Electric Power Distribution

Systems and Engineering

Linda Morand

Electric Power Distribution: Systems and Engineering

About the Book

This book on electric power distribution discusses the various mechanisms that regulate power transmission. Power is generated across a complex set of pathways and networks. Electric power distribution is a field of study that focuses on the transmission of power from the source of its generation to the end users. The aim of this text is to present researches that have transformed this discipline and aided its advancement. Coherent flow of topics, student-friendly language and extensive use of examples make this book an invaluable source of knowledge. This book is a vital tool for all researching and studying this field. It includes some of the vital pieces of work being conducted across the world, on various topics related to electric power grids and power distribution.

About the Editor

Linda Morand received her MSc in energy and power engineering from the University of Warwick, United Kingdom. She is a senior professor; and has a wide range of academic and teaching interests, which include hybrid generation systems, energy storage, power systems, waste energy management and renewable energy power generation. Morand is a noted researcher in the fields of power and energy engineering; and has produced numerous articles, journal papers and books in these areas.

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Electric Power Distribution: Systems and Engineering

Preface

Every book is initially just a concept; it takes months of research and hard work to give it the final shape in which the readers receive it. In its early stages, this book also went through rigorous reviewing. The notable contributions made by experts from across the globe were first molded into patterned chapters and then arranged in a sensibly sequential manner to bring out the best results.

This book on electric power distribution discusses the various mechanisms that regulate power transmission. Power is generated across a complex set of pathways and networks. Electric power distribution is a field of study that focuses on the transmission of power from the source of its generation to the end users. The aim of this text is to present researches that have transformed this discipline and aided its advancement. Coherent flow of topics, student-friendly language and extensive use of examples make this book an invaluable source of knowledge. This book is a vital tool for all researching and studying this field. It includes some of the vital pieces of work being conducted across the world, on various topics related to electric power grids and power distribution.

It has been my immense pleasure to be a part of this project and to contribute my years of learning in such a meaningful form. I would like to take this opportunity to thank all the people who have been associated with the completion of this book at any step.

Editor

Contents

1

Hybrid Wind Speed Prediction Based on a Self-Adaptive ARIMAX Model with an Exogenous WRF Simulation

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Abstract: Wind speed forecasting is difficult not only because of the influence of atmospheric dynamics but also for the impossibility of providing an accurate prediction with traditional statistical forecasting models that work by discovering an inner relationship within historical records. This paper develops a self-adaptive (SA) auto-regressive integrated moving average with exogenous variables (ARIMAX) model that is optimized very-short-term by the chaotic particle swarm optimization (CPSO) algorithm, known as the SA-ARIMA-CPSO approach, for wind speed prediction. The ARIMAX model chooses the wind speed result from the Weather Research and Forecasting (WRF) simulation as an exogenous input variable. Further, an SA strategy is applied to the ARIMAX process. When new information is available, the model process can be updated adaptively with parameters optimized by the CPSO algorithm. The proposed SA-ARIMA-CPSO approach enables the forecasting process to update training information and model parameters intelligently and adaptively. As tested using the 15-min wind speed data collected from a wind farm in Northern China, the improved method has the best performance compared with several other models.

Keywords: wind speed; self-adaptive strategy; ARIMAX; WRF simulation

1. Introduction

1.1. Time Series Forecasting and Wind Energy

Time series forecasting plays an essential role in many fields, especially in meteorology, economics and energy. Time series models produce forecasts by discovering the inner relationships within historical records. This paper focuses on wind speed forecasting, which is crucial in the whole life-cycle of wind farm construction and operation and is also the basic technique to guarantee the grid security of a wind-connected system. Wind power is economic and ecologically friendly, which makes it one of the most popular and promising alternative energy sources. Wind power accounts for approximately 10% of the national power use in many European countries, and for more than 15% in Spain, Germany and the US [1]. However, the main obstacle for wind industry development is the variability of output power, which seriously prevents wind power penetration and threatens grid security. To guarantee the security of the grid system, the dispatching department have to balance the grid's consumption and production within very small time intervals [2]. Moreover, because the lack of accurate information on wind occurrence, the efficiency of wind turbine may also be limited [3]. In actual power generation, wind predictions—especially the short-term forecasts—are important for scheduling, controlling and dispatching the energy conversion systems [4]. However, as the most important characteristic of wind, speed can be easily influenced by other meteorological factors, such as air pressure, air temperature and terrain [5]. Thus, wind speed prediction is not easy to address. Moreover, wind speed modelling has become one of the most difficult problems [6,7].

1.2. Wind Speed Forecasting: Existing Works

Many methods have been attempted to forecast wind speed. In general, they can be classified into two categories: physical and statistical methods. Physical methods are always referred to as meteorological predictions of wind speed, including the numerical approximation of models that describe the state of the atmosphere [8], such as the Weather Research and Forecasting (WRF) model [9]. These models always choose physical data such as topography information, pressure and temperature to forecast wind speed in the future [10,11]. As one of the current-generation physical models, WRF [9] is widely used in both research [12–14] and operational forecasts. Reference [13] used the WRF model to manage ocean surface wind simulations forced by different initial and boundary conditions. Reference [14] compared WRF with the Wind Atlas Analysis and Application Program (WAsP) model, to test the performance in terms of flow characteristics and energy yields estimates. Considering numerical weather prediction (NWP) models, one important issue is downscaling. Generally, two categories are focused on: dynamic and statistical downscaling methods. Dynamical downscaling methods have clear physical meanings and are unaffected by the observation data. However, they require large computational costs. Being different, statistical downscaling—including transfer function method (TFM), weather pattern method (WPM) and stochastic weather generator (SWG)—is simple to establish and needs a small amount of calculation, but it may be influenced strongly by observations [15]. Recently, many new statistical downscaling techniques have been developed, such as the similarity method, hidden Markov model (HMM), generalized linear model (GLM) and others [15].

Unlike physical models, statistical methods make forecasts by discovering the relationships in historical wind speed data and sometimes other variables (e.g., wind direction or temperature). The data used is recorded at the observation site or other nearby locations where data are available. Moreover, many statistical methods have been applied, such as the auto-regressive integrated moving average (ARIMA) model, Kalman filters, and the generalized auto-regressive conditional heteroscedasticity (GARCH) model, *etc.* The statistical models can be used at any stage during modelling, and they often merge various methods into one. Physical and statistical models each have their own advantages for wind speed prediction, but few forecasts use only one of them. The physical prediction results are just the first step of wind forecast; then, the physically predicted wind speed can be regarded as an auxiliary input to other statistical models [16–18]. Currently, grey models (GM) [19,20] and models based on artificial intelligence (AI) techniques [21,22] have been developed for this area, containing the artificial neural networks (ANNs) of multi-layer perceptrons (MLP) [23], radial basis function (RBF) [24], recurrent neural networks [25,26], and fuzzy logic [27,28].

As one of the most widely used time series approach, ARIMA has been used as an effective and efficient forecasting technique in many fields, including traffic, energy, and the economy. Generally, ARIMA is a linear model that represents both stationary and non-stationary series [29] and uses historical time series patterns to make forecasts for the future data trend. In terms of the wind speed prediction problem, which is studied in this paper, the ARIMA models are effective and suitable for short-term and very-short-term predictions. References [30–32] applied the auto-regressive moving average (ARMA) model to wind speed predictions with different time horizons. Furthermore, because wind-related data always show obvious periodicity, a seasonal ARIMA model can be defined with the consociation of a seasonal difference process [33]. Later, the fractional-ARIMA model was proposed by Kavasser and Seetharaman [34], which assumes that the differencing parameter d of ARIMA (p, d, q) is a fractionally continuous value in the interval $(-0.5, 0.5)$. Their model was used for wind speed prediction on the day-ahead and two-day-ahead time horizons in North Dakota. When there is little knowledge available or there is no suitable model relating the predicted variables to other explanatory factors, the ARIMA model is particularly useful [35]. Some articles made a hybrid approach by combining the ARIMA model with other methods. Studies take ARIMA as the first step of a hybrid method, and then the residual series of ARIMA can be regarded as the nonlinear part of the original series. Reference [36] developed a hybrid ARIMA-ANN model for hourly wind speed prediction. In their method, the ARIMA model was first used for wind speed forecasting, while the ANN was chosen to reduce the errors from the ARIMA models. Later, a hybrid method combined the seasonal ARIMA, and the least square support vector machine (LSSVM) was developed in Reference [5] for monthly wind speed prediction in the Hexi Corridor of China. Here, both ANN and LSSVM are quite effective for addressing series within nonlinear signals.

Improvement made on ARIMA has enhanced the model performance substantially. However, by considering either the improved ARIMA model or the ARIMA-combined hybrid methods for wind forecast, most approaches employ only the historical observations but not the factors of atmospheric dynamics. Some studies claimed that an accurate wind prediction method must include a numerical weather prediction (NWP)-based process [37].

1.3. Original Contribution: Developed Self-Adaptive Wind Speed Forecasting Strategy

The original contribution of this paper is the development of a self-adaptive (SA) auto-regressive integrated moving average with exogenous variables (ARIMAX) model optimized by the chaotic particle swarm optimization (CPSO) algorithm called the SA-ARIMAX-CPSO approach, which is applied to wind speed prediction. Specifically, the applied ARIMAX model takes the WRF simulation as an exogenous part, which makes the forecasting model a combination of both statistical and physical information. Moreover, the CPSO-driven SA strategy enables the proposed method to syncretize the previous model and the recently updated information. In this paper, the self-adaptation contains two parts. The first one is new model fitting, when the recent measurements or WRF data are available. This paper updates the fitting coefficients every time-step, while the WRF model runs once a day. The second one is adaptation process, where the optimal adaptive weights are determined only based on the training set.

On the issue of very-short-term wind speed prediction, models were established generally based on a statistical process, while the NWP simulations were typically used for short-term predictions. This is mainly due to the model accuracy and calculation costs. This paper develops a hybrid approach for very-short-term wind speed prediction combining both statistical and physical models, which has an acceptable amount of calculation and effective model performance. Specifically, the WRF model is now the current generation physics-based atmospheric model, which is widely applied; the ARIMA process is the typical time series model, which emphasizes modelling the relationship among historical observations. Thus, the proposed ARIMAX model in this paper considers not only the statistical information from historical wind speed observations but also the physical process of atmospheric motion.

Furthermore, this paper develops a SA strategy to apply for the ARIMAX method. Model parameters are always fixed values that are determined by the training data set; this may be unreasonable in a dynamic process. When new information is obtained, the prediction system should be updated. In this paper, the new information includes two parts—the newly updated measurement records and the WRF simulation result. From this opinion, this paper develops a SA-ARIMAX model, which has adaptive model parameters when the new information is available. During this process, the CPSO algorithm is applied to obtain the optimized parameters. Simulation results show that the developed SA-ARIMAX-CPSO method in this paper performs considerably better than the original auto-regressive moving average with exogenous variables (ARMAX), ARIMAX, and adaptive ARMAX models.

1.4. Structure of This Paper

The rest of this paper is organized as follows: Section 2 reviews the original ARIMAX model. Section 3 introduces the improved SA-ARIMA optimized by the CPSO algorithm. Section 4 shows the available data sets and model measurements. Sections 5 and 6 display the experiments and analysis. Afterward, conclusions are discussed in Section 7. Finally, acknowledgements and references are given.

2. Original ARIMAX Model

The developed ARIMAX model in this paper is a single-input and single-output (SISO) system, which is defined as follows:

$$A\left(z^{-1}\right)y(t) = B\left(z^{-1}\right)u(t) + C\left(z^{-1}\right)e(t) \tag{1}$$

The input data passes through a difference filter D times, where:

$$A\left(z^{-1}\right) = 1 - a_1 z^{-1} - \cdots - a_p z^{-p} \tag{2}$$

$$B\left(z^{-1}\right) = b_1 + b_2 z^{-1} + \cdots + b_q z^{-q+1} \tag{3}$$

$$C\left(z^{-1}\right) = 1 + c_1 z^{-1} + \cdots + c_r z^{-r} \tag{4}$$

$y(t)$ is the output at time t, $u(t)$ is the exogenous variable at time t, $e(t)$ is the white noise, and p, q and r are the orders of auto-regressive (AR), moving average (MA) and exogenous (X), respectively. Moreover, z^{-1} represents the delay operator, and $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are the parameters of AR, MA and X parts, respectively. It is assumed that the zero points of $A(z^{-1})$ and $C(z^{-1})$ are located in the unit circle. Equation (1) can be re-written as:

$$\begin{aligned} y(t) = a_1 y(t-1) + \cdots + a_p y(t-p) + b_1 u(t) + b_2 u(t-1) + \cdots + b_q u(t-q+1) \\ + e(t) + c_1 e(t-1) + \cdots + c_r e(t-r) \end{aligned} \tag{5}$$

To determine the model order, the most popular one is the Bayesian Information Criterion (BIC) [38]. Reference [39] provides a detailed discussion on order determination for the ARIMAX model by using the BIC method.

The parameters $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are obtained by the recursive maximum likelihood estimation method [40]. Thus:

$$\theta = \left[a_1, \ldots, a_p, b_1, \ldots, b_q, c_1, \ldots, c_r\right] \tag{6}$$

The recursive estimation of θ can be expressed as:

$$\theta(t+1) = \theta(t) + K(t)\left(y(t+1) - \varphi^T(t)\theta(t)\right) \tag{7}$$

where $\theta(0)$ can be any value, $\theta(i) = 0$ if $i < 0$, and:

$$K(t) = \frac{P(t)\varphi(t)}{1 + \varphi^T(t)P(t)\varphi(t)} \tag{8}$$

$$P(t+1) = P(t) - K(t)\varphi^T(t)P(t) \tag{9}$$

$$\begin{aligned}\varphi(t) = [&y(t-1),\ldots,y(t-p),u(t),\ldots,u(t-q+1),y(t-1)\\&-\varphi^T(t-1)\theta(t),\ldots,y(t-r)-\varphi^T(t-r)\theta(t-r+)]\end{aligned} \tag{10}$$

3. Self-Adaptive ARIMAX Optimized by CPSO Algorithm

3.1. Self-Adaptive ARIMAX (SA-ARIMAX) Method

In the original ARIMAX model introduced in Section 2, the model parameters $A\left(z^{-1}\right)$, $B\left(z^{-1}\right)$ and $C\left(z^{-1}\right)$ are fixed by the training data set. This is unreasonable in real applications. When new information is obtained, the forecast system should be updated. From this point of view, this paper develops a SA-ARIMAX model with adaptive model parameters.

The model parameters are denoted at time t as $A^{(t)}\left(z^{-1}\right)$, $B^{(t)}\left(z^{-1}\right)$, and $C^{(t)}\left(z^{-1}\right)$, as follows:

$$A^{(t)}\left(z^{-1}\right) = 1 - a_1^{(t)}z^{-1} - \cdots - a_p^{(t)}z^{-p} \tag{11}$$

$$B^{(t)}\left(z^{-1}\right) = b_1^{(t)} + b_2^{(t)}z^{-1} + \cdots + b_q^{(t)}z^{-q+1} \tag{12}$$

$$\varphi C^{(t)}\left(z^{-1}\right) = 1 + c_1^{(t)}z^{-1} + \cdots + c_r^{(t)}z^{-r} \tag{13}$$

Assuming that the model parameters at time t are estimated, Equation (5) can be re-rewritten as:

$$\begin{aligned}\hat{y}(t+1) = {}&a_1^{(t)}y(t) + \ldots + a_p^{(t)}y(t-p+1) + b_1^{(t)}u(t+1) + b_2^{(t)}u(t) + \ldots\\&+b_q^{(t)}u(t-p+2) + e(t+1) + c_1^{(t)}e(t) + \ldots + c_r^{(t)}e(t-r+1)\end{aligned} \tag{14}$$

When the new information is obtained at time $(t+1)$, the model parameters should be updated. As fitted by ARIMAX with the same model orders as previously stated, parameters are obtained and denoted as $\hat{A}^{(t)}\left(z^{-1}\right)$, $\hat{B}^{(t)}\left(z^{-1}\right)$, and $\hat{C}^{(t)}\left(z^{-1}\right)$. Then, at time $(t+1)$, the parameters of the forecasting model should be influenced not only by the parameters at time t, $A^{(t)}\left(z^{-1}\right)$, $B^{(t)}\left(z^{-1}\right)$, and $C^{(t)}\left(z^{-1}\right)$ but also by the new information $\hat{A}^{(t)}\left(z^{-1}\right)$, $\hat{B}^{(t)}\left(z^{-1}\right)$, and $\hat{C}^{(t)}\left(z^{-1}\right)$. Thus, this paper takes a weighted average of the two aspects, as:

$$A^{(t+1)}\left(z^{-1}\right) = (1-\alpha)\hat{A}^{(t+1)}\left(z^{-1}\right) + \alpha A^{(t)}\left(z^{-1}\right) \tag{15}$$

$$B^{(t+1)}\left(z^{-1}\right) = (1-\beta)\hat{B}^{(t+1)}\left(z^{-1}\right) + \beta B^{(t)}\left(z^{-1}\right) \tag{16}$$

$$C^{(t+1)}\left(z^{-1}\right) = (1-\gamma)\hat{C}^{(t+1)}\left(z^{-1}\right) + \gamma C^{(t)}\left(z^{-1}\right) \tag{17}$$

where $0 < \alpha, \beta, \gamma < 1$ are three weights.

3.2. Parameters in the SA-ARIMAX Model

There are two categories of parameters in the SA-ARIMAX model. One category are the ARIMAX parameters, named $A\left(z^{-1}\right)$, $B\left(z^{-1}\right)$ and $C\left(z^{-1}\right)$ and defined by Equations (11)–(13). This set of parameters can always be obtained by the least square (LS) method during the model fitting process. The other category is the self-adaptive parameters, α, β, and γ, defined in Equations (15)–(17) when applying the SA strategy to an ARIMAX process. It can be easily found that parameters α, β, and γ represent a weighted average between the historical and the newly fitted model parameters. Larger α, β, and γ prove that the prediction model takes more information from the historical model parameters, while smaller values of α, β, and γ prove that the newly fitted model parameters cause more influence on the final forecasting results.

Values of α, β, and γ affect the model performance by constructing a different information balance between the historical and newly fitted model parameters. The determination of α, β, and γ is difficult but quite essential. To search for the optimized parameters α, β, and γ during the SA process, this paper applies the CPSO algorithm, which is a swarm intelligent method. The combination with the CPSO algorithm enables the developed SA-ARIMAX model to absorb the newly updated information with an optimized coefficient.

3.3. Model Optimization by CPSO Algorithm

3.3.1. Working Principle of CPSO Algorithm

Particle swarm optimization (PSO) simulates the social psychological metaphor based on swarm intelligence. Two best values exist in the simulation process of PSO. For each particle in the problem space, the best value obtained up to now is denoted as $pBest$. In terms of the global version, the overall best solution achieved up to now is called $gBest$. The procedure for PSO can be expressed as shown in Appendix A [41,42].

3.3.2. Developed Method: SA-ARIMAX Optimized by CPSO (SA-ARIMAX-CPSO)

In this paper, the three coefficients, α, β, and γ, are optimized by the CPSO algorithm introduced in Section 3.3.1. Then, the prediction value at time $(t+1)$ can be calculated by Equation (14) using the optimized parameters. The developed self-adaptive ARIMAX method optimized by CPSO, called SA-ARIMAX-CPSO in this paper, can be divided into several steps as Appendix B shows. Figure 1 shows the flowchart.

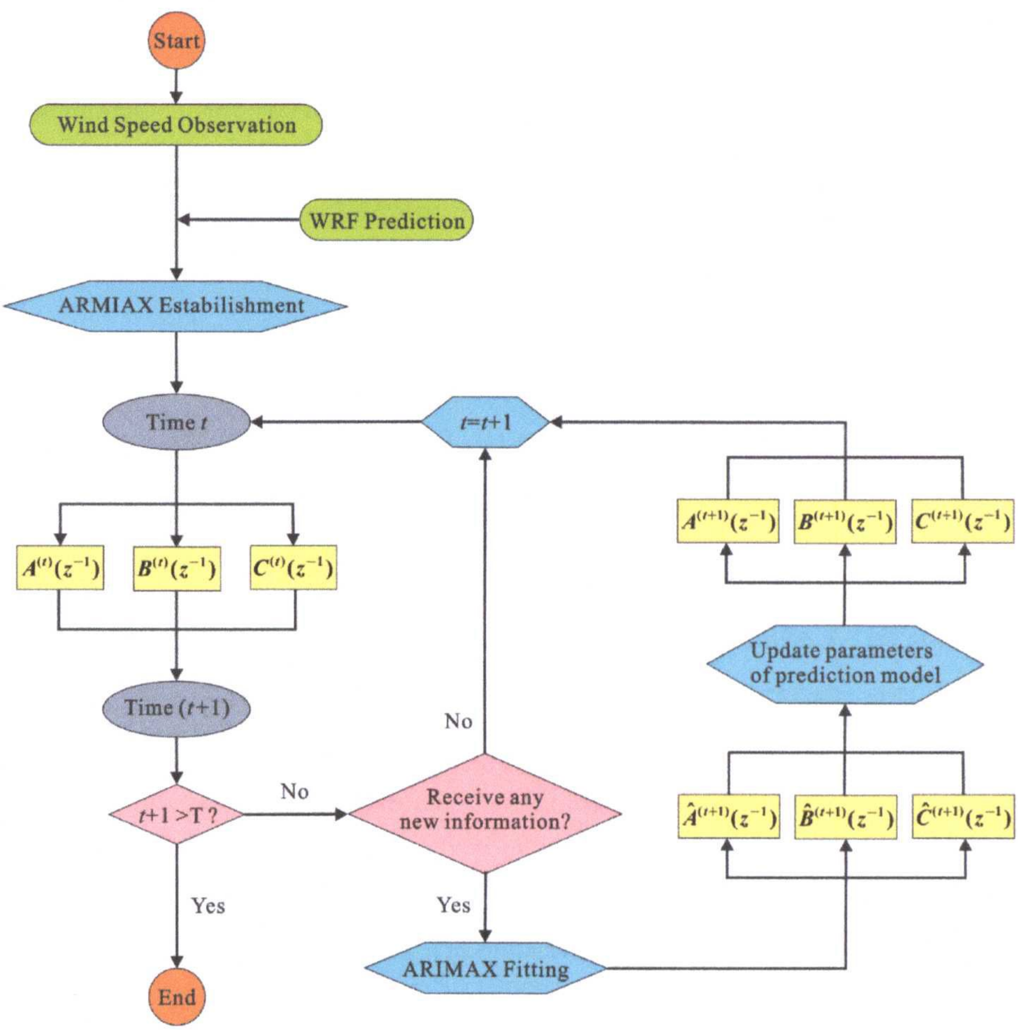

Figure 1. The flow chart of SA-ARIMAX-CPSO method.