Energy Conversion and Management 126 (2016) 748–758

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Selection of time window for wind power ramp prediction based on risk model

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ARTICLE INFO

Article history:
Received 3 June 2016
Received in revised form 21 August 2016
Accepted 22 August 2016
Available online 26 August 2016

Keywords:
Wind power ramp events
Time window
The minimum risk model
Ramp prediction

ABSTRACT

To reduce the harm of wind power ramp events in advance, an effective wind power ramp prediction system is needed. A new ramp prediction approach utilizing suitable selected time windows as units is proposed in this paper. Two risk factors are defined based on the performance analysis of ramp prediction, and the risk minimization principle is applied to build the risk model. Combining the correlation analysis and the statistical analysis of ramp duration, model constraints are studied. The optimal time window of industrial data is computed for ramp prediction based on a support vector regression model. Four evaluation indicators are chosen to verify that the proposed approach improves the performance of ramp prediction, and that the risk model is effective to select an optimal time window for prediction.

1. Introduction

Facing the increasing seriousness of energy crisis and environmental pollution, wind energy as a type of renewable energy has been widely utilized for power generation in power grid [1]. However, the safety and stability of power system is threatened by the fluctuation and uncertainty of wind power, e.g., the large change of wind power within a long period caused by ramp events [2]. Since wind resource is generally concentrated in geography, the wind mode is developed in large scale and high concentration, e.g., there is a total capacity of approximately 75.6 GW in China in 2012 [3]. The potential threat of wind power ramps becomes more serious, therefore, it is absolutely important for the electrical power system to predict ramps.

A down-ramp event was reported in Texas of America in 2008 [4], causing serious economy loss to the Electric Reliability Council of Texas (ERCOT). Current studies of ramp events including ramp detection, classification and prediction should be improved. Since ramp detection was based on predicted wind power data and ramp definitions [5], wind power prediction is the core of ramp detection and classification. Based on predicted ramp events, ramp classification was applied to distinguish different ramp categories so that system operators take the suitable and economic control strategies [6]. The basic issue of ramp prediction involves the time scale of wind power prediction. However, different time scales were defined in uniform ramp definitions [7]. An event having an amplitude change with at least 50% of the total capacity within 4 h was called a ramp in [8]. The minimum ramp duration was defined as 1 h in [9]. The durations of actual ramp events are still various. It is difficult to decide a suitable time scale of predicted wind power for ramp prediction, detection and classification according to current ramp studies. While the wind power prediction scale affects not only the accuracy and complexity of ramp prediction, but also the validity of extracting characteristics for ramp classification. Therefore, the first step of ramp prediction is to determine the prediction time scale.

In this paper, prediction time window is defined as the time scale of wind power prediction. A risk model for selecting a suitable time window is developed based on the criterion of minimum risk. Focusing on time windows, the risk of each window is analyzed when predicting wind power and ramp events. Since the optimal time window is selected according to the minimum risk, ramp prediction based on results of several continuous units has the advantages of accuracy and efficiency, e.g., overcoming the long-term unpredictability by partitioned short-term predictions, efficiency of ramp detection and ramp classification.

Compared with the existing prediction methods, the ramp prediction performance here can be improved greatly. Currently, methods to predict wind power of ramp events are divided into two types: statistical models and physical models [10]. The statistical models including time series forecasting models, neural network models, support vector regression models, etc., achieved good performance on short-term and very short-term wind power prediction [11–13]. It is necessary for the wind power of ramps to be predicted in a long period. Statistical models are dissatisfactory

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http://dx.doi.org/10.1016/j.enconman.2016.08.064
0196-8904/

Nomenclature

Abbreviations

Acc	Accuracy
BPA	Bonneville Power Administration
CC	correlation coefficient
ERCOT	Electric Reliability Council of Texas
ERM	empirical risk minimization
Err	Error
FN	false negative events
FP	false positive events
MAE	mean absolute error
MAPE	mean absolute percentage error
NREL	National Renewable Energy Library
NWP	numerical weather prediction
P	Precision
R	Recall
RMSE	root mean square error
SRM	structural risk minimization
SVM	support vector machine
SVR	support vector regression
TN	true negative events
TP	true positive events

Symbols

D	duration
$f(\mathbf{x})$	SVR prediction model
F_t	swinging door algorithm
$H(*)$	entropy function
$h(x)$	a mapping function
$I(*)$	mutual information function
$\boldsymbol{K}(*)$	kernel function
$L(X_i)$	loss function
N	number of all historical ramp events
$P(t)$	wind power at time t
$P(x, y)$	the joint probability of X and Y
$P(X_i)$	the probability of the ith ramp event
P_1, P_2	two risk factors
$r(*)$	risk sub-functions
$R(h)$	risk function
$R_{emp}(h)$	empirical risk function
R_{val}	threshold of ramp rate
T_{set}	training set
τ	time window size
$\boldsymbol{\omega}$, b	parameters of SVM
ω_i	weight coefficient of the ith sub-function

due to the cumulated error in the long-term prediction. Physical models make use of the atmospheric dynamics equation to predict climate change, e.g., long-term wind speed variation, making the long-term prediction of wind power possible. For example, the numerical weather prediction (NWP) system was utilized in wind power prediction [14]. However, drawbacks of physical models still exist. The sufficient ramp characteristics can't be extracted due to the low local accuracy. Therefore, the proposed prediction method is realized as follows: wind power of each time window is predicted by the statistical models, and the model parameters of adjacent windows are modified according to the laws of physics. In this way, advantages of both models are effectively combined to achieve precise wind power prediction in a long period. Meanwhile, the selected time windows are useful to be taken as the units of ramp detection and classification. The traditional methods locate a ramp event by detecting the predicted data series from the starting point, but they have low efficiency. At the same time, it is feasible to detect ramps. In addition, ramp classification is more meaningful by using extracted ramp characteristics of time windows, and combining with traditional classification methods, e.g. *k-means* and support vector machine (SVM) [15,16].

The size of time windows is important. If it is small, a ramp event cannot be predicted completely, and the false alarm rate will lower the prediction performance. On the other hand, if it is large, long-term wind power is difficult to predict precisely, meaning the risks of complexity and precision will increase [17]. Therefore, a suitable time window is proposed to minimize risks. The industrial wind power data of 2013 from Bonneville Power Administration (BPA) website is taken as the study case to validate the selected time window.

The remaining parts of this paper are organized as follows: The framework of selecting time window, data source is introduced in Section 2. The process of building the risk model is given in Section 3, including the theory of risk minimization, model establishment and solution. The approach to predict wind power ramp events is presented in Section 4, including wind power prediction model and ramp detecting algorithm. The wind power data from BPA website is used for the study case to select the optimal time window in Section 5, and the validity of the selected time window and the proposed approach are discussed. The conclusion of the paper is given in Section 6.

2. Framework and data sources

2.1. Description of the framework

Fig. 1 shows the framework to select the optimal time window and to predict wind power ramps. Based on the wind power data, historical ramp events are detected by applying ramp detection algorithms and ramp definitions. On the other hand, wind power data is partitioned into continuous units by a given time window size. Combining these two steps, windows are classified into ramp windows and non-ramp windows. Based on the ramp windows, the minimum risk models are developed to select the optimal size of time window. All the time windows are applied to train the short-term wind power prediction models. Combining the selected time window and prediction models, wind power is predicted and ramp events can be detected.

2.2. Description of data sources

The wind power data from Bonneville Power Administration (BPA) website has a sampling interval of 5 min, and so totally 105,120 samples in 2013. Generally, raw wind data often contains random noise, missing data and abnormal data caused by fault operation of wind turbines, so data preprocessing is required. Missing and abnormal data is corrected by interpolation methods (e.g. linear interpolation, spline interpolation, higher order interpolation and so on). The de-noising process is used to remove high frequency and random noise, wavelet de-noising [18] is applied to the wind power data set. After these preprocessing, the data from January to May is used as the training data set, the data of June is utilized as the validation data set, and the data of remaining months is applied as the testing data set.

According to Fig. 1, it is important to identify ramp events from historical wind power. A ramp definition containing three main