minimization as shown in eq.4.10.

Minimize $\frac{1}{2}\|w\|^2 + C\sum_{j=1}^{l}(\xi_j + \xi_j^*)$ (4.10)

Subject to

$$w^T\varphi(x) + b - y_j \leq \varepsilon + \xi_j$$

$$y_j - w^T\varphi(x) - b \leq \varepsilon + \xi_j^*$$

$$\xi_j, \xi_j^* \qquad \geq 0$$

Where, ξ_j, ξ_j^* are the relaxation factors. If there exists an error in fitting, ξ_j, ξ_j^* are greater than 0, otherwise, ξ_j, ξ_j^* are all equal to zero. The first term of the optimization function further smoothens the fitting function to improve generalization. The second term is to reduce the error. The next important parameter is the error penalty parameter C. For support vector regression, the performance is much affected by the value of C. It is analysed that C is a trade-off between the algorithm complexity and degree of mistakenly classified samples. Smaller values of C indicate the punishment for the empirical error of the original data is small and experience risk is high. If the value of C is larger, the empirical error penalty is larger and experience risk is small. The larger value of C also leads to high computational complexity also. Hence, the selection of appropriate penalty factor C has a great impact on the model convergence and its prediction performance. Another crucial factor, which is considered to be the core of support vector regression, is kernel function. It affects the performance of support vector regression. Determinations of appropriate kernel function and appropriate values to the various relevant parameters of the kernel function are significant steps in the performance of support vector regression.

Mostly four types of kernel functions, linear kernel, polynomial kernel, RBF kernel and sigmoid kernel are implemented in support vector regression. As construction of RBF kernel (Gauss kernel) is relatively easy, this is widely used at present. The function is as follows in eq.4.11.

$$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / 2\sigma^2) \qquad (4.11)$$

Where $\|x_i - x_j\|$ represents Euclidean distance, σ is the standard deviation , σ >0. Eq.4.11 can be redefined as in eq.4.12.

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \qquad (4.12)$$

Where $\gamma = -1/2\sigma^2$

4.3 Methodology

4.3.1 Data acquisition & statistical analysis

Meteorological data of diffuse irradiation, direct irradiation, temperature, and solar PV power of the year of 2014 is acquired from PV power plants located in Kolkata region of India. The data is collected from 100 KW PV plant. Using this data with the developed forecasting models, a day ahead PV power forecasting and a week ahead solar PV power forecasting are performed.

4.3.2 Parameter selection

The estimation of correlation factors indicates that the parameters most relevant to the PV capacity are chosen properly. It further decreases the complexity of forecasting computations. The use of irrelevant parameters in the training set can result in undesirable results. In order to identify the dependencies between the historical solar PV power, meteorological data such as direct irradiation, diffusion of irradiation, temperature and wind speed [14]-[15], correlation factors are calculated with the available data. Table 4.1 depicts the computed correlation factors. In the training of neural networks, the highly correlated data of historical PV power and direct irradiation, diffuse irradiation, and temperature are then used. The total radiation that hits the collector has two direct and diffuse irradiation components, respectively. It's explained that direct beam irradiation comes from the sun in a straight line. On bright days and clean sky, much of the solar irradiation is direct beam irradiation, whereas diffuse irradiation is the one that is spread by gases, aerosols, and pollutants from the direct beam. When the sky is bright, direct irradiation is successful, and then indirect irradiation is to be considered on cloudy days, which is well established by the correlation factors calculation as depicted in table 4.1. The expression of correlation factor is given by eq.4.13.

$$R\ x,y = \frac{cov(x,y)}{\sigma_x \sigma_y} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{4.13}$$

Where the variance of the variables x and y is represented by cov (x,y) and σ_x and σ_y are the standard deviations of the variables x and y. $\bar{x}$ and $\bar{y}$ indicate the mean values of the respective data sets.

Table 4.1: Correlation factors

Correlation factors			
Month data	Correlation factor of PV power and direct	Correlation factor of PV power and diffuse	Correlation factor of PV power and

	radiance	radiance	temperature
February'14	0.98	0.83	0.67
April'14	0.97	0.94	0.79
June'14	0.73	0.97	0.79
August'14	0.80	0.95	0.87
October'14	0.96	0.79	0.62
December'14	0.98	0.89	0.69

4.3.3 Normalization of the data

Forecasting accuracy can be affected by poor and missing data of the sample data collected. Data normalization increases the convergence rate and accuracy in training of the forecasting models. In order to organize the data, the acquired data is normalized. The formula is implemented to normalize the available data is given by eq.4.14. This normalization technique is implemented when the data is normally distributed.

$$x_{new} = \frac{(x-\mu)}{\sigma} \tag{4.14}$$

Where, μ is the mean of data set and σ is the standard deviation.

4.3.4 Training & testing of the models

After the selected data has been pre-processed, the data is clustered by applying K-means clustering technique for similar days of rainy days, cloudy days and sunny days. Therefore a three-layer feed forward neural network is developed. The three layers are described as input, output and hidden layers. Hidden layer neurons are optimized for best forecasting outcomes. By implementing particle swarm optimisation technique, the weights of the connections between layers are optimized.

Further RBF kernel function is used to design SVR model. Kernel only helps to perform nonlinear regression by mapping their inputs into high dimensional feature spaces indirectly. Here the selection of kernel, kernel parameters and regularization parameter C is crucial in the development of effective SVR model. Since RBF kernel is simple in construction with only one parameter γ, it is widely used in most of the applications. γ is the inverse of the standard deviation of RBF kernel (Gaussian kernel) which is used as similarity measure between two points. To achieve higher cross validation accuracy, values of the parameters C& γ are to be appropriate. Different SVR models are implemented based on the categorisation of sunny day, cloudy day and rainy day to forecast solar PV power as per weather conditions. The values of parameters used in the different models of this work are described in tables 4.2 & 4.3. Also, fig.4.3 describes the hybrid approach, proposed in this chapter.

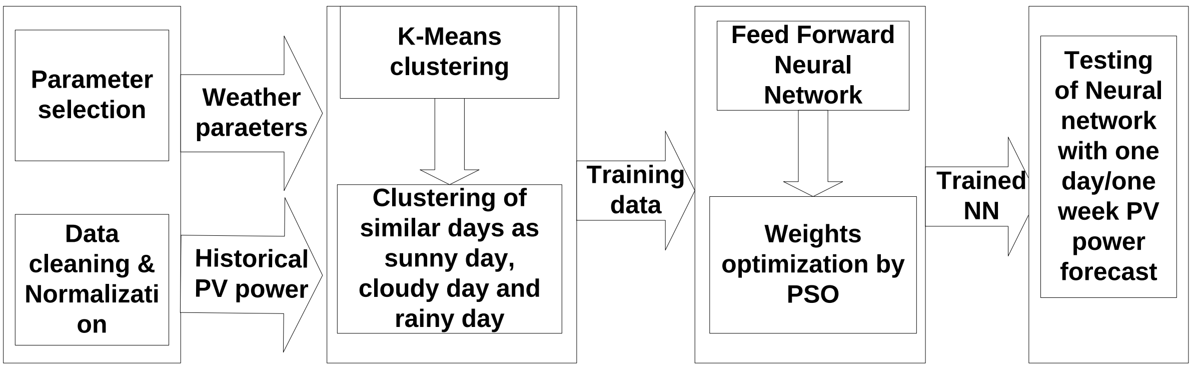

Fig.4.3: Block diagram for the proposed solar PV power forecasting approach (K-means based ANN-PSO)

Table 4.2: Parameters of ANN-PSO model

Hidden layer neurons	5
No. of iterations	1000
Population	10
tolerance	10^{-15}

Table 4.3: Parameters of SVR model

Kernel	Rbf
Tolerance	0.00001
Regularization parameter (C)	100
Gamma(γ)	1

4.4 Simulations & results

In this work, a hybrid model of K-means clustering, feed forward neural networks based on particle swarm optimization (PSO) is proposed to forecast solar PV power in short term PV power forecasting i.e. one day ahead solar PV power generation as well as one week ahead solar PV power forecasting. The forecasting results are validated with the comparison of solar PV power forecasting using data mining technique, SVR model. The above said solar PV power forecasting utilizes the data of the year 2014 from the PV plants located in Indian region Kolkata. The data consists of hourly NWP data like diffuse irradiation, direct irradiation temperature and hourly historical solar PV power generation data. The data is divided into two sets for training and testing. Initially, correlation factors are computed among historical solar PV power, direct irradiation, diffuse irradiation and temperature and depicted in table 4.1. As presented in table 4.1 except in the months June'14 and Aug'14, the historical solar PV power is highly correlated to direct irradiation. In the months June and August solar PV power is highly correlated to diffuse irradiation because of the rainy season. For solar PV power forecasting one day ahead, data of 29 or 30 days of each month is utilized to train ANN-PSO model. PV power generation of the last day of the respective month is forecasted. To implement the K-means clustering, every two months data is used for clustering to find similar days in the previous two months as per weather conditions of solar irradiation (KW/m^2) and temperature (^0C). Further, ANN-PSO model is trained with the cluster data which is similar to day of prediction considering solar irradiation and temperature as input parameters and PV power as target. To perform solar PV power forecasting a week ahead the whole year is clustered into three clusters representing rainy day, cloudy day and sunny day. Fig.4.4 (a) shows irradiation clusters of the year. Three weeks cluster data is used for training of neural network and the objective week's solar PV power is forecasted. Fig.4.4 (b) compares forecasted PV power by proposed model to actual PV power during training period for a day ahead forecasting in the month Aug'14. Along with different SVR models are developed to forecast solar PV power one day ahead and a week ahead. Design of support vector regression model mainly involves in an effective construction of kernel and there by choosing suitable values for regularization parameter C and γ. Optimization of C is significantly important to overcome the issue of misclassifying the training samples. A small value of γ indicates a large variance and large gamma leads to high bias and small variance. In this work, the kernel chosen is RBF kernel. The values of C and γ are optimized to 100 and 1 respectively by grid search method.

The forecasting accuracy of these models are analysed by calculating the two errors such as mean absolute error (MAE) and root mean squared error (RMSE) as given by eq.4.15 and eq.4.16 respectively.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_i - F_i| \tag{4.15}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2} \tag{4.16}$$

The significance of proper selection of input parameters is analysed as presented in table 4.4. In the months of June and august, there is higher correlation between diffuse irradiation and solar PV power than the correlation between direct irradiation and solar PV power, which affects the forecasting accuracy greatly as shown in table 4.4. Unlike in the months June and august, in the remaining months solar PV power is highly correlated to direct irradiation. From table 4.4 it is evident that the forecasting accuracy is highly influenced by the selection of appropriate input parameters. With direct irradiation as input parameter, the error in terms of MAE for one day ahead forecasting in the month June is 6.01 KW, whereas MAE is 1.17 KW only with diffuse irradiation as input parameter due to the high correlation between diffuse radiation and solar PV power generation in the respective month. Fig.4.5 clearly compares the forecasted PV power to actual power with variation of input parameters in solar PV power forecasting for a day ahead forecasting in the month June'14. Also, the clustering impact on forecasting accuracy is clearly indicated in table 4. 4 & 4.5 with the comparison of the error values in terms of MAE & RMSE between ANN-PSO model and ANN-PSO model along with K-means clustering. After the implementation of K-means clustering, forecasting accuracy is very much improved for ANN-PSO model and comparable to the forecasting accuracy of data mining technique SVR model as depicted in table 4.4 & 4.5. Fig.4.6 compares forecasted PV power of all three approaches mentioned in this chapter and actual solar PV power of 31stAug'14 considering direct irradiation and temperature as input parameters.

The proposed forecasting model performs better than SVR model in a week ahead forecasting in the months Apr'14 and Oct'14 with reduced errors in terms of MAE & RMSE as depicted in table 4.6. For one week i.e. 18th to 24th Oct'14, the forecasted solar PV power from all three forecasting approaches is compared to actual solar PV power in fig.4.7. In month of Apr'14, for a week ahead PV power forecasting i.e. 22nd to 28th Apr'14, the forecasting accuracy is good without the consideration of clustering technique as it is a summer season, the temperature ranges from 24.7^0 C to 44.8^0 C. But in case of solar PV power forecasting from 18th to 24th Oct'14, the error in terms of MAE is reduced from 8.38

KW to 5.26 KW with clustering the data by K-means clustering technique and used in training of ANN-PSO model.

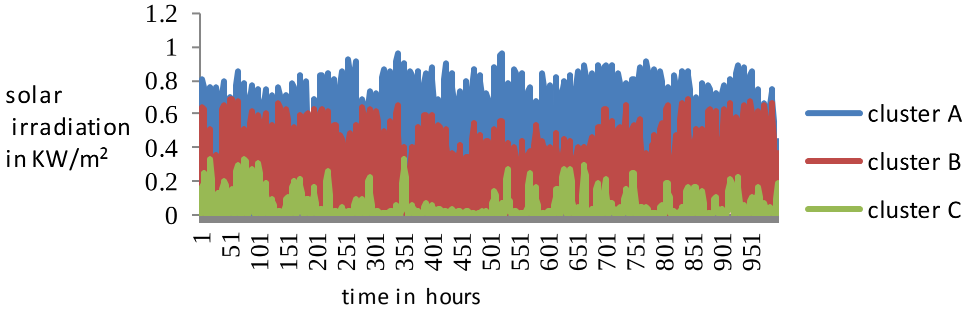

Fig.4.4 (a): Clusters of solar irradiation

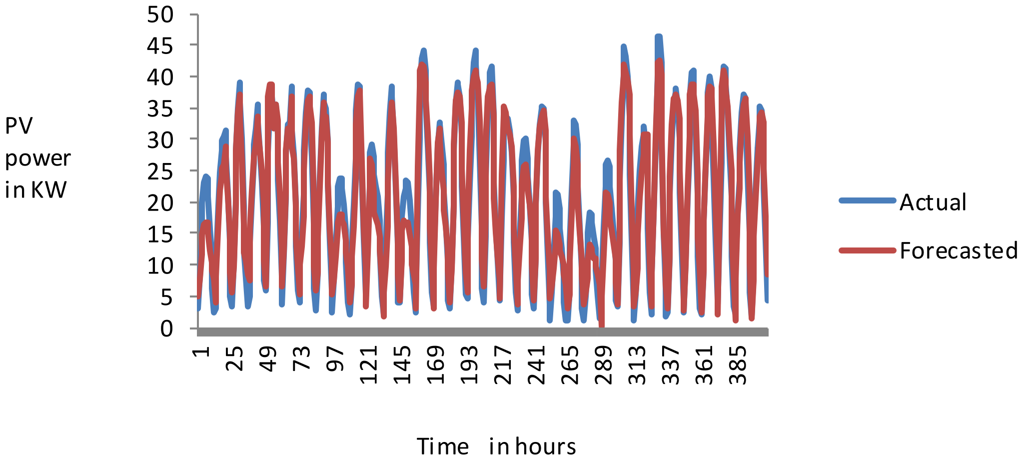

Fig.4.4 (b): Actual vs forecasted PV power for training data in the month of Aug'14 for proposed model

Table 4.4 .The impact of input parameters on forecasting

The impact of input parameters							
Input parameters	Objective day	MAE(KW)			RMSE(KW)		
		ANN-PSO	SVR	Proposed	ANN-PSO	SVR	Proposed
Direct irradiation	30th June'14	6.01	6.47	5.57	5.36	5.52	4.98

&temperature							
Diffuse irradiation & temperature	30th June'14	1.17	0.41	0.35	1.58	0.54	0.51
Direct irradiation &temperature	31st August'14	6.02	5.44	4.24	7.09	6.36	4.64
Diffuse radiance & temperature	31st August'14	1.37	0.48	0.41	1.58	0.58	0.52

Table 4.5: Results of one day ahead forecasting

One day ahead forecasting						
Objective day	MAE(KW)			RMSE(KW)		
	ANN-PSO	SVR	Proposed (K-means based ANN-PSO)	ANN-PSO	SVR	Proposed (K-means based ANN-PSO)
28th Feb 2014	4.99	4.72	4.54	4.97	4.98	4.95
30th Apr-2014	2.95	1.75	2.08	4.3	2.21	2.76
30th June-2014	1.17	0.41	0.35	1.58	0.54	0.51
31st Aug-2014	1.37	0.48	0.41	1.58	0.58	0.52
31st Oct-2014	4.54	1.88	1.86	5.26	2.41	2.07
29th Dec-2014	5.05	4.4	4.31	6.52	6.20	5.05

Table 4.6: Results of a week ahead forecasting

A week ahead forecasting						
Objective week	MAE(KW)			RMSE(KW)		
	ANN-PSO	SVR	Proposed(K-means based ANN-PSO)	ANN-PSO	SVR	Proposed(K-means based ANN-PSO)
22nd to 28th April	4.27	5.19	4.2	4.57	6.8	4.18
18th to 24th October	8.38	9.14	5.26	9.32	11.44	6.08

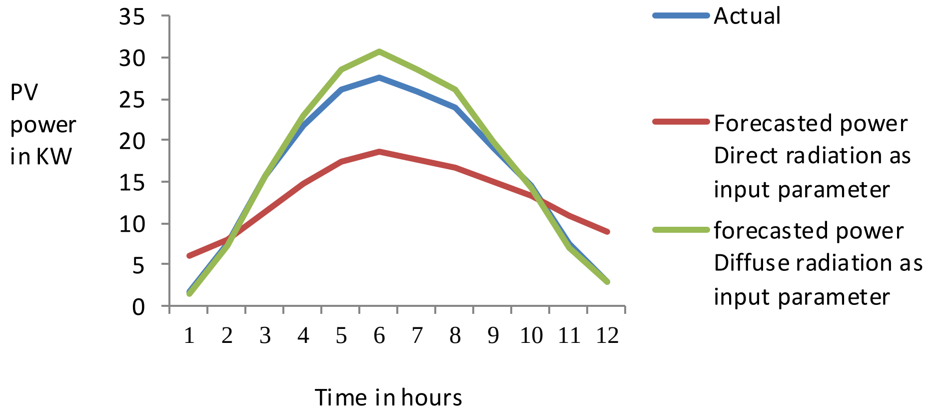

Fig.4.5: A day ahead forecasting in June'14 using ANN-PSO model

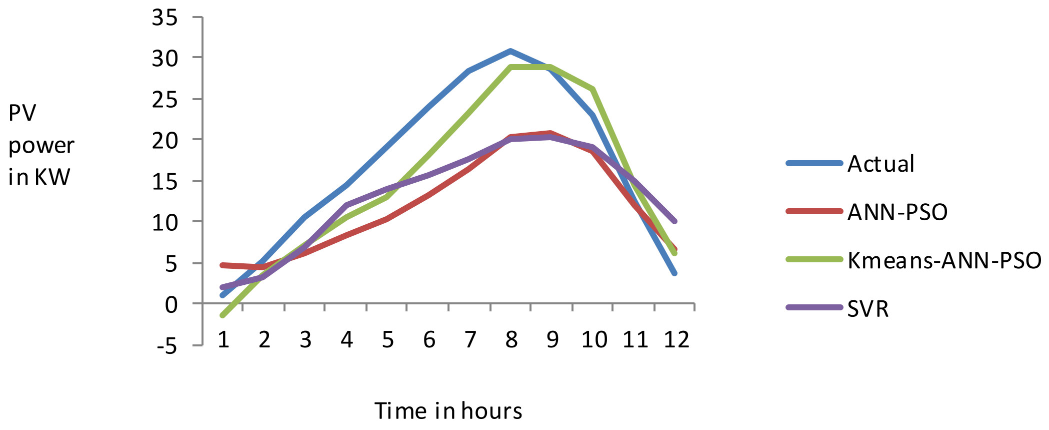

Fig.4.6: A day ahead forecasting in Aug'14 with all three approaches (Direct radiation & temperature as input parameters)

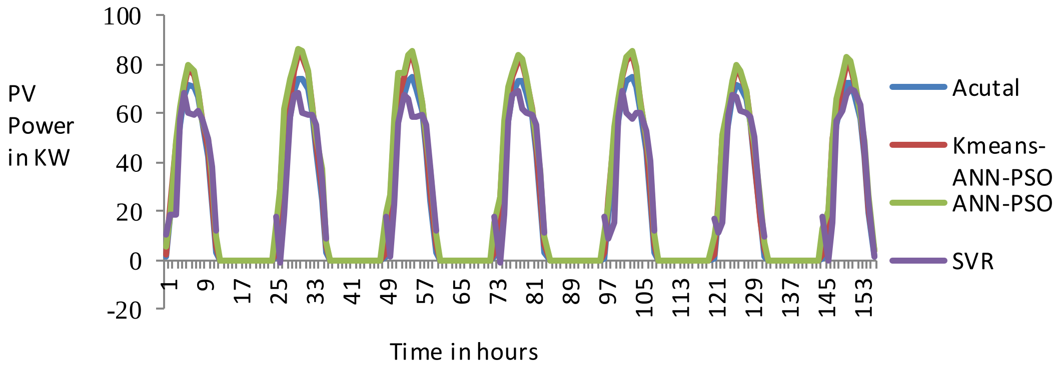

Fig.4.7: A week ahead forecasting from 18th to 24th Oct'14

4.5 Summary

This chapter basically explores the significance of solar irradiation on solar PV power generation and its forecasting. Work is continued on developing an appropriate hybrid model, ANN-PSO based on clustering by K-means. According to the evaluations, the meteorological condition-based clustering technique has a significant effect on solar PV power forecast a week ahead. The results indicate improvement in forecasting accuracy of ANN-PSO model with clustering. Although, SVR model forecasts solar PV power with similar accuracy in a day ahead forecasting, it suffers in a week ahead forecasting with high errors. However, clustering of K-means may not have the final answer at times. Therefore, the work of implementing fuzzy logic based K-means clustering in solar PV power forecasting may be continued. There is a possibility for further research to analyse the effect of other clustering algorithms like mean shift clustering; density based spatial clustering and Gaussian mixture etc. on forecasting accuracy. Furthermore, a hybrid model of SVR and optimization techniques like GA, PSO can be established to check the enhancement in forecasting accuracy.

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Chapter 5

SHORT TERM PRICE FORECASTING WITH THE IMPACT OF WIND POWER GENERATION

5.1 Introduction

Global warming is a major concern to the world as power generation from conventional sources cause 30 % environmental pollution [1]. Thus renewable energy (RE) generation is gaining attention in power sector, which is transforming the existing electricity market to RE enabled electricity market. The development of smart grids all over the world encourages large penetrations of wind and solar power generations. By the year 2019, world-wide the total cumulative installed electricity generation capacity from wind power and solar power amounted to 600 GW & 300 GW respectively [2]. Deregulation of electricity market across the globe has enabled competition in generation, transmission and distribution due to which electricity market price suffers with high volatility [3]. This makes both suppliers and consumers more interested in devising future electricity price strategies as electricity price forecasting assists the suppliers in trading and bidding of electricity and consumers can systematically manage their utilization of electricity [4].

Electricity price is strongly related to physical characteristics of a power system such as loads, meteorological conditions, fuel price, unit operating characteristics, emission allowances and transmission capacity and power generation. Electricity price is highly volatile and electricity market experiences price dynamics due to the unique features of electricity market such as non-storability and the need of power system stability. The major causes of volatility of modern electricity market include load uncertainty, fuel prices & its availability, intermittent nature of wind power and solar power generations, irregularity in hydro-electric production, unplanned outages and transmission constraints etc. [4]. Further the price forecasting in today's electricity market, amid wind & solar power penetrations is highly challenging one [5]-[8].

This chapter proposes a hybrid approach using long short term memory (LSTM) network and K-means clustering for short term electricity price forecasting to investigate the effect of wind power penetration of electricity price forecasting. The proposed model is implemented on real world historical data obtained from Austrian electricity market. The data contains electricity price, load, wind power generation and solar wind power generation data of the year 2016. The accuracy of the proposed model is compared with feed forward neural network- particle swarm optimization (FNN-PSO) and support vector regression (SVR) models. The simulation results show that the proposed model is superior to other two models in forecasting the price and the forecasting accuracy improves further with presence of wind power generation.

5.2 Techniques used in price forecasting

The various techniques such as K-means clustering, recurrent neural network (RNN) and LSTM network, FNN-PSO and SVR used in this work are described below.

5.2.1 K-means clustering

The aim of any clustering technique is to achieve intrinsic grouping of a set of data with large variations. K-means is one of the simplest unsupervised learning algorithms. This algorithm resolves clustering problems. Being a method of vector quantization, it gained wide popularity for cluster analysis in data mining [9]. The crucial steps involved in the algorithm are as follows.

i. Partition of the data into K number of non-empty subsets.

ii. Identifying the cluster centroids (mean points) of the current partition.

iii. Allotting each individual to a specific cluster.

iv. Compute the distance from each individual to own cluster mean and other clusters.

v. Allot the individuals to a cluster based on minimum distance from the centroid.

vi. After re-allotting the individuals, find the centroid of new clusters framed.

vii. Repeat steps 4, 5 & 6 until no more relocations occur.

The algorithm can be presented mathematically as follows.

Consider D is a set of n vectors

i.e. $D = \{X_1, X_2, X_3, ...X_i....X_n\}$ (5.1)

Where, X_i represents each record an m-dimensional vector.

$$X_i = \{X_{i1}, X_{i2}, X_{i3}, ...X_{im}\} \quad (5.2)$$

$$C_j = cluster(X_i) = \arg_j \min \left\| X_i - \mu_j \right\|^2$$

$$Distortion = \sum_{i=1}^{n} (X_i - C_i)^2 \quad (5.3)$$

The distortion is minimized by partially differentiating Distortion with respect to each cluster centre and equated to zero. In this work, to handle the high volatility of electricity price and to forecast electricity price with higher accuracy, clustering has been performed in two ways. Conventionally the electricity price is much dependant on the load demand of the region. Considering RE enabled electricity market, wind power generation is one more feature chosen for clustering. Firstly, the days of similar wind power pattern are clustered into three groups. To achieve this, a data set of maximum wind power, minimum wind power and average (mean) wind power of the day for all days of the year is prepared as per eq.5.4 and then K-means is applied to partition the data. Secondly, the days of similar load pattern are clustered into three groups. In order to partition the data into three groups, a data set of maximum load, minimum load and average (mean) load of the day is prepared as per eq.5.5, for which, K-means is applied to finally split the whole year data into three groups [10]-[11].

$$D_1 = [WP_{\max}, WP_{\min}, WP_{mean}] \tag{5.4}$$

$$D_2 = [L_{\max}, L_{\min}, L_{mean}] \tag{5.5}$$

Where $WP_{\max}, WP_{\min}, WP_{mean}$ represent day's maximum, day's minimum and day's average values of wind power generation respectively. Similarly $L_{\max}, L_{\min}, L_{mean}$ represent maximum, minimum and average values of the load for the day.

5.2.2 Recurrent neural networks

Conventional neural networks assume all the inputs and outputs are independent to each other. However RNNs take the advantage of sequential information. RNNs retain the information in each state and used for the next state. As shown in fig.5.1, RNN has a unique structure with chain of repeating modules.

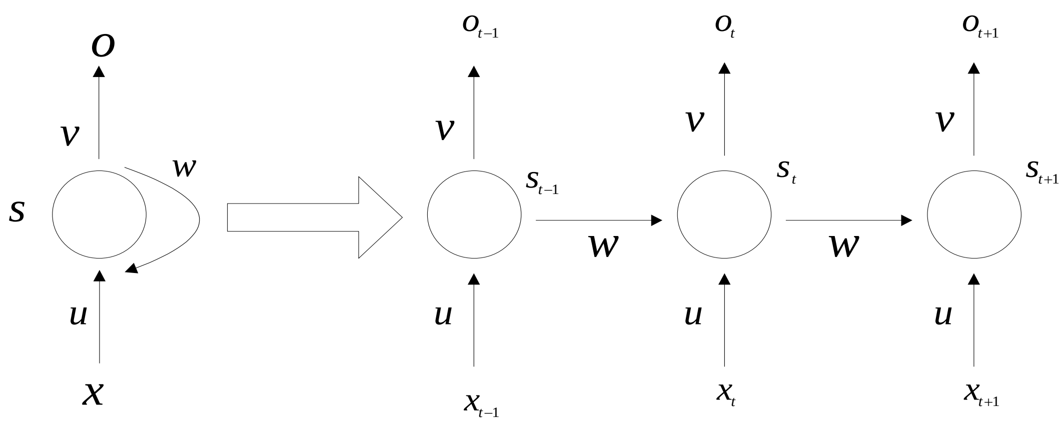

Fig.5.1: An unrolled RNN

An unrolled RNN is shown in fig.5.1. Accordingly

- x_t is the input at time step t.
- s_t is the hidden state at time step t. It replicates the memory of the network. Using previous hidden state and the input at the current step, s_t is calculated as $x_t = f(ux_t + ws_{(t-1)})$
- The function f is generally a non-linear one Ex. tan h
- s_{-1} is required to compute the first hidden state normally initialized to all zeroes.
- o_t is the output at step t $o_t = soft\max(vs_t)$
- Here s_t captures information from all previous time steps.
- The output is calculated only based on the memory at time t.
- Unlike a traditional deep neural network, a RNN implements same $u, v \,\&\, w$ across all steps. This effectively reduces the total number of parameters in the network.
- The main feature of an RNN is its hidden state, which captures some information about a sequence.

Due to some limitations of RNNs in handling long term dependencies, LSTMs grab the attention to address the issue.

5.2.3 LSTM networks

LSTM networks are special kind of RNNs, which can learn long term dependencies. The networks have the capability to remember information for long time. LSTMs have similar structure of RNN with the difference in the internal structure of repeating module as shown in fig.5.2. The repeating module has four layers unlike standard RNNs, which has single layer.

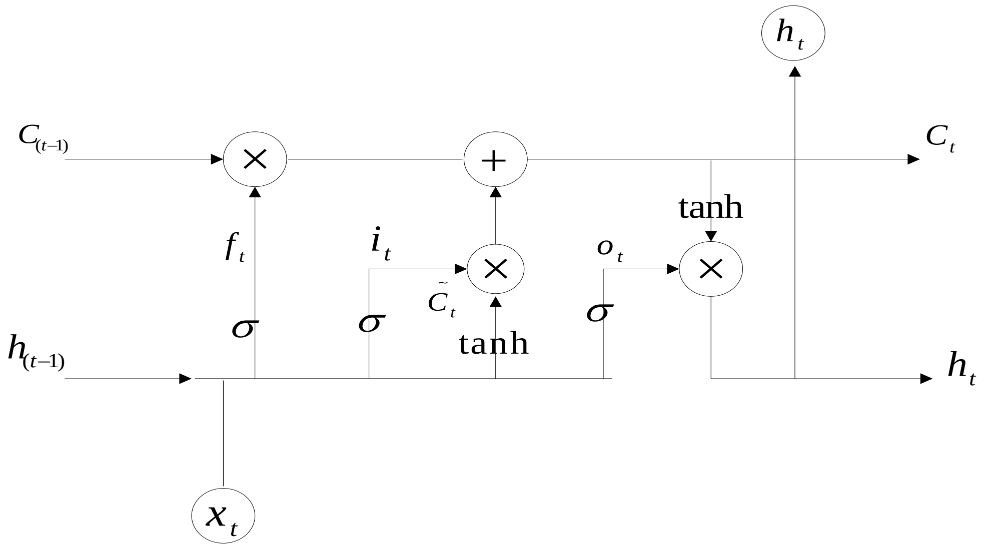

Fig.5.2: Internal structure of LSTM network

As shown in fig.5.2, the internal module performs four important tasks.

Task 1: Decides on retaining the old information. The output is obtained as per eq.5.6 for each number in the cell state and varies from 0 to 1.

$$f_t = \sigma(w_f.[h_{(t-1)}, x_t] + b_f) \qquad (5.6)$$

Task 2: It stores new information in the cell state.

It has two parts.

1) A sigmoid layer that decides the values to be updated .The output i_t is presented in eq.5.7.

$$i_t = \sigma(w_i.[h_{(t-1)}, x_t] + b_i) \qquad (5.7)$$

2) tanh layer computes a vector of new values i.e $\tilde{C}_t$ as per eq.5.8.

$$\tilde{C}_t = \tanh(w_c.[h_{(t-1)}, x_t] + b_c) \qquad (5.8)$$

Task 3: Combining i_t & $\tilde{C}_t$

Task 4: New cell state C_t is computed by updating the old cell state $C_{(t-1)}$ as per eq.5.9.

$$C_t = f_t * C_{(t-1)} + i_t * \tilde{C}_t \tag{5.9}$$

Finally the output is obtained as per equations 5.10 & 5.11.

$$o_t = \sigma(w_o.[h_{(t-1)}, x_t] + b_o) \tag{5.10}$$

$$h_t = o_t * \tanh(C_t) \tag{5.11}$$

Table 5.1: Parameters of LSTM model

Parameters	
Layers of LSTM	2
Number of neurons in layer 1	10
Number of neurons in layer 2	50
Optimizer	Adam
Loss function	Mean squared error
Epochs	180

Various parameters of LSTM model are listed in table 5.1. The number of neurons of the layer and number of epochs are optimized by grid search method.

5.2.4 Support vector regression

Support vector machine (SVM) looks at extremes of the data sets and draws a decision boundary line known as a hyper plane near the extreme points in the data set. SVM segregates the two classes by drawing on arbitrary separation lines known as support vectors [12].

If the classes are not linearly separable, a function is used to transform the data into high dimensional feature space. This process is computationally expensive. A kernel trick is used to reduce computational complexity. A function takes inputs as vectors in original space and returns dot product of vectors in the feature space is called kernel function. Using kernel, we can apply the dot product between two vectors so that every point is mapped into a high dimensional space via some transformation essentially we use it to transform a non-linear space into linear space. Some of popular kernel functions are polynomial, radial basis function and sigmoid. SVM solves mainly classification and regression analysis [13].

SVR aims to obtain a regression function $f : R^D \to R$ as in eq.5.12.

$$\begin{aligned} & y = f(x) = w^T \varphi(x) + b \\ & f : R^D \to R \\ & i = 1, 2......, l \end{aligned} \qquad (5.12)$$

Where $\varphi(x)$ is a function, which maps the data x from low dimension to high dimensional feature space, w is a weight vector and b indicates bias. Standard support vector regression adopts ε-insensitive function. ε is considered to be the accuracy with which all the training data is fitted with a linear function. The problem is converted to an objective function that is optimized to its minimization.

$$\text{Minimize} \qquad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \qquad (5.13)$$

Subject to

$$w^T \varphi(x) + b - y_i \le \varepsilon + \xi_i \quad , \; i = 1, 2......, l$$

$$y_i - w^T \varphi(x) - b \le \varepsilon + \xi_i^* \ , \quad i = 1, 2......, l$$

$$\xi_i, \xi_i^* \qquad \ge 0, \quad i = 1, 2......, l$$

Where ξ_i, ξ_i^* are the relaxation factors .In case of error in fitting, ξ_i, ξ_i^* are greater than 0, otherwise ξ_i, ξ_i^* are all equal to zero. The first term in equation 5.13 is the optimization function that smoothens the fitting function to improve generalization. The error is reduced by second term. The penalty parameter C affects the performance of support vector regression to great extent. C balances between the algorithm complexity and degree of mistakenly classified samples. Hence, choosing proper penalty factor C has a large impact on the model convergence and also leads to good prediction performance. The support vector regression (SVR) is centred to kernel function. The performance of support vector regression is much dependant on kernel function. Thus discovering appropriate kernel function and obtaining suitable values to the parameters of the kernel function have a great impact on the performance of support vector regression.

Mostly four types of kernel functions, linear kernel, polynomial kernel, RBF kernel and sigmoid kernel are implemented in support vector regression. As construction of RBF kernel (Gauss kernel) is relatively easy, this is widely used at present. The function of RBF kernel is presented in eq.5.14. Gamma (γ) is the inverse of ($2\sigma^2$), which is to be optimized to make SVR model perform well.

$$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / 2\sigma^2) \qquad (5.14)$$

Where σ >0

Where $\|x_i - x_j\|$ represents Euclidean distance, σ is the standard deviation , σ >0

Eq.5.14 can redefined as in eq.5.15

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2) \qquad (5.15)$$

Where $\gamma = 1/2\sigma^2$

Table 5.2: Parameters of SVR model

Parameters	
Kernel	RBF
Regularization parameter(C)	1
Gamma	0.1
Tolerance	0.00001

The parameters listed in table 5.2 are optimized by applying grid search method.

5.2.5 Feed forward neural networks

Artificial neural network (ANN) replicates human brain and its intelligence. The ANNs are non-linear in structure and used to model non-linear problems effectively. Feed forward neural networks (FNNs) are the basic type of ANNs and simpler than RNNs. Fig. 5.3 shows the structure of FNN used in the work. It consists three layers connected to each other in forward direction. The layers are input layer, hidden layer and output layer. In the network X_1, X_2 are the inputs; U&V are the connecting weights whereas b includes the bias to the nodes. Hidden layer's output is h and 'o' is the output of the network [14]-[16].

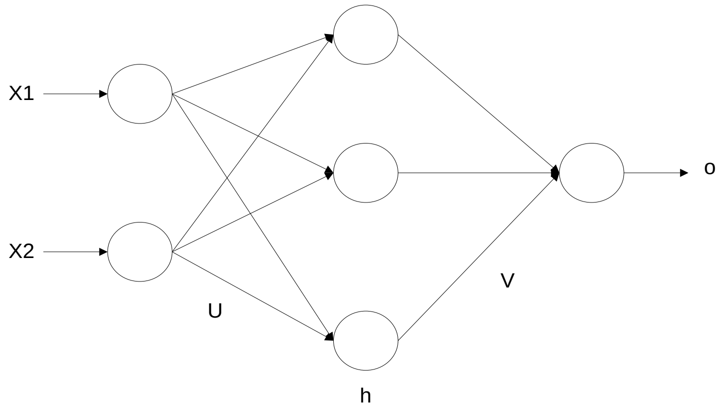

Fig.5.3: The structure of FNN

The output of hidden layer is computed as per eq.5.16 and the output of the network is obtained as per eq.5.17. The activation function f takes various functions like sigmoid, ramp and Gaussian. FNN in this work implements sigmoid function.

$$h_j = f(\sum_{i=1}^{n} U_{ij} x_i + b_j) \qquad (5.16)$$

The output is calculated as per eq.5.17

$$o = f(\sum_{i=1}^{m} V_i h_i + b) \qquad (5.17)$$

Further the optimization technique particle swarm optimization (PSO) is incorporated to adjust the weights of the FNN [17]-[18]. The optimized values of various parameters of the model are listed in table 5.3.

Table 5.3: Parameters of FNN-PSO model

Parameters	
Network layers	3
Hidden layer neurons	5
Population in PSO	10

Number of iterations	1000
Tolerance	10^{-15}

5.3 Methodology of the proposed model

The proposed model is presented in fig.5.4 through a flow chart. The data of Austrian electricity market is collected and normalized after pre-processing it. The data consists of an hourly data of historical electricity price, load, wind power generation and solar wind power generation of the year 2016. A data set of the days of similar load pattern is clustered into three groups by using K-means clustering technique. This clustering is performed by considering three parameters such as maximum load, minimum load and average (mean) load of the day. A data set of 30 similar days to day of prediction fed to the LSTM network where it is used for training the network. Various parameters of LSTM network such as number of neurons of the network layers and epochs as mentioned in table 5.1 are optimized with grid search method. After the training is complete, a separate data set is used for testing and forecasting of electricity price. In this chapter electricity price is forecasted one day ahead.

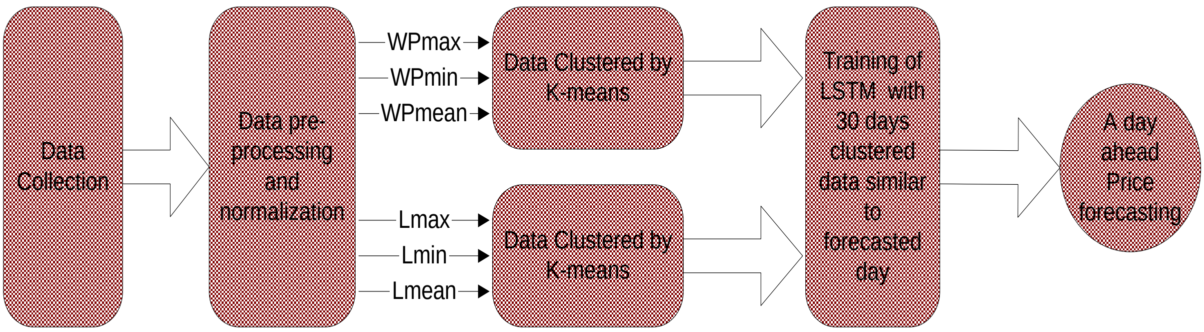

Fig.5.4: The proposed hybrid approach

5.4 Simulations & results

The historical data of Austrian electricity market for the year 2016 is used in the work carried. The data is pre-processed for the set of data contains hourly data of load, wind power generation, solar PV power generation and electricity price. As the data consists different features of different ranges hence normalized to the values less than or equal to 1. The variations in price data of the year 2016 are presented in fig.5.5. With the computation of correlation factors it is analysed that the wind power is highly correlated parameter to price than solar PV power after the load demand. The contribution of solar PV power generation to the grid is also very marginal. Thus, this work only focusses on the impact of wind power to electricity price. Then similar days of the year are clustered as per wind power generation into three clusters as shown in fig.5.6. Later, similar days of the year as per load demand are clustered into three clusters as depicted in fig.5.7. Then 30 days of clustered data based on wind power similar to day of prediction is considered for proper training of the LSTM network to forecast a day ahead electricity price of 6th Sep'16. The clustered data based on load is also used for training to compare the accuracy of forecasting. Without applying clustering also the same day's price is forecasted by training the LSTM with previous 30 days data. Similarly, using the SVR model and the FNN-PSO model the same day price is forecasted after training the models with previous 30 days data. To analyse the impact of wind power generation on electricity price forecasting, by only considering load as input, the model is trained and tested for forecasting electricity price of the same day and the forecasting accuracy is compared the accuracy of price forecasting, when both load & wind power are considered as input.

To evaluate the performance of forecasting models, three important evaluation factors are used. They are mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean squared error (RMSE).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_i - F_i| \tag{5.18}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \tag{5.19}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2} \qquad (5.20)$$

In eq.5.18, eq.5.19 & eq.5.20 A_i& F_i represent actual and forecasted values and N indicates total number of samples of forecasting period. As per eq.5.19 MAPE is widely used to evaluate the performance of any forecasting method. In price forecasting, the same may not work properly sometimes as the actual value is zero, MAPE would be infinity. Even large actual values also make improper MAPE computation. Thus as per modified equation in eq.5.21, MAPE is computed in the present work. The results are depicted in table 5.4.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{\bar{A}}\right| \qquad (5.21)$$

Where, A_i & F_i are the actual & forecasted values and $\bar{A}$ represents average value of N number of actual values.

Table 5.4: MAPE, MAE & RMSE values of a day ahead price forecasting

Approach	Input parameters	MAPE	MAE	RMSE
LSTM-Kmeans (based on load)	Load & wind power	8.29	2.90	5.01
LSTM-Kmeans (based on load)	Load	10.37	3.63	5.72
LSTM-Kmeans (based on wind power)	Load & wind power	12.16	5.26	5.67
LSTM-Kmeans (based on wind power)	Load	12.51	5.38	6.07
LSTM model	Load & wind power	12.71	5.46	6.05
SVR	Load & wind power	13.75	5.82	6.61
FNN-PSO	Load & wind power	16.18	5.67	7.65
FNN-PSO	Load	18.17	6.37	7.63

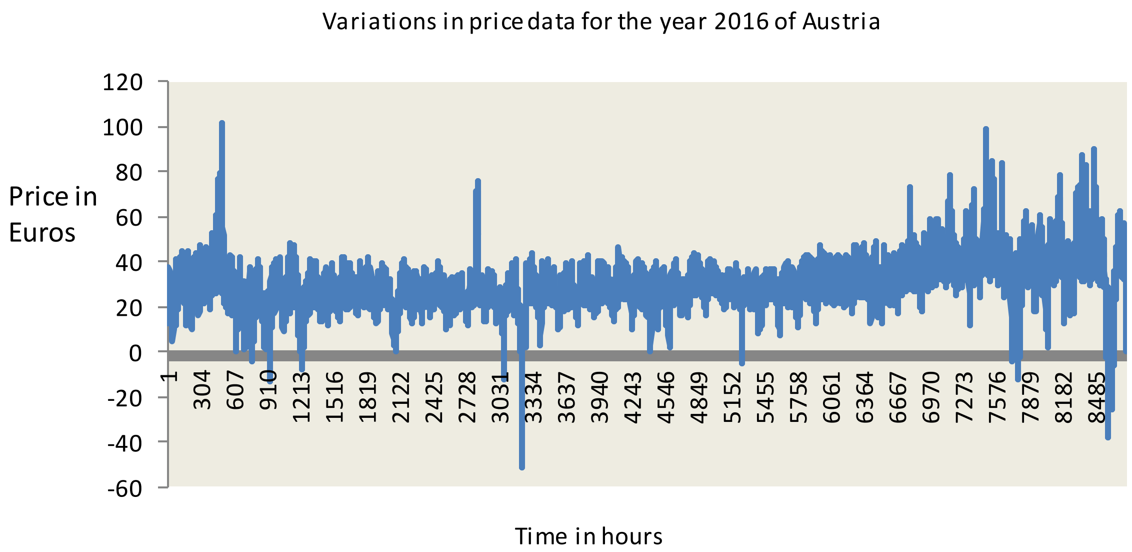

Fig.5.5: Price data of 2016

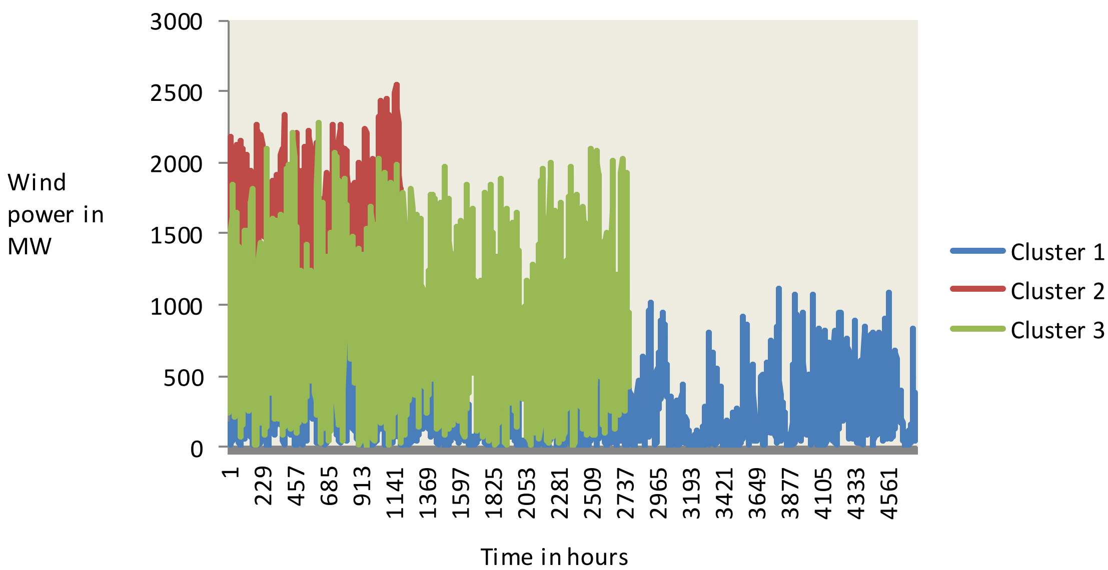

Fig.5.6: Wind power clusters of the year 2016 data

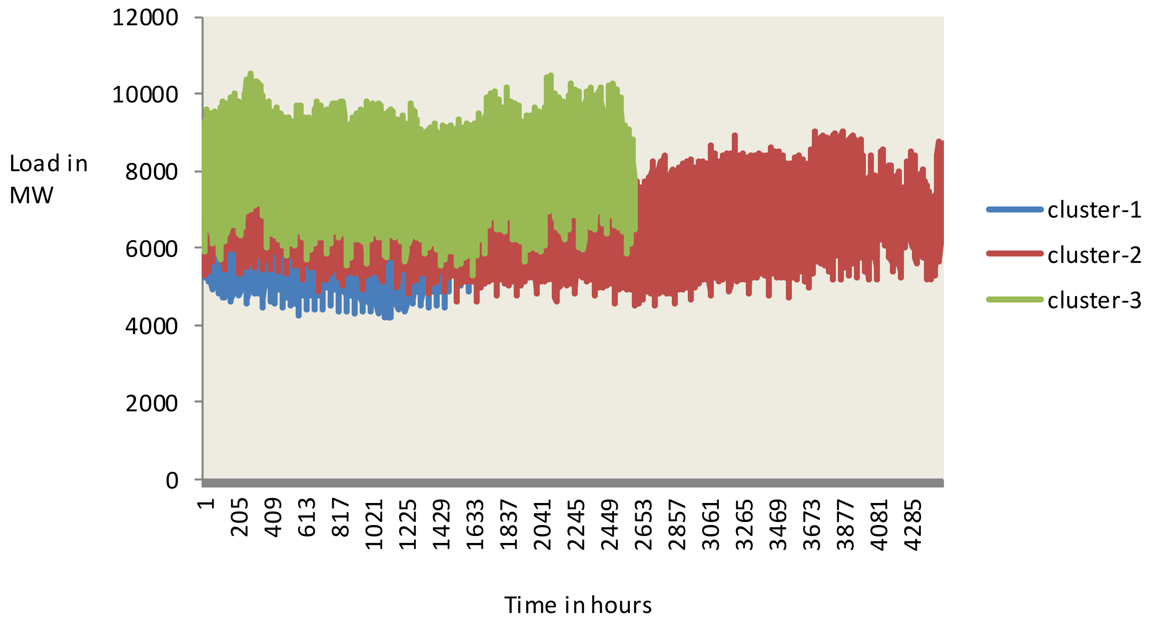

Fig.5.7: Load Clusters of the year 2016 data

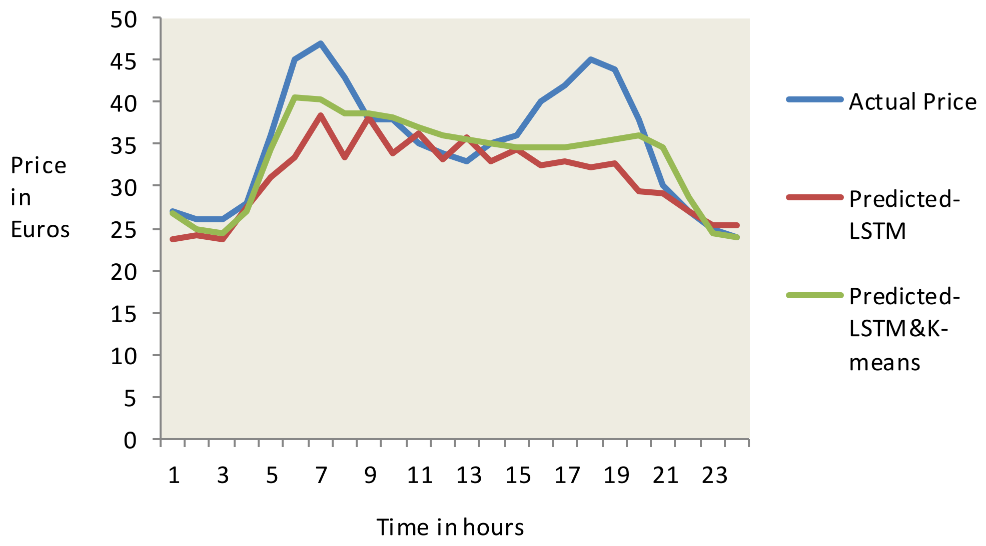

Fig.5.8: Predicted price vs actual price on 6thSep'16

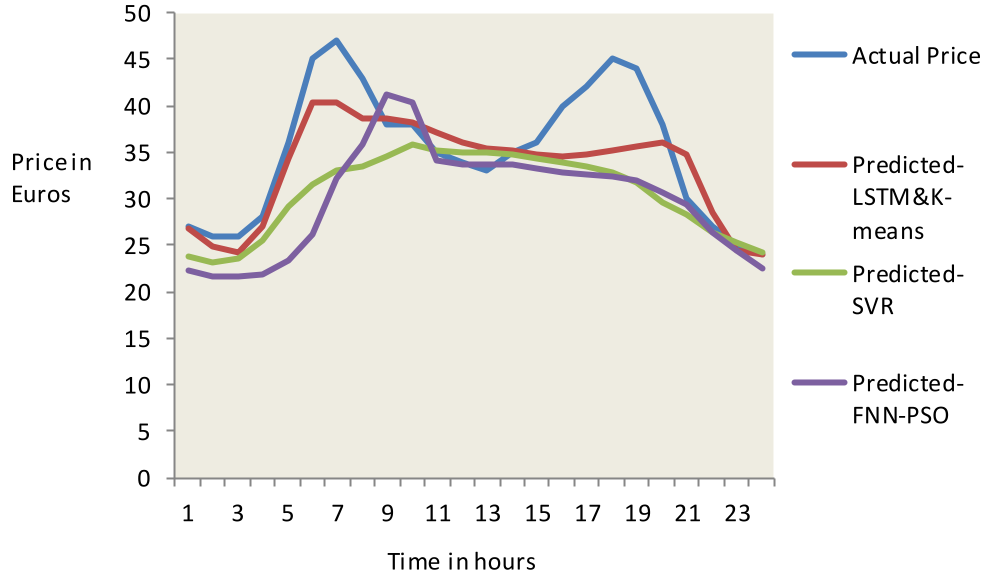

Fig.5.9: Predicted price vs actual price on 6thSep'16

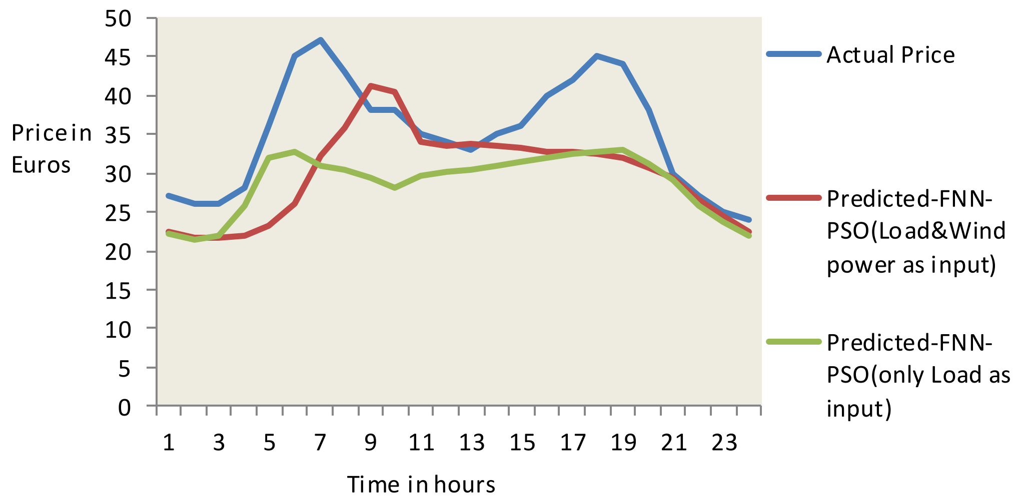

Fig.5.10: Predicted price vs actual price on 6thSep'16

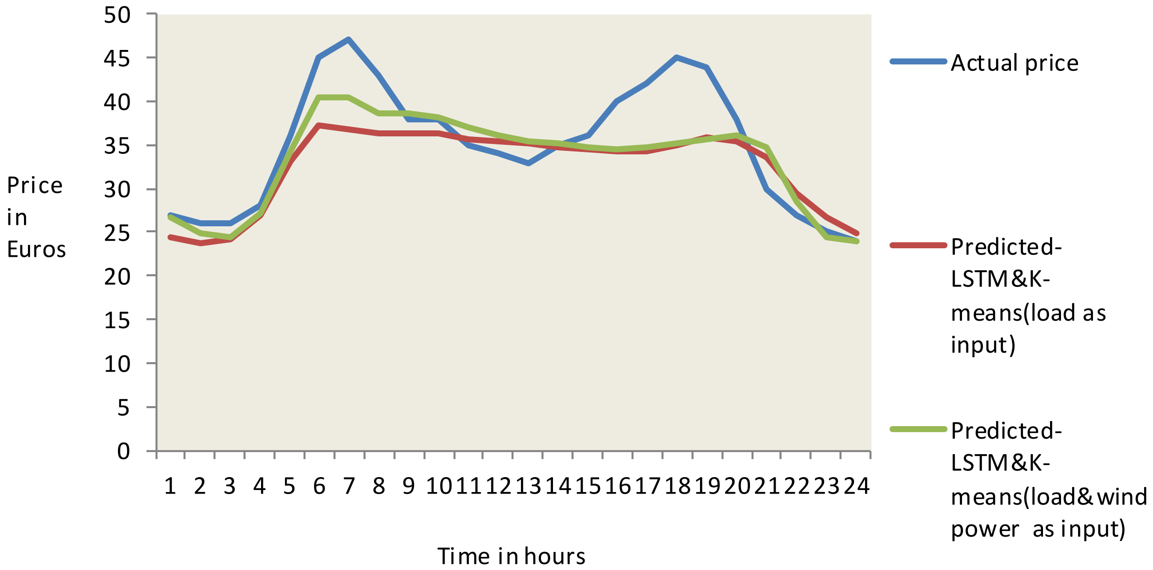

Fig.5.11: Predicted price vs actual price on 6th Sep'16

The plot in fig.5.8 compares actual price to predicted prices of the proposed model and the LSTM network for the day of prediction. It is clearly evident that the predicted price curve of the proposed model is closer to actual price curve. The second plot in fig.5.9 compares predicted price curve of the proposed model (LSTM & K-means) to predicted price curve of other models such as SVR model and FNN-PSO model and depicts the best accuracy by proposed model. The best performance of the proposed model is also depicted by errors computed and presented in table 5.5. In this work clustering of data is performed in two cases using K-means clustering technique. Based on wind power variations also the whole data is clustered and based on load variations also the data is clustered into three groups. The implementation of clustered data based on load has reported better forecasting performance with higher accuracy as presented in table 5.5. There is a significant error reduction in terms of MAPE, MAE & RMSE in price forecasting using proposed model when the model performs clustering according to load variations. The errors are lowest for the proposed model among all the models with minimum MAPE i.e. 8.29 %.The proficiency of the proposed model is further illustrated with the computation RMSE, which is lowest among all models. The proficiency of the SVR model is superior to FNN-PSO model and inferior to the proposed model. The plots in fig.5.10 & fig.5.11 clearly indicate the improvement in forecasting accuracy with the consideration of wind power as input, which is right indication of the impact of wind power generation on electricity price forecasting for renewable energy enabled electricity market. The improvement in forecasting accuracy also depends on the contribution of wind power generation to the power grid on the respective day of price forecasting.

5.5 Summary

Electricity price is a special commodity unlike any other commodity in the market. Its storage is not an easy task. It is influenced by many factors like load demand, power generations, time factor, industrial requirements, weather conditions, fuel prices and transmission constraints etc. Thus electricity market experiences a lot of fluctuations making price highly volatile. One of the recent concerns for the volatility is power generation from renewable energy sources. The work carried has suggested a suitable hybrid approach using K-means clustering and LSTM network for short term electricity price forecasting showing its proficiency in accurate price forecasting amid wind power penetration. The impact of wind power generation on price forecasting has been analysed and results depicted that the impact of wind power generation on the accuracy of price forecasting is significant with the considerable reduction in errors. However, it is also noticed that the contribution of wind power generation to the grid also matters in the forecasting period. Further the scope is left for implementing any other clustering technique other than K-means for future research and to analyse the impact of solar PV power generation also on price forecasting.

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Chapter 6

BOOTSTRAP AGGREGATION OF ENSEMBLE FOR SHORT TERM PRICE FORECASTING WITH THE IMPACT OF WIND & SOLAR POWER GENERATIONS

6.1. Introduction

With the deregulation and restructuring of the electric power industry, forecasting of electricity price has been the modus operandi to operate a power market. The economically non-storable commodity, electricity must be balanced out in terms of its production and consumption. Otherwise, maintaining the steady state frequency would become a major obstacle. Under deregulation, utility profit maximization takes over automatically, but with efficient markets this should also benefit consumers [1], introducing competition to reduce energy wastage and minimizing bills at the consumer end. The most distinct characteristic of electricity is its volatility due to non-storability and short-time users.

The hourly price series shows properties such as high frequency, non-constant mean and variance and high unusual price percentage due to uncontrolled events, sufficient to make the series stochastic and hence making forecasting complex. Electricity price forecasts provide crucial information which help utilities and consumers in the power market. This could assist generation companies in bidding and power exchange in trading. Efficient hourly price forecasting could also be beneficial in setting up highly precise bilateral contracts [2] and in generating schedule of a utility. The aim of this work is to inquire into the potential of ensemble learning to forecast nonlinear, non-stationary electricity prices. The contributions of this chapter are as follows:

1. The presented model is suitable for very short term electricity price forecasting, as it is flexible and follows the dynamics of price signals in addition to being computationally inexpensive.

2. Besides meteorological and historical parameters, renewable energy parameters are also considered for forecasting price.

3. Proposed model is compared with various benchmark models along with previously recommended ensemble model for the same problem and is observed to be most accurate.

In the presented model, independent outputs of the first stage of stacking phase, which comprises of extreme gradient boosted trees and random forest regressor, capable of learning distinct parts of the data, are advanced to the next stage, where bayesian linear regression is used as a meta-regressor, with the aim of improving the real-time price prediction performance. In the proposed model bootstrap aggregation of stacked model has been done in order to reduce the variance and further prevent overfitting [3]. The suitability and significance of the presented approach is illustrated by implementing it on real-world price data of Austrian electricity market in Europe. Florian Ziel et al. [4] analyzed the interrelation between electricity price of Energy Exchange Austria and other European markets. The EXAA issues day-ahead price earlier than other European exchanges, connected with Austria, therefore, enabling traders to use the Austria electricity price into their calculation. The selection of the features among all the considered parameters has been performed using the mutual information coefficient between the input parameters and output vector. The features used for the electricity price prediction were selected not only on the basis of its dependency on price, but also on the ease of data availability for different European markets, consequently the proposed model may be applied to other markets in future making it robust and reliable. In order to estimate the accuracy of forecasting we use metrics including root mean squared error and mean absolute error. Mean absolute percentage error (MAPE) metric can be misleading when applied to electricity price, this is due to the fact that electricity price may get significantly close to zero, resulting in a very large value of MAPE, regardless of the absolute error. To tackle this challenge we use a different metric, the mean arctangent absolute percentage error (MAAPE), which is proposed in [5]. Since, the mean error metrics only demonstrate the overall accuracy, and may arise from few accurate predictions, with a view to quantify the consistence of predictions we validate our model by evaluating the confidence interval of absolute error.

The study of short-term electricity price forecasting can be organized into three sub-categories, namely, statistical models, computational intelligence models and hybrid/ensemble models [6]. The statistical and computational intelligence are widely used approaches, but due to the nonlinear and stochastic characteristics of price series, statistical approaches, videlicet exponential smoothing, moving average, auto regression, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) [7] and generalized autoregressive conditional heteroskedastic (GARCH) [8] have proven to be incompetent [9]. On the other hand, the computational intelligence techniques [10]-[12] are flexible, capable of capturing complexities and non-linearity. Artificial neural networks (ANNs) are remarkable for short-term predictions and are easily implementable for electricity price forecasting [13]. The work [14] uses ANN to show the strong dependency of electricity price on trend in load demand and clearing price. A class of deep neural network, stacked denoising auto-encoder method is implemented to forecast day-ahead electricity price of US electricity markets, and was compared to conventional neural networks, multivariate adaptive regression splines and support vector regression [15]. However, as the relationship among price series vary with time, the ANN may lose the value of features captured by it [6].

A single prediction model fails when handling complex data. The hybrid models are better choice for capturing the pattern where the uncontrollable contingencies make the price predictions difficult. Similarly, Yang et al. [16] proposed a new hybrid model that combines wavelet transform with kernel extreme learning machine using adaptive particle swarm optimization parameter searching along with ARMA model. The above-mentioned hybrid models improve the performance significantly but the computational time was not taken into account. Low computational complexity is one of the most important criteria required for very short-term price forecasting as it makes re-training the model feasible. Probabilistic models [17] were also proposed with the aim of reduction in the computation time. Recently, Aggarwal et al. [18] introduced an ensemble of relevance vector regression and gradient boosting which has demonstrated high accuracy and low computational complexity, suitable for very-short term forecasting.

Along with the various approaches used for future price prediction, the feature selection also plays crucial role in short-term forecasting. The idea is to employ the historical prices and other estimated parameters to extrapolate the price. Global warming being a major concern to the world, solar energy and wind energy are most promising renewable energy sources to produce clean electricity. However, large integration of wind and solar energy sources into the grid increases the volatility due to their intermittent nature. In process of smart grid deployment, price forecasting plays significant role in a day-ahead deregulated market [19]. The real time electricity market aims to balance out the differences between day-ahead production/demand and actual production/demand and establishes real time local marginal price (LMP).

This chapter builds in the following way:

- It takes into consideration solar and wind renewable energy parameters along with climate conditions for forecasting electricity price.

- The methodology is based on bagging of a stacked generalized model on complete dataset.
- The model uses a combination of extreme gradient boosting and random forest.
- The evaluation utilizes MAAPE as error metric instead of MAPE due to the reasons as discussed previously.

6.2 Dataset and feature engineering

The dataset for the prediction of electricity price has been acquired via the ENTSO-E Transparency Platform. We utilize the data for day-ahead electricity price, load consumption, wind generation, humidity, temperature, etc. of Austria from the platform. The data collected from January 2015 to December 2016 possesses an hour granularity. The employed dataset has some missing values for electricity price which have been handled by mean imputation. The dataset is segmented into training and testing sets with the later consisting of seven consecutive days from the second half of each month in the dataset, while the remaining days are used for training. It may be clarified that the target variable for our forecasting problem, is day-ahead electricity price of the next hour. Feature engineering was accomplished to choose the optimum set of features and formulate new features from the existing ones in order to enhance the performance and accuracy of the forecasting models. Extraction of calendar pointers, specifically month, weekday and hour pointers from the utc-timestamp is carried out to obtain new categorical nominal features. Moreover, the day-ahead price is impacted by electricity generation and demand parameters such as solar generation, wind generation and load demand. Apart from these features we also use the historical electricity price data for forecasting day-ahead price at time t, represented as P(t), 24-hour window (one day) starting from the previous hour with hourly resolution is used. Importance of previous hour DA prices in the prediction is calculated using extra trees feature importance, as shown in fig.6.1. In fig.6.1, previous hours are specified on x-axis, importance is specified on y-axis. Only P(t-1), P(t-2), P(t-3), P(t-4), P(t-22), P(t-23), P(t-24) are observed to have a significant impact on the day-ahead price forecasts at time *t*, and are used as inputs. The feature selection for the remaining parameters was carried out by analysing the mutual information coefficients (y-axis) between input features (x-axis) and actual price target vector as shown in fig.6.2. Parameters having negligible or zero values have not been incorporated in the final feature set. The used input features for electricity price are depicted in fig.6.3.

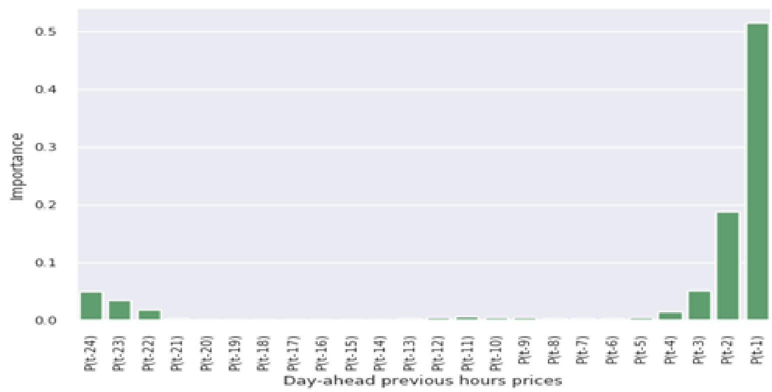

Fig.6.1: The impact of features on day ahead price forecast

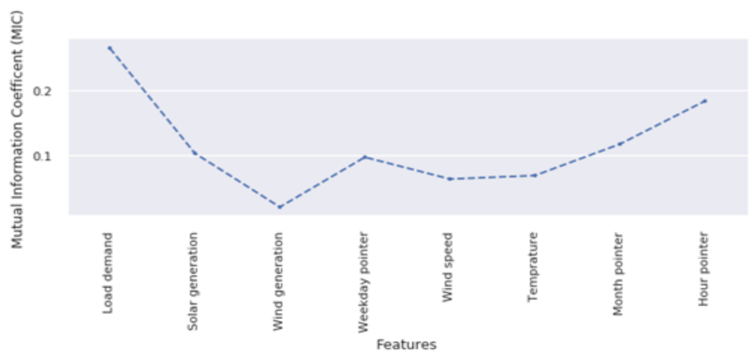

Fig.6.2: Mutual information coefficients of various input features

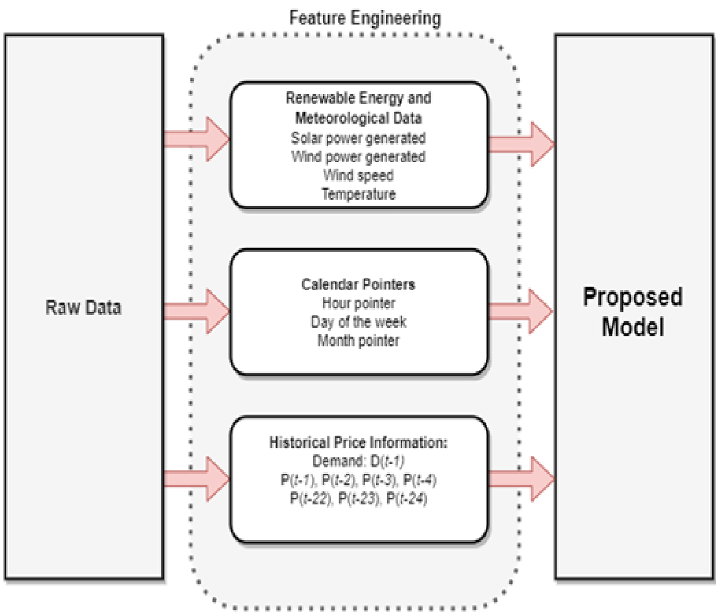

Fig.6.3: Input features for price forecast

6.3 Methodology

In this section we explain the proposed model which dominantly focuses on ensemble learning. The stacking phase comprises of two stages. In the first stage we ensemble extreme gradient boosted tree with random forest regressor, followed by the second stage which uses bayesian linear regression as a meta-regressor. The predictions of the stacking phase on bootstrapped sample points are then aggregated to obtain the electricity price forecasts. The end of this section illustrates the implementation of the developed model on Austria dataset including hyper parameter tuning and metrics used for the quantitative comparison of all the models in this study.

6.3.1 Bootstrapping the dataset

Bootstrap is used to quantify the uncertainty correlated to an estimator. Subsets are constructed by selecting sample points in a random manner from the ENTSO-E Austria price training set. The chosen points are replaced in the training set; this enables them to be included in a particular subset multiple times. In each such set fraction of total sample points are distinct [20]. Given the Austria electricity price training set $[\mathbf{xy}]$ consisting of N sample points, where $\mathbf{x}$ represents the input feature matrix with V features and $\mathbf{y}$ is the day-ahead electricity price target vector. Then, each bootstrapped set contains N' points with the same number of features, represented by:

$$\mathrm{B}^{(i)} = \left[\mathbf{b}_{\mathrm{x}}^{(i)}, \mathbf{b}_{\mathrm{y}}^{(i)}\right] \tag{6.1}$$

Where $B^{(i)}$ corresponds to the i^{th} bootstrapped set, $\mathbf{b}_{\mathrm{x}}^{(i)}$ and $\mathbf{b}_{\mathrm{y}}^{(i)}$ represent input feature matrix and output vector respectively formed by random sampling of the dataset. Hence, after resampling we obtain M distinct sets, $\left[\mathrm{B}^{(1)}, \mathrm{B}^{(2)}, ..., \mathrm{B}^{(M)}\right]$.

6.3.2 Stacking phase

a) First stage

This stage exploits the merits of two different decision tree ensemble techniques i.e. bagging and boosting. This stage builds upon the Bootstrapped datasets B_i.

I. Extreme gradient boosted trees

XGBoost algorithm realizes weak learners by optimization of the structured loss function. Instead of employing linear search method as in gradient boosting, it explicitly uses the first and second derivatives of the loss function. The performance of algorithm is further enhanced by, cache recognition, sparsity-aware algorithm, out-of-core computing and weighted quantile sketch algorithm [21].

For a given bootstrapped set $\mathrm{B}^{(i)} = \left[\mathbf{b}_{\mathrm{x}}^{(i)}, \mathbf{b}_{\mathrm{y}}^{(i)}\right]$ where $\mathbf{b}_{\mathrm{x}}^{(i)} = \left(\mathbf{b}_{\mathrm{x},1}^{(i)}, \mathbf{b}_{\mathrm{x},2}^{(i)}, ..., \mathbf{b}_{\mathrm{x},\mathrm{N}'}^{(i)}\right)^{\mathrm{T}}$ and $\mathbf{b}_{\mathrm{y}}^{(i)} = \left(b_{y,1}^{(i)}, b_{y,2}^{(i)}, ..., b_{y,N'}^{(i)}\right)^{\mathrm{T}}$, R additive functions are used by the tree based ensemble model to make output predictions.

$$f(\mathbf{b}_{x,j}^{(i)}) = \hat{b}_{y,j}^{(i)} = \sum_{r=1}^{R} f_r(\mathbf{b}_{x,j}^{(i)}), \qquad f_r \in F \tag{6.2}$$

Where, the space of regression trees is represented by F, given by $\{f(\mathbf{b}_{\mathrm{x}}^{(\mathrm{i})}) = w_{\mathrm{q}(\mathbf{b}_{\mathrm{x}}^{(\mathrm{i})})}\}$. Here in eq.6.2, each f_r is associated to leaf weights w and tree structure q.

$$L = \sum_{j=1}^{N'} l\left(b_{y,j}^{(i)}, \hat{b}_{y,j}^{(i)}\right) + \sum_{r=1}^{R} \Omega\left(f_r\right) \tag{6.3}$$

In eq.6.3, l is the denotation of the differentiable loss function and Ω estimates the complexity of the model, given as:

$$\Omega(f_{\mathrm{r}}) = \gamma \mathrm{T} + \frac{1}{2}\lambda \sum_{\mathrm{j}=1}^{\mathrm{T}} w_{\mathrm{j}}^{2} \tag{6.4}$$

γ in eq.6.4 signifies the minimum loss reduction necessary to generate a split, T is the number of leaves in the tree. The regularization term reduces over-fitting by smoothing the final learnt weights, λ is the L_2 regularization constant on weight w [22].

$$L(q) = -\frac{1}{2}\sum_{\mathrm{j}=1}^{\mathrm{T}} \frac{\left(\sum g_{\mathrm{t}}\right)^{2}}{\lambda + \sum h_{\mathrm{t}}} + \gamma T \tag{6.5}$$

In eq.6.5, g_t and h_t are the first a second derivatives respectively. Instead of relying on any distant metric, XGBoost maps the similarities between the data points through adaptive adjustments of neighbourhoods, therefore, beating the curse of dimensionality. It overcomes the problem of imbalanced dataset, moreover uses second-order gradients to converge faster and advance regularisation to improve model generalization. XGBoost aims to add new trees complimenting the existing ones, this generally enables improved price forecasting accuracy to the overall ensemble with lower number of trees. Furthermore, it is utilized to accommodate the stochastic variations in pricing signals which are a recurring property in dynamic electricity market.

II. Random forest regression

Random Forest is a significant adaptation of bootstrap aggregation; it trains independent decision trees on bootstrapped sets along with random feature-selection during the tree-growing procedure. The final output is predicted by averaging the output of each weak learner. The algorithm of random forest used in our model is illustrated as follows:

The property of variance reduction of bagging helps the aggregation of weak learners like decision trees to outperform a single strong learner. However, bagged trees do not significantly improve upon the bias of an individual tree. Moreover, in case of dependent variables, the variance of the average is given by:

$$\left(\rho + \frac{1-\rho}{T}\right)\sigma^2 \qquad (6.6)$$

Where, ρ is the pairwise correlation and σ^2 is the variance of each variable. It can be observed that for a large value of *T*, the above quantity becomes $\rho\sigma^2$, hence the reduction in variance is not substantial. Random Forest inculcates random feature-selection during the tree-descending process reducing the correlation between electricity price forecasting features further reducing the variance [23].

b) Second stage

For every bootstrapped set, each regressor in the first stage generates an N' dimensional output vector. The predictions of XGBoost (**g**) and Random Forest (**r**) are stacked together to obtain the input matrix [**g r**]. This matrix along with the target vector $\mathbf{b}_y$ of the previous stage forms the blending training set which is used for training Bayesian Linear regressor.

1. Bayesian linear regression

Bayesian linear regression uses a mechanism to deal with poorly distributed data. It allows the use of prior on the coefficients and on the noise so that in the absence of data, the priors dominate. It consists of the following two stages: (I) Treating the parameter vector (**w**) as a random variable as it is approximated from data which is inherently noisy, we estimate **w** using:

$$p(\mathbf{w} \mid \mathbf{X}, \mathbf{y}) = \frac{p(\mathbf{y} \mid \mathbf{X}, \mathbf{w})\, p(\mathbf{w})}{p(\mathbf{y} \mid \mathbf{X})} \quad (6.7)$$

Where, **X** is the input matrix and **y** is the output vector.

(II) The calculation of the predictive distribution of y^* given any new query $\mathbf{x}^*$ is given by:

$$p(y^* \mid \mathbf{x}^*, \mathbf{X}, \mathbf{y}) = \int p(y^* \mid \mathbf{w}, \mathbf{x}^*)\, p(\mathbf{w} \mid \mathbf{X}, \mathbf{y})\, d\mathbf{w} \quad (6.8)$$

In this implementation we use a particular form of Gaussian prior distribution which is used to include a regularization parameter in the estimation [24].

In stacking each model makes a significant contribution, the individual weaknesses and biases are offset by the strengths of other models. The stacking phase in our proposed model uses XGBoost to capture the various characteristics of the data, specifically the extremities by penalizing the errors. However, XGBoost is harder to tune and is highly sensitive to overfitting. Contrary to this, Random forests overcomes overfitting as the ensembles are not built on the residuals, the way XGBoost does. The Bayesian Linear regression model is used as the meta-regressor to optimally combine the first stage algorithms.

II. Aggregation of stacked generalization

The hour-ahead electricity price ($\mathbf{p}'$) is predicted by aggregating the outputs (**p**) of independent stacked models on M distinct bootstraps. The proposed model is shown in fig.6.4. In stacking, multiple models predict the same target, combining them may lead to overfitting. This limitation of stacked generalization is diminished with the help of bagging. Furthermore, bagging improves the accuracy of price prediction as it reduces the variance of individual models [25] and imparts the ability to ignore irrelevant features.

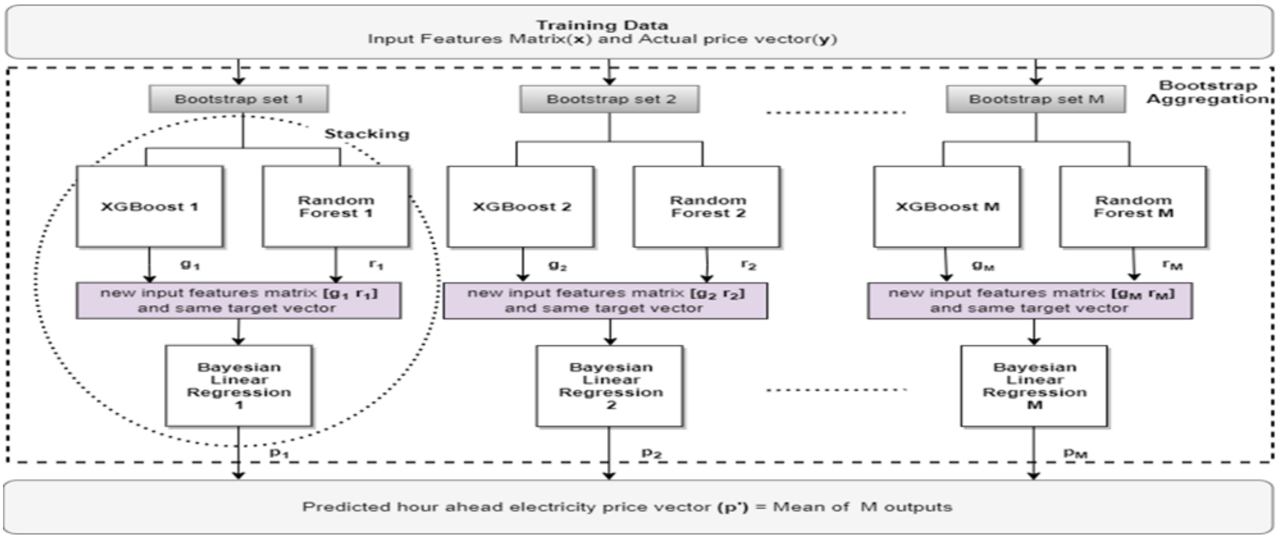

Fig.6.4: The proposed model for price forecasting

6.3.3 Hyper parameter tuning

We use random grid search with MAAPE as the scoring loss metric to perform 5-fold cross validated search over the hyper parameter settings as described in Table 6.1. The final selected values after 30 iterations of search are listed in the same table. For the remaining set of hyper parameter the respective default values have been used. It may be stated here that the number of points in each bootstrap set is chosen to be same as the total number of sample points in the complete Austria electricity price training set, i.e. $N' = N$, hence each set will contain approximately 63% unique points.

Table 6.1:Tuned Hyper parameters

Hyper parameter	Search Space	Value
RandomF_max_depth	[2,3,4,5,6,7,8]	3
RandomF_max_features	[12,15,20,25,30,None]	30
RandomF_n_estimators	[50,60,70,80,90,100,110,120]	70
XGBoost_max_depth	[2,3,4,5,6,7,8]	6

XGBoost_learning_rate	Log uniform(1e4, 1e+1)	0.3798
BayesianRegression_ α_1	Log uniform(1e-7, 1e-3)	4.8001e-07
BayesianRegression_ α_2	Log uniform(1e-7, 1e-3)	1.5269e-06
Bagging_bootstrap	[True ,False]	True
Bagging_n_estimators (M)	[10,30,50,70]	50

6.3.4 Evaluation metrics

The performance of various models is evaluated on the basis of these validation metrics: Mean arctangent absolute percentage error (MAAPE), Mean absolute Error (MAE) and Root mean squared error (RMSE). MAAPE is a variation of MAPE that considers the ratio of absolute error and real value as an angle instead of slope. Out of these three, MAAPE is given in terms of percentage, whereas, the other two are given as absolute values.

MAAPE is defined as:

$$\text{MAAPE} = \frac{1}{n}\sum_{t=1}^{n}\arctan\left(\left|\frac{y_t - p_t'}{y_t}\right|\right)\times 100\% \qquad (6.9)$$

MAE is defined as:

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}\left|y_t - p_t'\right| \qquad (6.10)$$

RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left|y_t - p_t'\right|^2} \qquad (6.11)$$

Where y_t is the actual price and p_t' is the predicted price, n is the number of observations in the test set. The confidence interval (CI) [26] for absolute error is calculated to measure the precision of forecasts. Let **c** be the N dimensional absolute error vector computed for each data point in the test set, the confidence interval range is given by

$$CI = \left[\bar{\mathbf{c}} - z\frac{\sigma}{\sqrt{N}}, \bar{\mathbf{c}} + z\frac{\sigma}{\sqrt{N}} \right] \tag{6.12}$$

Where, $\bar{c}$ and σ represent the mean and standard deviation values of vector **c** and z denotes the critical value. The critical value depends on the confidence level (C) which is specified beforehand. For standard normal distribution, the critical value is looked up in the z-table corresponding to the area enclosed by the curve which is a function of C and is equal to $2\times\left(1-\frac{(1-C)}{2}\right)$. For a confidence level of 95% and 99% the critical values are evaluated to be 1.96 and 2.576 respectively.

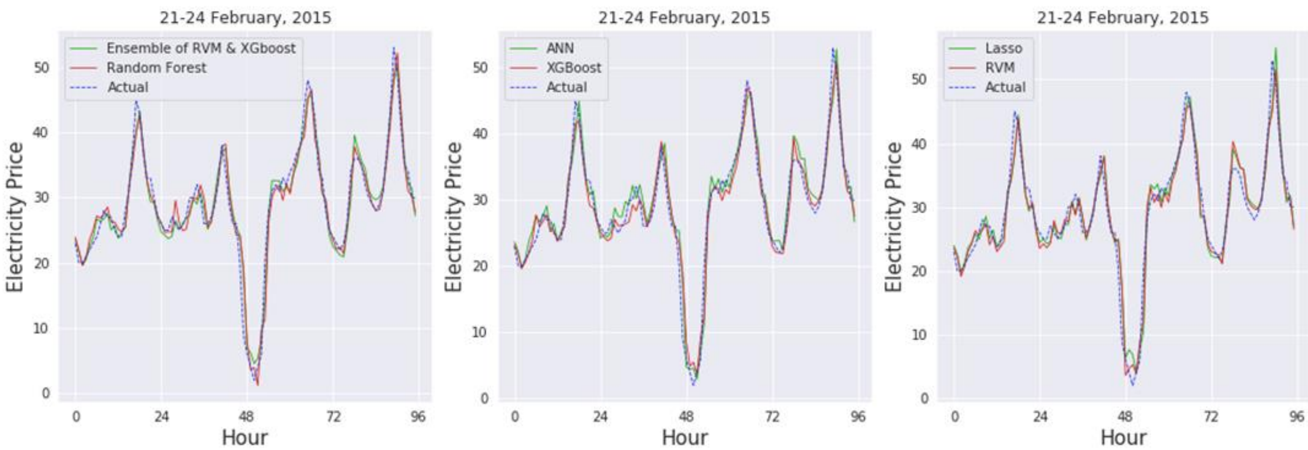

Fig.6.5: Comparison of forecasted price vs actual price for various models

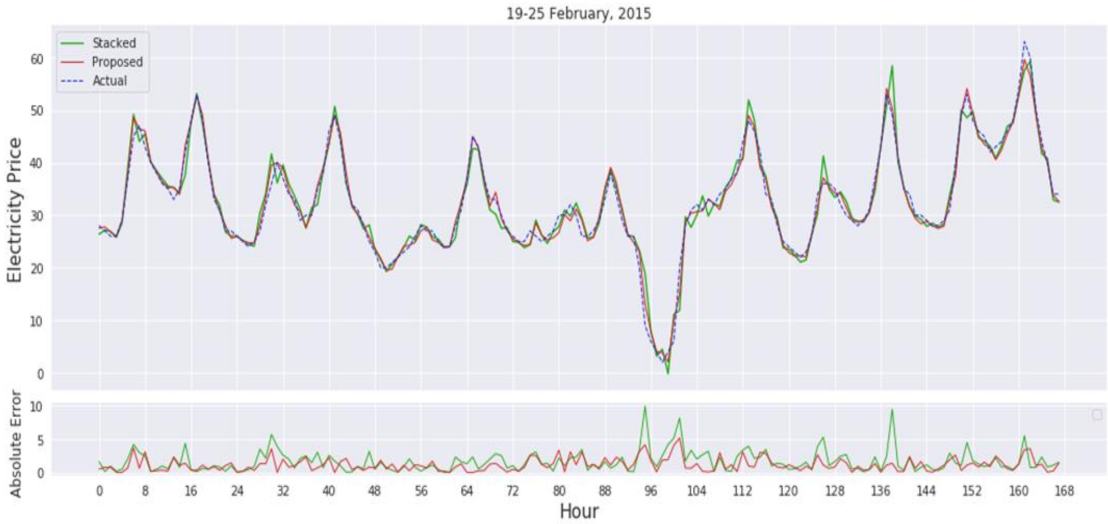

Fig.6.6: Comparison of forecasted price of stacked model and proposed model with actual price

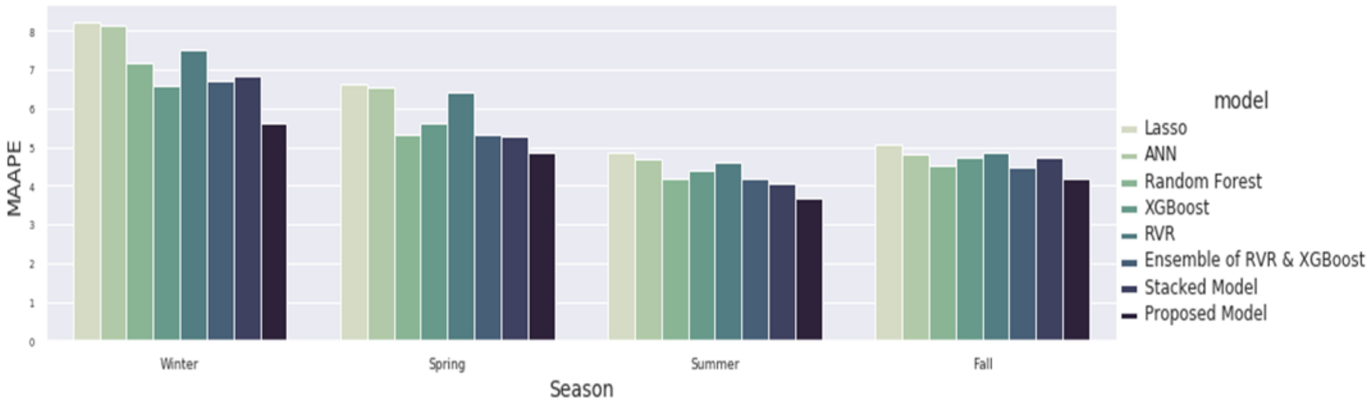

Fig.6.7: Comparison of MAAPE values of various models

6.4. Simulations & results

In this section we compare the presented model with benchmark models for electricity price forecasting. Artificial neural network (ANN), relevance vector machine (RVM), support vector machine (SVM), lasso regression, random forest regressor, adaboost and Xgboost have been previously used for the task. It should be emphasized that our model is an adaptation of the stacked model. Hence, in order to demonstrate the importance of bootstrap-aggregation in our work, we also compare the proposed model with the independent stacked model. All the models are trained using the same set of features and dataset as illustrated in section 6.2, this aids in the unbiased evaluation of all the models. To compute the average as well as seasonal performance metrics, our test set that comprises of consecutive days from each month in the dataset that expands over two-year period. The evaluation metrics, as mentioned in the previous section are assessed using eq.6.8, eq.6.9 and eq.6.10. MAAPE, RMSE and MAE for the test set are tabulated in table 6.2. The developed model outperforms other models and produces highly accurate day-ahead electricity price forecasts, which is vindicated by its dominant performance on the metrics. To evaluate the performance for different seasons, a random month from each season, for both the years is chosen. Electricity price forecasts for all the days in the test set corresponding to the chosen months are used for MAAPE calculation of all the four seasons, reported in table 6.4. The proposed ensemble is observed to outperform all other models with the lowest error percentage for all seasons.

To indicate the range over which the error varies for majority of the data points, we report the 95% and 99% confidence interval of absolute error for all the models evaluated in this study. From table 6.3 it may be inferred that of the upper limit of CI range for 95% confidence level is still below the lower limit of all the other models. From this, we discern that the electricity price forecasts made by the proposed ensemble model are consistently accurate compared to other models for majority of points in the test set.

For visualization purposes, the predicted values by various benchmark models for four consecutive days from test set corresponding to February, 2015 are shown in fig.6.6. Moreover, the predictions obtained by proposed and stacked models along with the absolute error for seven consecutive days from the same month are depicted in fig.6.7. The actual values are also plotted with the predicted values to visually compare the accuracy of all the models. On a more focused view in fig.6.6 at the times 41, 113 and 126 hours, it can be clearly noticed that the proposed model, unlike the stacked model avoids unnecessary spiking at price maxima. Additionally, the substantial overshooting just after price maxima observed at times 99 and 138 hours by the stacked model is overcome by bootstrap aggregation, resulting in a model that captures pricing trends more smoothly and adapts to the stochastic changes in electricity price.

Table 6.2: Error comparison of different models

Model	MAAPE (%)	RMSE	MAE
Lasso [27]	6.604	2.715	1.819
ANN [28]	6.499	2.639	1.775
Random Forest [29]	5.801	2.484	1.592
XGBoost [30]	5.857	2.448	1.610
RVM [31]	6.267	2.510	1.711
Ensemble of RVM and XGBoost [24]	5.439	2.179	1.485
Stacked Model	5.724	2.332	1.561
Proposed Model (BA + Stacked)	5.132	2.156	1.385

Table 6.3: Confidence Interval of Absolute Error

Model	95%		99%	
	Range	Interval	Range	Interval
Lasso [27]	[1.75,1.88]	3.42	[1.74,1.90]	4.49
ANN [28]	[1.71,1.84]	3.41	[1.69,1.85]	4.46
Random Forest [29]	[1.53,1.65]	3.69	[1.51,1.67]	4.85
XGBoost	[1.55,1.67]	3.85	[1.53,1.68]	4.64
RVM [31]	[1.65,1.77]	3.31	[1.64,1.78]	4.35

Ensemble of RVM and XGBoost [24]	[1.44,1.53]	3.03	[1.42,1.55]	4.37
Stacked model	[1.51,1.61]	3.36	[1.49,1.63]	4.49
Proposed (BA+ Stacked)	[1.33,1.43]	3.60	[1.32,1.45]	4.71

Table 6.4: Mean Arctangent Absolute Error (MAAPE) comparison of different models

Model	Winter	Spring	Summer	Fall
Lasso [27]	7.65	7.77	5.46	5.78
ANN [28]	7.69	7.61	5.41	5.50
Random Forest [29]	6.68	6.81	4.85	5.11
XGBoost	6.54	6.88	4.92	5.29
RVM [31]	7.19	7.45	5.19	5.37
Ensemble of RVM & XGBoost [24]	6.64	6.69	4.75	5.04
Stacked model	6.74	6.61	4.66	5.10
Proposed Model	5.81	6.20	4.23	4.48

6.5. Summary

This work investigates the potential of ensemble learning for very short-term forecasting of electricity price. The presented model combines the merits of bagging and boosting in the stacking phase and further reduces the overall variances imparted due to the stacking process by inculcating bootstrap aggregation. Apart from historic price and demand data, the model takes into consideration renewable energy parameters along with factors affecting its generation like wind speed and weather parameters, for making next hour electricity price predictions. The proposed model shows superior forecasting performance compared to various existing models, including previously proposed ensemble pipeline of boosted trees and RVM for the same task. An analytical and visual comparison between the independent stacked model and proposed models depicts the importance of bagging in our work. In price-directed smart grids consumers adjust their consumption schedule and strategize purchasing in order to minimize energy cost, making next hour price forecasting an important tool. The presented model not only captures dynamic changes in price signals, it does so without being computationally complex.

6.6 References

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Chapter 7

ELECTRICITY MARKET MODELS FOR RENEWABLE ENERGY ENABLED INDIAN ELECTRICITY MARKET

Important Terminology in Indian Electricity Market

PGCIL –Power Grid Corporation India Limited

ISO - Independent system operator

SEB-State Electricity Board

MNRE-Ministry of new renewable Energy

NLDC-National Load dispatch centre

SLDC-State Load dispatch centre

RLDC-Regional Load Dispatch centre

CTU- Central Transmission Utility

CERC-Central Electricity Regulatory Commission

SERC-State Electricity Regulatory Commission

PX-Power Exchange

SC-Scheduling Coordinator

UI-Unscheduled interchange mechanism

PPA-Power Purchase Agreements

REMC-Renewable Energy Management Centre

NTP-National Tariff Policy

RPO-Renewable Purchase Obligation

FITs-Feed in Tariffs

REC-Renewable Energy Certificate

NAPCC-National Action Plan for Climate Change

CEA-Central Electricity Authority

FERC-Federal Energy Regulation Commission

CFD-Contract for Differences

ADR-Alternative Dispute Resolution

BRP-Balance Responsible Parties

CGU-Central Generating Utility

SGU-State Generating Utility

IPP- Independent Power Producer

SDU-State Distribution Utility

DISCOM -Distribution Company

MCP- Market Clearing Price

Important Literature in Indian Electricity Market

Power Exchange (PX): RLDC provides ATC information to PX. Thus, PX is an ISO receives bids from suppliers, bulk customers, traders, DISCOM's for a day ahead or an hour ahead schedule and finalises the market price based on demand and available power generation. Then PX informs day ahead/hour ahead scheduling to RLDC. PX manages day ahead and hour ahead markets.

In the day ahead market, participants would bid supply and demand for the next day's 24 hours. This market starts at 6.00 am and closes at 1.00PM of the day ahead of the trading day. Based on all unit specific supply bids and location specific demand bids, the ISO determines whether there are any transmission congestions and increase of congestion, the ISO uses adjustment bids to submit and adjusted schedule to schedule coordinators.

Market working

- Generation/load bidding in day ahead market
- Calculation of MCP
- Adjustment of bids
- Congestion management using adjustment bids
- Generation/load bidding in hour ahead market
- Supplemental energy bids
- Settlement procedure and calculations of average price for actual consumption and production.

NLDC: National Load Dispatch Centre (NLDC) works for optimum scheduling and dispatch of electricity among RLDCs.

RLDC: The RLDCs shall be the Apex Body to ensure integrated operation of power system in the concerned region.

SLDC: It is responsible for optimum scheduling and dispatch of electricity in the state.

SC: Scheduling coordinator can directly bid or self-schedule resources as well as handle the settlement process.

Electricity Trader: It means a person who has been granted a licence to undertake trading in electricity market.

Franchisee: It means a person authorised by a distribution licensee to distribute electricity on its behalf in a particular area within this area of supply.

Open Access: The non-discriminatory provision for the use of transmission lines or distribution system or associated facilities with such times or system by any licensee or consumer or a person engaged in accordance with the regulations specified by the appropriate commission.

Licensee: A person who has been granted a licence.

Vertical Integration: It is an arrangement where the same company owns all the different aspects of making, selling and delivering a product or a service.

Wheeling: It refers to the transfer of electric power through transmission and distribution lines from one utility's service area to another's. Wheeling can occur between two adjacent utilities in different states.

Retail Wheeling: Loads can choose suppliers apart from the respective connection to the distribution network.

Market Power: It is defined as owning the ability by a seller or a group of sellers to drive price over a competitive level, control the total output or exclude competitors from a relevant market for a significant period of time.

Ancillary Services: These are defined as services which are required to support the transmission of capacity and energy from resources to loads while keeping a reliable operation of the transmission system of a transmission provider in accordance with good quality of practice.

Trading: It means purchase of electricity for resale thereof and the expression "trade" shall be construed accordingly.

Utility: It means the electric lines or electrical plant and includes all lands, buildings, works and materials attached there to belonging to any person acting as a Generating company or licensee under the provisions of the Electricity Act.

7.1 Introduction

The world is already seeing the consequences of 1^0 C rise in temperature above pre-industrial levels through more extreme weather, rising sea levels, and diminishing Arctic sea ice among other changes. Now the special report on global warming by the intergovernmental panel for climate change (IPCC) estimates the increase in global warming of 1.5^0C above pre-industrial levels which may further deteriorate the environmental conditions. Significantly de-carbonizing existing energy systems by devoting in renewable energy systems, which mainly includes solar, at a record scale and pace is required to address such effects of global warming [1]. The depletion of conventional energy sources such as fossil fuel is one another factor that promotes renewable energy sources strategically to meet the global electricity demand [2]. In India, the central government and the state governments have put in place various policies and mechanisms to promote solar energy, including financial incentives for certain categories of users.

The renewable energy component is increasing every year in the electricity market in

India and overseas as well. As of now, the installed capacity of renewable energy is 78.31 GW that comprises 35.63 GW from wind energy, 28.18 GW from solar energy, 9.91 GW from bio and 4.59 GW from small hydro. Further 67.38 GW more capacity of renewable energy is in the process of addition. By 2030, India commits to increase non-fossil based energy resources to 40 % of the electricity capacity installed. The government of India has planned to increase solar energy capacity to 100 GW by 2022, out of which 40% has to come from the consumer category in the form of rooftop and similar small scale solar energy systems. To some extent, the ministry of new and renewable energy (MNRE) also enforces renewable energy purchase obligation to bulk consumers. To address critical issues like the uncertainty of renewable energy generation, as assigned by the Govt. of India the power grid corporation of India limited (PGCIL) has initiated the establishment of the renewable energy management centers (REMCs) with the technical assistance of German Govt. at the state level and central level in the year 2016 and actual implementation started since 2017 [3]. To deliver rising demand for electricity in an environmentally friendly way through the promotion of renewable energy, many Indian states came up with many guidelines and policies in recent years. The guidelines for the procurement of power from solar power projects more than 5MW through long term PPA and the procurement of power from solar power projects below 5 MW capacities at feed in tariff mentioned clearly in the solar policies of the states in India [4].

The entry of RE sources in an already restructured and deregulated electricity market will make it more competitive, dynamic, and add to the complexity of operation and decision making [5]. The increasing penetration of renewable energy may lead to many new issues and challenges such as time scale of operation, price volatility, security and reliability [6]. Although many market models are established for restructured electricity market in international domain, which mostly depend on conventional power generation. However, to handle the obstacles due to renewable energy power generation, new market models are anticipated for present Indian electricity market. This paper presents many market models to handle the situations arising due to increase dominance of RE in Indian electricity market. To develop market models in the scenario of Indian electricity market enabled by renewable energy sources, various policies of MNRE such as renewable energy certificate (REC), RE promotion policies of various Indian states such as power purchase agreement (PPA) and feed in tariff are applied. A new entity called balance responsible parties (BRP) is introduced in second and third models developed in this work to enhance the assistance to market participants for RE enabled Indian electricity market.

Remaining sections are structured as follows. Section 2 describes the evolution of Indian electricity market. Section 3 presents various market models proposed for RE enabled Indian electricity market whereas section 4 analyses and compares all the proposed models. Section 5 describes the proposed operating mechanism for RE enabled Indian electricity market and section 6 presents the conclusion.

7.2 Evaluation of Indian electricity market

In India before independence, under the provisions of Indian electricity act 1910 private entities used to supply the power in their locality. Indian electricity industry underwent the process of nationalization by virtue of the foresaid act of 1948. This act paved the way for formation of State Electricity Boards (SEBs) to deal with generation, transmission and distribution of electricity in states. Subsequently many large power generation projects were established by central govt. to provide power to various states. SEBs became inefficient with time and suffered financially, hence central sector generation and transmission were separated in 1992, but distribution of electricity remained monopoly in the hands of SEBs [7], [8].

Going ahead with restructuring of Indian power sector in 2001, States divided generation, transmission and distribution into separate corporate entities. But power purchase and distribution still remains in the hand of SEBs indicating its monopoly referred to be a single buyer model, which neither benefited sellers nor buyers in order to get competitive market price. In the further transformation process, the independent regulatory bodies have been established at central level and states to rationalize electricity tariff, formulise transport policies regarding subsidies and also to promote efficient and environmentally friendly policies.

The Electricity Act 2003 focuses on supply of electricity to all areas, rationalization of electricity tariff, ensuring transparent policies regarding subsidies, promotion of efficient and environmentally benign policies, and constitution of central electricity authority (CEA), regulatory commissions and establishment of appellate tribunal [7]. It provides open access and encourages privatization as well as competition. Hence, many bulk consumers are turning into producers also, which leads to distributed generation in the power system a lot. Also the solar and wind generation are getting connected to the grid at several locations in distributed manner. The power grid is becoming smart by adding many devices and technologies to manage such changes.

In such a restructured dynamic electricity market where renewable energy (RE) power generation, will dominate in future, appropriate market models need to be developed to minimize the electricity price and increase the efficiency of operations.

7.3 Proposed market models for RE enabled Indian electricity market

Traditional electricity market works with three major restructured models named PoolCo model, bilateral contracts model and hybrid model [9]. A PoolCo model consists of a power exchange (PX) which handles the bids submitted by sellers and buyers by analysing supply and demand of the following day and finalise the optimal price, which is market clearing price (MCP). In bilateral contract model, traders are allowed to negotiate the price without interference of system operators. In this model customers can contact directly to power generating companies. However, the hybrid model incorporates different features in both versions. Here PX may exist and customers are also allowed to contact suppliers directly. This model provides good flexibility to customers and utilities as well.

In this chapter, market models for renewable energy enabled electricity market based on rigorous study on renewable energy policies of various countries and different states in India. Also literature review on existing market models & proposed market models by researchers assist in developing the market models in this paper. Single buyer model and Pool market model have been proposed for Malaysia electricity supply industry [10]. Emission trading schemes are introduced to reduce CO_2 emission and to promote renewable energy in European countries [11].To encourage wider adoption of renewable energy, UK implements many schemes for financial support such as feed in tariff and renewable obligation [12]-[13].Transmission expansion planning techniques are provided for enhancing penetrations from renewable energy sources and to deal with the complexity related to integration of smart grid technology and electricity market [14]. The impact of increased wind power penetration to the grid on Iberian electricity market (Spain & Portugal) has been emphasized for having reduced spot prices [15]. The electricity market model for Irish has been proposed, that targets for contribution of wind power to 37 % of total power generation by 2020 exploring the curtailment of excess wind power generation and storage options [16]. The impact of variable generation from renewable energy sources on the trading of electricity market and the need to formulate few strategies of demand side management based on grid operating conditions & reliability are emphasized [17]. To meet the growing demand for power in an environmentally sustainable manner i.e. in the promotion of renewable energy, several states of India came up with many guidelines and policies in recent years. The guidelines for the procurement of power from solar power projects more than 5 MW through long term PPA and the procurement of power from solar power projects below 5 MW capacities at feed in tariff mentioned clearly in the solar policies of the states in India [4].

The market models for markets with large scale integration of renewable energy generation are proposed in following sections.

7.3.1 Energy pool model

This model is consisting of solar power plants, wind power plants, IPPs, CGU, SGU, PX, SDU, DISCOM's and retailers. PX purchases power from all generating units through online bidding. Then distributing units will purchase the power from pool to supply the power in their respective areas. Being ISO, power pool finalises one MCP by matching the supply and demand curves. This is the simplest structure as shown in fig.7.1, not entertaining private entities into the market. This model exhibits monopoly leaving no choice to consumers in selecting the supplier on distribution side. In this model, the DISCOM's, SDUs and retailers have dedicated consumers. Hence competition at supply side is minimum in this model. This model may be free from congestion except peak demand hours. Perhaps, reliability of the model depends on the performance of the respective distributors. Social obligation may be covered by distribution companies.

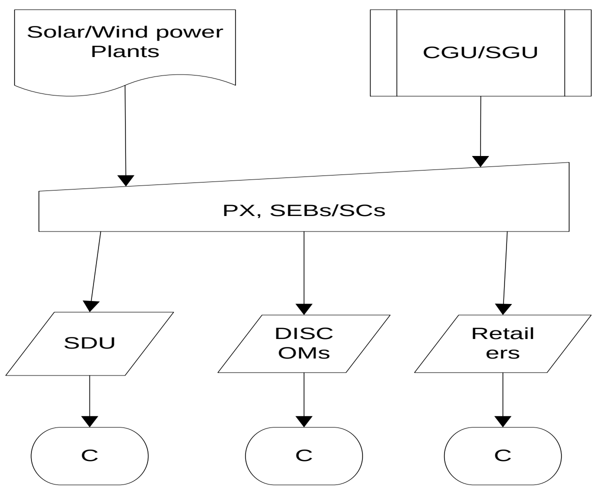

Fig.7.1: Energy pool model

7.3.2 Renewable energy pool model

In this model, it is proposed to have separate power trading for renewable energy and non-renewable energy and two power pools as shown in fig.7.2. Conventional generating units submit bids directly to PX and PX finalises MCP by matching the bids. On the other hand, Solar/ wind power plants bid through BRP, an intermediate entity between solar/ wind power plants and consumers. BRP receives a day ahead solar/ wind power forecast from REMC. In case solar/ wind power generation is less, BRP takes the responsibility to fulfil the balance power generation by purchasing power from the PX. In case of excess power generation BRP also can submit bids to PX for the sale of power. At distribution level, open access will be given to consumers.

In this model, there will be proper competition because of separate trading for conventional energy and renewable energy. Also this model provides more competition than previous model due to which tariff may be lower and consumers will get benefited. Implementation of this model is easy and operation is less complex, however congestion may occur due to wheeling at distribution level.

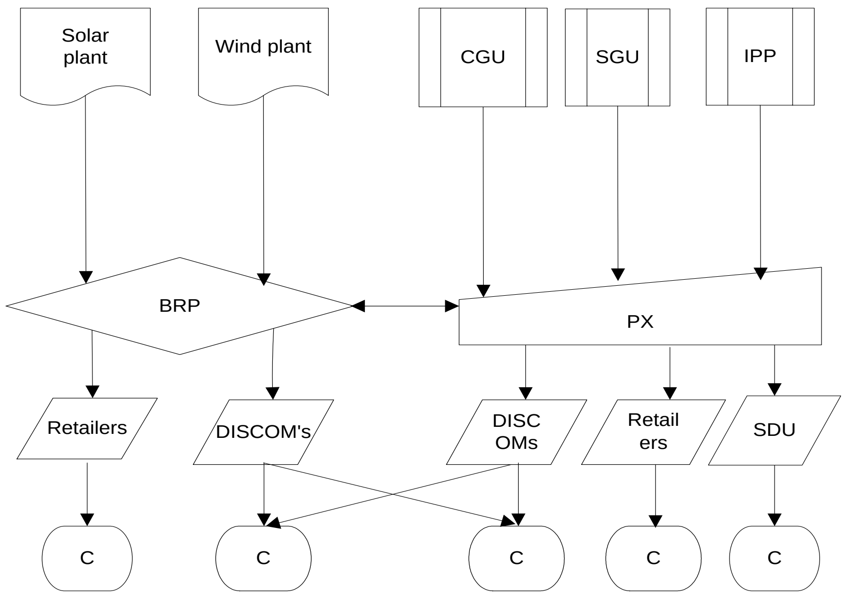

Fig.7.2: Renewable energy pool model

7.3.3 Renewable energy bilateral contracts model with BRP

In this model as shown in fig.7.3, along with entities like CGU, SGU, solar/ wind power plants, PX, DISCOM's, retailers and consumers a new entity called BRP is added to deal with uncertainty of renewable energy [18]. Solar/ wind power plants can go for long term bilateral contracts by making PPA with distributors/ consumers through BRP. In case solar/ wind power generation is less, BRP takes the responsibility to fulfil the balance power generation by purchasing power from CGU/SGU. On the other hand, BRP also can submit bids to sell excess power from solar/ wind plants to PX in a day ahead or hour ahead market along with CGU and SGU. Above said bilateral contracts would be supported by the incentives and subsidies of the state governments to promote renewable energy. The consumers in bilateral contracts will be supplied from renewable energy suppliers through BRP.

By matching supply and demand curves, MCP will be finalized in a day ahead market by PX. DISCOM's and Retailers can purchase power directly from the PX whereas consumer will purchase power from DISCOM's, retailers.

This model establishes the structure of hybrid model, which enjoys both bilateral contracts and power pool. This model promotes renewable energy and encourages bulk consumers to use renewable energy. In fact, bulk consumers can also fulfil renewable energy purchase obligation by the governments. Compared to renewable energy pool model, this model may be complex to operate due to the additional entity BRP. At distribution level, DISCOM's have dedicated consumers so competition will be less which may increase the electricity price in pool. The reliability of this model depends upon the performance of DISCOM's and BRP.

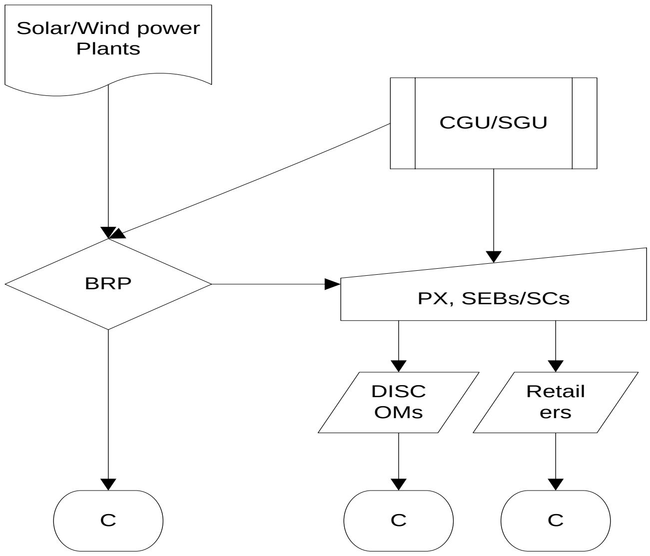

Fig.7.3: Renewable energy bilateral contracts model with BRP

7.3.4 Energy pool model with bilateral contracts of DISCOM's and RES

In this model as shown in fig.7.4, solar/ wind power plants will have bilateral contracts with DISCOMs and also they can sell excess power to the pool. At the same time DISCOMs in bilateral contracts may purchase the power from pool as and when required in case of power shortage. In this model, solar projects of less than 5 MW are allowed to sell power directly to the pool under guidelines set by the state governments and MNRE. The solar power projects less than 5 MW shall feed into grid based upon feed in tariff (FIT) determined by state electricity commission to the extent power required with in the state [4]. The DISCOMs would establish bilateral contracts with Solar PV or wind power plant owners by making long term PPAs, selected through competitive bidding based upon the guidelines, notified by ministry of power.

This model is also one type of hybrid model for power trading. In this model, bilateral contracts with long term PPA will be signed between solar/ wind power companies and DISCOM's. Hence DISCOM's will take care of the uncertainty in renewable energy.

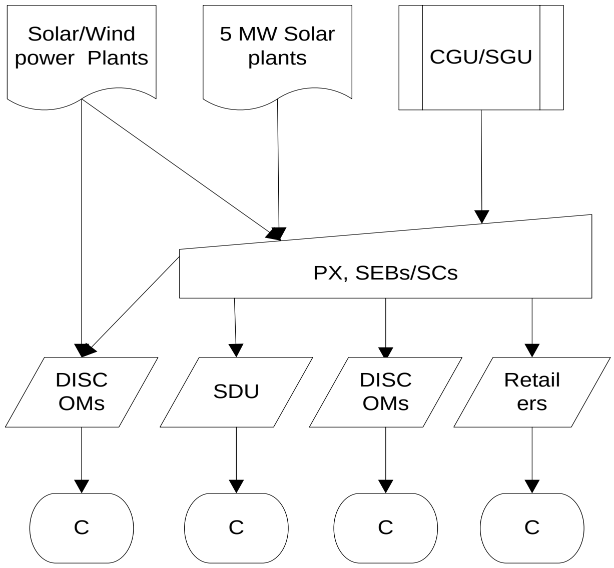

Fig.7.4: Power pool model with bilateral contracts of DISCOM's and RES

7.3.5 Flexible market model with wheeling at distribution level

It is similar to previous model, where DISCOM's may have bilateral contracts with solar/ wind power plants and also purchase power from pool, however in this model, power wheeling is introduced at distribution level [19]. Open access enables the bulk consumers to buy power from the open market. Instead of buying power from the local utility monopoly, the consumers can choose from many competitive companies. Thus, the suppliers under open access have to incur various charges for using the grid.

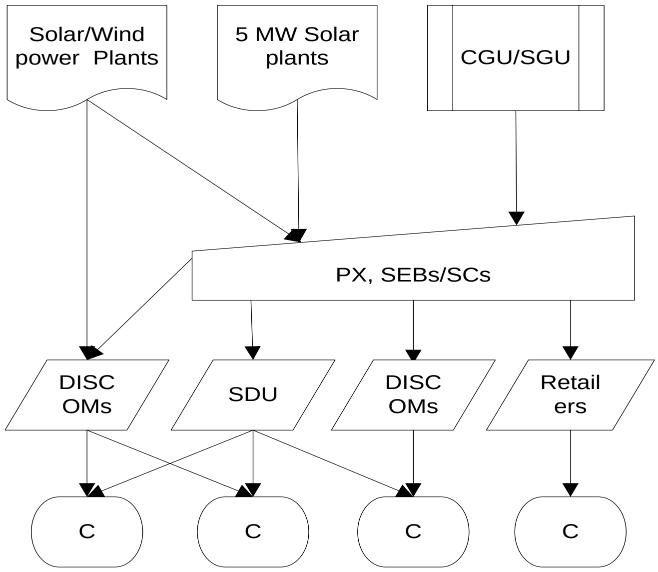

Fig.7.5: Flexible market model with wheeling at distribution level

The model shown in fig.7.5, has got flexibility in a way that the consumer may choose its distributor, thereby introducing competition at distribution level which may result in lower tariff and better service to the consumer.

7.3.6 Open access model for bulk consumers

Here in this model, the bulk consumers can purchase power from any power companies, DISCOMs or pool. The small consumers also have open access to different distributors, which overcomes monopoly at distribution level as presented in fig.7.6.This enables heavy users with more than 1MW connected load to buy cheap power from the open market. The open market allows the consumers to select from a number of competitive power companies rather than being forced to buy power from local utility monopoly. With open access provision, regular power supply is ensured to Industrial& commercial consumers at competitive rates. Also consumers can meet their Renewable purchase obligations.

The power shortage can be effectively reduced by open access as many solar energy/ wind energy companies directly transmit power to some load centres. The open market allows the consumers to purchase power from any company, which increases the competition in the market and makes the price less. Open access may be either Interstate open access or intra state open access [20].

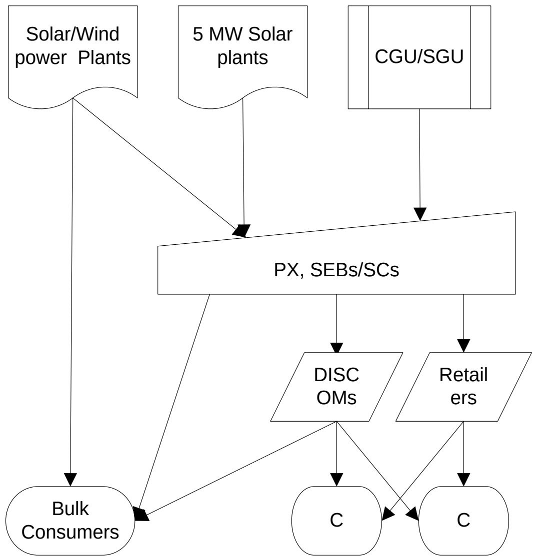

Fig.7.6: Open access model for bulk consumers

7.3.7 Flexible market model for consumers and distributors

Unlike above models, this model as shown in fig.7.7 does not contain any power pool. The DISCOMs/ SDUs may purchase power from CGU/ SGU/ solar/ wind power plants. At distribution level also, the consumer has flexibility to choose the distributor. The distributor will possess distribution licensee for more than one consumer or area. Further, the bulk consumers will be given flexibility to purchase power either from any DISCOM/ SDU or directly from solar/ wind power plants. To make solar/ wind power plants compete with CGU/ SGU the state governments and MNRE are supposed to announce some attractive incentives and subsidies to DISCOM's/ bulk consumers for purchasing power from solar/ wind power plants. In this multi-buyer or Multi-seller system, one of the major tasks is to have a market based solution with economic efficiency for congestion management [21]. Most of the buyers are interested in purchase power from cheapest generator available. Of course, this leads to overloading of cheaper generators. If congestion occurs, price will be settled area wise. Areas with excess generation will have lower prices and area with excess load will have higher prices [22]. In this model competition is introduced at transmission as well as distribution level.

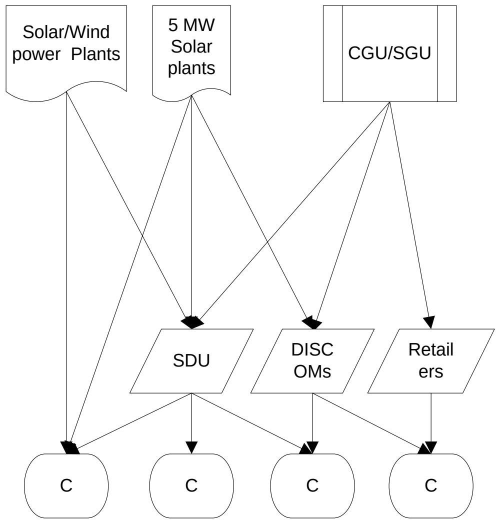

Fig.7.7: Flexible market model for consumers and distributors

7.4 Comparative analysis

All the above proposed models in section 7.3 have been compared for various features such as implementation, competition, congestion, tariff and reliability and the highlights are presented in table 7.1.

Table 7.1: Comparison of proposed models

Model	Implementation of the model	Market Competition	Congestion	Power Tariff	Reliability of power supply
Energy pool model	simple and easy	less	Nil	more	Inferior
Renewable energy pool model	a little difficulty involved	medium	Less	medium	Good
Renewable energy bilateral contracts model	not so easy	Less	Less	more	Inferior

with BRP					
Energy pool model with bilateral contracts of DISCOM's and RES	Easy	Less	Less	more	Inferior
Flexible market model with wheeling at distribution	Difficult	More	More	less	Better
Open access model for bulk consumers	Difficult	More	More	lower tariffs	Better
Flexible market model for consumers and distributors	difficult	most competitive	More	lowest	Best

7.5 Operating mechanism

Operating mechanism explains the functioning of electricity market with the coordination of power network. This section proposes operating mechanism of future Indian electricity market with high level of penetration of wind and solar generation as shown in fig.7.8. SLDC forecasts load a day ahead and an hour ahead, REMC forecasts solar power/ wind power generations a day ahead. This forecasting information is further conveyed to RLDC, which analyses ATC and sends the information regarding ATC and forecasting data to PX. At the same time, SLDC and RLDC will be coordinating with REMC for the details of renewable energy. At PX, all generating units will participate in bidding. Then, PX finalises MCP for a day ahead power schedule and sends information to RLDC. Under the supreme control of PGCIL, with the coordination of NLDC, RLDC & SLDC plan and monitor the scheduling/ dispatching of power for a day ahead in the respective state. The steps involved in the operation of the market are shown in fig.7.9 through a flowchart.

This operating mechanism also includes entities like RE generators and Renewable energy certificate (REC). RECs would be issued to RE generators. These RECs are purchased by any consumer in order to meet its renewable purchase obligation [23]. REC will be issued to RE generators by central agency like NLDC. RE generators would submit bids to PX for remaining power generation excluding RECs.

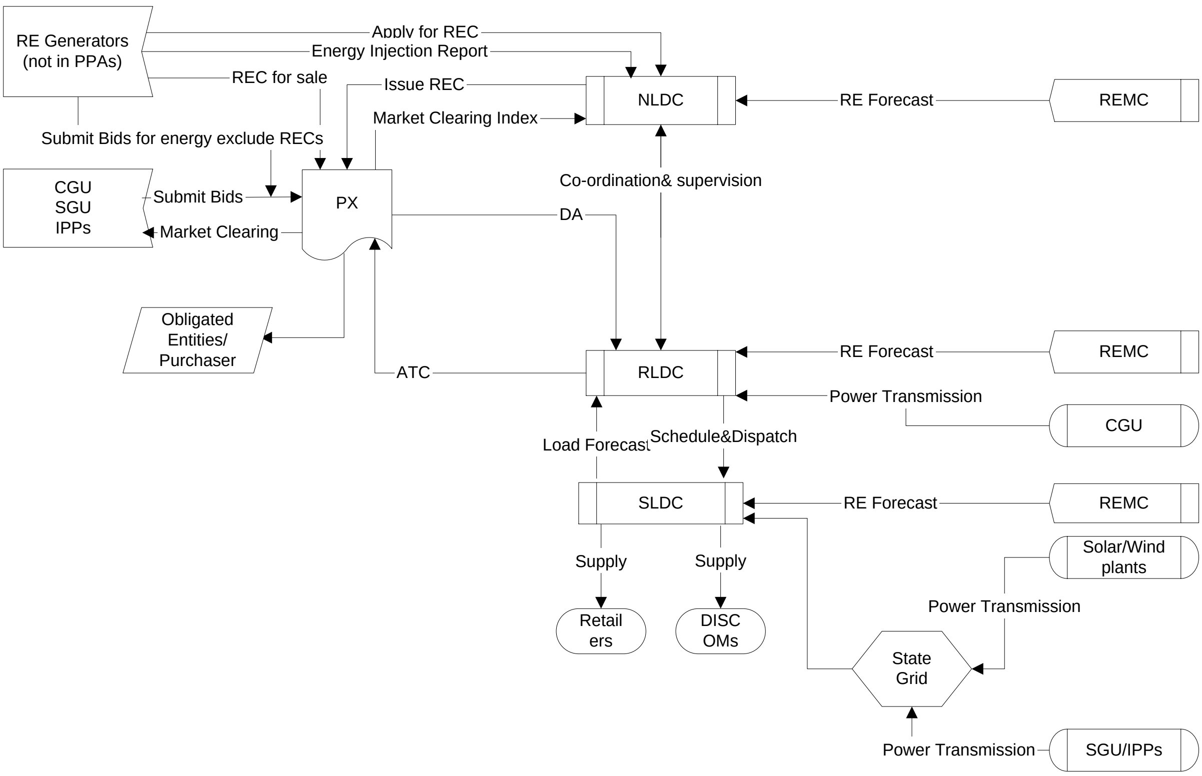

Fig.7.8: Operating mechanism of Indian electricity market

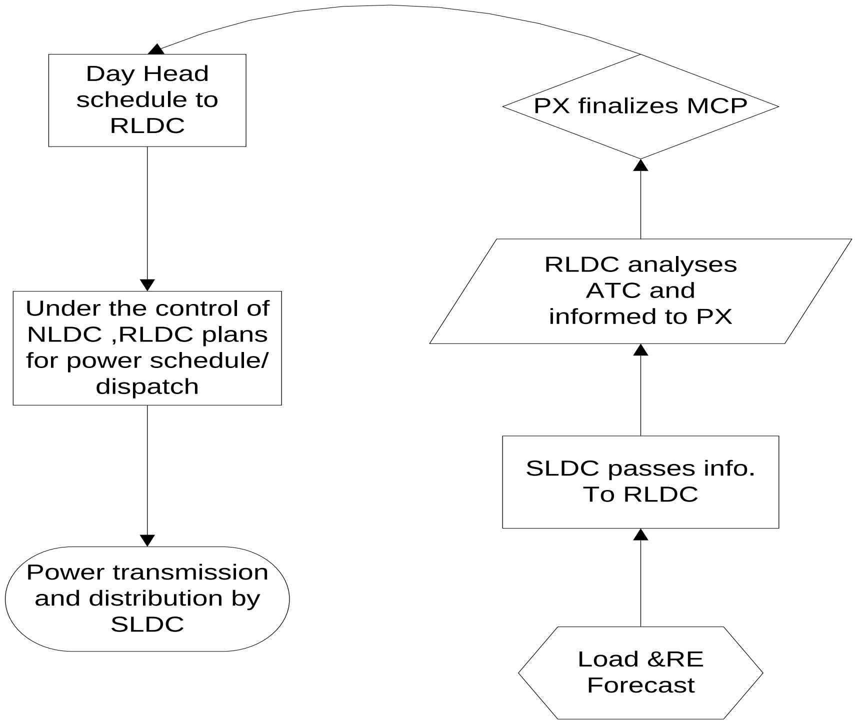

Fig.7.9: Flow chart for operating mechanism

7.6 Summary

The increasing demand of clean power with good quality and scalable consumption has put a pressure on power companies to increase the renewable energy integration in to the grid. However intermittent nature of solar and wind generation forces the market operators to look for new energy trading models and operating mechanism. Considering various aspects like the growth of RE generation, MNRE policies, state wise targets of RE generation, competition in the market and reliable power supply to the consumers, this chapter has proposed seven different market models and has made a comparative study of all the models. The operating mechanism is proposed to operate such a market has many new components.

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Chapter 8

CONCLUSION

The uncertainty associated with wind power generation poses safety concerns to the power grid and lays roadblocks in achieving higher penetration of wind power into the grid. To overcome this difficulty, wind power forecasting (WPF) is evolved to be an appropriate way for power grid operators. Hence, various techniques and models are being developed in forecasting wind power. In chapter 2, NARX neural network is used to predict wind speed and wind power. A good accuracy in wind speed forecasting is demonstrated using this method. Though, the wind power forecasting projects reliability, the prediction accuracy can be improved with the development of a hybrid model to forecast wind power along with fuzzy system and data mining techniques like support vector machine to classify the historical data. In this chapter along with conventional neural network models, a statistical approach is also implemented in short term WPF to assess and compare their performances. The work is executed by using GRNN, RBFN and SVR models. In one day ahead WPF, the SVR approach is more consistent and reliable. The GRNN model is also performing consistently. At higher wind speeds the RBFN model is not able to predict wind power. The cases where there is a highly correlated data, the RBFN model depicts its performance with good accuracy. The work can be preceded with the design of a hybrid model consisting neural networks and SVR by elevating their respective merits. Also a hybrid model of SVR and suitable optimization technique like particle swarm optimization technique in tuning parameters of SVR model may be developed to improve the accuracy in short term WPF for highly dynamic cases also.

The volatility of wind power is a major issue to the power sector to be addressed. WPF is found to be an appropriate way to deal it. However, it is very much essential to analyse the reliability of the forecasting technique applied. Forecasting wind power using GRNN, RBFN and Hybrid GRNN-RBFN is carried out in 3rd Chapter to address this issue. Uncertainty in WPF is evaluated with the computations of confidence intervals. GRNN has performed consistently in all months of 2014 with significant reliability, which is ensured with the narrowest confidence interval of MAPE values in WPF for all months. The cases where there is highly correlated data, RBFN improves its performance. Further Hybrid GRNN-RBFN is designed to forecast wind power emphasizing proper assignment of weights to each neural network in parallel topology. In addition, confidence intervals on MAPE are evaluated to assess the uncertainty in prediction by the models used in this work. Hybrid neural network provides better accuracy in forecasting, if a single neural network is not reliable in forecasting. Various topologies like series, parallel and series parallel connections can be designed to increase the accuracy in wind power forecasting.

Basically chapter 4 explores the significance of solar irradiation on solar PV power generation and its forecasting. The work is continued to develop a suitable hybrid model, ANN-PSO based on K-means clustering. As per evaluations, there is a significant effect of meteorological condition based clustering technique on a week ahead solar PV power forecasting. The results indicate improvement in forecasting accuracy of ANN-PSO model with clustering. Although, SVR model forecasts solar PV power with similar accuracy in a day ahead forecasting, it suffers in a week ahead forecasting with high errors. However, sometimes K-means clustering may not provide final solution. Hence, the work may be continued to implement fuzzy logic based K-means clustering in solar PV power forecasting. There is a scope for further research to analyse the effect of other clustering algorithms like mean shift clustering, density based spatial clustering and Gaussian Mixture etc. on forecasting accuracy. Further, a hybrid model of SVR and optimization techniques like GA, PSO can be developed to check the improvement in forecasting accuracy.

Electricity price is a special commodity unlike any other commodity in the market. Its storage is not an easy task. It is influenced by many factors like load demand, power generations, time factor, industrial requirements, weather conditions, fuel prices and transmission constraints etc. Thus electricity market experiences a lot of fluctuations making price highly volatile. One of the recent concerns for the volatility is power generation from renewable energy sources. The work carried in chapter 5 has suggested a suitable hybrid approach using K-means clustering and LSTM network for short term electricity price forecasting showing its proficiency in accurate price forecasting amid wind power penetration. The impact of wind power generation on price forecasting has been analysed and results depicted that the impact of wind power generation on the accuracy of price forecasting is significant with the considerable reduction in errors. However, it is also noticed that the contribution of wind power generation to the grid also matters in the forecasting period. Further the scope is left for implementing any other clustering technique other than K-means for future research and to analyse the impact of solar PV power generation also on price forecasting.

The work in chapter 6 investigates the potential of ensemble learning for very short-term forecasting of electricity price. The work develops a stacked model that integrates extreme gradient boosting and bagging based tree ensemble regressors using bayesian linear regression technique, improving upon individual technique's bias and variance limitations. This stacked model's overall performance is further enhanced using bootstrap aggregation, which helps in adapting to the stochastic price changes by avoiding spiking and overfitting. The model is implemented on real-world historical data obtained from Austrian electricity market. The growing dependence on renewable sources impact the spot prices and are included in our forecasting model. The performance of the proposed methodology is compared to six state-of-the-art electricity price forecasting models. The proposed ensemble with a minimal mean absolute error of 1.38 clearly demonstrates superiority over other tested models with regards to accuracy of electricity price forecasts. Additionally, the model is found to perform consistently with a confidence interval of absolute error of ±3.6% as well as suitable for online training with a computation time of 135s.

The increasing demand of clean power with good quality and scalable consumption has put a pressure on power companies to increase the renewable energy integration in to the grid. However intermittent nature of solar and wind generation forces the market operators to look for new energy trading models and operating mechanism. Considering various aspects like the growth of RE generation, MNRE policies, state wise targets of RE generation, competition in the market and reliable power supply to the consumers, 7^{th} chapter has proposed seven different market models for RE enabled Indian electricity market and has made a comparative study of all the models. All the proposed models have been compared for various features such as implementation, competition, congestion, tariff and reliability. It is well established that every model has both merits and demerits. Mainly, the requirements of market participants will be crucial in the implementation of the model. Further, the operating mechanism with many new components is also proposed to operate such a market.

Appendix

Sample training and testing data used from Belgium wind farms

Wind speed	Wind power in MW
43.2	1299.17
35.2	1292.969
33.3	1294.071
32.4	1302.089
35.2	1306.519
35.2	1310.968
37	1307.285
36	1323.109
40.7	1316.356
40.7	1288.359
37	1274.804
36	1273.864
33.3	1283.661
33.3	1257.03
38.9	1256.767
39.6	1196.057
40.7	1033.464
40.7	1006.243
27.8	1089.018
28.8	1098.102
27.8	1110.776
27.8	1216.687
25.9	1219.033
25.2	1224.631
29.6	1209.446
29.6	1204.431
29.6	1228.573
28.8	1215.606
33.3	1201.853
33.3	1181.769
25.9	1167.195
25.2	1148.11
24.1	1128.025
24.1	1117.765
24.1	1149.079
21.6	1152.294
20.4	1136.664
20.4	1165.087

Sample training and testing data used from US wind farms

density at hub height (kg/m^3)	power (MW)	surface air pressure (Pa)	air temperature at 2m (K)	wind direction at 100m (deg)	wind speed at 100m (m/s)
1.07	16	0	274.265	339.993	15.451
1.071	16	0	274.207	340.355	15.216
1.071	16	0	274.115	340.729	14.822
1.071	16	0	274.008	340.982	14.386
1.072	16	0	273.801	341.108	13.995
1.072	16	0	273.642	341.179	13.657
1.072	16	0	273.52	341.328	13.376
1.073	16	0	273.404	341.35	13.223
1.073	15.991	0	273.316	341.07	13.171
1.073	15.955	0	273.233	340.757	13.049
1.073	15.888	0	273.154	340.246	12.823
1.073	15.801	0	273.093	339.559	12.53
1.074	15.697	0	273.023	338.746	12.179
1.074	15.388	0	272.882	338.493	11.78
1.074	15.136	0	272.757	339.015	11.499
1.074	14.958	0	272.644	339.257	11.301
1.074	14.772	0	272.519	339.949	11.093
1.075	14.428	0	272.412	341.46	10.861
1.075	14.181	0	272.29	341.91	10.733
1.075	13.915	0	272.165	340.735	10.596
1.075	12.984	0	271.973	339.114	10.113
1.076	11.378	0	271.765	339.85	9.463
1.077	9.42	0	271.442	342.251	8.752
1.077	7.719	0	271.198	343.877	8.142
1.078	6.707	0	271.051	343.926	7.779
1.078	6.29	0	271.033	343.492	7.614
1.079	6.149	0	271.009	344.454	7.55
1.079	6.306	0	271.03	345.739	7.62
1.079	6.848	0	270.984	346.47	7.827
1.079	7.649	0	270.932	347.283	8.114
1.078	8.298	0	270.923	348.217	8.346
1.079	8.597	0	270.887	349.266	8.453
1.079	8.674	0	270.914	350.431	8.481
1.079	8.846	0	271.006	351.606	8.542
1.079	8.975	0	271.051	352.727	8.587
1.079	8.993	0	271.048	353.902	8.594

Sample training and testing data used from Indian wind farms

Wind power in KW	Wind speed in m/s
5.833	4.289
4.74	4.058
1.955	3.267
0.229	2.201
0.025	1.613
0.323	2.325
1.39	3.038
2.943	3.592
4.635	4.027
5.401	4.206
4.66	4.038
3.685	3.799
2.671	3.506
1.865	3.225
1.678	3.161
2.656	3.496
5.282	4.18
9.824	5.013
14.929	5.724
19.277	6.223
22.258	6.536
24.915	6.794
27.228	7.004
28.355	7.1
28.53	7.118
23.926	6.699
10.856	5.171
5.403	4.207
7.282	4.581
7.765	4.66
6.84	4.498
6.51	4.434
6.299	4.383
5.611	4.251
4.113	3.899
3.692	3.801
4.554	4.015

Sample training and testing data used from Indian solar PV plants

Solar PV power in KW	Direct irradiance in kW/m2	Diffuse irradiance in kW/m2	Temperature ºC
0	0	0.001	10.303
12.233	0.087	0.061	11.994
36.482	0.312	0.108	14.58
55.625	0.545	0.121	17.237
66.892	0.716	0.126	21.518
72.346	0.805	0.13	23.498
70.081	0.761	0.143	24.208
65.007	0.686	0.142	24.485
54.152	0.535	0.137	24.318
35.653	0.301	0.128	23.489
14.051	0.094	0.08	21.417
0.211	0.003	0.007	18.16
0	0	0	17.187
0	0	0	16.832
0	0	0	16.621
0	0	0	16.3
0	0	0	15.744
0	0	0	14.983
0	0	0	14.261
0	0	0	13.734
0	0	0	13.327
0	0	0	12.962
0	0	0	12.605
0	0	0	12.262
0	0	0.001	11.957
11.733	0.082	0.062	13.822
34.972	0.291	0.114	16.051
53.408	0.512	0.131	19.126
64.633	0.676	0.139	22.79
69.92	0.759	0.145	24.686
65.07	0.662	0.172	25.41
60.033	0.59	0.171	25.733
49.366	0.45	0.161	25.643
32.779	0.258	0.139	25.01
12.584	0.078	0.081	23.244
0.19	0.003	0.007	20.34
0	0	0	19.441
0	0	0	18.929

Sample training and testing data used from Austrian electricity market

Load in MW	Price in Euros	solar power generation in MW	wind power generation in MW
5977	18	0	152
5727	17	0	110
5407	14	0	56
5314	13	0	39
5401	14	0	34
5406	16	0	32
5761	18	8	34
5954	23	13	32
6325	26	37	42
6645	27	71	50
6797	29	100	46
6727	29	116	50
6589	28	114	50
6552	28	87	57
6604	29	45	60
6903	32	15	52
7382	37	7	46
7438	38	7	44
7163	36	0	58
6831	32	0	110
6460	28	0	103
6552	27	0	50
6214	24	0	20
5975	26	0	14
5680	25	0	29
5531	22	0	50
5379	20	0	101
5462	16	0	148
5784	17	0	159
6091	19	0	146
6714	25	8	159
7182	27	14	207
7545	29	36	292
7732	29	61	408
7870	28	79	448
7691	26	87	532
7714	24	81	601
7557	24	60	605
7664	22	31	652

Data links

https://data.open-power-system-data.org/time_series/2019-05-15

www.weather-and-climate.com/average-monthly-Rainfall-Temperature-Sunshine,Brussels,Belgium

http://www.elia.be/en/grid-data/power-generation/wind-power

Answers to the questions and suggestions of the examiners

Examiner 1

Suggestions:

Minor modifications related to data inconsistency as also in sentence syntax aspect at a number of places are required to be incorporated in the theses. In a sense, I would recommend the author to reread the theses and correct the grammatical aspects specifically in sentence syntax as also bring consistency in data taken from various literatures but reference year of data taken and source are not mentioned. Some statements are not clearly understood such as, "India's power sector is one of the largest and has a capacity of 156092.23MW". In the immediate next sentence, the India's installed capacity is shown 369 GW. Such data inconsistency needs to be corrected by taking such data from only one reference year and authentic source rather than taking from various sources using different reporting years.

Answer: The data presented has been corrected as per latest statistics in the power sector in India and world-wide and proper sources are referred. To the best of my knowledge, the grammatical aspects have been corrected.

Examiner 2

Chapter 1

Questions:

1. Scholar has summarized the research gaps but not sure how many of them addressed in this dissertation?

Answer

The following five research gaps have been addressed in the research work.

1. Many authors analyzed the performance of the models of wind power forecasting either by calculating MAPE or RMSE, but not with both the evaluation factors. (Chapter 2)
2. As renewable power forecasting has a great role in the operation of a smart grid, the reliability of forecasting model has to be checked with the analysis of uncertainty in the prediction. (Chapter 3)
3. The uncertainty in wind speed forecasting and wind power forecasting shall be analysed using the developed hybrid model. (Chapter 3)
4. Many authors tested and validated the forecasting model developed using the data of one location. Further, the location dependency of the model can be verified using the data from more than one location. (Chapter 2)
5. In Smart grid scenario, the effect of renewable energy on Electricity Market price could be investigated. (Chapter 5 and Chapter 6)

2. Also there are many gaps are loosely defined and one approach could be that only highlight those gaps which are being addressed in this work.

Answer: Most of the gaps are addressed in the thesis work.

Chapter 2

Suggestions:

1. Show and describe the training and testing data; Belgium wind farm, US wind farm and Indian wind farm.

Answer: As per the reviewer suggestion, sample testing and training data is included in the appendix of the thesis.

Questions:

1. During the training section, the researcher fine-tuned the NARX model to achieve maximum accuracy result. However, the number of nodes and hidden layers is not presented in discussion or conclusion part. Similar to one day ahead forecasting, the fine-tuned parameter of GRNN, RBFN and SVR are not presented.

Answer: The tuned parameters are presented in table 2.1 for NARX model. For GRNN, RBFN and SVR models, values of tuned parameters are mentioned in section 2.3.4 (Simulations & results).

2. Why the researcher considered both MAPE and RMSE?

Answer: MAPE stands for mean absolute percentage error and RMSE stands for root mean squared error. The MAPE is popular as it is easy to both understand and compute. A forecast method that minimises the MAPE will lead to forecasts of the median in percentage form, while minimising the RMSE will lead to forecasts of the mean. In some cases, where actual values are lower, MAPE will be higher values and accuracy and reliability of the forecasting model may not be evaluated correctly. Thus along with MAPE, calculation of RMSE is used to improve the prediction accuracy.

Chapter 3

Suggestions:

1. Add labels of blue and green line in Figures 3.5, 3.6.
2. Show how uncertainty analysis help to evaluate the forecasting models in conclusion part.
3. The research should mention that other hybrid GRNN-RBFN's topology should be add in further study.

Answer: All the above suggestions are incorporated in the thesis.

Questions:

1. Why the research selected only the parallel hybrid GRNN-RBFN the test in this study?

Answer: The parallel topology has come out to be better than series topology.

2. In Equation 3.9, MAPE value always be positive value. But in Table 3.6, there are negative value MAPE in RBFN model. Why it happened?

Answer: Table 3.6 projects confidence intervals (CI) computed on the set of MAPE values. The calculation steps of confidence intervals are shown in equations 3.11, 3.12 and 3.13 as mentioned below. As per equation 3.13, if Mean(X) is less than margin of error (E), the lower boundary can be negative.

SE= $\sigma/\sqrt{n}$ (3.11)
Where n is the sample size.
Margin of error E = t * SE (3.12)
CI= Mean (X) ± E (3.13)

Chapter 4

Suggestions:

1. Shows results of both training and testing part. The researcher can analyze more on under fitting and overfitting model.

Answer: As per the suggestion, the training results are included in figure 4.5(b).

Questions:

1. After interpreting with the one-day ahead simulation results, it seems like if the research developed K-mean based SVR. The result of K-mean based SVR might be better than K-mean based ANN-PSO.

Answer: K-means technique is mainly used to classify or group the data. SVR is itself a classifier. Thus, K-means along with ANN-PSO model was used.

Chapter 5

Suggestions:

1. Figures 5.6 and 5.7 are not clear. The researcher may re-plot the graphs.

Answer: Figures 5.6 and 5.7 are redrawn but as they represent hourly clustered data for the whole year which is a large data set, they may lack clarity. The importance of the figures is to project three different clusters.

Chapter 6

Suggestions:

1. Due to this chapter focus on short-term forecasting, the researcher may present computational time for each model.

Answer: Computational time for proposed model is 135 sec where as for other models it ranges from 60 sec to 120 sec.

Questions:

1. What are the input parameters for training and testing the forecasting models? The researcher mentioned that day-head price, load consumption, humidity, temperature, etc. will be used to train the model but not clearly described in methodology part.

Answer: The discussion on the selection of input parameters is presented separately in the section 6.2, Dataset and feature engineering. The input parameters considered are electricity generation, solar generation, wind generation, load demand, historical electricity price, calendar pointers, wind speed and temperature.

2. What if there are error on input parameter, is it will affect to the forecasting model's performance?

Answer: The error on input parameter definitely affects the forecasting model's performance. The impact varies as per the number of samples with error.

Chapter 7

Questions:

1. What is the current production in non-fossil source in India electricity market? There mentions only installed capacity in introduction part.

Answer: Renewable energy has a share of 23.39 % in the total installed generation capacity in India i.e. 368.98 GW, up to 29th February 2020.

2. The results in Table 7.1 are presented in term of quality not quantity. What indicators of each matrix that the researcher measure for different proposed market models? For example; how do the researcher define null, less and more congestion?

Answer: Table 7.1 compares various market models proposed in the research work among some features such as implementation, competition, congestion, tariff and reliability. All the above features describe the quality of the specified market model. Quality depends on the type of the market model, but quantity depends on the specified electricity market.