Journal of Autonomous Intelligence (2021) Volume 4 Issue 2.
doi: 10.32629/jai.v4i2.501

Original Research Article

Prediction of Wind Power Generation with Modern Artificial Intelligence Technology

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ABSTRACT

In view of the continuous growth of energy demand and interest in environmental protection, the use of clean energy to replace fossil fuels is a global trend. Wind energy is the fastest growing renewable energy in the world in recent years. However, in the case of Mexico, there are still some difficulties in promoting its use in some areas of the national territory. One difficulty is knowing in advance how much energy can be injected into the grid. This paper introduces the development of artificial intelligence technology for wind power generation prediction based on multi-year meteorological information. In particular, the potential application of Bayesian network in these prediction applications is studied in detail. A weather forecasting method based on Dynamic Bayesian network (RBD) is proposed. The forecasting system was tested using meteorological data from the regional wind energy technology center (CERT) of the National Institute of Electricity and Clean Energy (INEEL) in Oaxaca, Mexico. The results are compared with the time series prediction results. The results show that dynamic Bayesian network is a promising wind power generation prediction tool.

Keywords: *Wind power generation, Power prediction, Artificial intelligence, Dynamic Bayesian network*

ARTICLE INFO
Received: Aug 21, 2021
Accepted: Oct 19, 2021
Available online: Oct 25, 2021

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CITATION
Pablo Héctor IG, Alberto RB, Mónica BP, *et al*. Prediction of Wind Power Generation with Modern Artificial Intelligence Technology and Prediction of Wind Power Generation with Artificial Intelligence Tools 2021; 4(2): 52-62. doi: 10.32629/jai.v4i2.501

1. Introduction

The continuous growth of energy demand and the depletion of fossil and nuclear energy, coupled with the need to protect the environment, make the intensive and extensive use of renewable energy attractive and necessary. Compared with traditional energy, renewable energy has inexhaustible advantages. Its operation cost and the generation of pollution sources, especially the emission of carbon dioxide, are very expensive. However, some of their main disadvantages, such as the intermittent and variability of solar energy, are difficult to predict. These two disadvantages are very important, because in the power grid, in order to meet the requirements of power grid operation specifications, it is necessary to maintain a balance between the power consumption and its power generation. For example, if the electricity generated by wind power shows variability in the amount of electricity generated, non-distributable electricity will be considered, which may lead to quality or power interruption.

Wind power generation is affected by atmospheric parameters, such as wind speed and direction, temperature, humidity and pressure, as well as internal factors, such as maintenance plan and design constraints. On the one hand, it is obvious that the prediction of wind power generation makes the control, management, maintenance and planning of power dispatching possible. On the other hand, the impact of good dispatching is transformed into significant economic savings and better utiliza-tion of renewable resources by power suppliers. When user demand and supplier scheduling are esti-mated synchronously, the benefit is greater. There-fore, it is best to develop a method to adjust the sup-ply of wind farms according to wind conditions. These forecasts must have such a prediction range to help calculate the power output and improve the fit-ting of the actual demand curve.

Wind power prediction can be realized by phys-ical methods and random methods. All physicists are based on physical considerations of terrain, such as roughness, terrain and obstacles, and the atmos-phere, where they simulate the crazy contours of the wind. In the stochastic model, the prediction is based on the analysis of data series and the use of time se-ries, statistical technology and artificial intelligence technology.

This paper presents an artificial intelligence (AI) method based on Dynamic Bayesian Network (DBN) and machine learning, which is a good wind forecast-ing method. DBN is an extension of static Bayesian network or simple Bayesian Network (BN). Its main features are:

- They allow coding of knowledge and management experience and help users maintain their models to improve their confidence in the accuracy of the models.
- They use multiple model learning algorithms based on historical data to deal with different types of applications.
- They have a powerful reasoning mechanism to respond to information queries given some evidence.
- The output of dynamic Bayesian network is probability distribution, not a point prediction value.

They allow handling noisy or incomplete information and are ideal for intermittent processes.This paper expounds two kinds of original input: academic input and technical input. Academic contribution corresponds to the development of DBN on short-term prognosis. Specifically, it is part of the construction originally proposed by DBN[1]. When calculating data sets in the form of time series, it is extended to prediction applications. Especially in this case, it is used to predict the wind and generate electricity on the 5-hour horizon. This recommendation is demonstrated by predicting the wind speed and direction of Oaxaca, Mexico, using two years of historical data from a wind speed measurement station in the region. On the other hand, technical inputs include the development of proprietary software tools[2], which allow dynamic Bayesian networks to be learned from data. This tool is used to perform the experienments. Finally, the absolute error of the model is used to evaluate the quality of the wind speed. The results are compared with the traditional prediction methods, the average error is acceptable, lower than other methods, and satisfactory results are obtained.

The structure of the rest of this paper is as follows: the next section briefly introduces the prediction of wind power generation. The next section introduces the Bayesian network and dynamic Bayesian network tools for wind power generation prediction. Experiments and results will be described, analyzed and evaluated in the following section. Finally, Finally, the last section concludes the article and presents future work.

2. Wind prediction

The wind power prediction corresponds to the offshore power generation of an aircraft at a certain time in the future. Weather forecasting can be carried out on different time scales. Short term predictions range from milliseconds to a few milliseconds and are used to actively control aerogenerators. Forecasts made within hours or up to 3 days are medium-term and contribute to power system management of the energy system and its trading. These predictions help to determine the use of traditional plants (*unit commitment*) and the optimal scheduling of these plants *(economic dispatch).* The 5–7 day forecast is called long-term forecast and is used for maintenance planning.

Wind energy is the kinetic energy generated by mass airflow. In this case, it is stable and predictable on an annual scale, but it depends on weather conditions on a smaller time scale. Meteorological conditions produce changes directly in air mass movement according to incident solar radiation, ambient temperature, relative humidity, atmospheric pressure, altitude and latitude. These changes may be cyclical in days, months, seasons, seasons or years. The speed of the wind may be very small, from 2 km/h in the breeze to 120 km/h in the hurricane, lasting from a few seconds to a few days.

Wind energy generates electricity by converting kinetic energy into mechanical energy, which is then converted into electrical energy by wind turbines. According to Bates law, the maximum wind energy available to wind turbines is 59.3%[3], but the maximum wind energy of commercial wind turbines is 75% to 80% of the Bates limit[4]. The available power when the wind passes through a vertical area at a certain speed is determined by

$$p = \frac{1}{2}\rho A v^3 \tag{1}$$

Where ρ is the air density. Within the operating temperature range of Oaxaca, the air density is assumed to be constant. **Figure 1** corresponds to the power curve of the wind turbine and shows the power generation as a function of wind speed. The power curve characterizes the air generator. The minimum speed at which power begins to be generated is called the starting speed and is typically 3 m/s or 4 m/s. With the increase of speed, the power also increases. The wind turbine runs under partial load until it reaches the rated speed and matches the rated power. The wind turbine is designed to produce maximum power at a speed between rated speed and stop speed, which corresponds to the maximum speed at which the wind turbine operates under safe conditions, with a typical speed of 25 m/s.

Wind energy prediction can be carried out directly or indirectly. In the first case, the estimation is realized by directly describing the power output of the electrical power variables. In the second case, it predicts the behavior of wind by estimating meteorological variables and the correlation between power curve and electric power.

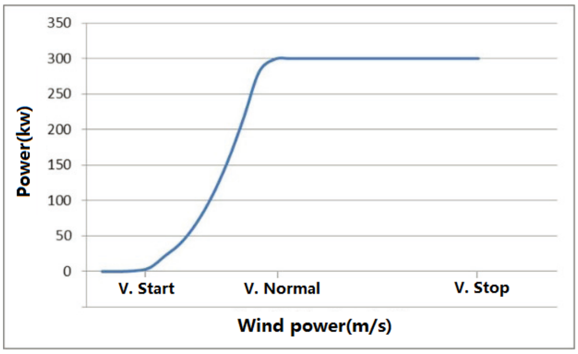

Figure 1. Wind turbine power curve

The models used for prediction can be divided into two categories[5]: physical models[6]and stochastic models[7]. Physical methods are based on physical considerations of terrain, such as roughness, terrain and obstacles, and atmosphere, and simulate local wind profiles. These models include numerical weather prediction (NWP)[6], sky image analysis[8]and power generation system

In the stochastic model, the prediction is based on data sequence analysis and carried out through various technologies:

Time series. When data is available, they use historical data. The prediction of variables is completed by multiple transfer values of the same variable.

Statisticians. They use statistical functions to estimate the value of a given variable and the historical data of that variable and other related variables.

Artificial intelligence (AI). This includes building models using automatic learning algorithms, expert knowledge, or a mixture of both.

The main statistical methods include AR, ARMA and ARIMA[9]. On the other hand, the current wind field prediction models based on time series and statistical models include ALEASOFT, AEOLIS, CASANDRA, CENER, GARRAD HASSAN, METEOROLOGICA, METEOSIM or METEOTEMP[10]. They are based on the prediction of atmospheric changes by some numerical models, and do not have enough accuracy to predict the horizon wind speed of more than 5 hours. As another option to solve this problem, we can find a method to solve complex problems that cannot be solved by traditional methods by using artificial intelligence tools such as artificial neural network (ANN)[11], Bayesian network[12], fuzzy logic and support vector machine[13]. These methods "learn" the relationship between prediction and measurement series. These methods usually provide better results within 2–4 hours, depending on the method selected. In addition, artificial intelligence methods usually provide better results than statistical methods.

An effective prediction technology developed by artificial intelligence community is Dynamic Probabilistic Graphical Models (DPGM). Many of the problems listed can be solved by using this method. Its main features are:

(1) Represents a conditional dependency between variables.

(2) This is a kind of reasoning technology with uncertain process and environment.

(3) It can represent the structure and parameters of expert knowledge.

(4) It represents the result in the form of probability distribution, not in the form of point value.

(5) Because MGPDs has the ability to express conditional independence, it implicitly excludes irrelevant variables.

Despite these characteristics, in order to support the assumption that this technology can achieve good results, different models must be established and evaluated. The main DPGMs are Bayesian networks and Markov networks.

In this paper, Bayesian Dynamic Network (BDN) is used to predict wind speed and direction, as described below. BDN links wind speed and direction with ambient temperature, relative humidity and solar radiation to predict the probability of wind speed and direction in the future. Then, the power generated by the power characteristic curve of the wind turbine is mapped. Then it briefly introduces the method of predicting wind power generation.

3. Bayesian networks and Dynamic Bayesian Networks

The problem of wind power generation is the variability of its power fluctuation and availability. I mean, it's an uncertain question. Among the ideal artificial intelligence methods for dealing with uncertain problems, Bayesian network (BN) has been proved to be practical in general practical applications, especially in alternative energy[14]. BN represents the dependent and independent relationship between process or system variables. They are based on Bayes' theorem, which links the conditional probability of events or assumptions *H* of given evidence *E* and *P* (H|E) *with* the conditional probability h and *P* (H|E) of given evidence E,

$$P(H|\ E)=\frac{P(E|\ H)P(H)}{P(E)} \tag{2}$$

BNs are AI methods because they allow the knowledge of certain processes to be represented in two ways. First, the network structure represents the dependence and independence between variables.Second, the parameters represent the quantitative knowledge of the process. Parameters refer to the terms *P (E|H)* and *P* (H). The term *P* (*E*|*h*) is easily found in historical data, such as disease and symptoms, equipment failure and impact measurement. Then *P* (*H*/*E*) is given by equation (2).

Formally speaking, BN is a directed acyclic $G=(N,E)$, that allows the representation of knowledge in applications dealing with uncertainty[12,15]. A N node represents a set of $X=\{X_1,X_2,\ldots,X_n\}$ random variables. The arcs E in the structure represents the probabilistic relationship between nodes. If $Pa(X_i)$ is the parent node set X_{i^*} of a node, the Bayesian network structure corresponds to the joint probability distribution of the application, as shown below:

$$P(X_1,X_2,\ldots,X_n)=\prod_{i=1}^{n}P\left(X_i|\ Pa(X_i)\right) \tag{3}$$

Among $Pa(X_i)$ them, it represents the parent node of the variable node, which further means that for each variable in X_i the network, BN, RB, X_i when it has the information of the parent node, it is conditionally independent of the non child nodes in $\mathrm{Pa}(\mathrm{X_i})$ the network. In summary, BN represents the dependency and independence between variables in the application.

For dependencies, they are quantified in the form of the Conditional Probability Table (CPT) of the child node value, given the value of the parent node *P* (*E*|*H*). All TPCS and a priori probability vectors P (*H*) of child nodes need to be provided.

Once the process knowledge is captured in the analysis, the probabilistic inference process can be performed, that is, the evidence *e* is used to assign a value to the cone node, and the probability of some assumptions *P* (*H*|E = e) can be calculated. This is equivalent to calculating the marginal probability of the unknown variable, given the known variable *P* (X|*e*)).

The BN described so far infers according to the information at a given time point and the evidence in the model. In other words, there is no time dependence. However, some applications, such as wind forecasting, want to establish conditional models between current and past meteorological variables to calculate future values. In order to consider weather factors in Bayesian prediction model, dynamic Bayesian network (RBD) is developed.

In dynamic applications, the working universe is not only a variable, but also a time series variable that changes with time. Space now consists of $X^{(t)} = \left\{X_1^{(t)}, X_2^{(t)}, \ldots, X_n^{(t)}\right\}$ a $X_i^{(t)}$ collection of X_i time t variables. Then, the prediction $P\left(X_i^T | X_j^{(t)}\right)$ problem X_i^T becomes a time $T, i \neq j$ variable.

Obviously, the spatial combination of variables at different time points represents a very complex set. Therefore, the assumptions are as follows:

(1) They are considered time intervals, or discrete [1] time. Therefore, $X^t = X^{(0)}, X^{(1)}, \ldots, X^{(t)} y$ therefore. $P\left(X^{(0:T)}\right) = \prod_{t=0}^{T-1} P\left(X^{(t+1)} | X^{(0:t)}\right)$ This means that some values of the T future depend on all values of the past $(0:T)$ and present.

(2) The system is Markovian. This $P\left(X^{(0)}, X^{(1)}, \ldots, X^{(\mathrm{T})}\right) = . \prod_{t=0}^{T-1} P\left(\mathbf{X}^{(t+1)} | \mathbf{X}^{(t)}\right)$. In other words, the future has nothing to do with the past and the present.

(3) The system is stationary. That's $P\left(X^{(t+1)} | X^{(t)}\right)$ it. Everything's t is the same. This means that the state of the next process depends on the current state, just like in any part of the sample (every year, spring or winter).

The BDN creation program developed in this project was inspired by the BDN proposal[1]. This mechanism, as well as the assumption that the system is Markovian, allows the creation of a two-stage Bayesian Network $P\left(\mathbf{X}^{(t+1)} | \mathbf{X}^{(t)}\right)$ to define t anything in the process. This network is called a transition network. **Figure 2** shows the network transformation learned in the case study. Each node represents the meteorological variables involved in the analysis, in which the left layer corresponds to the weather and t the right layer corresponds $t+1$ to the weather. Note that all variables depend on the previous time, and some variables, such as temperature (Temp_1), depend on the current value of solar radiation in addition to the previous Relative Humidity (RH) and Solar Radiation (SR).

Under the third assumption, the system is such that the BND required for future unit time prediction is realized by expanding the transition network at (N + 1) layer or stage. For example, if time data is used and needs to be predicted to 5 hours, BDN is formed by expanding the transmission network to layer 6. Considering that the first layer corresponds to the input layer and each of the five layers contains a prediction for the next hour, it is considered to be six layers. **Figure 3** shows the BDN results of wind forecast on the 5-hour horizon.

To sum up, the learning process of 5-hour power prediction in this project is summarized as follows:

(1) Divide the historical database into two groups. Data for training NBD and data for verifying NBD performance. Note that the data must be a time series, not just a set of records.

(2) If the time base of the original data is less than the required time base, the average value is mapped to the variable value in the required step.

(3) Use uniform division to discrete continuous values.

[1] The symbols used are as follows. Bold capital letters represent variable sets, such as ***X.*** capital letters represent variables, such as X.

(4) Copy training data in two columns of NAS, including records in each row (x (T), X (T + 1)). The learning algorithm of Bayesian network is used to construct the transition network. In this project, the hugin package[16] was used to build the network in **Figure 2.**

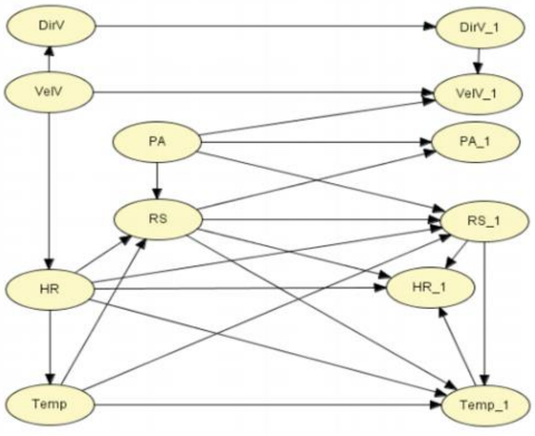

Figure 2. Experimental case study of network transition

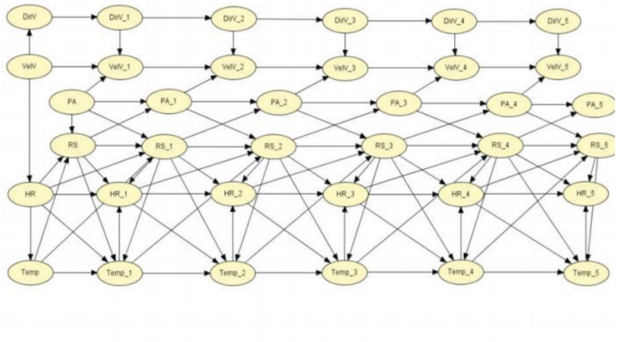

Figure 3. Dynamic Bayesian network results for 5-hour prediction

(5) Expand the transition network on the (N + 1) time slice to form the BND as shown in **Figure 3**. As mentioned earlier, for the horizon with N stages in the future, the (N + 1) layer is required.

(6) The EM algorithm (Expectation-Maximization)[17] is used to learn the model parameters corresponding to the child node conditional probability matrix and the root node prior probability vector in **Figure 3**.

The size of BND increases in layers according to the stages of the predicted horizon. However, this method is limited to the prediction of small stages in the future, because more than 10 or 12 stages will make the Bayesian model impractical due to the number of nodes in reasoning[18].

The reasoning in the model includes assigning values in the variable layer of time t and predicting the probability of the sixth layer in the network. The result is the posterior probability distribution of all variables including wind speed.

4. Experiments and result

These experiments were conducted at INEEL regional wind energy technology center (CERT) in Ventosa, Oaxaca, Mexico. Its infrastructure is designed to install up to 5 MW of wind power, which can be integrated with different capacities and models of wind turbines.

CERT sells electricity produced by Japan's 300 kW KOMAI wind turbine, which was donated to INEEL by the global environment facility (GEF) through the United Nations Development Programme (UNDP).

The historical wind data and other meteorological variables obtained from the center consist of time series marked with date and time, which lasted for more than two years. The information collected includes: Ambient temperature (Temp), Relative Humidity (RH), Solar Radiation (SR), Wind Direction (DirV) and wind speed (VelV) at two different heights on the ground. Record the data every ten minutes. The data of 2012 and 2013 are used for training, and the data of January and February 2014 are used to test our system. Preliminary results are presented in[19].

As mentioned above, the model is learned from the weather data of CERT from January 2012 to December 2013. The model is shown in **Figure 3**. The experiment was tested on the time data from January to February 2014. In order to evaluate the performance of the prediction system according to specific weather conditions, experiments under charging current conditions were carried out in a specific time. For example, we loaded the evidence at 0:00 (midnight) and compared it with the prognosis at 5:00. The experiment was conducted from 12:00 to 17:00 (half a day). There are significant differences in solar radiation and temperature between the two periods.

The experiment was carried out by the following methods:

(1) Obtain historical data from the meteorological record variables of a location, mainly including speed and wind direction.

(2) The learning prediction model follows the method described in the previous section.

(3) Use the historical test data of to learn BND feedback with value at a given time point. Through probability propagation, the future posterior probability distribution of N layer wind speed is obtained. This is achieved through the *Hugin* package or any other probabilistic model processing package.

(5) Numerical calculation and comparison with the measured data file. This will be described in detail below.

(6) Difference calculation and prediction error estimation.

Alternatively, RBD training (step 3) can use the current value to predict the next N hours (or stages) in some cases. It is worth mentioning that the prediction error is calculated after n stages are completed.

Figure 4 shows the wind speed forecast results in February. The vertical axis represents the wind speed (M/s). The horizontal axis represents an example of the experiment, once every hour every day. The lines with "Measured" and "Estimated" represent the measured and predicted wind speed do, respectively. As shown in the figure, the predicted value is very close to the actual value in some times, while the difference is more significant in others.

The deviation between the predicted value and the measured value is quantified by error. The inertial measurement error is calculated by the following formula:

$$E_{\text{Inst}} = \frac{\left(VelV_{\text{real}} - VelV_{\text{foreast}}\right)}{\left(V_{\max} - V_{\min}\right)} \times 100 \tag{4}$$

Velocity $VelV_{\text{real}}$ measurement and VelV prediction are predictive. Instrument engineers use this mechanism when evaluating equipment. This value is divided by the difference between the actual value and the predicted value by the full scale of the instrument. In this project, we assume $V_{\max} = 25\text{m/s}, yV_{\min} = 0\text{m/s}$.

Wind speed is a difficult variable to predict because of its uncertainty and natural volatility. The average error of 0–5 hours is 8.21%, and the average error of 12–17 hours is 5.76%. In **Figure 4**, the maximum error is more than 19%, while the minimum error is almost 0. Most errors are less than 5%. Although this seems to be a huge error in somecase, the literature shows that a wind prediction system with this average error is promising[20].

The literature suggests that in addition to the measurement of single point prediction error, the uncertainty of probability prediction should also be considered[5,21]. These references suggest the necessity of calculating probabilistic models given numerical weather prediction (NWP) models. Because our prediction mechanism is probabilistic, we get the probability distribution of wind speed under given weather conditions in the next 5 hours. To calculate the NWP, the expected value of the posterior probability vector was used, that is, V_{est}=s$_n$ $V\,elV_iP_i$ where $V\,elV_i$ is the central value of the interval i, and P_i is the probability of the interval.

The uncertainty estimation of wind forecast is calculated by Quantile mechanism[20]. The posterior probability distribution of a given wind speed, $P_{t+k'}$ where t the current time is k the current time and is the prediction range (the number of previous q_{t+k}^{α} time slices), $\alpha \in [0,1]$ and the quantile with parameters x is $\text{prob}\left(P_{t+k} < x\right) = \alpha$ defined as the given value.

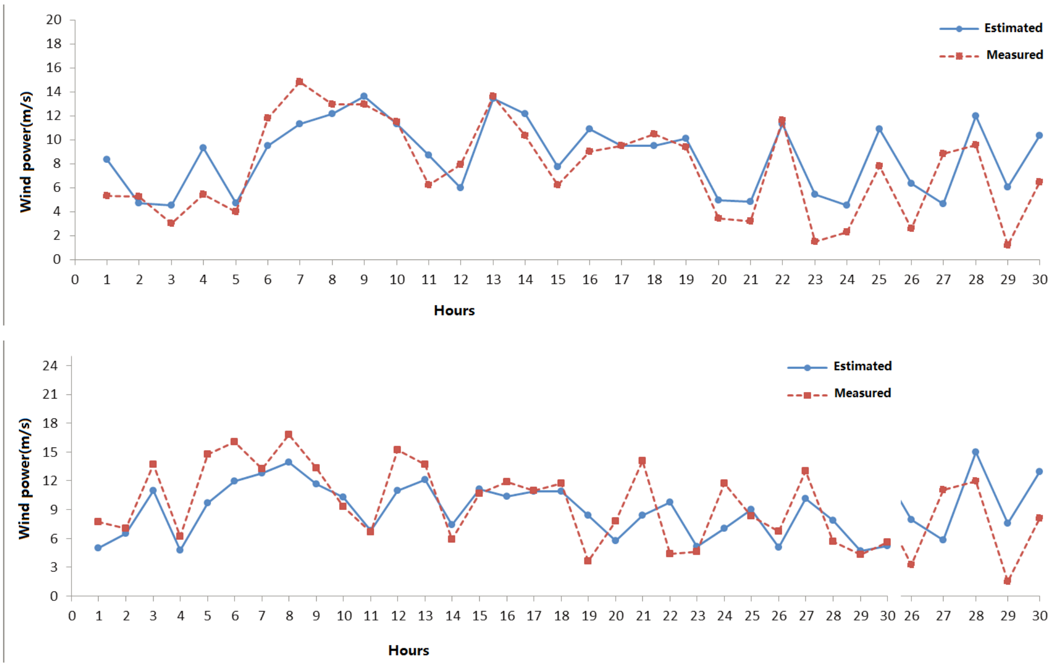

Figure 4. The experimental results of wind speed in 0-5 hours and 12-17 hours are predicted by partial plot. The lines marked "Measured" and "Estimated" represent actual and predicted values. Actual and predicted values are in M/s.

Figure 5 shows the results of the same experiment as **Figure 4** with the two quantiles of 20% and 80%, forming a confidence interval with a probability of 60%. The mechanism stipulates that the expected power generation of a given horizon is 1 to 1.6 MW, with a probability of 60%. In order to complete the evaluation of the experiment, **Table 1** shows the different error measurements of the above two experiments[21]. As we have observed, the experiments carried out from 12 to 17 show small errors. On the other hand, another measure for calculating the error in the prediction problem is the average quadratic error (RMS), which is consistent with the average error of prediction, which is defined as (Osman, 2001):

$$rms = \left[\frac{1}{n}\sum_{i=1}^{n} E_{\mathrm{Inst}}^{2}\right]^{\frac{1}{2}} \qquad (5)$$

Where E_{Inst} is the instrument error defined in equation 3.

The errors reported in **Table 1** are derived from the data of 30 cases of 0 hours (or 12 hours), i.e. 1 month. In each experiment, the actual value was compared with the predicted value. Calculate the error using equations 3 and 5. A negative number in the first line indicates overestimation because the estimated value is greater than the actual value. **Table 1** compares the predicted values of different indicators of the two experiments. Efforts during the day are better than efforts at night.

In order to compare our prediction results with other traditional time series statistical methods, **Table 2** shows the results of these methods, which are obtained from a set of experience in the same scene and data set.

Table 1. Experimental result error

Error type	Experiment 0-5h	Experiment 12–17 hours
Percentage	-4.4	-2.3
Absolute percentage	8.21	5.67
Minimum value	0.17	0.18
Maximum	19.4	17.36
Mean square error	9.84	7.28

Table 2. Experimental result error of traditional method

	AR model command	Ma command	Map	Reach
Human Resources Department	44	0	0.235171	45
Arms	12	30	0.271023	52.5
Alima (a)	6	27	0.365057	27.5
Alima (b)	6	27	0.280259	35

(a) Average adjustment
(b) Do not adjust the average

The first column shows the experimental model. AR is a 44 order autoregressive model. ARMA is an autoregressive model of moving average (MA), with AR of order 12 and MA of order 30. The latter two models are the 6th and 27th order AR integrals of AR and MA, respectively[22]. The difference between the two methods is that in data preprocessing, the average value is subtracted from all values to predict time invariance (adjusted to the average value). The fourth and fifth columns are absolute error - half percentage point (MAPE) and directional accuracy (DA). MAPE and DA measure the accuracy of the model and predict the future accuracy respectively. Both indicators are expressed as percentages. Ideally, a good prediction model can obtain low map and high DA. MAPE and DA are calculated by comparing the predicted value with the actual value. **Figure 6** shows the results of a short experiment using time series statistics.

By qualitatively comparing the BND results (**Figure 4**) with the results of the time series method (**Figure 6**), it can be seen that the fact of using multiple variables rather than historical variables in the prediction represents a performance advantage. **Figure** 4 shows that the curve tracking between measurement and prediction is larger than that in **Figure 6**.

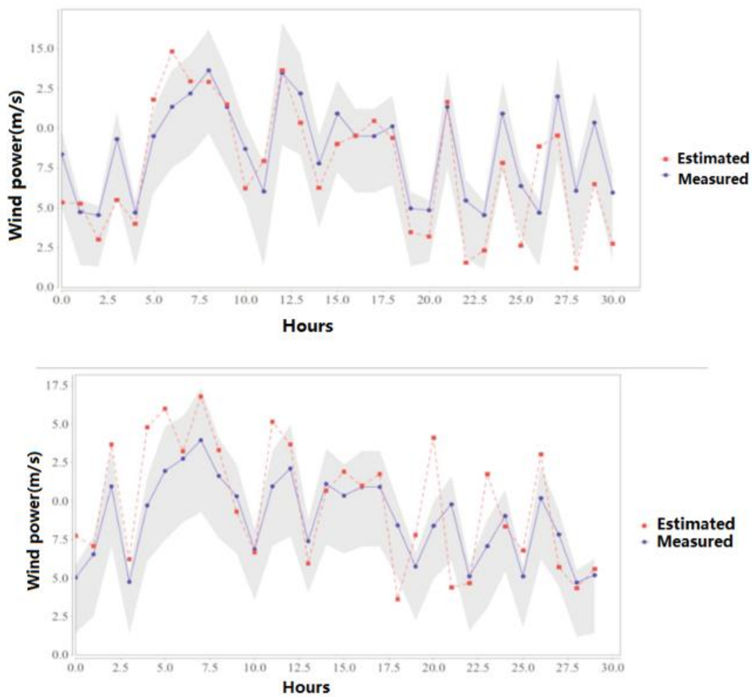

Figure 5. The experimental results are 0–5 hours and 12–17 hours, with certain uncertainty. The area shown represents a 60% probability. Red indicates the measured speed and blue indicates the estimated speed.

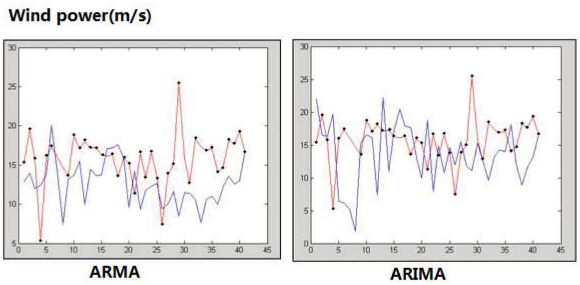

Figure 6. ARMA and ARIMA methods are used to match the experimental results. The red line represents the actual value and the blue line represents the predicted value. Horizontal axis timing.

5. Conclusions and future work

The prediction of wind power generation is an inevitable requirement for the expansion of clean power generation. Bayesian network is a technology used to deal with intelligent systems with uncertainty. This paper presents a new application of dynamic Bayesian network in wind power generation prediction. The most important contribution of this paper is the development of dynamic models dedicated to short-term power forecasting and the methods of learning these models. The innovation of our BND lies in the corresponding relationship between the assumption of prediction problem and the formation of BND structure, which corresponds to the BND classical structure proposed by Murphy[1].

A method of building wind prediction model using dynamic Bayesian network and multi-layer perceptron is proposed[23]. The two prediction models are evaluated and compared to select the model with the highest performance. In the case of Bayesian model, it is recalibrated recursively to restore the accuracy lost due to variable discretization. The novelty of this method is that it compares two techniques with different property variables (discrete variables and continuous variables) and different strength. In this way, it can make better use of the power of approximate functions and methods to deal with uncertainty.

This paper introduces the development of the mathematical formula of dynamic Bayesian network. Preliminary results were published in Ibargüengoytia [19]. In addition, the construction method and theory of Bayesian network proposed by us are described in detail. This paper also describes the measurement error, and discusses the supplementary use of Bayesian model and artificial neural network.

The experiment is carried out on the data of CERT and INEEL meteorological station in La Ventosa, Oaxaca. The results show that artificial intelligence is very helpful in solving the problem of renewable energy. Artificial intelligence provides learning and knowledge representation mechanism, which can be transformed into more effective problem solving methods.

This research work is a preface to a broad theme. Future work in this area will focus on analyzing whether there is any place nearby that can provide useful information for improving prediction, that is, developing dynamic spatial models to improve prediction performance. In addition, the condition that the prediction process is a Markovian process will be studied, and the consequences of this restriction will be analyzed. Finally, the time series will be reviewed to determine whether they are time series, and if not, a BND model will be defined for each stage. This method is compared with other nonlinear time series prediction models.

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledgement

This project was partially supported by CEMIE-Eolic projects 174919 and P12, both from the SENER-Conacyt Sustainability Fund, and the National Institute of Electricity and Clean Energies (INEEL). Mónica Borunda thanks Conacyt for her position as chair researcher number 71557, and INEEL for her hospitality.

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