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Performance Analysis of Wind Power Prediction using ANFIS and Gaussian-SVM

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Abstract: Wind energy is one of the most economical sources of renewable electricity, with the largest resources available in the world. It is one of the most promising sources of clean energy and extends its reach to electricity production. Today, wind technologies are making a significant contribution to the growing clean electricity market worldwide. The rapid growth of wind energy and the increase in wind energy production require serious research in various fields. Because wind energy depends on time, it is variable and intermittent on different time scales. Therefore, accurate wind energy prediction is considered an important contribution to the reliable integration of large scale wind energy. Wind energy forecasting methods can be used to plan the ownership, planning and delivery of activities by network operators to maximize electricity traders' revenues. The increasing prevalence of wind power in power plants raises important questions arising from their intermittent and uncertain nature. These challenges require a precise prediction tool for wind power generation to plan the efficient operation of electrical systems and ensure reliability of supply. In this research work two classifier's performance are evaluated on the real-time dataset. The accuracy of the models has been measured using four performance metrics namely, the Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error(MAPE). From the result analysis it has been concluded that gaussian SVM outperforms better as compared to the ANFIS model. The result is analysed on different testing dataset of different seasons and averaged error is used to analyse the performance measures.

Keywords: Wind Power, ANFIS, SVM, Prediction, MSE, RMSE, MAE, MAPE.

I. INTRODUCTION

The use of renewable energy sources, mainly wind power generation, has produced excellent thinking in many countries. Wind energy is one of the sources of renewable energy with the lowest cost of electricity production and the largest resource available. As a result, some countries recognize that wind energy is an important opportunity for the next generation of energy. This increase installed wind capacity by over 30% every year. And according to the wind and the green peace graph by 2020 12% of the total production of electricity by wind energy with about 30 GW are reached [8].

For wind prediction, different methods are classified according to time scales or methods. The temporal classification of wind forecasting approaches is not yet clear. However, with reference to a large number of studies in this area, the wind forecast can be divided into three categories based on the forecast horizon:
Immediate-short-term (8hours-ahead) forecasting
Short-term (day-ahead) forecasting
Long-term (multiple-days-ahead) forecasting

The use of renewable energy sources (in short: wind, solar, geothermal, water and biomass), is gradually increasing worldwide [4]. There are two moments in recent decades which have marked the definitive bet on renewable energy as an effective alternative to electricity production using fossil fuels:

- The first serious interest on the industrial world concerning renewable energy has been triggered by the Arab oil embargo in the early 70's of last century. Starting that time people recognized the dangers of fossil fuels-addiction and some policies that favor the implementation of renewable energy sources have been launched.
- The second moment was precisely the advent of competition in the electricity sector. Indeed, the demands of competition in electricity markets necessitate a re-evaluation of renewable energy policies. Restructuring the electric power industry has refocused attention on renewable energy and on the policies that affect it in competitive electricity markets. The development of renewable energy, which reduces dependence on fossil fuels, does not need to be imported, and generally produces fewer and less toxic pollutants than fossil fuels is crucial for the sustainable development of future generations.

Wind power generation is increasing all over the world and the electricity sector has to integrate this "intermittent" power source into the electricity grid. The problem of integrating huge amounts of wind power into power network could be solved by using accurate wind speed or wind power forecasting.

Recently, several techniques have been developed to forecast the wind power and speed. Existing techniques can be classified as statistical, physical and time series modeling techniques based on the forecasting models they used [1]. Currently, it is observed that researchers employ a combination of statistical model and physical methods besides each other to get an optimal approach that is applicable for longer horizons of prediction systems. In these techniques statistical model plays auxiliary role to data collected by physical methods.

Physical method or deterministic method is based on lower atmosphere or numerical weather prediction (NWP) using weather forecast data like temperature, pressure, surface roughness and obstacles. In general, wind speed obtained from the local meteorological service and transformed to the wind turbines at the wind farm is converted to wind power [5].

Statistical method is based on vast amount of historical data without considering meteorological conditions. It usually involved artificial intelligence (neural networks, neuro-fuzzy networks) and time series analysis approaches.

Hybrid method which combines physical methods and statistical methods, particularly uses weather forecasts and time series analysis.

II. Related Work

In [15], a new hybrid and evolutionary forecasting method was presented, based on a combination of evolutionary PSO and ANFIS algorithms to predict the next 24 hours ahead, with a time step of 15 minutes for wind power production in Portugal, without exogenous or weather data. The proposed forecasting system was compared with other forecasting approaches, such as ARIMA, NN, Data Mining, and others.

In [16], a forecasting model was proposed based on multi observation points divided into 2 stages, to predict the speed and direction of wind in stage 1, and stage 2 uses the obtained data from stage 1 to predict the wind power output of the wind farm utilising dependent power curves. The study is performed with physical data from a wind farm at an Australian island. The proposed method was also compared with the grey model and persistence model.

In [17], a forecasting method was presented with a switching regime based on artificial intelligence to predict wind power, specifically the extreme events associated with the uncertainty of numerical weather prediction (NWP). The NN used was based on resonance theory and probabilistic methods, and was tested at two different wind farms, namely one in Denmark with historical data from 2000 to 2002 and one at Crete, Greece, with historical data from 2006 to 2008.

In [18], the problem regarding the large penetration of new wind farms into the electric grid was tackled, reviewing the pros and cons, and the advances in wind power forecasting approaches.

A NN was proposed to predict the active and reactive power in the electrical grid using the study case of a wind farm in Germany. The time step of this approach is 1 hour to predict from 24 to 48 hours ahead.

In [19], a probabilistic model forecasting of wind power was proposed, which uses prediction points and uncertainty data from deterministic models. These results come from the quality of NWP data, daily wind power forecasting, and weather stability (speed and direction of wind). Also, this forecasting approach used a combination of a multiple NN with PSO algorithm. The historical data used comes from the wind farms located in Denmark and Greece. Furthermore, this method predicts the wind power for the next 60 hours ahead.

In [20], a wind power forecasting approach was proposed based on 3 models of WT and SVM to predict, with a time step of 1 to 3 hours ahead, the wind power output of a wind farm located in the State of Texas, USA. Model 1 is ensemble accordingly with the wind-drives characteristics and WT principles. Model 2 combines the wind-driven characteristic with a substitution of Kernel RBF functions. While model 3 is a combination of the two previous models and the output is the wind power forecast.

In [21], a wind speed and wind power forecasting method was proposed for the next 30 hours ahead using in a first stage a combination of WT and NN to predict the wind speed, and in the second stage a feed forward NN to create a non-linear mapping between the wind speed and wind power results. These results were obtained without weather variables and performed for a wind farm located in Denver, USA.

In [22] a Support Vector Machines (SVM) model for short-term wind speed is proposed and its performance is evaluated and compared with several artificial neural network (ANN) based approaches. A case study based on a real database regarding three years for predicting wind speed at 5 minutes intervals is presented.

In [23] an adaptive neuro-fuzzy inference systems based approach is used to develop wind power prediction model. To demonstrate the effectiveness of the proposed method, it is tested based on practical information of wind power generation profile a wind turbine installed at a practical case study microgrid in Beijing. The proposed model is compared with BP neural network based and a hybrid GA-BP NN based models. Evaluation of forecasting performance is made with the persistence forecasting method as a reference model, and results are compared with actual scenario.

III. Proposed Methodology

In the current scenario, an algorithm is proposed which provide a way to predict the wave power. Figure 1 shows the overall architecture for prediction of wave power. Following diagram describes flow of wind power Prediction System

The proposed algorithm is divided into three sections i.e. data collection and preprocessing and finally forecasting using ANFIS as well as SVM. In first stage the wind-power generation data from Elia, Belgium's electricity transmission system is collected for one year data i.e. from 2017-2018. Elia is a transmission system operator in Belgium. The load, interconnection, generation and balancing data can be downloaded on the elia.be website [14]. Based on the historical data of wind power in 2017 and 2018 from elia.be, the model is established with the ANFIS and SVM. After training and testing, the model gives a prediction for wind power in the proceeding 24 hours. This section introduces innovative computational intelligence architecture, as shown in figure 3.1, for the purpose of wind power prediction. A novel Fuzzy-based approach to wind data plagiarism detection, based on Fuzzy C-Means and the Adaptive-Neuro Fuzzy Inference System (ANFIS) as well as Gaussian Kernel based Support Vector Machine(SVM). The proposed framework consists of three phases i.e. Preprocessing, Post Processing Phase and Prediction Phase. Below each stage is described individually in details.

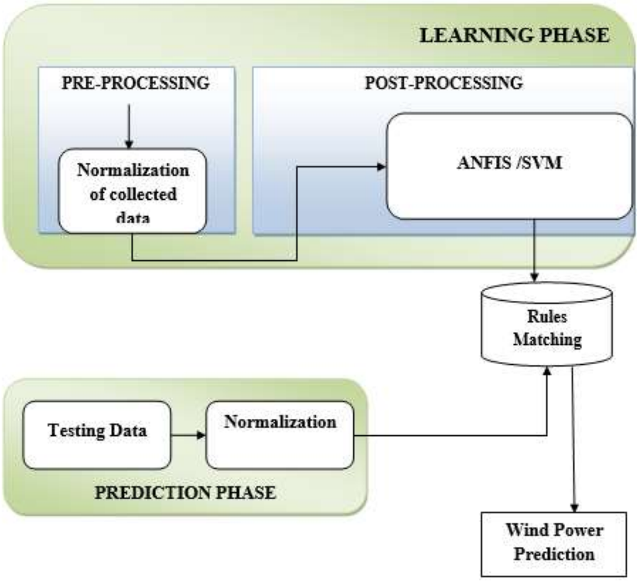


Figure 1: Flow Diagram of Electric Load Forecasting

A. Preprocessing Phase

The purpose of the Pre-processing phase is to normalize the data collected.

B. Post-Processing Phase

First of all the dataset is divided into training and testing data set. Testing data is created such as to predict 24 hours wind power using ANFIS classifier as well gaussian kernel based SVM classifiers.

Adaptive Neuro Fuzzy Inference system (ANFIS)

Step 1: Fuzzy C-Means (FCM) clustering

It is used to generate a cluster collection, each cluster containing the data identified by a collection of similar identifiers. One of the processes of dividing data elements into classes is the grouping of data. In data clustering, the elements of the same class are as similar as possible and the elements of different classes are as different as possible. Depending on the type of data and the purpose for which clustering is used, different similarity measures can be used to position elements in classes, with the degree of similarity that controls how the clusters are formed.

Formally, let V (n * k) be the wind data file n * k by size array containing the wind data file vectors vi such that V = [v1; v2; v3; :::; vn], where each file carrier contains k number of entities. Let c be the number of groups and the total number of wind files, 2 <= c <n. The matrix V is inserted into the FCM algorithm, which is a list of cluster centers X = x1; :::; xc is a membership matrix U, in which each element contains the total membership of a wind data file vk belonging to the group ci. FCM updates cluster centers and membership levels of each wind data file using the goal function.

Step 2: ANFIS Classification

The fuzzy grouping uses inference models based on adaptive neuro-fuzzy systems. ANFIS is a type of artificial neural network based on the Takagi Sugeno fuzzy inference system. Because it integrates both neural networks and the principles of fuzzy logic, it has the potential to capture the benefits of both in a single framework.
The adaptive inference system of neurofuzzle (ANFIS) [26] is a class of adaptive networks whose functionality corresponds to a fuzzy inference system (FIS) that automatically generates a fuzzy rule and membership functions (MF). The output of this system can be defined by the following equation:

$$\Upsilon = \sum_{k=1}^{n} \{\left(\left(\prod_{l=1}^{L} MF(k,l)(X(l)\right)(Z^k)\right) / (\sum_{k=1}^{n}(\prod_{l=1}^{L} MF(k,l)(X(l)))\} \quad (1)$$

Where, MF is the membership function, X(l) (l = 1, 2, …, L) is the lth input and Z^k is the output of lth fuzzy rule. ANFIS adjusts the parameters of Sugeno type inference system using the neural networks. ypically, the network topology of the adaptive neuro-fuzzy inference system [26] consists of connected nodes determined by parameters that change according to particular learning rules that minimize the error.
One possible set of rules is shown as an example in Equations :
Rule 1: If x is equal to a_1, y is equal to b_1, and z is equal to c_1,

then $f_1 = p_1x + q_1y + r_1y + s_1$ (2)

Rule 2: If x is equal to A_2, y is equal to B_2, and z is equal to c_2,

then $f_2 = p_2x + q_2y + r_2z + s_2$ (3)

Gaussian Kernel based Support Vector Machine (SVM)

This is for classification and regression problems. SVM classifies data into different classes by identifying a hyperplan (line) that separates learning data into classes. The hyperplane's identification, which maximizes the distance between classes, increases the probability of generalizing secret data. SVM offers the best classification performance i.e. the accuracy of the training set. It does not overflow the data.

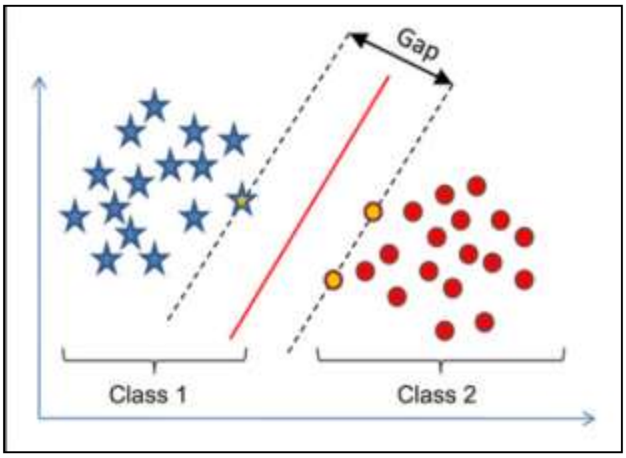


Figure 2: SVM Classifier

SVM does not make strong assumptions about the data. Show more efficiency in the correct classification of future data. SVM is classified into two categories, i. H. Linear and non-linear. In a linear approach, training data is represented by a line, i.e. hyperplane, shown separately.

Consider the problem of separating the set of training vectors belonging to two distinct classes,

G = {(x_i; y_i); i = 1; 2;:::;N} with a

hyperplane $w^T*(x) + b = 0$ (xi is the ith input vector, yi ∈ {−1; 1} is known binary target), the original SVM classi1er satisfies the following conditions:

$$w^T{*}\phi(x_i) + b \geq 1 \text{ if } y_i = 1$$
$$w^T{*}\phi(x_i) + b \leq 1 \text{ if } y_i = -1 \quad (4)$$

where ϕ: $R^n \rightarrow R^m$ is the feature map mapping the input space to a usually high dimensional feature space where the data points become linearly separable.

The distance of a point xi from the hyperplane is

$$d(x_i, w, b) = \frac{|w^T * \emptyset(x_i) + b|}{|w^2|} \quad (5)$$

The margin is 2/|w| according to its definition. Hence, we can find the hyperplane that optimally separates the data by solving the optimization problem:

$$min\emptyset(w) = \frac{1}{2}|w|^2 \quad (6)$$

For the inseparable linear problem, we first assign the data to another large space H using a non-linear mapping, which we call Φ. So we use the linear model to achieve classification in new space H. Through defined "kernel function" k, is converted as follows:

$$max \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j k(\vec{x_i} * \vec{x_j}) \quad (7)$$

$$s.t. \sum_{i=1}^{l} a_i y_i = 0 \qquad 0 \leq a_i \leq C, \quad (8)$$
$$i=1,2,\ldots\ldots\ldots l$$

And corresponding classification decision function is converted as follows:

$$f(x) = sign\left[\sum_{i=1}^{l} a_i y_i k(\vec{x_i} * \vec{x}) + b\right] \quad (9)$$

The selection of kernel function aims to take the place of inner product of basic function. The kernel function investigates the non-separable problems as follows:

$$k(x_i x_j) = \exp(-\gamma||x_i - x_j|| \quad (10)$$

IV. RESULT ANALYSIS

A. Dataset Description

A news dataset from Elia, Belgium's electricity transmission system is collected for one year data i.e. from 2017-2018. Elia is a transmission system operator in Belgium. The load, interconnection, generation and balancing data can be downloaded on the elia.be website [37]. Based on the historical data of wind power in 2017 and 2018 from elia.be, the model is established using the ANFIS and SVM. After training and testing, the model gives a prediction for wind power in the proceeding 24 hours.

B. Performance Parameters

Mean Square Error (MSE)

MSE of any estimator (classifier) measures the average squares of errors or deviations, i,e. the difference between the estimator and what is estimated. MSE is a risk function corresponding to the expected value of the squared error loss.

$$MSE = \frac{1}{N}(Target_{value} - Obtained_{value}) \quad (11)$$

Root Mean Square Error (RMSE)

RMSE is a parameter that determines the difference in squares between the output and the input.

$$RMSE = \sqrt{MSE} \quad (12)$$

Mean Absolute Error (MAE)

MAE measures the average size of errors in a series of forecasts regardless of their direction. This is the average of absolute differences between prediction and actual observation, in which all individual differences are also weighted.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \quad (13)$$

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a measure of the predictive accuracy of a forecasting method in statistics, for example in estimating the trend. It usually expresses the precision in percentage and is defined by the formula:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{Target_{value} - Obtained_{value}}{Target_{value}} \quad (14)$$

In this research work the wind power dataset is used to predict the 24hr ahead wind power prediction. This prediction is performed for all the four seasons i.e. summer, spring, autumn and winter using ANFIS classifier and gaussian kernel based classifier. Table I-Table IV illustrates performance analysis of both the classifiers.

Table I: Training and Testing Data Performance for Summer Season

SUMMER SEASON					
Training Data		MSE	RMSE	MAE	MAPE
	ANFIS	4.7408	2.1773	1.9065	0.0016
	SVM	0.0034	0.0584	1.3052	0.0013

SUMMER SEASON					
Testing Data		MSE	RMSE	MAE	MAPE
	ANFIS	5.6941	2.3862	2.207	0.0024
	SVM	0.0019	0.0433	0.8222	0.0013

Table II: Training and Testing Data Performance for Spring Season

SPRING SEASON					
Training Data		MSE	RMSE	MAE	MAPE
	ANFIS	6.6817	2.5849	1.852	0.0014
	SVM	9.50E-04	0.0308	0.6891	0.0067

SPRING SEASON					
Testing Data		MSE	RMSE	MAE	MAPE
	ANFIS	13.9595	3.7362	3.4102	0.0026
	SVM	0.0012	3.50E-02	0.6646	7.54E-04

Table III: Training and Testing Data Performance for Winter Season

WINTER SEASON					
Training Data		MSE	RMSE	MAE	MAPE
	ANFIS	398.7114	19.9678	15.446	0.0022
	SVM	0.003	0.0546	1.2219	2.67E-04

WINTER SEASON					
Testing Data		MSE	RMSE	MAE	MAPE
	ANFIS	0.4992	0.7066	0.6755	4.93E-04
	SVM	0.0011	0.0332	0.6304	7.30E-04

Table IV: Training and Testing Data Performance for Autumn Season

AUTUMN SEASON					
Training Data		MSE	RMSE	MAE	MAPE
	ANFIS	22.262	4.7183	4.1035	0.0015
	SVM	9.10E-04	0.0302	0.6744	0.0012

AUTUMN SEASON					
Testing Data		MSE	RMSE	MAE	MAPE
	ANFIS	30.8806	5.557	4.9589	7.23E-04
	SVM	0.0025	5.00E-02	0.9503	4.88E-04

Table V and VI summarize the performance evaluation of the ANFIS and gaussian SVM classifiers during the testing periods i.e. Summer, Spring, Winter, Autumn season and gaussian SVM achieved the average highest performance as compared to ANFIS with respect to all performance measures.

Table V: Averaged Performance Evaluation of ANFIS

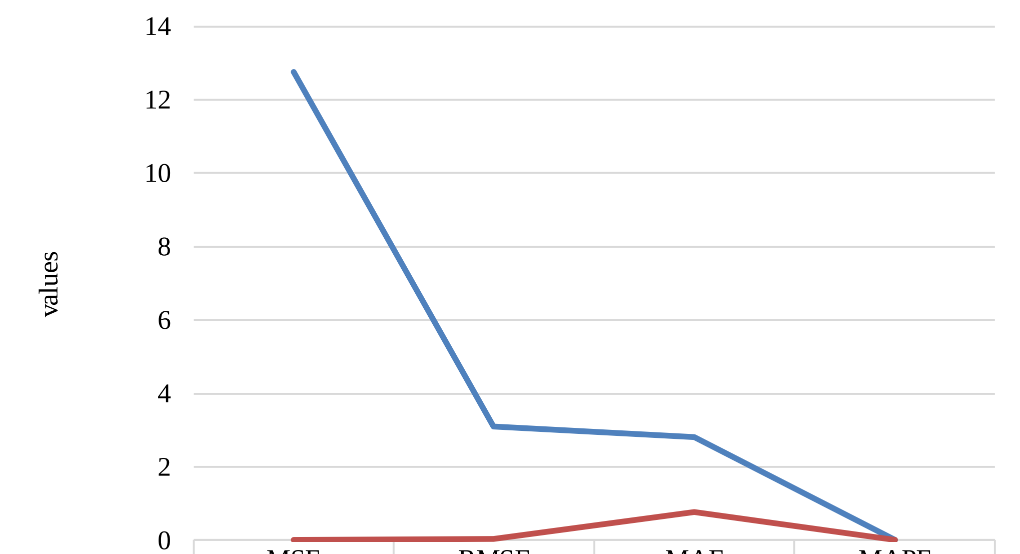
	MSE	**RMSE**	**MAE**	**MAPE**
SUMMER	5.6941	2.3862	2.207	0.0024
SPRING	13.9595	3.7362	3.4102	0.0026
WINTER	0.4992	0.7066	0.6755	4.93E-04
AUTUMN	30.8806	5.557	4.9589	7.23E-04
AVERAGE	12.75835	3.0965	2.8129	0.001554

Table VI: Averaged Performance Evaluation of Gaussian SVM

	MSE	**RMSE**	**MAE**	**MAPE**
SUMMER	0.0019	0.0433	0.8222	0.0013
SPRING	0.0012	3.50E-02	0.6646	7.54E-04
WINTER	0.0011	0.0332	0.6304	7.30E-04
AUTUMN	0.0025	5.00E-02	0.9503	4.88E-04
AVERAGE	0.001675	0.040375	0.766875	0.000818

Table VII: Comparative Performance Evaluation of Gaussian SVM and ANFIS

PARAMETERS	**ANFIS**	**SVM**
MSE	12.75835	0.001675
RMSE	3.0965	0.040375
MAE	2.8129	0.766875
MAPE	0.001554	0.000818



	MSE	RMSE	MAE	MAPE
ANFIS	12.75835	3.0965	2.8129	0.001553915
SVM	0.001675	0.040375	0.766875	0.000817858

Figure 3: Comparative Performance Evaluation of Gaussian SVM and ANFIS

Figure 6 illustrates the performance evaluation of the ANFIS and gaussian SVM classifiers during the testing periods i.e. Summer, Spring, Winter, Autumn season and gaussian SVM achieved the average highest performance as compared to ANFIS with respect to all performance measures.

V. Conclusion

Wind energy has become one of the most important renewable energy sources in the world for its advantages: less pollution, flexible investments, reduced construction time and less land use. However, the uncertainty of wind speed and wind direction makes it difficult to predict wind energy.

This research provides an overview of various tools with different techniques used to predict the performance of wind farms taking into account different time scales. Several forecasting models that have their characteristics have been discussed. Furthermore, the accuracy of the predictive models and the source of the error were highlighted. It is difficult to evaluate the performance of different models because the existing applications were different. In this research work two classifier's performance are evaluated on the real-time dataset. MSE, RMSE, MAE and MAPE are used as a performance parameter. From the result analysis it has been concluded that gaussian SVM outperforms better as compared to the ANFIS model. The result is analysed on different testing dataset of different seasons and averaged error is used to analyse the performance measures. Precise wind energy prediction models can certainly help transform wind farms into wind turbines. Future work will expand this research by forecasting wind speed and performance for long-term forecasts.

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