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Technical note

Data mining and wind power prediction: A literature review

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ABSTRACT

Wind power generated by wind turbines has a non-schedulable nature due to the stochastic nature of meteorological conditions. Hence, wind power predictions are required for few seconds to one week ahead in turbine control, load tracking, pre-load sharing, power system management and energy trading. In order to overcome problems in the predictions, many different wind power prediction models have been used to achieve in the literature. Data mining and its applications have more attention in recent years. This paper presents a review study banned on very short-term, short-term, medium-term and long-term wind power predictions. The studies available in the literature have been evaluated and criticized in consideration with their prediction accuracies and deficiencies. It is shown that adaptive neuro-fuzzy inference systems, neural networks and multilayer perceptrons give better results in wind power predictions.

1. Introduction

Fossil fuels are consuming day by day all over the world and the need for electric energy is increasing. This current state leads electric energy producers to utilize renewable energy sources such as wind, solar, geothermal and biomass. The wind energy has significant advantages with respect to other sources in terms of installation and generation costs. The most crucial indicator of this case is that the utilization ratio of wind energy has shown an average growth rate of 30% during the last 15 years. In addition, the installed global cumulative wind power capacity increased to 197.039 GW in 2010 while it was about 6.1 GW in 1996 [1].

The performance of wind turbines has not been analyzed sufficiently during the rapid development process of wind energy systems. Wind power has an intermittent and variable structure, so it is necessary to determine that where, when and how much wind power will be utilized in different time scales. Thus, more effective and efficient system installations are realized. For these reasons, wind power generated by wind turbines has to be predicted and in this stage, data mining techniques come into prominence for accurate predictions. Data mining has risen from the intersection of machine learning, pattern recognition, statistics, database management systems, intelligent systems and data visualization and maintains its development in this context [2].

This paper provides a brief review on data mining and a detailed review on wind power prediction. The main contributions of this paper are the emphasis on adapting user-centered interactive approach to knowledge discovery process in databases and the determination of the best prediction models for very-short term, short-term, medium-term and long-term wind power prediction. Besides, many deficiencies in the literature explained comprehensively and the solutions related to them are proposed in an acceptable way.

This paper is organized as follows. Section 2 describes data mining, knowledge discovery process in databases and user-centered interactive approach. Section 3 presents data mining techniques with a few samples. Very-short term, short-term, medium-term and long term wind power predictions are compared and evaluated in Section 4. Finally, prospects and conclusion are available in Section 5 and Section 6 respectively.

2. Data mining

Data mining is the process in databases to discover and to reveal previously unknown, hidden, meaningful and useful patterns [3,4]. The stages taking part in knowledge discovery process in databases are shown in Fig. 1 [5].

Data preprocessing includes the stages of data cleaning, data integration and data reduction. Missing and faulty data are removed from the database in the stage of data cleaning.

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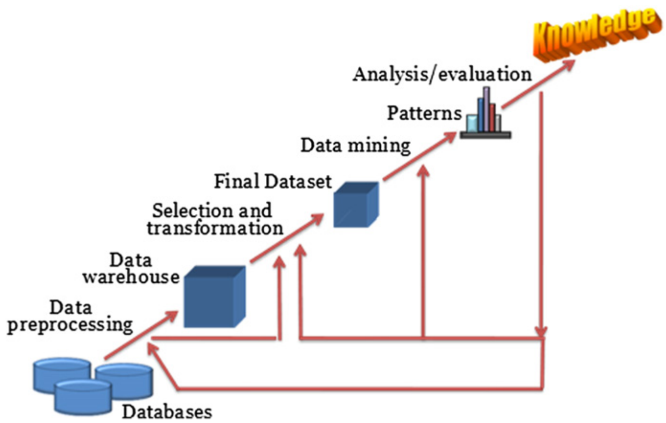

Fig. 1. Knowledge discovery process in databases.

Knowledge domain experts have also the option to complete missing data. Different data types obtained from different databases are converted into a single type in data integration. If it is considered that analysis results will not change, the number of data and variables are reduced for a short-term analysis process in data reduction. A set of samples which are appropriate for the query are determined in data selection. A processable and convenient data form is performed for data mining techniques in data transformation. As a result, data mining techniques are applied to the final data in data mining stage and the knowledge discovered is evaluated according to validity, novelty and utility criteria in the pattern evaluation stage. Knowledge discovery process in databases contains many repetitions, transitions between stages and forward-backward movements [6,7].

Adaptability and efficiency of the knowledge discovery process are ignored in Fig. 1 and so, the knowledge discovery process concentrates on finding the patterns remained hidden in databases autonomously [8]. However, users can be enabled in order to determine the most suitable data mining technique through adapting a user-centered interactive approach to knowledge discovery process. Thus, users achieve the most useful and meaningful patterns for themselves [8,9]. The interactivity features called navigation, information acquisition, manipulation, evaluation and explanation should be added to knowledge discovery processes to perform user-centered interactive data mining systems [8,10]. Besides, user-centered interactive data mining systems not only have flexible usage, minimum design structure, error prevention mechanism but also minimize the memory load of users [11].

3. Data mining techniques

Many approaches, methods and algorithms have been developed in the field of data mining. Data mining techniques are classified as characterization and discrimination, classification, cluster analysis, association analysis, outlier analysis and evolution analysis [6,12]. These techniques are briefly described as below.

Characterization is used for summarizing the general characteristics of any dataset. However, discrimination is utilized for determining the diversities among different datasets. The products whose sales rates are over 25% for a year in a shopping center are based on the characterization technique. Whereas, comparison of the products whose sales rates increased up to 10% and the products whose sales rates decreased up to 15% is based on the discrimination technique [13].

Classification is used for determining the class of a new observation utilizing available classes of the observations in training set [14]. Grouping the customers as the ones who paid in a three-day period and the ones who paid over a three-day period is based on the classification technique. Decision trees, regression analysis, artificial neural networks, support vector machines, Naïve Bayes algorithm, k-nearest neighbor algorithm and genetic algorithm are among the classification techniques [15].

Cluster analysis is used for clustering similar data structures in any dataset [16]. Determining the real group of the musical instruments according to their sound signals is based on the clustering technique [17]. Hierarchical methods, partitioning methods, density-based methods, grid-based methods and heuristic methods are among the clustering techniques [16].

The association analysis discovers relationships among observations and determines which observations can be realized together [18]. Apriori algorithm is one of the techniques used in association analysis. Many data mining techniques detect the exceptions as a noise but the exceptions can contain more information with respect to other observations. For this reason, outlier analysis is used in the stage of analyzing the observations that differ from the data distribution model of available dataset [19]. As the last technique, the main aim of evolution analysis is to reveal time-varying tendencies of the observations within the dataset [20].

4. Data mining in wind energy systems

Many applications of data mining have been achieved in wind energy systems as summarized in Fig. 2. However, wind power prediction is still one of the biggest challenges in wind energy systems due to its intermittence and variability. As can be seen in Fig. 2, many studies are about wind prediction and related topics. As a result, it is needed to predict wind power produced by wind turbines for few seconds to 1 week ahead. Thus, dispatchers make decisions and plans about turbine control, load tracking, pre-load sharing, power system management, energy trading, maintenance and repair of the turbine. For this purpose, very short-term, short-term, medium-term and long-term time scales are used for wind power prediction in practice [31,32]. Detailed reviews on wind power predictions will be presented in the subsections considering recent published papers.

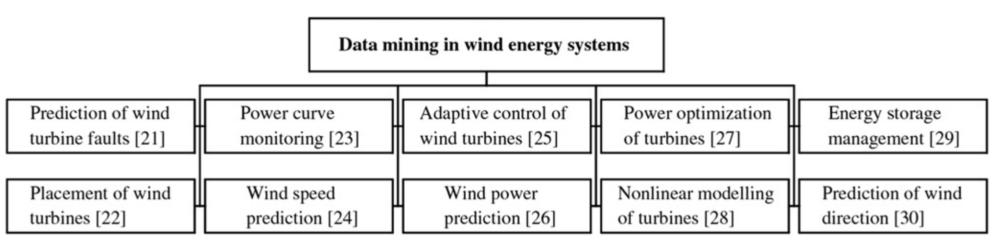

Fig. 2. Different applications of data mining in wind energy systems.

Table 1
Different methodologies applied for very short-term wind power predictions.

Ref.	Input data	Recording intervals	Total dataset in		Models used in the studies
			Training	Test	
[33]	Wind power, wind speed, wind direction	10-min	1500 –	 –	Third-order regression model, first-order artificial neural network model
[34,35]	Total wind farm power	1-min	20,160 14,400	 5760	Adaptive neuro-fuzzy inference system
[36]	Wind power	10-min	8000 6000	 2000	Markov-switching autoregressive model
[37]	Wind power, wind speed	10-min	4347 3476	 871	Multilayer perceptron, REP tree, M5P tree, bagging tree, combination of k-nearest neighbor algorithm and principal component analysis
[38]	Wind power	10-min	28-month 20-month	 8-month	First order Markov chain model, second order Markov chain model
[39]	Wind power, wind speed, wind generator speed, voltage and current in all phases	1-sec	3-h –	 –	Autoregressive moving average model, functional autoregressive moving average model, focus time-delay neural network model
[40]	Wind power, wind speed, wind direction, rotor speed, generator torque, blade pitch angle	10-sec	80,000 60,000	 20,000	Neural network model, boosting tree, random forest, support vector machine, k-nearest neighbor algorithm
[41]	Wind power, wind speed	1-sec	900-min –	 –	Artificial neural network model along with adaptive Bayesian learning and Gaussian process approximation
[42–45]	Wind power	15-min	24-h –	 –	Autoregressive integrated moving average model, neural networks, neural networks with wavelet transform, wavelet neuro-fuzzy model, combination of particle swarm optimization and adaptive-network-based fuzzy inference system
[46]	Wind power	10-min	470 370	 100	Combination of wavelet transform, weighted one-rank local-region method and first-order one-variable grey differential equation model

4.1. Very short-term wind power prediction

Very short-term wind power predictions are used for turbine control and load tracking and include the predictions for few seconds to 30 min ahead [31]. Different methodologies applied in this time scale are summarized in Table 1 and Table 2 based on recent publications.

For instance, in [37], wind power and wind speed parameters were recorded at 10-min intervals and total dataset resulted in 4347 observations (3476 data points for training and 871 data points for test). Multilayer perceptron, REP tree, M5P tree, bagging tree, combination of k-nearest neighbor algorithm and principal component analysis were used to construct power prediction models. The combination of k-nearest neighbor algorithm and principal component analysis outperforms the other four algorithms in terms of prediction accuracy. The mean absolute error of this technique is about 2255 kW at 10-min ahead prediction.

In general overview, artificial neural network models and adaptive neuro-fuzzy inference systems give better results with respect to other methods used in very short-term wind power prediction. If it is necessary to prefer one of these methods, the adaptive neuro-fuzzy inference system is proposed. However, there are only two meteorological towers in [33], power production scenarios are not sufficient in [34,35,46], the parameter uncertainty is not considered adaptively in [36], the weighted voting method is not adapted to the k-nearest neighbor algorithm in [37], the prediction accuracy decreases in case the prediction horizon increases in [38,40,41], the mean absolute error of focus time-delay neural network model increases with dynamic model of the wind turbine in [39].

4.2. Short-term wind power prediction

Short-term wind power predictions are utilized for pre-load sharing and include the predictions from 30 min to 6 h [31].

Table 2
Performances of methodologies applied for very short-term wind power predictions.

Ref.	Proposed model	Prediction intervals	MAE (kW)	MAPE (%)	NMAE (%)	NRMSE (%)
[33]	First-order artificial neural network model	10-min	25.90	–	–	–
[34,35]	Adaptive neuro-fuzzy inference system	5-min	–	–	1.390	1.980
[36]	Markov-switching autoregressive model	10-min	–	–	2.200	3.790
[37]	Combination of k-nearest neighbor algorithm and principal component analysis	10-min	2255	–	–	–
[38]	Second order Markov chain model	10-min	–	–	–	16
[39]	Focus time-delay neural network model	15-min	64.52	–	–	–
[40]	Neural network model	10-sec	7.341	–	–	–
[41]	Artificial neural network model along with adaptive Bayesian learning and Gaussian process approximation	5-min	–	–	2.500	2.900
[42–45]	Combination of particle swarm optimization and adaptive-network-based fuzzy inference system	15-min	–	3.130	–	–
[46]	Combination of wavelet transform, weighted one-rank local-region method and first-order one-variable grey differential equation model	10-min	–	18.39	3.680	4.620

Abbreviations: MAE: Mean absolute error, MAPE: Mean absolute percentage error, NMAE: Normalized mean absolute error, NRMSE: Normalized root mean square error.

Table 3
Different methodologies applied for short-term wind power predictions.

Ref.	Input data	Recording intervals	Total dataset in		Models used in the studies
			Training	Test	
[47]	Wind power	1-h	4-month 80-day	 40-day	Combination of neuro-fuzzy and artificial neural network model
[48]	Weather data, wind power	1-h	3.5-year 2-year	 1.5 year	Artificial neural network, k-nearest neighbor algorithm based on particle swarm optimization, k-nearest neighbor algorithm based on differential evolution, artificial neural network based on particle swarm optimization and artificial neural network based on differential evolution models
[49]	Wind power	1-h	6-month 3-month	 3-month	Autoregressive moving average model, artificial neural network model and artificial neural network model based on wavelet transform
[50]	Wind speed, wind power	1-h	742 593	 149	Support vector machine regression, multilayer perceptron, M5P tree, REP tree, bagging tree
[51]	Wind speed, wind power	1-h	8760 5840	 2920	Cascaded, parallel and separated multilayer feed-forward neural network models trained by a simultaneous perturbation stochastic approximation (SPSA) algorithm
[52]	Wind speed, wind power	1-h	1-month 20-day	 10-day	Support vector machine model, piecewise support vector machine model based on genetic algorithm
[53]	Wind speed	10-min	1440 1296	 144	Back propagation neural network model, momentum back propagation neural network model, genetic back propagation neural network model
[54]	Wind power, wind speed	10-min	4-year –	 –	Artificial neural network model, autoregressive integrated moving average model, autoregressive integrated moving average model with exogenous variables, adaptive neuro-fuzzy inference system
[55]	Wind power, wind speed	1-h	400 150	 250	Improved time series model based on wavelet transform (WT), back propagation neural network model
[56]	Wind speed, wind power	1-h	5-year 3-year	 2-year	Autoregressive moving average model, multilayer feed-forward neural network model, Elman back propagation network model, multilayer perceptron, adaptive neuro-fuzzy inference system

Different methodologies carried out in this time scale are presented in Table 3 and Table 4.

Autoregressive moving average models, support vector machines and multilayer perceptrons have a wide range of application in short-term wind power prediction. However, artificial neural network models based on wavelet transform or particle swarm optimization and feed forward and back propagation neural network models come into prominence in general overview. In addition to these, the mean absolute percentage error obtained in the 0–10 MW class is better than the one obtained in 10–67.35 MW class in [47], the errors get accumulated in case the number of prediction steps increases in [50,52,55,56], the errors occur at the points with high wind speed and low wind speed in [51], the parameters of temperature, humidity, air density, etc. which affect the wind speed did not considered in [53], the numerical weather prediction values could not be achieved accurately because of the very short time in [54].

4.3. Medium-term and long-term wind power prediction

Medium-term wind power predictions are used for power system management and energy trading and include the predictions for 6 h to 1 day ahead. However, long-term wind power predictions are utilized for maintenance and repair of the wind turbine and include the predictions from 1 day to 1 week [31]. Different methodologies performed in this time scale are given in Table 5 and Table 6.

Artificial neural network models, adaptive neuro-fuzzy inference systems and multilayer perceptrons are the most popular types employed in medium-term and long-term wind power prediction. In fact, it is obvious that multilayer perceptrons demonstrates better performance in terms of prediction accuracy for 6 h to 3 days ahead prediction. However, the prediction error increases in case the prediction time lengthens in [57] and the seasonal performance of the proposed models cannot be validated in [59].

Table 4
Performances of methodologies applied for short-term wind power predictions.

Ref.	Proposed Model	Prediction intervals	MAE (kW)	MAPE (%)	MRE (%)	RMSE (kW)	NMAPE (%)	NRMSE (%)	IMPR (%)
[47]	Combination of neuro-fuzzy and artificial neural network model	6-h	–	10.46	–	–	–	–	–
[48]	Artificial neural network based on particle swarm optimization	1-h	–	–	–	–	–	–	9.8
[49]	Artificial neural network model based on wavelet transform	3-h	5210	–	–	–	–	–	–
[50]	Multilayer perceptron	1-h	5937		19.31		–		–
[51]	Cascaded multilayer feed-forward neural network models trained by SPSA	1-h	43.41	–	–	64.58	–	–	–
[52]	Piecewise support vector machine model based on genetic algorithm	3-h	–	–	10.88	–	–	–	–
[53]	Genetic back propagation neural network model	3-h	3.53	–	2.38	4.031	–	–	–
[54]	Adaptive neuro-fuzzy inference system	1-h	–	–	–	–	–	2.34	–
[55]	Improved time series model based on the WT	5-h	70.72	1.42	–	–	–	–	–
[56]	Multilayer perceptron	6-h	–	–	–	–	11.19	–	–

Abbreviations: MAE: Mean absolute error, MAPE: Mean absolute percentage error, MRE: Mean relative error, RMSE: Root mean square error, NRMSE: Normalized root mean square error, IMPR: Mean improvement ratio, NMAPE: Normalized mean absolute percentage error, SPSA: Simultaneous perturbation stochastic approximation, WT: Wavelet transform.

Table 5
Different methodologies applied for medium-term and long-term wind power predictions.

Ref.	Input data	Recording intervals	Total dataset		Model(s)
			Training	Testing	
[47]	Wind power	1-h	4-month 2/3-month	 1/3-month	Combination of neuro-fuzzy and artificial neural network model
[54]	Wind power, wind speed	10-min	4-year –	 –	Artificial neural network model, autoregressive integrated moving average model, autoregressive integrated moving average model with exogenous variables, adaptive neuro-fuzzy inference system
[56]	Wind speed, wind power	1-h	5-year 3-year	 2-year	Autoregressive moving average model, multilayer feed-forward neural network model, Elman back propagation network model, multilayer perceptron, adaptive neuro-fuzzy inference system
[57]	Wind speed	1-day/3-day	365/121		Recurrent neural network model, feed-forward neural network model
[58]	Wind power, wind speed, wind direction	1-h	4224 3264	 960	Infinite impulse response multilayer perceptron, local activation feedback multilayer network model, diagonal recurrent neural network model
[59]	Wind power, wind speed, wind direction, air density, potential temperature	1-h	2250 1798	 452	Support vector machine regression, multilayer perceptron, radial basis function, classification and regression tree, random forest
[60]	Wind power, wind speed, wind direction, air pressure, temperature, humidity	0.5-h	54-week 52-week	 2-week	Neuro-fuzzy network model

5. Discussion and prospects

Wind power prediction techniques reviewed in this paper have their own characteristics and give effective results in different situations. However, the main advantage of this study on the basis of literature is that the models which are able to give better performance for different time scales are specified for very-short term, short-term, medium-term and long-term wind power predictions. Adaptive neuro-fuzzy inference systems in very-short term wind power prediction, artificial neural network models in short-term wind power prediction, multilayer perceptrons in medium-term and long-term wind power predictions are considered as the convenient and efficient models.

Many deficiencies and important points in the literature and the solutions proposed in this paper are summarized as follows:

- the systems developed for wind power prediction include often very-short term and short-term time scales. Future studies should focus on medium-term and long-term wind power predictions in order to increase the performance of wind energy systems in terms of power system management, energy trading, maintenance and repair of the wind turbines.
- the works are mainly focused on prediction, optimization, monitoring, control, modeling, and managements in wind energy systems.
- there have been no standard databases to test and compare the developed systems properly. A database having the types of input parameters, the recording intervals of data, the number of training and test data and the error metrics in a standard way can be constructed for each time scale in wind power prediction.
- many classification techniques have been used in data mining for different applications. Clustering and association techniques of data mining should be also considered for the purpose of obtaining different inferences. For instance, an agglomerative hierarchical clustering method can be used for making the feasibility analysis of wind energy systems.
- the specifications containing information about total datasets, training sets, test sets and data recording intervals are rarely available in the literature studies. These specifications should

Table 6
Performances of methodologies applied for medium-term and long-term wind power predictions.

Ref.	Proposed Model	Prediction intervals	MAE (kW)	MAPE (%)	RMSE (kW)	NMAPE (%)	NRMSE (%)
[47]	Combination of neuro-fuzzy and artificial neural network model	12-h	–	11.66	–	–	–
		18-h	–	9.94	–	–	–
		24-h	–	10.22	–	–	–
[54]	Adaptive neuro-fuzzy inference system	1-day	–	–	–	–	3.10
[56]	Multilayer perceptron	12-h	–	–	–	13.19	–
	Elman back propagation network model	24-h	–	–	–	14.77	–
[57]	Recurrent neural network model	1-day	–	–	–	–	–
		3-day	–	–	–	–	–
[58]	Infinite impulse response multilayer perceptron	72-h	1211	–	1526	–	–
[59]	Multilayer perceptron	9-h	8.41	–	–	–	–
		10-h	11.06	–	–	–	–
		11-h	11.19	–	–-	–	–
		12-h	11.49	–	–	–	–
		42-h	11.81	–	–	–	–
		51-h	10.97	–	–	–	–
		63-h	11.88	–	–	–	–
		84-h	10.57	–	–	–	–
[60]	Neuro-fuzzy network models	1-day	–	–	10.33	–	–

Abbreviations: MAE: Mean absolute error; MAPE: Mean absolute percentage error; RMSE: Root mean square error; NMAPE: Normalized mean absolute percentage error; NRMSE: Normalized root mean square error.

be considered in future studies in order to evaluate prediction models properly.

- the seasonal performance of power prediction models developed has not been considered. Therefore, the datasets including a four-season period can be used in order to evaluate the performance of the models developed if they are dependent on the dataset or not.
- many studies reviewed in this study have shown that there is no standard metric used for comparison. Most of studies use their own error metrics for the purpose of giving power prediction results. Mean absolute error, mean absolute percentage error and normalized root mean square error metrics are mostly preferred in the literature and can be commonly used for making a simple and acceptable evaluation.
- wind power and wind speed have mostly been used as input parameters in the power prediction models developed. Wind direction, air temperature, atmosphere pressure, solar radiation, relative humidity and rainfall can be also considered for a comprehensive analysis due to their impacts on wind power.
- many studies have their own time scales for very short-term, short-term, medium-term and long-term periods. Time scales can also be standardized as in this paper for the consistency of the literature or better comparison.
- a user-centered interactive design approach should be adapted to the platforms designed for wind power prediction and these platforms have to include all of time scales for different intended uses. Thus, users will be able to specify the most appropriate data mining algorithms to their problems.
- multiple data visualization techniques should be utilized in wind power prediction for the aim of providing understandable prediction results. For instance, a dendrogram graph can be used instead of a text representation in case of giving the prediction results for a clustering operation.
- physical models make many mathematical calculations and need more time in wind power predictions. On the other hand, data mining models provide the time and the cost savings. Therefore, the usage of data mining models should be weighted in wind power predictions.

6. Conclusions

In this paper, data mining and the techniques used in data mining have first been reviewed briefly. It has been found that a user-centered interactive approach has to be applied to the knowledge discovery process in databases. Thus, wind power prediction models are achieved in an adaptive and effective way and the more acceptable inferences related to wind power prediction are obtained for dispatchers. Cluster analysis and association analysis have also to be tried in wind power prediction for the purpose of increasing the prediction accuracy.

Many different data mining applications used in wind energy systems are summarized and wind power prediction time scales are also reviewed in details.

The studies on wind power prediction techniques have been also reviewed in this paper to summarize their own characteristics and give effective results in different situations. The important points were discussed in Section 5.

As a result of this study, it can be said that adaptive neuro-fuzzy inference systems, neural networks and multilayer perceptrons increase the prediction accuracies in very short-term, short-term, medium-term and long-term wind power predictions, respectively. In addition to that the forecast error of an aggregated wind power system is smaller than the forecast error of single wind farms due to the spatial smoothing effect.

It is finally recommended that future studies on wind power prediction should consider the comments given in Section 5 in order to achieve better results.

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