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# Model of selecting prediction window in ramps forecasting

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ABSTRACT

Prediction of wind power ramp events is important to the stability operation of power system, it is realized by combining wind power prediction of several continuous units for long-term power prediction, then using detecting algorithms to extract ramps. A prediction unit is a prediction time window. Its size impacts the accuracy of predicting ramps, and an optimization model is proposed to select the suitable window size. First, a swinging door algorithm is applied to extract ramp events from historical data. A model for optimizing the time window size is established based on the minimum non-ramp data in a ramp window. The solution of the proposed model is discussed, including the selection of variables, constraints and algorithm. The model presented in this paper is tested, and performance of selected time window is discussed. Computational analysis demonstrates the validity of the model.



## 1. Introduction

Generation of electricity from the wind is expanding in response to environmental concerns [1]. The generated output of wind farm fluctuates and may adversely impact stability of a power system. There are many harmful wind events caused by the variability of wind, one of the most harmful events is a wind power ramp event, a large change of wind power over a short period of time [2]. For example, The Electric Reliability Council of Texas (ERCOT) declared system emergency due to the rapid and large down-ramp in 2008 [3]. As the installed capacity of wind farms grows, wind power ramp events (WPREs) require to be studied urgently to mitigate the adverse impacts of ramp events [4].

Ramp prediction is the basis for detection and control of ramp events. Currently, research on WPREs is still a new area. The published references mainly focused on ramp definition, classification, prediction, and detection. To define a ramp event for studying, Potter et al. [5] considered ramps as events that lasted at least 1 h. Greaves et al. [6] defined a ramp as an event causing at least 50% change of the installed capacity within 4 h. Three main characteristics: the ramp amplitude, the ramp duration, and the ramp rate were considered in ramp definitions [7]. Based on these definitions, some ramp detection algorithms were proposed, e.g., the dynamic programming recursion method based on a number of scoring functions [8], a swinging door algorithm extracting WPREs by the National Renewable Energy Laboratory (NREL) in Ref. [9]. Detected ramp events are classified into different categories by using *k*-means, SVM and other algorithms in Refs. [10,11], then the classification results direct system operators to take targeted control measures. An effective ramp control system requires an accurate ramp prediction system as the foundation.

Prediction time scale related to ramp duration (one of the basic ramp characteristics) is important to the precision of ramp prediction. For example, an unsuitable prediction time scale affects that ramp events cannot be detected completely since different ramp duration were defined according to [5,6]. On the other hand, prediction time scale affects the precision of wind power prediction which is one of two important steps in ramp prediction besides ramp detection [12]. Traditional wind power prediction (WPP) algorithms were grouped into two categories: physic-based and statistical models. Most physics-based models utilize the meteorological dynamic equations to predict wind speed, e.g., the numerical weather prediction system (NWPs), then determine wind power by transforming the predicted wind speed [13]. These methods offer advantage at capturing the wind trend over a long-term time scale, but the precision of local prediction is low. The statistical models emphasize the correlation between different variables in prediction. Auto-regression moving average (ARMA) model, Kalman filter model, neural network (NN), and other intelligent algorithms were applied in Refs. [14–16]. These models

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tend to perform well in prediction over short-term time scale, and error will increase as the time scale enlarges. Wind power prediction with high precision guarantee effective ramp detection, therefore it is seen that selecting a suitable time scale is important to the selection of an accurate WPP algorithm, and related to the precision of ramp prediction.

This paper proposes an optimization method to select a suitable time window (namely the prediction time scale) for ramp prediction. First, this method used a suitable definition to detect historical ramp events, then divided ramp window and non-ramp window based on location of historical ramps. An effective ramp prediction system requires high efficiency with less redundant prediction. Therefore, the optimization model selecting time window is built to minimize the non-ramp related data in a time window. Then the selected time window is taken as the prediction unit in long-term wind power prediction, and a hybrid model is used as the prediction model to improve precision [17,18]. The industrial wind data is taken in case study to validate the proposed method.

The rest of this paper is structured as follows. The basic concept of optimization of the time window size is presented in Section 2. Section 3 introduces the data sources and variables used in modelling. Section 4 presents details of the optimization concept outlined in Section 2. Computational results based on the wind data provided by the Bonneville Power Administration (BPA) are discussed in Section 5. Section 6 concludes the paper.

## 2. The concept of time window sizing

Since the duration of ramp events varies [19], an optimal time window needs to be determined. When a series of data points are divided by the given time window, a time window may contain ramp and non-ramp relevant data. The windows containing ramp data are called ramp windows, vice versa non-ramp windows. The non-ramp data in ramp window is required to be minimized to improve prediction efficiency.

Assuming the size of an optimal time window is $\tau$, the optimization concept of window size is illustrated in Fig. 1.

Considering the start and end time of a ramp is random, the time between two ramps is considered in optimization. In Fig. 1, *trs* is the time from the end of the follow-up ramp (Ramp 1) to the start of the current ramp (Ramp 2), *tre* represents the time from the end of the last follow-up to the end of the preceding ramp. In order to guarantee Ramp 2 locate in predicting unit (time window), the time period (from O to T) is assumed to be divided into $n$ equal size windows. Each window contains $\tau$ data points. There are $n$-1 non-ramp windows in the period of *trs*, and Ramp 2 occurs at the $n$th time window which is a ramp window (see Fig. 1). Taking a ramp window as a studying object, its wind power data is assumed as $\{y_i\}$, and contains two categories of data points defined in (1).

$$\delta_i = \begin{cases} 1, & y_i \in RampEvent \\ 0, & y_i \notin RampEvent \end{cases} \tag{1}$$

where, $y_i$ is the $i$th data point in the ramp window, and $i = 1,2,\cdots,\tau$. $\delta$ is a Boolean function, if $y_i$ is a ramp data point, $\delta_i = 1$, if not, $\delta_i = 0$. Then data set $\{y_i \mid \delta_i = 0\}$ in the ramp window is defined as non-ramp data, the corresponding time (e.g., $\Delta t_1$ and $\Delta t_2$) are defined as non-ramp relevant time. Since the length of non-ramp relevant time is related to sampling interval, the number of sampling data points is more suitable in modelling. Then the objective function for selecting the optimal time window size is proposed, the non-ramp data in all ramp windows is minimized as stated in (2).

$$\min \quad \sum_n \left| \tau - length(\delta_{n,i} = 1) \right| \tag{2}$$

where, $\tau$ is the number of data points in each time window. $n$ is the number of ramp windows in the total data set. $\delta_{n,i}$ represents the $i$th value of function $\delta$ in the $n$th ramp window.

## 3. Data sources and selection of input variables

### 3.1. Data sources

Wind power data from the Bonneville Power Administration (BPA) is used in this study. The number of data points sampled at 5 min intervals is 105,120. The data from January to May is taken as the training data set, the data of June is taken as the validation data set, and the data of rest months is taken as the testing data set. Before selecting time window size for WPREs prediction and analysis, some necessary data pre-processing steps are done, such as de-noising process, missing data processing and so on.

### 3.2. Extraction of ramp events

The first step in data analysis is identification of the historical ramp events from the BPA data set. The swinging door algorithm was proposed in Ref. [9] to extract approximately linear trend from wind power data, as illustrated in Fig. 2.

Fig. 2 illustrates the process extracting linear trend from wind power variance. Assuming starting to test from point O, a tolerance $\varepsilon$ (a "door") is defined. The value of wind power increases from Point O to Point A, and reaches the peak at Point B which is the extreme point on the upper bound. Then the value of wind power decrease from Point B to Point C. Since the upper bound is limited by Point B, the lower bound is limited to Point D due to the "door" size. Through this description, the swinging door likes a parallelogram (green dotted box) consisting of the starting point and the

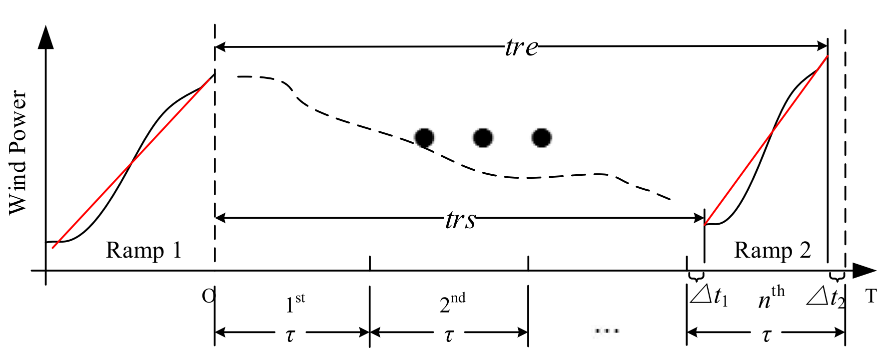


**Fig. 1.** Illustration of the time window size optimization.