Emperical survey and analysis of Forcasting techniques for Wind based RE Generation

Syed Ali Umair Tirmizi
Computer Science , SSE
Lahore University of Management Science
LUMS
1803000@lums.edu.pk

Dr Naveed Arshad
Computer Science , SSE
Lahore University of Management Science
LUMS

***Abstract*—With increasing need for renewables energy as the world moves to lower carbon footprint and rapidly evolving smart grid comes a need for developing better energy generation prediction model. As the world moves to renewable sources of energy, introducing them into smart grid , This also raises need to predict their trend, their expected outcome and their consistency as most of renewables are forces of nature which are never constant. Wind is one of the most important source of renewable but it presents challenges. Wind RE is extremely unreliable in terms of consistency and constantly changing. This presents a certain opportunity in terms of prediction as wind also depends on various elements such as temperature , altitude , and location such as closeness to sea. In this paper , we look pervious work done in last decade pertaining to wind prediction for wind based RE and form an empirical analysis based on results obtained , environment factors and contribution , error rate , locality forming as survey of best known implementation of wind prediction and generation system around the globe.**

***Keywords*—Forecasting ; Wind Energy ; Renewable ; Wind power generation ; Artificial Intelligence**

I. INTRODUCTION

As the world amounts to renewable power generation all elements of renewable energy (RE) are taking precedence over non-renewable sources such as coal , oil and natural gas. With depleting resources and majority of these non-renewable reserves limited to certain areas which are effected by economic and socio-political situation has made RE extremely important todays smart grid. In 2020 world was stuck by new virus pandemic which diluted the economy of non-renewable as world went into lock down , crashing the crude oil price [1] with Oil prices recording the hardest cut after 1991 dropping 30% and reaching negative. On the other hand , amid global lockdown and social distancing , renewable demand has seen a sharp rise as renewable resources do have the cost associated with transportation and not effected by stock market. According to IEA Global energy review 2020 , Q1 2020, global use of renewable energy in all sectors increased by about 1.5% relative to Q1 2019 [2] . Renewable electricity generation increased by almost 3% amid COVID-19 lockdown which indicates strong reliance in RE for economic recovery. Wind is the second source after PV Solar to dominate in Q1 2020 with more expectation as more countries will turn to economic recovery in rest of the quarters. Figure 1 by IEA shows how wind RE growth has little impact by COVID-19.

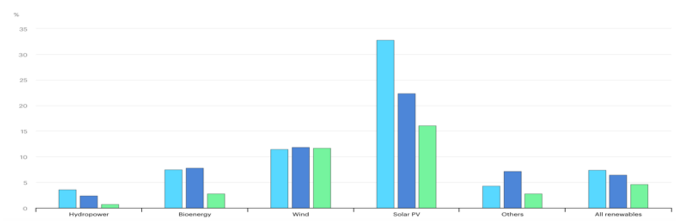


Figure 1. Growth of RE in years 2018-2020

This presents the need for better structuring of RE energy generation. Wind energy is unreliable when compared to solar PV as while solar can be predicted quite accurately wind relies on many factors such as location , temperature , distance from see , common wind corridors. Even more difficult is high wind areas are sometime not easily accessible. Major problem in wind power prediction also include data gathering as data is often unreliable or small in size for sampling and analysis. Data is also sometimes not consistent enough for accurate prediction.

In this paper we will look at various application of wind prediction and wind power generation setups done in past decade. This empirical analysis will consist of wind application followed by analysis in terms of success , prediction rate and acceptance in grid. We will look at novel approaches in prediction algorithms and rank them based on success considering environmental and geolocational feature.

In next section we discuss other related research paper that focus on wind renewable energy. Section 3 will discuss different techniques applied in wind power prediction. Section 4 provides model section. Section 5 will provide a matrix for applying best techniques based on topological feature and conclusion of the paper.

II. RELATED WORK

Renewables prediction has long been part of research. Especially in fields of electrical engineering and computer science multiple fields are now part of goal for achieve reliable power generation and prediction using renewable for smart grid. Ma Lie work [3] presented an overview if wind speed based forecasting models which comprised on introduction to using ANN and Fuzzy Logic models for wind power generation prediction with key statistics being wind speed providing a good comparison between NWP , ARMA and traditional SVM model. Wen Yeau Chang out of St John University in [4] provided literature review on various classification techniques used for training different models in wind prediction algorithms. It talks about various work done using new computational algorithms for artificial intelligence such as ANFIS , ARIMA-ANN , ARIMA-SVM, GFS (Global forecasting system and WRF in a hybrid approach without going into depth of what the key input statistics was. Xioachen .al in 2011 [5] gave insights to different forecasting models explaining the till then research on short and long term forecasting while touching various projects in hybrid forecasting such as WILMAR project , ANEMOS platform by EU.

ANN is one of the popular prediction techniques used for wind prediction. Work in [6][7][8] give comprehensive references to techniques that use artificial neural networks for wind power generation. A group out of Dongbei University presented a survey study [9] on various empirical mode decompositions with over references to 8 different strategies for wind prediction comprising of 48 different hybrid machine learning models such as ANN , Cuckoo Search and various forecasting evaluation techniques. Similarly Jaesung al. in [10] review the current and future advances in wind speed based power forecasting enhancing the work in [3] by giving a survey of various approaches that were applicable such as localization complexity based MAE normalization , MRI based forecasting using Kalman filtering. Other references to future of wind power generation has also been covered in various surveys such as one by European experts in [11] where industrial revolution pertaining to wind power were covered such as multi-rotor turbines, power transmission systems , diffuser-augmented turbines, EH devices and various fundamental device that would be applicable in future of Europe's journey to Wind power. Prediction of wind based RE using advance machine learning algorithms has been explored previously. A team used data from Tamil Nadu India to predict Energy generation. The modeling was done using MATLAB toolbox. The model accuracy is evaluated by comparing the simulated results with the actual measured values at the wind farms and is found to be in good agreement. [15]. Kusiak, A provided prediction, generation and fault detection in wind generation in their survey work [16]. Prediction of wind-RE using EH-WSNs depending on the energy generation profile of latest condition was introduced in work by S Kosunalp [17] which also was tested against two popular energy predictors, EWMA and Pro-Energy which underperformed compared to the work done. Not only live data but historical data from metrological centers have been used combined with data science techniques to develop efficient machine learning algorithm that achieve close to real performance in terms of wind based energy generation. Ma Y.J work in Feed forward neural net based wind prediction model which encompassed hybridization of wavelet transform (WT) and ant colony optimization algorithm (ACO) achieved reliable 24 hour ahead prediction [18] . Other machine learning techniques also have been used as well such as deep learning. Manero, J work deals with the application of Deep Learning to wind time series on US's NREL. Recurrent Neural Network Architectures was developed and evaluated on the largest dataset available for wind and showed promise in terms of lower error rate [19]. Saleh A.E also presented a system for hybrid neuro-fuzzy power prediction system combined fuzzy logic rule based system with neural feedback. Modified Fuzzy C-Means (FCM) is used to implement hybrid optimization method by the work that has good prediction accuracy and provides a useful qualitative description of the prediction system [20].

While these research surveys cover various techniques there is no comparative or empirical analysis done which indicates the ranking of such techniques and useful-ness in locations which want to shift on Wind based power generation. Also most of the techniques focus on forecasting algorithms such as [3][6][7] and generating forecast for wind speed in short term like [12][13][14]. This leaves a gap in research which would be research goal of our work. We will try to evaluate various algorithms and forecasting techniques along with other factors such as performance , application context and topological factors.

III. WIND POWER FORECASTING APPLICATION AND PROJECTS

In this sections , we will look at some of the previous application of wind forecasting both long and short term forecasting project and analyze them based on performances , geo-location , complexity and results.

A. Short Term Forecasting

In 2011 , The Authors in [21] describe a proposed NNWT approach for prediction of short term energy generation by wind which is basically a combination of common algorithm of Neural Network (NN) and WT (Wavelet Transformation) which is basically a decomposed time series of wind and power into better behaved constitutive. The 3 layered feed-forward NN was used and trained using Levenberg – Marquardt Algorithm which uses Hessian matrix and gradient vector for derivatives. This proposed approach was tested for data collected in wind farms in Portugal with National Electric Grid data used for training with algorithm returning +3 hours prediction into future. Procedure is repeated to achieve +6 , +12 and finally 24 hours into future. Proposed solution is tested on 4 days randomly corresponding to 4 seasons of Portugal and results indicate that NNWT approach resulted in lower MAPE percentage with MAPE having average value of only 6.97% beating likes of ARIMA , Persistence with both of them achieving more MAPE as shown in figure below. This also indicates the even upto 3% is achieved in days of Fall which shows extremely less error. However , while the approach is quick and effective , there is less indication about the data used. The data summary is missing and how NN was trained with data from the Grid. Which parts of Portugal was the data from and which areas do the wind farm reside. The geo location features of wind farms are also not present. The locality of wind farms , their difference from sea level , their distance from common wind route and sea level , their production capabilities along with climate of areas are not mention.

Day	MAPE (%)	$\sqrt{SSE}$(MW)	SDE (MW)
Winter	9.23	606.15	38.80
Spring	9.55	533.62	37.61
Summer	5.97	218.11	15.99
Fall	3.14	211.38	15.97

MAPE per season in [21]

Another such work in similar country was by same author was in [22] with short term wind power forecasting in Portugal using a newer version of WT which used Wavelet-PSO-ANFIS. WT is same approach discussed in [21] however this time the author used another class of feed forward algorithm called ANFIS which combines self-learning ability of NN and linguistic expression function of fuzzy interface. A heuristic algorithm called particle Swarm Optimization (PSO) was also used as for initials and final weight optimization in ANFIS's multilayer. The paper presents many details of how the hybrid approach first build data matrix using wind power times series into WT coefficient signals followed by ANFIS model coupled with convergences and PSO optimization with decisioning and reconstruction of wavelet and data. NMEA based performance analysis was conducted and found that WPA achieved extremely less NMEA average as compared to previous techniques such as NNWT , NF , WNF , ARIMA and more. The paper also describes MAPE results in which an average of 4.98 was acheieved which is much lower to previous research in NNWT in [21] with improved performance in winter season with MAPE result upto 6 percent while state of the art WNF achieved 8 percent . Figure below shows forecasting compared to actual results.

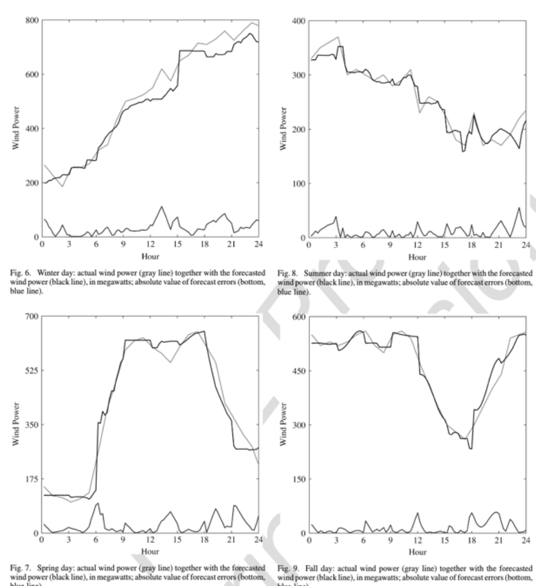


Fig. 6. Winter day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

Fig. 8. Summer day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

Fig. 7. Spring day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

Fig. 9. Fall day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

Contrary to such approach in [22], a team from University of Tokyo in [23] focused more performing on-line forecasting using multi-timescale model (ARXN) with resolution of 20km from data of Japans Meteorological Agency (JMA) and SCADA data from wind farms in Tohoku Area with total installed capacity if 243 MW. The geographical data shows with DEM of 50m and land use data with 100 m with horizontal resolution of 20 km and temporal resolution of 3 hours in order for forecasting up to 51 hours. The SCADA data from forms was collected and average 10 mins for input in ARXN model . The results were collected and inputted into model which showed up to decrease in Root mean square error from 10% to 9.5% when the forecasting time increased from 1 hour in future to 24 hours. The data was further validated for next 14 days as well , sampled and added to curve of RMSE however data was apparently only collected in moth of April (in those 14 days) which may present similar climate over Tohoku region. Small scale forecasting is often a challenge in wind power as grid rely on very accurate prediction however small scale prediction is not often simple as show in [23] with more consistency achieved when forecasting time was increased from few hours to 24 hours period. In [24] A gaussian process approximation approach was design in which predictive features are adaptively optimized at given time to predict feature value of generation. The Bayesian framework predicted using data from Guadeloupean archipelago (French West Indies) which has around 24.98 MW. The characteristics of farm are shown in the region below in Table 1.

Table 1. Wind characteristics around Guadeloupe's wind farms.

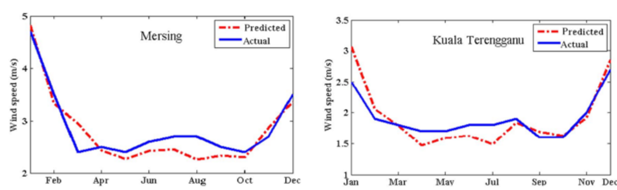
Wind farm location	Mean wind speed (m/s)	Mean wind direction	σ (m/s)	Weibull shape parameter	Weibull scale parameter
DESIRADE II	9.1 m/s	92°	3.1	3.2	10.1
DESIRADE III	7.4 m/s	111°	2.5	3.3	8.3
MARIE-GALANTE	8.0 m/s	95°	2.8	3.1	8.9
PETIT-CANAL	8.0 m/s	93°	3.0	3	9.1

In both cases , NN and Bayesian learning was used, NN was build out of units of 3 layered structure with weights with biased added. The perceptron with single hidden layer of sigmoid unit and linear output was used for NN in short term prediction in which optimal input found was 5. Performance was evaluated using wind farm with capacity of 7 MW located at 60m above sea level. The test was divided into 2 offline versions yielding and compared to persistence model using MEA and RMSE criteria with conclusion drawing a decrease in both compared to persistence model. Not only Bayesian but other statistical models have been used for short term prediction. Of the them in recent work in [25] in 2015 , They use first order and second order markov chain for prediction which divides time into intervals of 10 mins. Techniques such as MSE and predictor calibration are used for estimation and refinement.

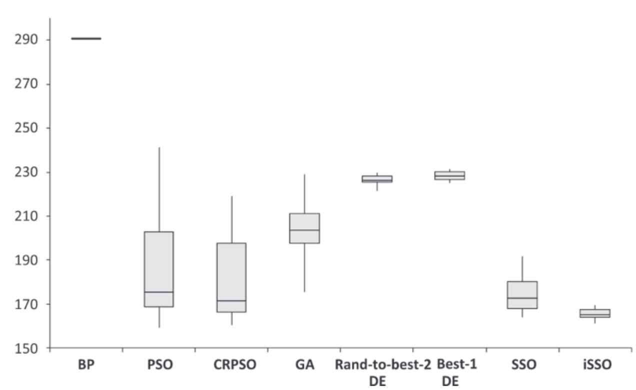
B. Long term Prediction

In terms of long term prediction , data collection over large period is issues. Earlier before data was collected in limited time span for experimental analysis for however in recent time with increase in IoT data collection has become easier. We will look at recent work in long term forecasting for wind power.

Pattern recognition has grown in last decade with data used in data mining and data science techniques. HB Azad in [26] used pattern recognition and neutral network in combined techniques. The data collected is in from Mersing and Kaula , Malaysia with Malaysian wind corridor providing separate averages on wind speed during north and south monsoon region (7 m/s and 15 m/s). The wind speed are collected over period of 4 years with those wind speed the methodology uses NN to predict next year's monthly wind speed prediction which in result will give monthly prediction of wind power generation. This is supported by other pattern recognition techniques which provide more granular prediction from daily to monthly trend. NARX neural network are used with training first for six month and then prediction. The prediction is evaluated using trial and error method and showed better prediction in Mersing over Kaula. While in 50% (Mersing) and 75 (Kaula) showed less than 1 m/s wind speed difference , some cases there was 8 m/s. The graph below shows prediction against actual values



Another approach was in long term study in Mai Liao Wind Farm in Taiwan where in 2 stages with multi-layer perception ANN which 7 various variants such as PSO , SSO , DE and more. The wind farm provided the data for upto 5 years from 2002 to 2007. The evaluation was based on various elements and all 7 algorithms in MLP NN were used. The box plot below shows best combination on MLP NN variant.



ANOVA was used for analysis of data and key features like MSE were used to find evaluation. This also included thresholds such as CPU time for evaluating performance of algorithm in terms of computer time while focusing on accuracy as well. Similarly other classification methods have been used such as SVM in [27]. The approach uses empirical mode decomposition and SVR method for however this experiment was on small scale done on apartment building in Singapore. The comparison is done between 3 known method Ye2011, Han2011, Guo2012 and shows better performance than all 3.

In general long term prediction work is limited as the data collection over larger period and granularity demands are large effort from wind farms. More farms in the world are starting digitizing but for long term accuracy such as accurate month wind speed rate it would take time for research to develop.

C. Types of Approches

In most cases there are 3 different types of approaches for wind power generation.

We can divide the type of approach based on prediction model used in it. In most cases the prediction models are based on common AI techniques and common output out of the model is wind speed and time series along with it. The prediction algorithm can be used for long and short term forecasting based on time and data available as well as target forecast. In Section A most of the farms or area had non-continuous streams of data hence forecasting was often short term. Moreover it also depends on algorithms parameter as well. Topological based algorithms such as [23] can only be short term as data is limited and more based on topology. Long term data such as in [26] need high granular data. We have divided the approaches in 3 different techniques and showing which approach is ideal for which case

- Statistical and computational Approach :

Statistical approach focuses on using statistical techniques for prediction. The artificial intelligence approach belongs to the statistical approach. The essence of the artificial intelligence approach is to establish the relationship between input and output by artificial intelligence methods, rather than using the analytical method. NN is the choice with variants such as ANSIF , MLP and other artificial neural networks being used in examples such as [21][24][25]. This approach provide great deal of flexibility with variants allowing tweaking the approach based on data available. These approaches work extremely well in low amount of data and provide both long term and short term forecasting with error rate of less than 6%. In some cases prediction are so close that there is less than 1 m/s of speed generation. Not only the flexibility of data is present but also the flexibility of parameters. Techniques such neural network can have multiple layer , combinatory approach and can accept multiple inputs as well. This mean not only wind speed can be input but other features such as temperature , latitude etc as done in [28]. The advantage of Artificial Neural Networks (ANNs) is to know the relation between inputs and outputs by a non-statistical approach neural networks can easily learn from the input and output mapping during the training phase. This allows the neural models to perform well, even without the researchers' knowledge of the problem.

The advantage related to the other methods is to provide relatively inexpensive models of statistical projection that do not require any data other than historical wind power generation data. However, the prediction accuracy for these models falls significantly when the time horizon is extended.

- Physical Approach:

Topological feature extort a great extent on wind power generation. Some approaches that focus on these metrological feature have been used as well. This involves collecting data and predicting based on GIS and other early feature. This type of approach is accurate but only limited to smaller prediction as data collection and topological data is difficult. Also this means we need constant access to wind farms with horizontal and temporal data being corrected based on distance.

- Hybrid approach:

Usually, the combination of different approaches, such as physical and statistical approaches, models combining short and medium term, etc., is commonly referred to as a mixed or hybrid model approach . According to [29], the object of hybrid models is to benefit themselves from the advantages of each model and obtain optimum overall forecast performance. Since the information contained in the individual forecasting method is limited, the hybrid method can maximize the available information, integrate information from individual models, and make the best use of the advantages of various forecasting methods, thereby improving prediction accuracy.

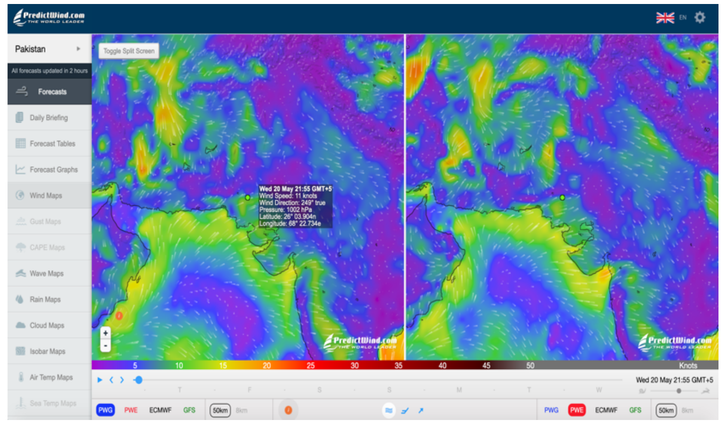
In all we found that forecasting can be achieved in various ways using various techniques and can implement various approaches to achieve solution. However some approaches such as statistical modelling proved to more effective in terms of both reliability and quickness.

- Commercial Forecasting:

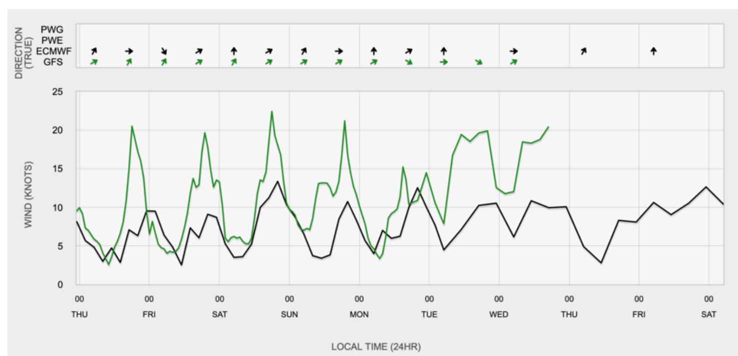
Some commercial company offers wind forecasting as well. Geostorm claims they forecast production for a whole fleet of wind farms for tup to 14 days ahead. Using historic data and adding turbine types into the calculation, They calibrate forecasts to set up and teach algorithms to make forecasts. Currently they are operational in Germany, Denmark, Norway, Sweden and Scotland. According to their R&D division their models including the European Centre for Medium-Range Weather Forecasts (ECMWF) and Global Forecast System (GFS), as well as high-resolution short-range models, such as the High Resolution Rapid Refresh model.

Metrologica (Madrid, Spain) is another commercial firm that provides wind farm forecasting to independently operating wind farm as well as run by government. According to their website they use Ready-to-use data, integrating latest updates from major NWP models, real-time production, asset availability and optimized calibration based on historical power generation data to provide accurate prediction. They provide forecasting services worldwide, currently implanted in over 65 countries.

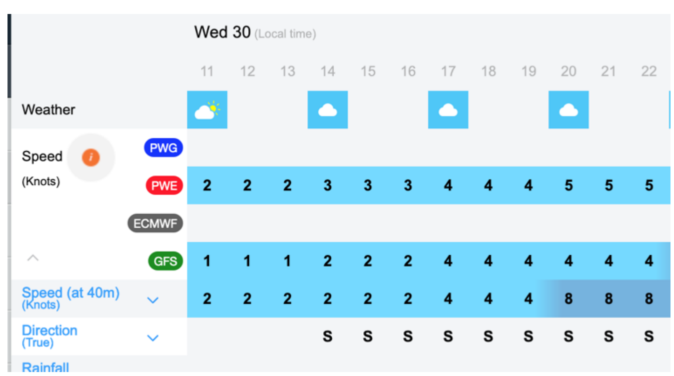
WindPredict.com offers free statistical data to user who need wind prediction for various commercial and pleasure activities. We were able to request a 10 mins live access to their data application which offers live timeseries prediction data from 4 different data collections.



This graph shows a pin location near Hyderabad Sindh which shows forecast graph for 24hours with wind direction in wind knotts



The prediction also provides a data table for 40 m windspeed along with direction which can be directly imported for further data analysis in form of JSON object and directly queried from their advance API feature which is limited to commercial users.



Wed 30 (Local time)		11	12	13	14	15	16	17	18	19	20	21	22
Weather													
Speed (Knots)	PWG												
	PWE	2	2	2	3	3	3	4	4	4	5	5	5
	ECMWF												
	GFS	1	1	1	2	2	2	4	4	4	4	4	4
Speed (at 40m) (Knots)		2	2	2	2	2	2	4	4	4	8	8	8
Direction (True)					S	S	S	S	S	S	S	S	S
Rainfall													

IV. DECISION MATRIX

A. In this approch we will design a decision matrix of sort to help researches / energy expert find a better approch of picking the best wind prediction model for their need. The decision matrix has been given divided into 3 major approches

B. The Time-scale of forecasting

The timeframe of forecasting defines how long would the model predict from the current time input.
Ultra-short-term forecast: From a few minutes to 1 h ahead.

- Short-term forecast: From one hour to several hours ahead.
- Ultra-short-term forecast: From a few minutes to 1 h ahead.
- Medium term forecast: From several hours to one week ahead.
- Long-term forecast: From one week to one year or more ahead.

We presented only short and long term as they can cover wide area of both sperctrum.
The decision would be based on following key factors

- Prediction Expectation of Grid : How much of forecasting does the grid demands. Small scale grid require lower but granular forecasting for load management as showing in work in [24] in French West Indies as they need to manage load of the island more than predicting yearly out.
- Data Available : Most small scale grids do not have capability to log data hence the data available is limited , not consistent and missing some datapoints often.
- Input factors : In most cases for small scale grid only one input factor is required which is wind speed however for larger grid as they may comprise of other RE sources such as PV solar and hydro power hence factor such as temperature , pressure also become viable variable.

C. Topology :

The area is extremely important as it put certain level of uncertainty into the model and may cause inconsistency in prediction. Predictions are based on data and if data set is not large enough (which is common case for most wind plants) we need to have certain level of flexibility in prediction model to include that. This requires that model offers flexibility and optimization which is why often neural networks are preferred as they offer various kernels , sigmoid , various variants with different characteristics. In [30] , the paper used 8 different optimizations techniques (MO- Whale Optimization algorithms) for judging best case again 6 different cities , at different time and seasons taking out the topological biased-ness and inconsistency out of the equation.

D. Type of Approach:

Approach is dependent on data , the model and type of operation grid has. This also depends on type of approach that has been best suited for areas. Areas which are highly volatile may need more real time short term forecasting through physical approaches such as in Japan [23]. For low cost area statistical data gather is limited so small forecasting using ANN , ANFIS and SNN may be better.

E. Cost of whole process:

Cost is an important factor while deciding. Large scale farms can hold to do large level forecasting over time which may require extra surveillance , data gathering and more man power while small scale farm may yield to lower cost over larger period predictions with little compromise on accuracy.

Taking account of these decision matrix one can decide which approach is applicable and may yield

V. DECISION FLOW

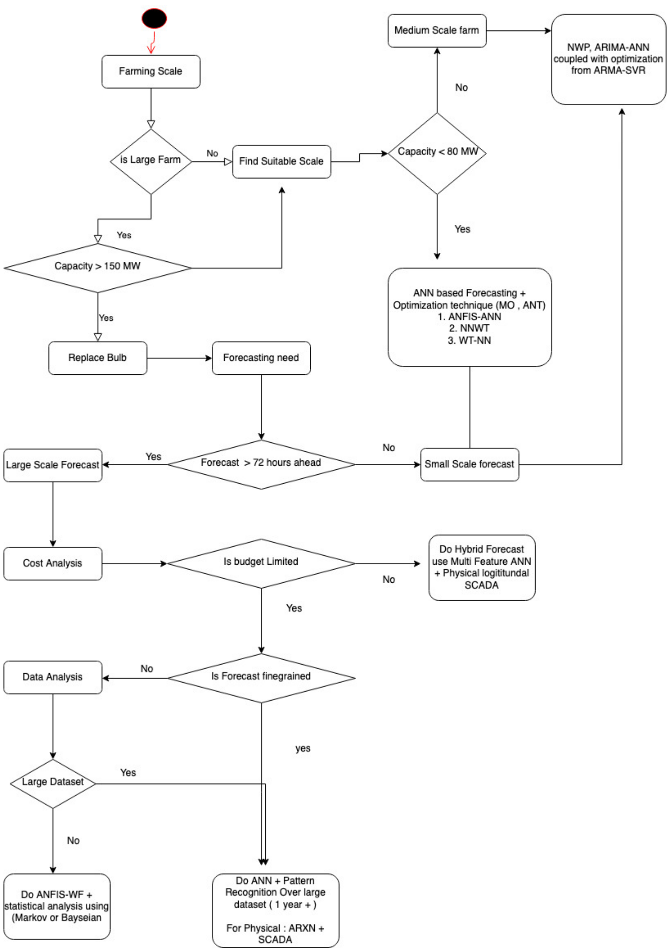
For simplicity , Our work encompasses a decision matrix (Section IV) however making decision based on factor can vary from project to project. In this study we present a semantic algorithm presented in the form flow chart for decision making the techniques used for forecasting wind speed and eventual wind generation. The is makes decision making for farms and power authorities to pick best techniques based on empirical analysis done above.
The algorithm is based on fine grained decision on above matrix.

The idea is first decide the scale on farm and then go for prediction size based on available budget. The flow chart may be compressed based on number of option however does provide the overview on how different techniques are applicable.

The farm size if large will often have large budget require forecasting which is fine grained and over large period. While live data is also available hence such can be achieved by number of forecasting method combined. ANRX along with SCADA is best geographical technique and it should be combined with best analytical technique which is WF-ANFIS with Optimization which can give fine grained forecasting with live data prediction. Long term prediction is also a functionality ANN in NARX-ANN variant which can give up to 1 year prediction (decomposed into monthly and hour prediction)

Small / Medium scale farm output is often less than 150 MW with small scale farm are often under 80 MW. The approach would best is statistical because with small dataset it can provide a MSE < 10% using advance statisical technique. Small scale farm are often crippled by funds hence small scale forecast of 24 hour is best possible case which is achievable with ANN. It have can be NNWT (MAPE < 7% or ANFIS (< 5 %) or ARIMA which is standard.

The flow chart is attached here (and after reference for clearer image)

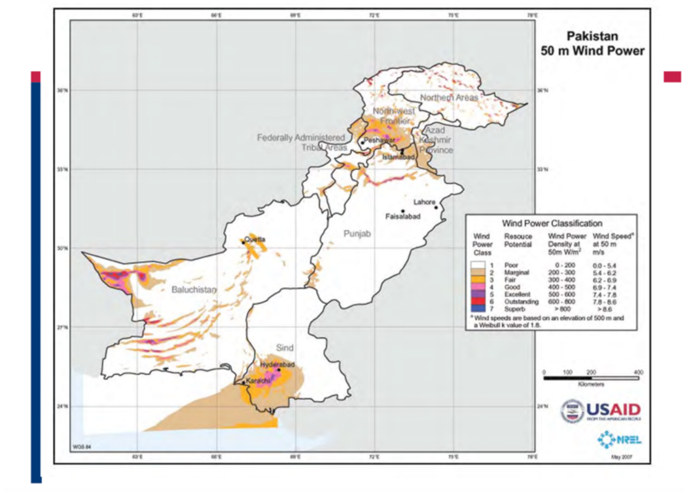


VI. Case Study : Pakistan

Pakistan presents a unique opportunity to explore forecasting of wind energy in terms output , locality and which approach could be best used.

A. Wind Corridors of Pakistan and Comparison with Other Countries

Wind corridors are located at major coastal areas of Pakistan, According to meteorological study conducted in [Baloch et al., 2015b] that It is projected for wind energy scenario, that around 0.5 TW can be produced at the end of 2016. In the Sindh wind corridor zones, the wind speed reaches approximately about 5–12 m/s which is often comparable to wind speed we saw in applications done in Malaysia and often in areas of Netherlands. Not only that but according to [Mazhar H. 2016] around at 50m in Southern region of Jamshoro winds speed can reach upto 14 m/s. Map below shows wind speed corridors of Pakistan which were recorded by USAID in collaboration with World Bank (best resolution image after reference)



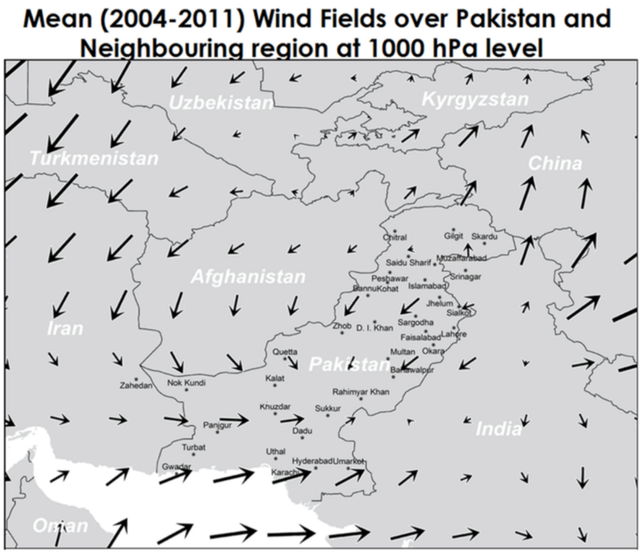
Other wind project include Jhimpir under Alternative Energy Development Board (AEDB) which in Thatta , Sindh. The Zorlu Energy Putin Power Plant is the first wind power plant in Pakistan. The wind farm is being developed in Jhimpir, by Zorlu Energy Pakistan the local subsidiary of a Turkish company. The total cost of project is $136 million and has capacity of ~ 56 MW. Pakistani Govt. also has issued LOI of 100 MW Wind power plant to FFCEL. Pakistani Govt. has plans to achieve electric power up to 2500 MW by the end of 2015 from wind energy to bring down energy shortage however USAID does predict data 150,000 MW capacity. In 2003-2011 , research group under USAID concluded following statistical summary of wind density in different cities of Pakistan

S. No.	Cities	2003	2004	2005	2006	2007	2008	2009	2010	2011
1	Islamabad	7.0	6.83	6.16	5.58	6.75	6.66	7.66	5.08	6.83
2	Okara	6.58	7.66	4.91	7.33	8.0	7.75	6.08	7.0	8.25
3	Sargodha	8.83	9.16	7.17	7.25	7.17	8.58	6.75	7.08	7.83
4	Sialkot	7.08	8.33	8.0	7.08	9.16	7.75	6.83	6.0	7.66
5	Lahore	8.83	7.91	7.166	8.41	10.3	8.66	6.66	8.83	6.33
6	Multan	7.66	8.91	9.25	7.42	6.42	7.92	7.17	7.087	6.42
7	Faisalabad	7.58	7.75	8.33	7.75	8.33	7.75	7.83	6.25	7.25
8	Bahawalpur	6.16	7.66	8.25	5.91	9.91	5.66	7.08	7.0	6.08

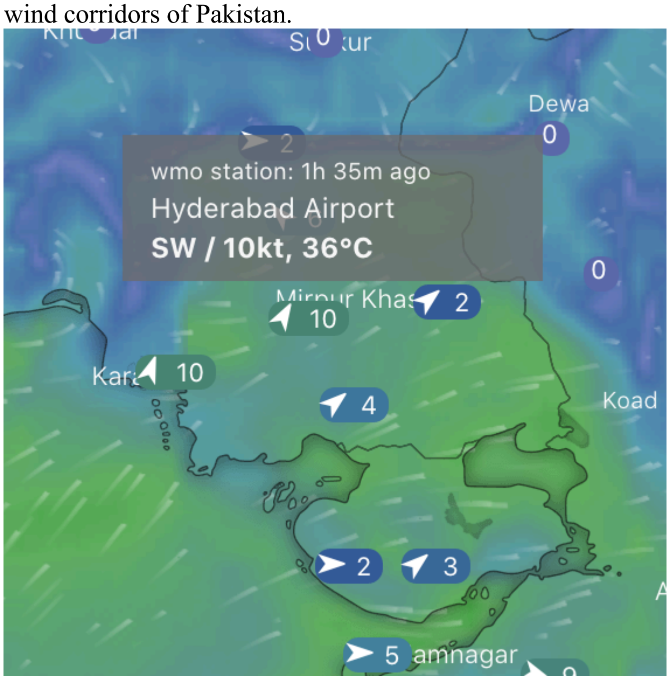
wind density over different cities

In comparison to other countries such as China , US which are not only economic power house but have strong research division and advance data collection such as multiple satellite which contribute to live data. On the other hand countries like Malaysia and European nations have different geo-location which contributes a lot of wind speed. EU have winter breezes while Malaysia has costal winds. US also have most of wind farms that are productive in areas such as West Coast area. California and Oregon host most farms with also some high capacity i.e 600+ MW in desert region of Texas . Similar is the case with Bada Bagh (Tamil Nadu , India) and Tafila Wind Farm (Jordan) that use desert winds for production. Pakistan comparison to these area in both geo-graphical term is very similar.

Looking at the research by NREL's SARI-Energy the areas shown in Pakistan wind corridor are Sindh coastal areas with desert region of Thar desert just above. They are experience high pressure area due to temperature which can reach upto 50 C in summer.



Morocco is another country which has undertaken a vast wind energy program, to support the development of renewable energy and energy efficiency in the country. The Moroccan Integrated Wind Energy Project, spanning over a period of 10 years with a total investment estimated at $3.25 billion, will enable the country to bring the installed capacity, from wind energy, from 280 MW in 2010 to 2000 MW in 2020. However all of 3 countries do not have advance wind forecasting capacity. Also Pakistan has limited Metrological station which provide live data. Here is a live grab from windy.com which shows only data from 4 stations located in wind corridors of Pakistan.



B. Accessibility

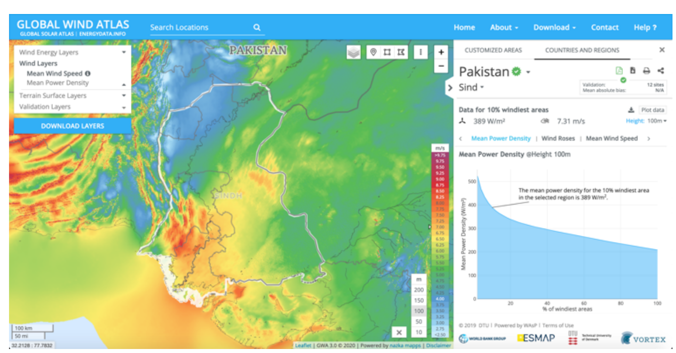
The wind corridors in south part of Sindh are most idea location to be accessible around the year. Although temperate in some areas may lead up to 50 C but motorways and flat plain near Indus river allow the accessibility all year long. This accessibility is also improved by CPEC (Pak-China economic corridor) which provides intratarsal support including budget , grants and oversite to energy projects

C. Cost and Expected Power generation

Pakistan economic conditions are often instable and lack of stability often leads to only short term planning. Although major source of power in hydro in Pakistan , some IPP and coal power is also part of grid system. Relability on wind is not expected as much however considering cost to solar PV and hydro wind can provide quick alternatives which is why cost wise Pakistan would like to setup small but effective grid for wind power. This means that need of forecast may not be highly required however may be need for short term forecast as load management in Pakistan is always an issue. This mean any forecasting techniques must be short term in goals but should be consistent enough. This says that ideally statistical approach as such sigmoud based ANN would be idea.

D. Data availbility :

Wind data is scares in Pakistan as wind energy was never planned. This makes the data very limited. Major data sources include Geological survey of Pakistan (GSP) , Global Wind Atlas through World bank also provide datasets for 2018 is highly detailed for Pakistan in 2018 but only has one year worth of data in form of JSON. The data is showing below which shows win speed , density and height per data



Other sources that have wind data pertaining to Pakistan which under Alternative Energy Development Board which release a wind map under their 2019 policy which shows little data. Another source was Energy Sector Management Assistance Program (ESMAP) funded project in 2016 which collected 12 cities wind data however was closed for public access.

In Pakistan most data is with government institution and is confidential for most hence availability of data from organizations such as World Bank , UN and Asian Development Bank are major public data which means any forecasting techniques must be reliable on small and limited data.

This means choice of data should be from Small forecasting NN network which fulfills all the criteria of above. We saw that in ANN performed way better than SVR and other Gaussian techniques. ANFIS coupled with Optimization techniques is viable option as it is fast , and reliable with MAES of lower than 4.99% in some case.

VII. Conclusion

This paper provides an empirical analysis of the world done in past decade along with detail analysis of location , models and how each model performed with detailed analysis of how each error rate was effected. This was followed by a matrix for deciding which forecasting techniques to use. We also presented Pakistan as case study with areas in Sindh province as potential candidate. We found that according to circumstance short term forecasting techniques which rely on small data set can perform better than most such as ANFIS NN. The optimization techniques can yield better output by optimizing other factors such as monsoon season and temperature.

References:

Albulescu, Claudiu. "Coronavirus and oil price crash." *Available at SSRN 3553452* (2020).

IEA (2020), Global Energy Review 2020, IEA, Paris https://www.iea.org/reports/global-energy-review-2020

Lei, Ma, Luan Shiyan, Jiang Chuanwen, Liu Hongling, and Zhang Yan. "A review on the forecasting of wind speed and generated power." *Renewable and Sustainable Energy Reviews* 13, no. 4 (2009): 915-920.

Chang, Wen-Yeau. "A literature review of wind forecasting methods." *Journal of Power and Energy Engineering* 2, no. 04 (2014): 161.

Wang, Xiaochen, Peng Guo, and Xiaobin Huang. "A review of wind power forecasting models." *Energy procedia* 12 (2011): 770-778.

Marugán, Alberto Pliego, Fausto Pedro García Márquez, Jesus María Pinar Perez, and Diego Ruiz-Hernández. "A survey of artificial neural network in wind energy systems." *Applied energy* 228 (2018): 1822-1836.

Soteris A. Kalogirou, Renewable and Sustainable Energy Reviews, Volume 5, Issue 4, December 2001, Pages 373–401. DOI: 10.1016/S1364-0321(01)00006-5.

Li, Gong, and Jing Shi. "On comparing three artificial neural networks for wind speed forecasting." *Applied Energy* 87, no. 7 (2010): 2313-2320.

Wang, Jianzhou, Yiliao Song, Feng Liu, and Ru Hou. "Analysis and application of forecasting models in wind power integration: A review of multi-step-ahead wind speed forecasting models." *Renewable and Sustainable Energy Reviews* 60 (2016): 960-981

Jung, Jaesung, and Robert P. Broadwater. "Current status and future advances for wind speed and power forecasting." *Renewable and Sustainable Energy Reviews* 31 (2014): 762-777.

Watson, S., Moro, A., Reis, V., Baniotopoulos, C., Barth, S., Bartoli, G., Bauer, F., Boelman, E., Bosse, D., Cherubini, A. and Croce, A., 2019. Future emerging technologies in the wind power sector: A European perspective. *Renewable and Sustainable Energy Reviews*, *113*, p.109270.

Soman, Saurabh S., Hamidreza Zareipour, Om Malik, and Paras Mandal. "A review of wind power and wind speed forecasting methods with different time horizons." In *North American Power Symposium 2010*, pp. 1-8. IEEE, 2010.

Cadenas, Erasmo, and Wilfrido Rivera. "Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks." *Renewable Energy* 34, no. 1 (2009): 274-278.

Liu, D., Niu, D., Wang, H. and Fan, L., 2014. Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. *Renewable Energy*, *62*, pp.592-597.

Mabel, M.C. and Fernandez, E., 2008. Analysis of wind power generation and prediction using ANN: A case study. Renewable energy, 33(5), pp.986-992.

Kusiak, A., Zhang, Z. and Verma, A., 2013. Prediction, operations, and condition monitoring in wind energy. energy, 60, pp.1-12.

. Kosunalp, S., 2017. An energy prediction algorithm for wind-powered wireless sensor networks with energy harvesting. Energy, 139, pp.1275-1280.

Ma, Y.J. and Zhai, M.Y., 2019. A dual-step integrated machine learning model for 24h-ahead wind energy generation prediction based on actual measurement data and environmental factors. Applied Sciences, 9(10), p.2125

Manero, J., Béjar, J. and Cortés, U., 2018, November. Predicting wind energy generation with recurrent neural networks. In International Conference on Intelligent Data Engineering and Automated Learning (pp. 89-98). Springer, Cham

Saleh, A.E., Moustafa, M.S., Abo-Al-Ez, K.M. and Abdullah, A.A., 2016. A hybrid neuro-fuzzy power prediction system for wind energy generation. International Journal of Electrical Power & Energy Systems, 74, pp.384-395.

Catalão, João Paulo da Silva, Hugo Miguel Inácio Pousinho, and Vıctor Manuel Fernandes Mendes. "Short-term wind power forecasting in Portugal by neural networks and wavelet transform." *Renewable energy* 36, no. 4 (2011): 1245-1251.

Catalao, J. P. S., H. M. I. Pousinho, and V. M. F. Mendes. "Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal." *IEEE Transactions on sustainable energy* 2, no. 1 (2010): 50-59.

Yamaguchi, A., Ishihara, T., Sakai, K., Ogawa, T. and Fujino, Y., 2007, May. A physical-statistical approach for the regional wind power forecasting. In Proceedings of the European Wind Energy Conference EWEC, Milan (IT) (Vol. 31).

Mbuvha, Rendani. "Bayesian neural networks for short term wind power forecasting." (2017).

Carpinone, A., Massimiliano Giorgio, Roberto Langella, and Alfredo Testa. "Markov chain modeling for very-short-term wind power forecasting." *Electric Power Systems Research* 122 (2015): 152-158.

Azad, Hanieh Borhan, Saad Mekhilef, and Vellapa Gounder Ganapathy. "Long-term wind speed forecasting and general pattern recognition using neural networks." *IEEE Transactions on Sustainable Energy* 5, no. 2 (2014): 546-553.

Ren, Y., Suganthan, P.N. and Srikanth, N., 2014. A novel empirical mode decomposition with support vector regression for wind speed forecasting. *IEEE transactions on neural networks and learning systems*, *27*(8), pp.1793-1798.

Huld, T. and Amillo, A.M.G., 2015. Estimating PV module performance over large geographical regions: The role of irradiance, air temperature, wind speed and solar spectrum. *Energies*, *8*(6), pp.5159-5181.

Chang, W.-Y. A literature review of wind forecasting methods. *J. Power Energy Eng.* 2014, *2*, 161–168

Wang, Jianzhou, Pei Du, Tong Niu, and Wendong Yang. "A novel hybrid system based on a new proposed algorithm—Multi-Objective Whale Optimization Algorithm for wind speed forecasting." *Applied energy* 208 (2017): 344-360.