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Wind Power Prediction by using Matrix Factorization Technique

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Abstract- *As we know that, the wind energy provides opportunities to generate power cheaply and cleanly without affecting the environment. But due to rapid growth of wind power generation in the recent years, accurate wind power prediction is necessary for reliable power system operation. This paper introduced a method of short term wind power prediction for a wind power plant by using matrix factorization technique based on historical data of wind speed. We have taken ten years of historical wind speed data of Rotterdam, Netherland and Schiphol, Netherlands. From this wind speed data one to nine year of data has taken as training data set and last one year (10th year) of data has taken as test data set. The test data set has taken as fix and the training data set has taken as different (changing the size of training data set) for measured results. The test results of the prediction are presented and analyzed in this thesis. The prediction proposed is shown to achieve a high accuracy with respect to the measured data.*

Index Terms— *Matrix Factorization, MyMediaLite, Wind Speed Prediction, Optimization of Error*

I. INTRODUCTION

Electricity is generated in different of ways. Apart from solar power generation, other forms of electricity generation are in same way that primary energy pushes prime mover, and then the prime mover drives generators to generate electricity. Wind energy has many characteristic which other fossil energy doesn't have, such as clean, intermittent and randomness. This is because the wind is a natural phenomenon. Wind energy converts into mechanical energy in the way that wind blow through fans to drive rotor rotation. And then the energy converts into electricity without generating pollution and radiation which will be generated in the electricity conversion process of conventional energy. The reason why the demand for wind power around grows involves many aspects, including the shortage of energy, change in climate, the progress of economy and technology etc.

As of the end of 2016, the worldwide total cumulative installed electricity generation capacity from wind power amounted to 486,790 MW, an increase of 12.5% compared to the previous year. Installations increased by 54,642 MW, 63,330 MW, 51,675 MW and 36,023 MW in 2016, 2015, 2014 and 2013 respectively [1]. Since 2010 more than half of all new wind power was added outside of the traditional markets of Europe and North America, mainly driven by the continuing boom in China and India. At the end of 2015, China had 145 GW of wind power installed. In 2015, China installed close to half of the world's added wind power capacity.

Several countries have achieved relatively high levels of wind power penetration, such as 39% of stationary electricity production in Denmark, 18% in Portugal, 16% in Spain, 14% in Ireland and 9% in Germany in 2010. As of 2011, 83 countries around the world are using wind power on a commercial basis. Wind power's share of worldwide electricity usage at the end of 2014 was 3.1% [1].

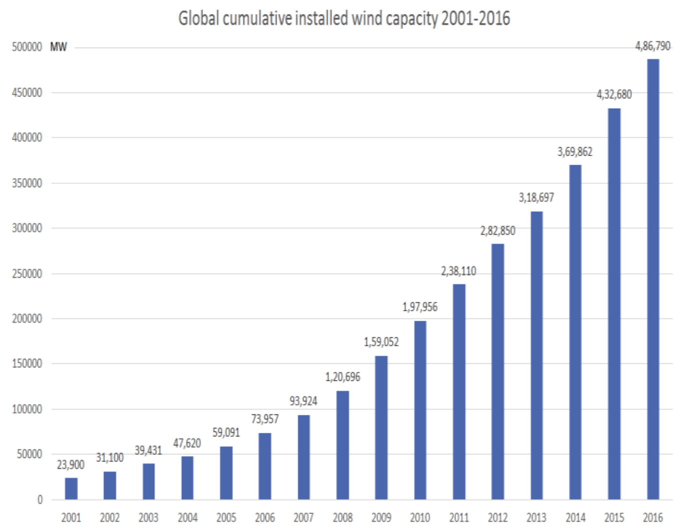

Fig. 1 Worldwide Wind power installed capacity (2001-2006)

It has been estimated by the World Wind Energy Association (WWEA) that by the year of 2020 around 12% of the world's electricity will be available through wind power, making wind energy one of the fastest growing energy resources [2] but integrating wind energy into existing electricity supply systems has been a challenge and numerous objections have been put forward by traditional energy suppliers and grid operators, especially for large-scale use of this energy source. The biggest concern is that availability mainly depends on meteorological conditions and production cannot be adjusted as conveniently as other more conventional energy sources, this is because of our inability to control the wind. A single Wind Turbine (WT) is highly variable and its dependency on wind conditions can result in zero output for more than thousands of hours during the course of a year, however, aggregating wind power generation over bigger areas decreases this chance.

This is where wind power forecasting systems come into play, a technology that can greatly improve the integration of wind energy into electricity supply systems as forecasting systems provide information on how much wind power can be expected at any given point within the next few hours or days.

The productions of wind turbine power rely on the energy carry in the wind. Wind power density is a fundamental measuring unit of the energy that carried by the wind or area's power per unit normal to wind azimuth. As Equation (1) where v is horizontal element of the mean free Stream wind velocity (m/s), A is area (m^2), P is wind power (W/m^2) and p is air density (kg/m^3).

$$P = 0.5\rho A v^3 (1)$$

Nevertheless, both air density and wind velocity are usually not consistent, outcomes in characteristics of strong dynamic power generation through a wind turbine. This characteristic of dynamic power production has two key aspects. For instance, from temporal and geographic point of view and if we see from geographic perspective, each turbine's power outputs rely on its wind farm geographic location that is usually different. The industry standard is associate the power of turbine to the hub height wind velocity [3].

There are many forecasting methods available. These methods can be cataloged into numeric weather prediction (NWP) methods, statistical methods, methods based upon artificial neural networks (ANNs), and hybrid approaches. NWP methods could be the most accurate technique for short-term forecasting. However, in general, statistical, ANN methods, or several advanced hybrid methods based on observations perform more accurately over the very short-term forecast range [4].

There are some drawbacks of neural networks. First, they have been criticized as being useful for prediction, but not always in understanding a model. It is true that early implementations of neural networks were criticized as "black box" prediction engines; however, with the new tools on the market today, this criticism is debatable. Secondly, neural networks are susceptible to over-training. If a network with a large capacity for learning is trained using too few data examples to support that capacity, the network first sets about learning the general trends of the data [5]. This is desirable, but then the network continues to learn very specific features of the training data, which is usually undesirable. Such networks are said to have memorized their training data, and lack the ability to generalize. Thus, For avoid this drawbacks of ANN method for prediction we moved on other method of prediction is Matrix Factorization.

Generally, Matrix factorization technique has used in recommender system. Recommender system have mainly two task like predict the user rating of particular item and second one is recommendation of top items. But in this paper we used matrix factorization technique for wind speed prediction only.

Most of the matrix factorization models are based on the linear factor model. In a linear factor model, wind speed matrix is modeled as the product of a day's coefficient matrix and an hour's factor matrix. During the training step, a low rank approximation matrix is fitted under the given loss function. One of the most commonly used loss function is sum-squared error. The sum-squared error optimized low rank approximation can be found using Singular Value Decomposition (SVD) or QR factorization [6].

The values of wind power distributions are needed for site selection, performance prediction and planning of wind turbines. Moreover, prediction of wind speed is needed for any regional inventory wind energy studies in advance. In this sense, the establishment of a model for wind speed correlation in a region is of great importance in the management of wind energy resources for power generation as well as in other research fields related to energy conservation [7]. The scope of this paper is confined to the statistical approach of forecasting of wind speeds and power using real experimental data collected over a period of ten years. Specific wind data from the Rotterdam, Netherland and Schiphol, Netherland were used to obtain both one step-ahead forecasts of wind speeds and power. The tools used for forecasting are Matrix Factorization (MF), MyMediaLite Recommender System Library and nonlinear models built with Visual studio computer software.

II. MATRIX FACTORIZATION

Some of the most successful realizations of latent factor models are based on matrix factorization. In its basic form, matrix factorization characterizes both hours and days by vectors of factors inferred from hour wind speed patterns. High correspondence between hour and day factors leads to a prediction. These methods have become popular in recent years by combining good scalability with predictive accuracy. In addition, they offer much flexibility for modeling various real-life situations. Prediction systems rely on different types of input data, which are often placed in a matrix with one dimension representing days and the other dimension representing hours.

A. *Basic Matrix Factorization Model*

Matrix factorization models map both days and hours to a joint latent factor space of dimensionality f, such that day-hour interactions are modeled as inner products in that space. Accordingly, each hour h is associated with vector$\mathrm{q_h} \in \mathrm{R^f}$, and each day d is associated with a vector $\mathrm{p_d} \in \mathrm{R^f}$. For a given hour h, the elements of $\mathrm{q_h}$measure the extent to which the hour possesses those factors, positive or negative. For a given day d, the elements of $\mathrm{p_d}$measure the extent of interest the day has in hour that are high on the corresponding factors, again, positive or negative. The resulting dot product$\mathrm{q_h^T p_d}$ captures the interaction between day d and hour h—the day's overall wind speed in the hour's characteristics. This approximates day d's wind speed of hour h, which is denoted by $\mathrm{w_{dh}}$, leading to the estimate

$$\widehat{\mathrm{w_{dh}}} = \mathrm{q_h^T p_d} \qquad (2)$$

The major challenge is computing the mapping of each hour and day to factor vectors$\mathrm{q_h}, \mathrm{p_d} \in \mathrm{R^f}$. After the prediction system completes this mapping, it can easily estimate the wind speed of any hour of any day by using equation (2).

Such a model is closely related to singular value decomposition(SVD), a well-established technique for identifyinglatent semantic factors in information retrieval. Applying SVD in the collaborative filtering domain requires factoring the day-hour wind speed matrix. This often raises difficulties due to the high portion of missing values caused by sparseness in the day-hour wind speed matrix. Conventional SVD is undefined when knowledge about the matrix is incomplete. Moreover, carelessly addressing only the relatively few known entries is highly prone to over fitting.

Earlier systems relied on imputation to fill in missing wind speed and make the wind speed matrix dense [8]. However, imputation can be very expensive as it significantly increases the amount of data. In addition, inaccurate imputation might distort the data considerably. To learn the factor vectors ($\mathrm{q_h}$ and $\mathrm{p_d}$), the system minimizes the regularized squared error on the set of known wind speeds:

$$\min_{q,p} \sum_{(d,h)\in k} (\mathrm{w_{dh}} - \mathrm{q_h^T p_d})^2 + \lambda(||\mathrm{q_h}||^2 + ||\mathrm{p_d}||^2) \quad (3)$$

Here, k is the set of the (d, h) pairs for which $\mathrm{w_{dh}}$ is known (the training set).

The system learns the model by fitting the previously observed wind speed. However, the goal is to generalize those previous wind speeds in a way that predicts future, unknown wind speeds. The second term of the formula is the regularization term, which ensures that the system does not over fit on the available data. Cross-validation (the day of different splits of training set and test set) is often used to avoid this. The λ factor determines to which extent the available wind speeds are regularized. The regularization avoids over fitting, which implies that the previous wind speeds are formed into general notions and thus can be used for future predictions. Thus, the system should avoid over fitting the observed data by regularizing the learned parameters, whose magnitudes are penalized.

B. Learning Algorithms

Two approaches to minimizing equation (3) are stochastic gradient descent (SGD) and alternating least squares (ALS).

1. Stochastic gradient descent

There are several ways to minimize the given function for regularized squared errors, one of which is 'stochastic gradient descent'. This is a learning algorithm that loops through the different wind speeds in the training set and for every case a prediction is made and then compares is to the actual wind speed to calculate the error:

$$e_{dh} = w_{dh} - q_h^T p_d \qquad (4)$$

It then modifies the parameters proportional to γ in the opposite direction of the gradient or derivative in that point:

$$q_h \leftarrow q_h + \gamma\,(e_{dh}.p_d - \lambda.q_h)$$
$$p_d \leftarrow p_d + \gamma\,(e_{dh}.q_h - \lambda.p_d)$$

This way the optimal parameters are learned as the looping continues, leading to the eventual best set of parameters for every day-hour pair. The looping process continues until all cases are treated or when convergence takes place then no more modifications are made to q_h and p_d . However because it has to run through all of the possible cases this involves many calculations. In recent research it has been shown that this kind of learning algorithm involves too many calculations to be feasible for large datasets.

2. Alternating least squares

An alternative to the stochastic gradient descent approach is the 'alternating least squares' approach. In this approach one of the feature vectors (q_h, p_d) is fixed. This causes the formula of the regularized least squares to become quadratic and can then be solved to find their optima's. It then rotates between fixing the day vector p_d and the hour vector q_h by doing this the 'regularized least squares' is decreased in every step until no more change is made by fixing one of the vectors (convergence). This method has the benefit, comparing to stochastic gradient descent, that in sparse training sets it does not loop endlessly through all the empty cases, however it starts with a certain value, which reduces the workload of the learning algorithm. In research is also mentioned that because of the constant fixing of one feature vector for a day or a hour it can perform its calculations in parallel, which also reduces the running time.

When allp_d's are fixed, the system recomputed theq_h's by solving a least-squares problem

$$\|W - PQ^T\|$$

We can fix the matrix P and Q one by one, such that minimization problem would be equivalent to

$$W = PQ^T$$
$$Q^T = (P^T P)^{-1} P^T W \quad \text{(P is Fix)}$$
$$P = WQ(Q^T Q)^{-1} \quad \text{(Q is Fix)}$$

Learning rule:

$$Q^T \leftarrow (P^T P)^{-1} P^T W$$
$$P \leftarrow WQ(Q^T Q)^{-1}$$

While in general stochastic gradient descent is easier and faster than ALS, ALS is favorable in at least two cases. The first is when the system can use parallelization. In ALS, the system computes each q_h independently of the other hour factors and computes each p_d independently of the other day factors. This gives rise to potentially massive parallelization of the algorithm. The second case is for systems centered on implicit data. Because the training set cannot be considered sparse, looping over each single training case—as gradient descent does—would not be practical. ALS can efficiently handle such cases.

III. MY MEDIA LITE LIBRARY

MyMediaLite is an open-source library of recommender system algorithms [9]. It focuses on two scenarios in collaborative filtering: Rating Prediction and Item Prediction from positive-only implicit feedback. It contains state-of-the-art algorithms for both tasks and does not require deep knowledge of programming to use. It was written in C#, but since then many applications have been made to modify it through other languages, like java, Python, etc. Its applications so far have mostly been for research purposes and development of new recommender algorithms, nevertheless it could also be used quite easily by companies to implement a recommender system. Besides the available algorithms it also provides the possibility of using self-developed recommender algorithms and the possibility to evaluate a recommender system on certain criteria like 'Root Mean Square Error (RMSE)' and 'Mean Average Error (MAE)'. The framework can be compared to a similar recommender system library called 'Duine Recommender' [10]. This library provided a set of recommender system algorithms together with the possibility of combining these algorithms (hybridizer) to form a hybrid recommender system. However as it was last updated in 2009, it does not offer state-of-the-art recommender algorithms, unlike the MyMediaLite framework, which was updated December 31st 2015.

To use the functionalities of the MyMediaLite framework the library only has to be downloaded and can then be accessed with the command-line tool which is available in every operating system. Its flexibility and extensibility have also been proven in several cases (such as the KDD Cup). It is both capable of making accurate recommendations as well as producing feasible runtimes for the available algorithms.

The rating files can be in different formats, it supports both integer and non-integer ratings. It consists of the user ID, the item ID and the rating value. The different values can be separated by a tab (.tsv), a whitespace or a comma (.csv), where tsv stands for "tab-separated values and csv stands for comma-separated values. It also allows for time and date stamping as this is often crucial for time-aware recommenders. The timestamps are given by a number, e.g. "978300760" and date stamps are written as "2005-12-04" for example. These are put behind the user ID, item ID and rating value and are separated by the same character that was used in the separation between the ID's and the rating value. An example of rating data with a date and time stamp is given by [6]:

Rating data with dates and times

5951	50	5	"2009-08-05 00:50:30"
5951	223	5	"2009-08-02 17:19:33"
5951	260	5	"2010-05-04 21:21:03"
5951	293	5	"2009-09-25 05:04:24"
5951	356	4	"2010-06-30 02:07:57"
5951	364	3	"2010-06-11 04:54:41"
5951	457	3	"2010-06-11 14:26:32"

Fig.2 rating data with date and time stamp

But, in our case we have wind speed data with day and hours. Thus, we have three columns in the csv file like Day Id, Hour Id, and Wind Speed Id respectively.

IV. RESULTS AND DISCUSSION

A. Analysis of wind speed data

The wind speed characteristics in two selected locations in the Rotterdam, Netherlands and Schiphol, Netherlands were investigated using wind speed data. We have taken ten year of wind speed data of Rotterdam, Netherlands and Schiphol, Netherlands. Here, Rotterdam wind speed data considered as a WF-1(Wind Farm-1) and Schiphol wind speed data considered as a WF-2(Wind farm-2). From the ten years of wind speed data, last one year of data taken as a test data set and one to nine year of data taken as a training data set. We will change the training data set (one year to nine year) and Test data set is a fixed for all the result. First of all we will predict the last two hour of wind speed for all the day of test data set by taking different training set.

The analytic graph of ten year wind speed for WF-1 and WF-2 are following:

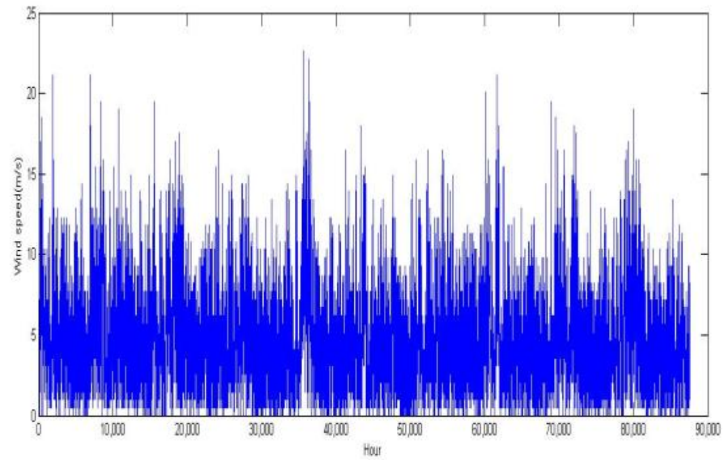

Fig. 3 Ten years wind speed data of WF-1

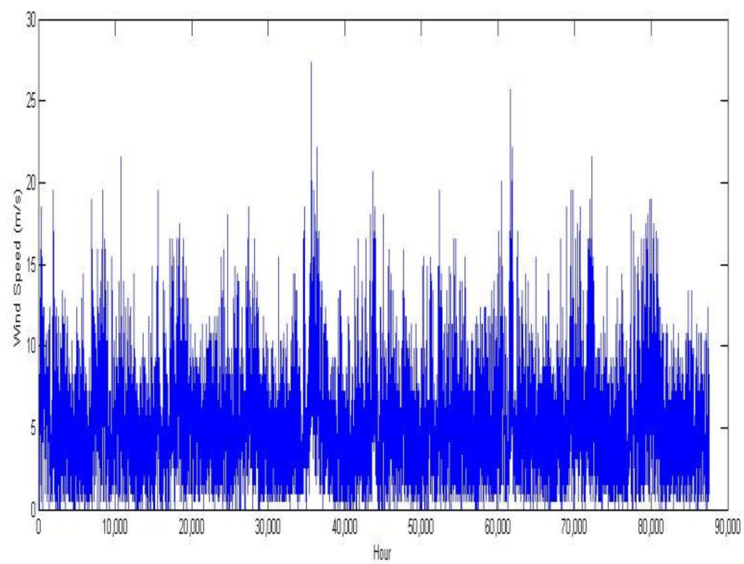

Fig. 4 Ten years wind speed data of WF-2

B. *Results of Error on 23h and 24h*

In the test data set, we have taken 1 to 22 hour as a known wind speed and 23 and 24 hour wind speed are unknown. So we will predict the wind speed on 23 and 24 hour of all the days of test data set and measure the errors for rank of matrix 1 to 24. First we taken only one year of data as a training data set and predict the wind speed on 23 and 24 hour of all the days of test data set and measured the different errors like maximum error, minimum error, mean absolute error and root mean square error on the 23 hour and 24 hour of the test data set showing in Fig.5 and Fig.6 for WF- and WF-2 respectively.

Now, same as we take 2 to 9 year of data as a training data set and calculate the different errors on 23 hour and 24 hour. By analysis of these all graphs of the error we can say that the error on 24 hour is larger than the error on 23 hour. Thus, if we predict wind speed is only one hour then the error will be minimum compared to error on second hour prediction.

C. *Results of minimum error on 23h and 24h*

From the all the year of training data set we get minimum error for all the size of training set (1 to 9 years)for both the wind farm. The minimum error shows in Fig. 7 and Fig. 8

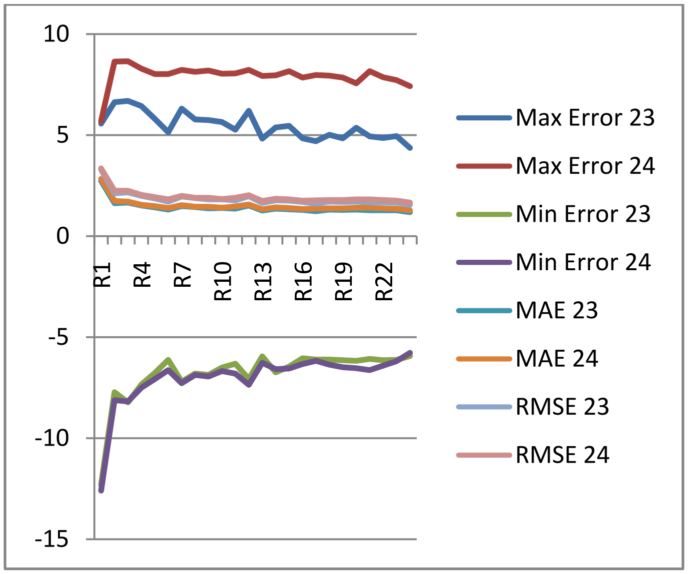

Fig. 5 WF-1 one year training data

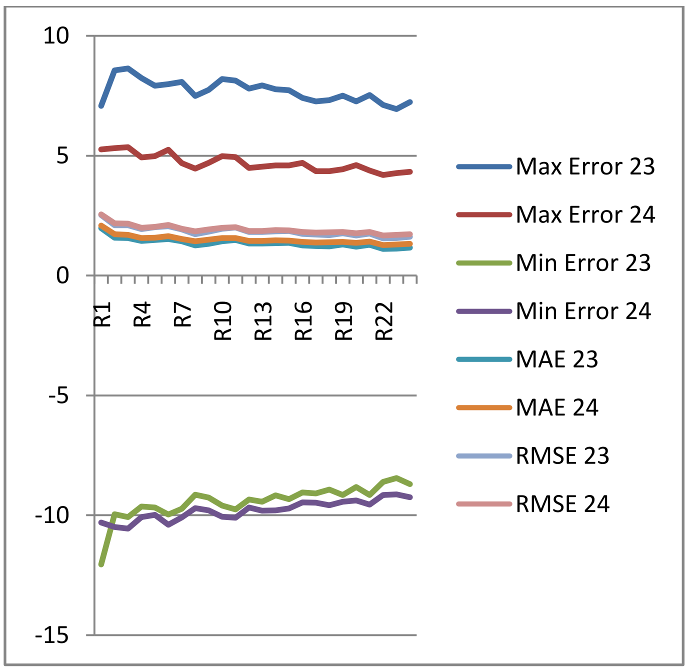

Fig. 6 WF-2 one year training data

D. Condition for minimum errors

We get minimum error on different point of the graph. In the following table we have indicated the minimum error on particular point (size of training data set and rank of factorization).

Here, different error like Maximum Error 23, Maximum Error 24, Minimum Error 23, Minimum Error 24, MAE 23, MAE 24, RMSE 23 and RMSE 24 are minimum for the particular size of training data set and rank of factorization of matrix. For WF-1 size of training data set are three, four and nine years for minimization of errors. For WF-2 size of training data set are four, seven and eight years for minimization of errors. Table 1 and Table 2 are showing the minimum error of particular conditions for WF-1 and WF-2 respectively. For this all particular condition of minimum errors we have optimized which condition will better for prediction of wind speed for particular wind farm.

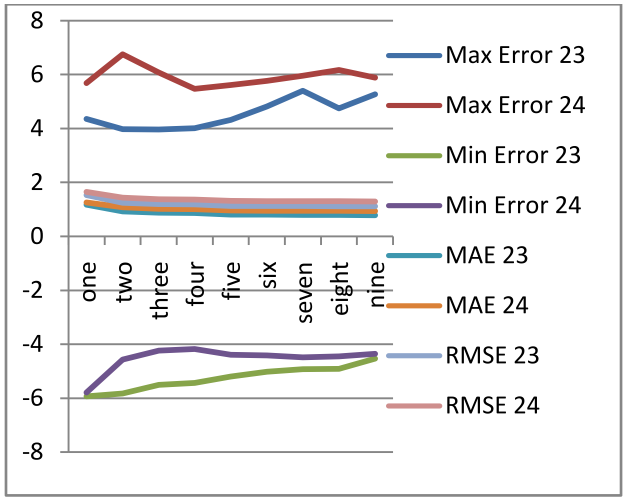

Fig. 7 WF-1 minimum errors

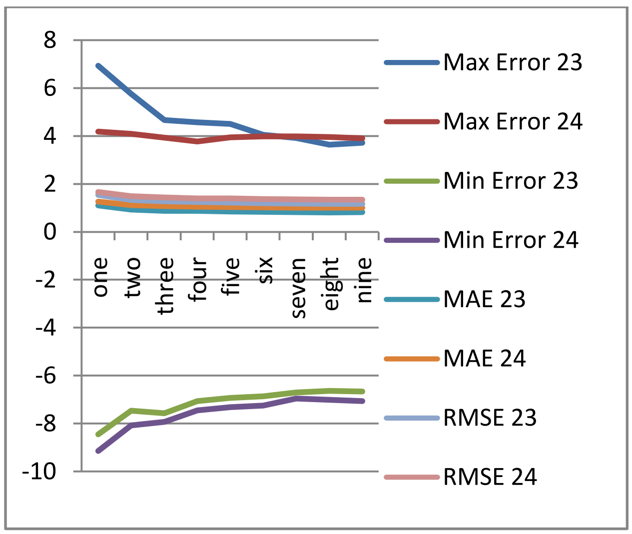

Fig. 8 WF-2 minimum errors

Table 1 Condition of minimum error for WF- 1

WF-1	Minimum error	Condition
Max23	3.968	3 year and R6
Max24	5.475	4 year and R13
Min23	-4.530	9 year and R18
Min24	-4.176	4 year and R11
MAE23	0.792	9 year and R24
MAE24	0.935	9 year and R12
RMSE23	1.122	9 year and R20
RMSE24	1.299	9 year and R12

Table 2 Condition of minimum error for WF- 1

WF-1	**Minimum error**	**Condition**
Max23	3.640	8 year and R9
Max24	3.776	4 year and R22
Min23	-6.629	8 year and R23
Min24	-6.955	7 year and R9
MAE23	0.817	8 year and R23
MAE24	1.016	8 year and R23
RMSE23	1.175	8 year and R23
RMSE24	1.348	8 year and R23

E. Optimization of condition for minimum errors

For the optimization of condition for minimum errors we have predicted hourly wind speed of last one day as well as last ten days for both the wind farm. For the prediction of hourly wind speed we have shifted each element of matrix on the left side and first element of each rows are shifted on last element of their upper row. Here, some tables are given for the Maximum error, Minimum error, MAE and RMSE of the hourly wind speed prediction for last one day and last ten days of both the wind farm.

Table 3 Min. errors condition analysis of one day wind speed prediction for WF-1

Condition	**Max. error**	**Min. error**	**MAE**	**RMSE**
9 year and R12	1.435	-0.851	0.552	0.660
9 year and R18	1.442	-1.067	0.572	0.688
9 year and R20	1.239	-1.067	0.555	**0.653**
9 year and R24	1.501	-0.982	0.562	0.684
4 year and R11	1.515	-0.882	0.569	0.697
4 year and R13	1.611	-0.941	0.562	0.684
3 year and R6	1.529	-0.624	0.648	0.769

Table 4 Min. errors condition analysis of ten days wind speed prediction for WF-1

Condition	**Max. error**	**Min. error**	**MAE**	**RMSE**
9 year and R12	4.231	-3.723	0.809	1.082
9 year and R18	3.945	-3.666	0.804	1.072
9 year and R20	3.855	-3.615	0.798	**1.049**
9 year and R24	4.109	-3.711	0.795	1.067
4 year and R11	4.789	-3.807	0.909	1.204
4 year and R13	4.974	-3.825	0.902	1.201
3 year and R6	4.443	-4.234	1.039	1.345

Table 5 Min. errors condition analysis of one day wind speed prediction for WF-2

Condition	Max. error	Min. error	MAE	RMSE
8 year and R9	1.849	-1.261	0.644	0.829
8 year and R11	1.851	-1.037	0.591	0.767
8 year and R23	1.844	-1.056	0.559	**0.759**
7 year and R9	1.836	-1.184	0.583	0.782
4 year and R22	1.883	-1.239	0.646	0.854

Table 6 Min. errors condition analysis of ten day wind speed prediction for WF-2

Condition	Max. error	Min. error	MAE	RMSE
8 year and R9	4.203	-4.891	0.918	1.233
8 year and R11	3.997	-4.643	0.897	1.185
8 year and R23	3.594	-4.440	0.854	**1.136**
7 year and R9	4.163	-4.823	0.901	1.202
4 year and R22	4.093	-4.689	0.916	1.216

Each and every wind farms have different characteristics of the wind speed. Thus, the selection of training set size and rank of matrix factorization are different for different wind farm. From the analysis of the condition of minimum error for WF-1 and WF-2 are different. According to the relation between wind energy and system operation action [14] they consider RMSE is the minimum as possible. By analyzed these conditions we get minimum RMSE when we selected nine year training data set and Rank 20 for WF-1. And we get minimum RMSE when we selected eight year training data set and Rank 23.

Thus, we get best results for hourly wind speed prediction by selecting nine year training data set and Rank 20 for WF-1 and by selecting eight year training data set and Rank23.

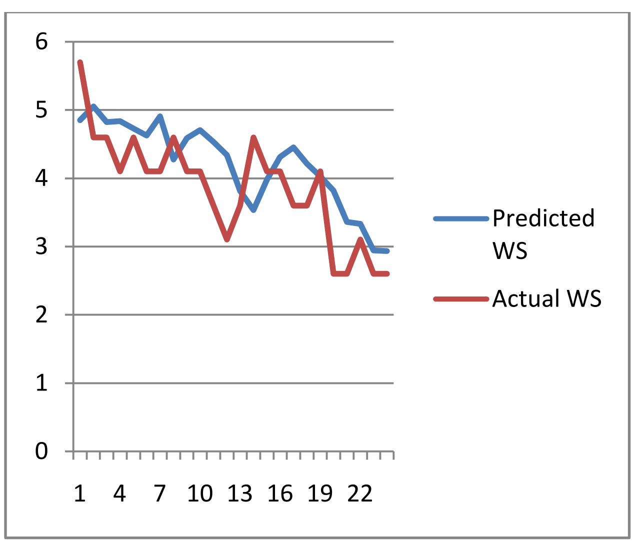

Fig. 9 Hourly wind speed prediction for one day of WF-1

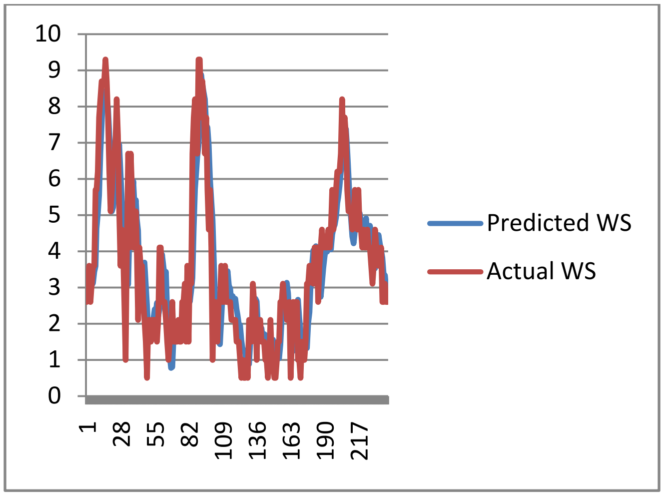

Fig. 10 Hourly wind speed prediction for ten days of WF-1

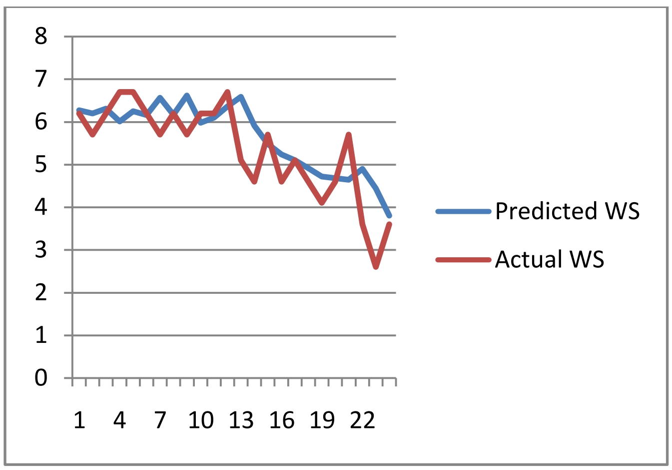

Fig. 11 Hourly wind speed prediction for one day of WF-2

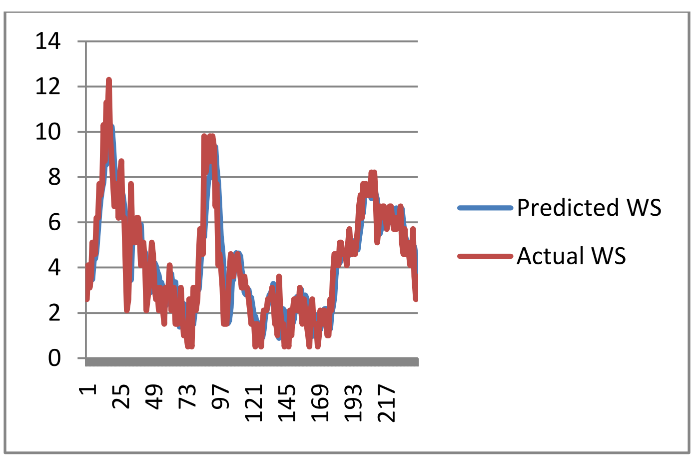

Fig. 12 Hourly wind speed prediction for ten days of WF-2

After predicting this wind speed we can predict the wind power by using the equation (1).

V. CONCLUSION

This paper intends to present the basics on prediction of wind speed with Matrix Factorization, define different errors like maximum error, minimum error, MAE, RMSE. However, these errors changed with change in the size of training data set. And these errors are changed with different wind farm characteristics. If we increase the duration of prediction the MAE and RMSE are also increased. For the different number of factorization of the matrix these are also changed. As we decreased the training data set and rank of factorization the time taken for the output of prediction is also decreased in visual studio (MyMediaLite Library).

A general conclusion that may be drawn from the obtained results is that both wind farms, if we increase the duration of prediction the MAE and RMSE are also increased. And the MAE and RMSE are decreased with more historical data of wind speed. Matrix Factorization method achieve slightly better prediction, but they need Re-factorization during prediction of each and every hour wind speed prediction. The predicted wind speed is much more accurate when the predictions are performed with an hour in advance than when they are done with more than one hour prediction, as it is error on 23 hour and 24 hour.

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