

# Short-term Power Forecasting Method and Application of Wind Farm

Xiaohu Yang<sup>1,a</sup>, Rong Ju<sup>1,a</sup>, Zhe Yuan<sup>1,a</sup>, Zhenya Zhang<sup>1,a</sup>

<sup>1</sup>School of Electrical and Automation Engineering, Nanjing Normal University, Nanjing 210042, China.

**Abstract:** The prediction of output power of wind farm has important value and significance to the normal operation of some large-scale wind power system. In this paper, the related prediction methods and practical application are studied, and the short-term power forecasting method of the wind power of the vector machine-Markov chain is proposed.

## 1 INTRODUCTION

With the rapid development of industry, human demand for energy is increasing. At present, 75% of energy demand still depends on fossil fuels such as coal, oil, and natural gas. The burning of these fossil fuels releases a large amount of harmful substances, and the impact on the environment and climate has threatened human survival. On the other hand, fossil fuels available on the planet are also becoming scarce. Experts predict that coal can be mined for 221 years, oil can be mined for 39 years, and natural gas can only be used for 60 years. The problem of sustainable development of energy has become imminent. Wind energy has become a powerful alternative to traditional energy sources due to its clean, pollution-free and renewable characteristics, and it has received extensive attention from countries around the world. The global reserves of wind energy resources are enormous, reaching as high as 53 trillion yuan each year, which is more than 10 times that of hydropower. If we can make full use of global wind energy resources, we can expect to reach twice the global electricity demand in 2020.

With the introduction and development of large-scale grid-connected wind power generation units, wind farms composed of multiple wind turbines have begun to appear in areas with abundant wind resources, and have been incorporated into regional power grids. However, in practice, some large-scale electric generating units will normally influence the entire power system during the process of access. In this regard, in practice, we must pay more attention to the forecasting work of wind farm power generation.

## 2 BASIC THEORY

### 2.1. Relevant Vector Machine Basic Theory

Given a set of training sample  $\{x_n, y_n\}, n = 1, 2, \dots, n$ ,  $x$  is an N-dimensional input vector and  $y$  is a one-dimensional output vector. Define the Regression Model for Relevant Vector Machines as

$$y_n = \sum_{i=1}^N \omega_i \varphi_i(x) + \omega_0 + \varepsilon_n \quad (1)$$

Where:  $\omega_i$  is the weight parameter;  $\omega_0$  is the initial value of the weight parameter;  $\varphi_i(x)$  is the nonlinear basis function;  $\varphi_i(x) = K(x, x_i)$ ,  $K(\cdot)$  is the selected kernel function.  $\varepsilon_n$  is a Gaussian noise with mean 0 and its variance is  $\sigma^2$ .

Assuming that the output  $y_n$  are independent of each other, the likelihood estimation distribution for the given training set  $\{x_n, y_n\}$  is

$$p(y | \omega, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left(-\frac{y - \varphi\omega}{2\sigma^2}\right) \quad (2)$$

In the formula:

$$y = (y_1 \dots y_N)^T \quad (3)$$

$$\varphi = (\varphi(x_1) \dots \varphi(x_N))^T \quad (4)$$

$$\varphi(x_N) = [1, K(x_N, x_1), K(x_N, x_2) \dots K(x_N, x_N)] \quad (5)$$

There are many parameters in the model. If the maximum likelihood estimation function is used to calculate the weights  $\omega$  and  $\sigma^2$  variance, it will easily lead to data overfitting. This problem should avoid in actual prediction. Therefore, it is feasible to use sparse Bayes to

\* Corresponding author: [a253654748@qq.com](mailto:a253654748@qq.com)

assign zero mean Gaussian prior probability distribution to  $\omega$ , i.e.

$$p(\omega | \alpha) = \prod_{i=0}^N N(\omega_i | 0, 1 / \alpha_i) \quad (6)$$

Where:  $\alpha$  is a vector that satisfies the  $N+1$ -dimensional hyperparameter distribution. In this way, each weight corresponds to a hyperparameter, which controls the parameter changes due to the prior distribution and ensures the high sparsity of the correlation vector machine.

Based on the prior probability distribution and likelihood distribution, the posterior probability distribution of all unknown parameters is obtained as<sup>[1]</sup>

$$p(\omega | y, \alpha, \sigma^2) = 2\pi^{-(N+1)/2} |m|^{1/2} e^{-(\omega-\mu)^T m^{-1} (\omega-\mu)} \quad (7)$$

Among them, the posterior consensus variance matrix is

$$m = (\sigma^{-2} \phi^T \phi + A)^{-1} \quad (8)$$

$$\mu = \sigma^{-2} m \phi^T y \quad (9)$$

$$A = \text{diag}(\alpha_0, \alpha_1, \dots, \alpha_N) \quad (10)$$

In order to determine the weight of the model  $\omega$ , the optimal value of the hyperparameter must be found. Its iterative algorithm is

$$\gamma_i = (1 - \alpha_i N_{ii}) \quad (11)$$

$$\alpha_i^{new} = \gamma_i / \mu_i^2 \quad (12)$$

$$\sigma^{new} = \sqrt{\frac{\|y - \phi\mu\|}{n - \sum i \gamma_i}} \quad (13)$$

Where:  $\mu_i$  is the  $i$ -th posterior average weight;  $N_{ii}$  posterior covariance matrix;  $n$  is the number of sample data.

If a new input is given as  $x_*$ , the probability distribution of its corresponding output obeys the Gaussian distribution, i.e.

$$p(y_* | y, a, \sigma^2) = N(y_* | y, \sigma_*^2) \quad (14)$$

In the formula,  $y_*$  is the predicted value corresponding to  $x_*$ , i.e.

$$y_* = \mu^T \phi(x_*) \quad (15)$$

## 2.2. The Basic Theory of Markov Chain

The Markov process is a random process with no post-effects, i.e., changes in the future state are not affected by various states in the past. The time and state are discrete processes for the Markov chain<sup>[2]</sup>.

Definition: random process  $\{x(t_{n-1}), t \in T\}$ , for any finite time series  $x(t_1), x(t_2), \dots, x(t_n)$ , corresponding state  $a_1, a_2, \dots, a_n \in A$ , there

$$p\{x(t_n) \leq a_n | x(t_{n-1}), \dots, x(t_1)\} = p\{x(t_n) \leq a_n | x(t_{n-1})\} \quad (16)$$

Define this process as a Markov process.

Definition: If the random process  $\{x(t), t \in T\}$ , the conditional probability for any integer and state  $a_1, a_2, \dots, a_n \in A$  is satisfied

$$p\{x_n = a_n | x_1 = a_1, \dots, x_{n-1} = a_{n-1}\} = p\{x_{n-1} = a_{n-1}\} \quad (17)$$

This process is called a Markov chain. The conditional probability  $p\{x_n = j | x_{n-1} = i\}$  represents the probability that the time  $n$  is transferred to the state  $j$  with the system  $n-1 = i$ , i.e.

$$p = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \dots & p_{nm} \end{bmatrix} \quad (18)$$

The  $k$ -step transition probability can be calculated by the formula  $p^{(k)} = p^k$ .

## 3 POWER FORECAST

### 3.1. Overview of Power Forecast

In practice, the forecasting methods for wind power can be divided into three prediction modes: medium-long-term, short-term, and ultra-short-term. In the current stage of development, short-term forecast for wind power can be mainly divided into physical and statistical modes. The physical mode is based on weather forecast data and uses the relevant mathematical relations to calculate the actual output data of the wind farm, and then draw the relevant power prediction curve. The statistical method is based on relevant historical data and the actual data related to the output of the wind farm and then build a systematic data prediction model. As a result, the prediction and analysis of the generation power of wind electric field is carried out

by means of prediction parameters. In practice, physical methods are based on the influence of objective factors such as prediction accuracy, and the impact of various physical conditions on the actual wind farms is relatively serious. However, the forecasting data of statistical methods in practice has a certain degree of accuracy. In this regard, statistical methods are mainly used for forecasting in the international field.

The statistical methods for short-term wind power forecasting at this stage mainly cover the following types: time series, grey theory, neural network NNS (neural networks), and support vector machine (support vector machine)<sup>[3]</sup>. The simplest method is the time series method, but it has certain error in practice. The grey theory prediction model has a certain degree of dependability, but its actual prediction result is an interval range, and there is no accurate numerical value. In practice, the overall topology of neural network method is relatively compact, and it has a certain degree of accuracy comparing to other methods. However, a large amount of historical information and data are used and the actual time spent is excessive. The support vector machine method has certain simplicity, its overall robust performance is relatively good, and the actual prediction accuracy is relatively high. However, in practice, the actual selection conditions for a specific kernel function are relatively strict, and the number of applications is excessive. Summary and related influences such as local minimum values are likely to appear in the summary. Among them, the relevance vector machine (RVM) is a sparse probability model proposed by Tipping through the overall Bayesian framework, which is the focus of research at this stage. In practice, the advantages of the correlation vector machine and support vector machine are similar, but it is relatively flexible in the actual selection process of the kernel function. It can introduce relevant hyperparameters and can effectively reduce the complexity of the overall calculation.

The generation of forecast error can be said to be an inevitable result in the entire wind power forecast. In practice, relevant errors should be corrected and optimized in a timely manner to fundamentally improve the accuracy of its overall forecast. In practice, this can be achieved through the existing error-correction model ECM (automatic error correction model), autoregressive and moving average model (ARMA), local simulation approximation, and periodic extrapolation, least square method, Markov chain and other related methods to repair it. Among them, the least squares method and the Markov chain method have certain accuracy with respect to other methods, while the Markov chain method has more remarkable effects on the problems of random volatility description<sup>[4]</sup>.

### 3.2. The Practical Application of Short Term Power Forecast

This article mainly explores practical data such as actual wind speed, temperature, atmospheric pressure, and wind power generation power in a small wind farm area as the main training samples. During the operation, it ensures that the average sample is taken every 10 minutes, and 100

sets of data training are performed continuously. Then, it is tested through continuous 32 kinds of data. In practice, MATLAB software is used to perform related programming calculations. The actual data curves such as wind speed, temperature and pressure are finally obtained as follows.

In the diagram, it can be understood that the wind speed, temperature, and pressure data of the actual wind farm are generated randomly, and there is no inherent law to follow.

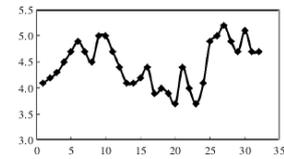


Figure 1: Wind speed variation diagram of wind farm.

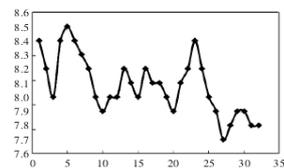


Figure 2: The temperature variation diagram of wind farm.

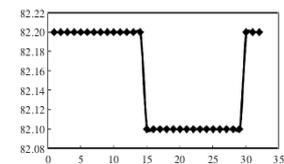


Figure 3: Atmospheric pressure variation diagram of wind farm.

In the operation process, wind power prediction is performed through the same data samples based on the related principles of neural networks and support vector machines. In practice, it can be understood that the relative vector machine and the Markov chain fusion method have a certain degree of accuracy relative to other methods, and can minimize the average absolute error and the average relative error value. At the same time, based on the actual results, it can be understood that the relative error and absolute error existing in the prediction process can be effectively reduced compared with other methods in practice, but its current error rate is still 13%. It is because of the following points:

First, the relationship between wind turbine power generation and wind speed must be within the rated start-up wind speed and cut-out wind speed range before it can be effectively met<sup>[5]</sup>. When it is relatively low, the output power of the wind turbine is zero, above which it is cut out. At wind speed, the fan output power is its maximum value<sup>[6]</sup>.

Second, the original input data is mainly due to the three-dimensional factors of wind speed, related atmospheric pressure and temperature factors, and there are no relevant factors such as wind direction factors, terrain conditions, and atmospheric turbulence, where the relevant prediction model in RVM-Markov can be applicable to various dimensions.

## 4 CONCLUSION

This paper mainly analyses the specific prediction of the relevant vector machine principle in the short-term power of the wind farm, and proposes a wind power forecasting method jointly developed by a correlation vector machine and a Markov chain. In practice, the short-term power prediction model of wind farm is obtained by applying the basic principle of relevant vector machine. Then, through the improvement and optimization of the actual error of the existence of the Markov chain and the least square method, the repair model of short-term power error of a wind farm is constructed. Then use the side model to develop the wind farm power forecast. The model then performs wind farm power forecasting through the side model. This model can effectively meet the related forecasting demand of the power system for the actual short-term power of the wind farm.

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