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Optimisation of time window size for wind power ramps prediction

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Abstract: A new long-term wind power prediction approach based on time windows is proposed to improve the accuracy and efficiency of wind power ramp prediction. An optimisation model is built to select the optimal time window size which is the key point of the wind power forecasting. First, a swinging door algorithm is applied to identify historical ramp events, and historical data is divided into several sections by assumed time window size. Then, windows are classified into ramp windows and non-ramp windows, and the non-ramp data of ramp windows is required to be minimal. The variables, parameters, and constraints of the model are investigated in the study, and a kind of genetic algorithm is utilised to achieve the optimal solution. The model presented in this study is validated by the study case of actual wind farms, and evaluation and discussion demonstrate the validity of the proposed approach.

1 Introduction

The development of wind power is expanding in response to energy crisis and environmental concerns. In some areas which have a large amount of wind resources, wind power industry is being developed in the large-scale and high-concentration mode [1]. However, the fluctuation of wind power may do great harm to the stability of power system as the installed capacity grows fast, and the research on wind power ramp events (WPREs) will mitigate the potential threat on the security of power grid [2].

A ramp event implies a large change of wind power over a short period of time [3]. The Electric Reliability Council of Texas reported system emergency due to the rapid and large down-ramp in 2008 [4], then more attentions were paid on its research. The literatures about WPREs have mainly focused on ramp definition, classification, prediction, and detection. Ramp definitions are used to detect ramps from wind power data, and to analyse ramps' influence on power grid. Four ramp definitions based on three main characteristics: the ramp amplitude, the ramp duration, and the ramp rate were provided in [5]. Ramp detection is an important part of ramp prediction, its results provide the data for ramp classification and other research. A number of scoring functions and a dynamic programming recursion method were proposed to detect WPREs in [6]. A swinging door method was applied to detect WPREs by the National Renewable Energy Laboratory in [7]. Measures to mitigate ramp damage are taken based on results of ramp prediction and classification. Traditional classification algorithms [e.g. *k*-means and support vector machine (SVM)] were utilised to classify WPREs in [8, 9]. Ramp prediction is the most important part in ramp analysis, it provides the foundation of other analysis [10].

In [10], regression models and event detection models are two groups of ramp prediction methods. The former models are just used to predict the value of a ramp characteristic [11], and the latter are mainly used in ramp prediction. In the event detection models, wind power prediction (WPP) is the core of ramp prediction which detect ramps from predicted wind power [12, 13]. There are many types of prediction methods, and they are classified based on different prediction scales, e.g. short-term prediction, medium-term prediction and long-term prediction. In [14], Potter *et al.* considered ramps as events that last at least one hour. Greaves *et al.* [15] defined a ramp as an event causing at least 50% change of the installed capacity in 4 h, therefore ramp prediction requires medium- or long-term WPP. On the other hand, the algorithms of WPP are grouped into three classes: physical, statistical, and hybrid models. Physical models utilise the meteorological dynamic equations to predict wind speed, e.g. the numerical weather prediction (NWP) system, then determine wind power based on relation between wind speed and wind power [16]. These methods offer advantages at capturing the wind trend over a long-term horizon, but the precision is low in long term. Statistical models emphasise the correlation between different variables in prediction. Auto-regression moving average model, Kalman filter model, neural network (NN), and intelligent algorithms were applied in [17–19]. These models perform well in prediction over short-term horizons, but errors will accumulate in the long term. Hybrid models combine the advantages of physical and statistical models, and improve the accuracy of WPP in medium- and long-term [20, 21]. Therefore, hybrid models are good choices to predict wind power for ramp analysis.

A new hybrid approach is proposed to improve the accuracy and efficiency of ramp prediction. This approach divides the long-term WPP into short-term prediction in time windows. Short-term prediction in time window is realised by statistical models, and long-term trend is determined by physical models. The key point of this approach is to select a suitable time window size. The selection of time window size constraints the prediction bound of statistical models, and guarantees the statistical errors in limited range. On the other hand, by classifying time windows into ramp windows and non-ramp windows, it is useful to reduce computing resources in ramp detection and classification. However, there are no references reported to study this issue. An optimisation model selecting time window is proposed based on minimising the non-ramp data of time windows. An optimal window size is useful to improve the efficiency of predicting WPREs, industrial data is used to validate the established model in this paper.

The rest of this paper is organised as follows. The basic concept of optimising the time window size is discussed in Section 2. Section 3 introduces the data sources and variables used in modelling. Section 4 presents details of building the optimisation model for selecting time window size. Computational results based on the wind data provided by the Bonneville Power Administration (BPA) are discussed in Section 5, and the selected time window size is discussed. Section 6 concludes the paper.

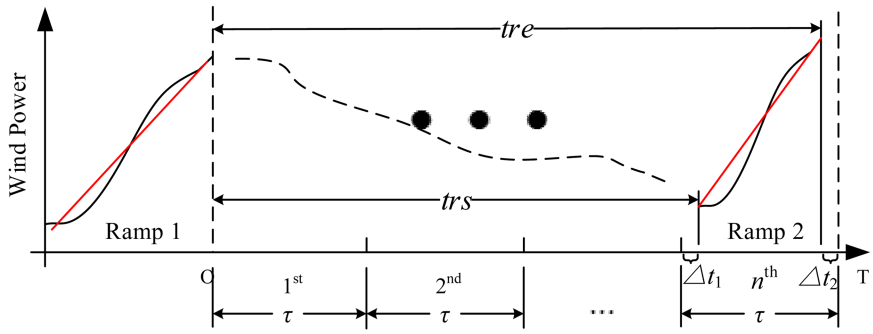

Fig. 1 *Illustration of the time window size optimisation*

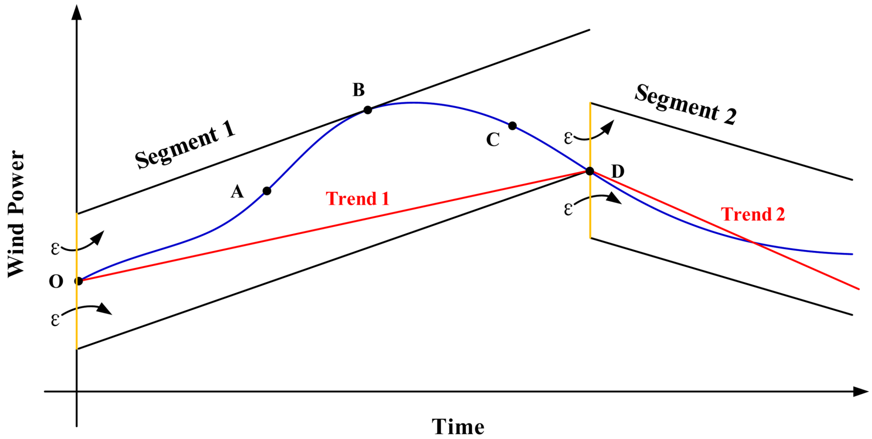

Fig. 2 *Schematic diagram of the swinging door algorithm*

2 Concept of optimising time window size

Since the duration of ramp events varies [22], an optimal window size needs to be determined for predicting ramp events validly. When a series of historical data are divided by the given time window size, 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 needs to be minimised in order to improve prediction efficiency.

Assuming the size of an optimal time window is τ, the optimisation 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 modelling. 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 locates in a predicting unit (time window), the time period (from O to T) is assumed to be divided into n equal size windows. Each window contains τ sampling points. There are $n-1$ non-ramp windows in the period of *trs*, and Ramp 2 occurs at the nth time window which is a ramp window (see Fig. 1). Taking a ramp window as an example, its wind power data is assumed as $\{y_i\}$, and having two categories of data points defined in the following equation.

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

where, y_i is the ith data point in the ramp window, and $i = 1,2,\ldots,\tau$. δ is a Boolean function, if y_i is a ramp data point, $\delta_i = 1$, otherwise, $\delta_i = 0$. Then data set $\{y_i \mid \delta_i = 0\}$ in the ramp window is defined as non-ramp data, the corresponding time (e.g. Δt_1 and Δt_2) are defined as non-ramp relevant time. Since the value of non-ramp relevant time depends on the sampling interval, the number of sampling points is more suitable as variable in modelling. Then the objective function for selecting the optimal time window size is proposed, the non-ramp data in all ramp windows is minimised as stated in the following equation.

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

where, τ 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 ith value of function δ in the nth ramp window.

3 Data sources and selection of input variables

3.1 Data sources

Wind power data from the BPA is used in this paper. The number of data points sampled at 5 min intervals is 105,120, and the installed capacity of the data is 5000 MW. Data needs to be pre-processed before selecting time window size for WPREs prediction and analysis, e.g. de-noising process, missing data processing and etc.

3.2 Extraction of ramp events

Identification of the historical ramp events from the BPA data set is the first step in data analysis. The swinging door algorithm was proposed in [7] to extract approximately linear trend from wind power data, illustrated in Fig. 2.

Fig. 2 illustrates the process extracting linear trend segments from wind power data. Assuming starting to test from point O, a tolerance ε (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. As a result, the linear trend of segment 1 is extracted from point O to point D. Similarly, linear trend of segment 2 is extracted by starting from point D. With these segments having linear trend, ramp events are identified based on ramp definition shown in the following equation [5].

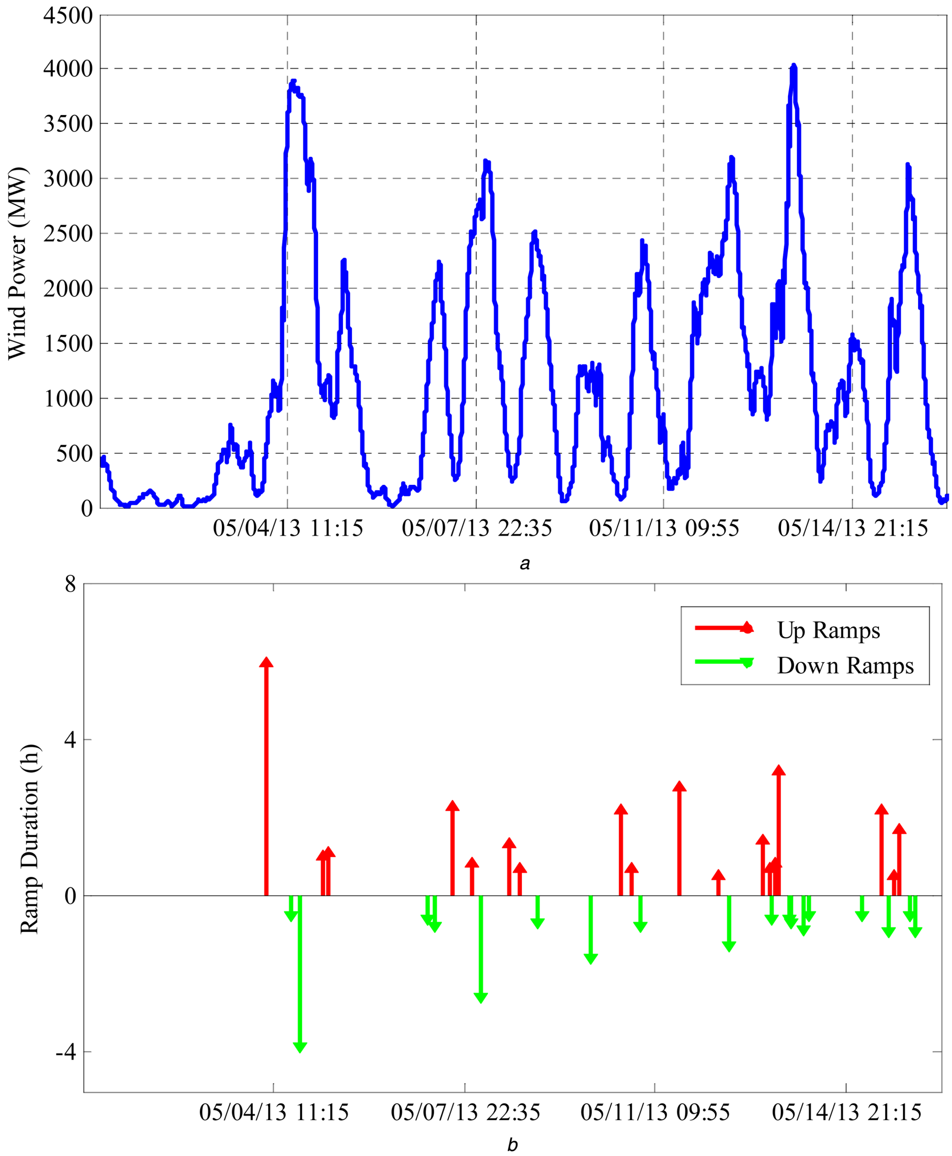

Fig. 3 *Results of historical ramp identification in May 2013*
(a) Wind power and, ***(b)*** ramp events

$$\frac{|y_{t+p} - y_t|}{p} > R_{\text{val}} \quad (3)$$

where y_t represents wind power data at time t; p represents the duration of the test data; R_{val} represents the threshold established for ramp events. This definition (3) states that an event is a ramp when the change of wind power is larger than the threshold R_{val}. The value of R_{val} was defined as 50% change of the installed capacity in 4 h [15], and the minimum ramp duration is defined as 0.5 h, then R_{val} is calculated as (50%*5000 MW)/4 $h = 625$ MW/h by considering the installed capacity of data source.

The ramp events are extracted from the historical data by the swinging door algorithm. Fig. 3 illustrates the identification of ramps from historical wind power in May 2013. The curve depicts the variance of wind power in Fig. 3*a*. The red lines (above the horizontal axis) in Fig. 3*b* represent the up-ramp events and the green lines represent the down-ramp events. The length of each line represents ramp duration.

3.3 Selection of input variables

The key point of selecting optimal time window size is to minimise the non-ramp data in ramp window. Assuming the ith ramp event of the data sets is E_i, the window contains E_i is called a ramp window. It is clear that ramp durations are different with each other in Fig. 3. Therefore, time is an important variable when selecting time window. The starting and stopping time of a ramp are also not suitable to describe in model, hence this paper proposes to utilise *trs* and *tre* to describe the time relation in Fig. 1. By extracting these two variables from each ramp event, Fig. 4 shows the distribution of $\{trs\}$ and $\{tre\}$.

From the distributions of *trs* and *tre* in Fig. 4, it is seen that time between two neighbouring ramp events is random, and the duration of a ramp event is reflected through the pair of value *trs* and *tre*. Therefore, these two variables are feasible as input variables and possible to make sure no information missed.

4 Establishment and solution of optimisation model

The suitable way to express non-ramp information is using non-ramp data or non-ramp time. Δt_1 and Δt_2 represent non-ramp time in a ramp window in Fig. 1. The purpose of (2) is to minimise the non-ramp information, another expression describing (2) is defined in the following equation.

$$\min \quad (\Delta t_1)^2 + (\Delta t_2)^2 \quad (4)$$

where $|\Delta t|$ represents the length of time period Δt. Ignoring the issue of sampling interval, $|\Delta t|$ is computed as the number of data points in the period of Δt.

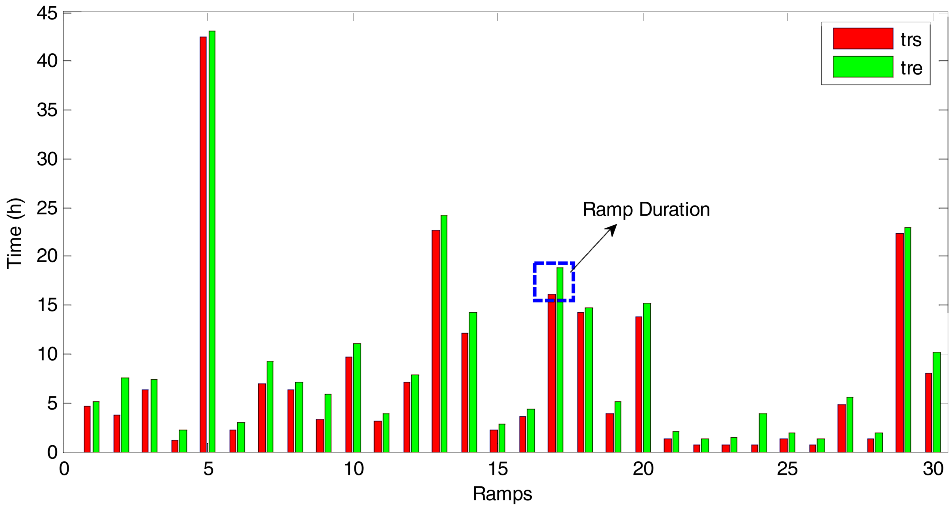

Fig. 4 *Distributions of variables trs and tre*

4.1 Minimum non-ramp time of a ramp window

Minimising the non-ramp information is important for the effectiveness of ramp prediction and analysis. Taking a historical ramp event E_i as an example, using (4) as the objection function, model (5) is derived.

$$d_i = \min \left\{ \left(\Delta t_{1,i}\right)^2 + \left(\Delta t_{2,i}\right)^2 \right\}$$
$$\text{s.t.} \quad \begin{cases} \Delta t_{1,i} = \left| t_{\text{rs}}^i - (n_i - 1)\tau \right| \\ \Delta t_{2,i} = \left| n_i \tau - t_{\text{re}}^i \right| \\ n_i \in Z^+ \end{cases} \tag{5}$$

where t_{rs}^i and t_{re}^i are the value of *trs* and *tre* when taking ramp E_i as example, respectively. τ represents the size of time window, n_i means there are n_i-1 non-ramp windows between E_{i-1} and E_i. d_i represents the minimum non-ramp time in the ith ramp window. If the value of τ is given, then the function d_i calculating non-ramp time is about variable n_i. A optimal solution exists when $d_i(n_i)$ is a convex function. Similarly, when the value of n_i is given, the optimal value of τ is achieved. As a result, it is concluded that there exists a specific pair of τ and n_i for each ramp event to guarantee the non-ramp time minimum in the ramp window.

4.2 Minimum non-ramp time of the whole data sets

According to model (5), different window size will be calculated when taking different ramp events for study, it means that the window size analysing one ramp may be different with that of other ramp analysing. Selecting the optimal time window is to find the suitable size minimising the non-ramp information for the whole data sets. The total minimum non-ramp time is expressed in (6) on the basis of (5).

$$\min_{\tau} \quad \sum_i d_i(\tau) \tag{6}$$

where $d_i(\tau)$ represents the optimal non-ramp time of the ith ramp event. Considering that the time window is used for ramp prediction and analysis, and that ramp duration has the limitation of minimum value in [14], setting the definition domain is useful to reduce the computing resources. Change of wind power in a very short period is a pulse, not a ramp, hence the minimum constraint of window size is defined as T_m. Then (6) is rewritten as.

$$\min_{\tau} \quad \sum_i d_i(\tau)$$
$$\text{s.t.} \quad \tau \geq T_m \tag{7}$$

4.3 Selection of parameters and algorithm

Through (5)–(7), it is obvious that these models are both about two variables (τ and n). Before solving this model, the parameter selection and the constraints of these two variables should be taken into account.

Assuming the followed ramp is detected in the n_ith (limited to be positive integer) time window, then the number of time windows between two ramp events is n_i-1. That means a complete time window should be applied in ramp prediction and analysis. Combining Fig. 1 and formula (5) and (8) is used to find the optimal value of n_i.

$$\left[\frac{t_{\text{rs}}^i}{\tau} \right] + 1 \leq n_i \leq \left[\frac{t_{\text{re}}^i}{\tau} \right] \tag{8}$$

where t_{rs}^i and t_{re}^i represent the starting and ending time of E_i from the ending of $E_{i\text{-}1}$, and $[x]$ is the maximum integer less than x.

Variable τ representing the time window size also needs constraints. As described in (7), the constraint should limit the minimum value. There are two factors to decide the value of the minimum parameter T_m. On the one hand, T_m should be larger than the minimum duration of historical WPREs. On the other hand, T_m should guarantee to predict a ramp event in a time window validly. Considering these two requirements, this paper proposes to select the average value of ramp durations as T_m in the following equation.

$$T_m = \sum_i p_i \times \left(t_{\text{rs}}^i - t_{\text{re}}^i \right) \tag{9}$$

where the ramp duration is reflected by the difference of *trs* and *tre*, p_i represents the probability of each ramp duration. This paper analyses the statistical characteristics of historical ramp events in Fig. 3 to obtain the value of p_i. Since all ramp events are treated equally, the value of T_m is selected as the average ramp duration. The average ramp duration of historical WPREs is 1.35 h. It means that WPREs can be predicted at the average level when the minimum time window $T_m = 1.35$ h. Considering the sampling interval, the value of T_m is set to 1.5 h.

The models can be solved when the constraints and the parameter values are given. The objective function expressed as $\Phi(\tau, N)$ is non-linear on variable τ and vector $\boldsymbol{N}$, $\boldsymbol{N} = [n_1, n_2, \ldots]^{\text{T}}$. The traditional numerical calculation methods are not convenient in this case since the solution of N is related to each individual ramp event and τ is related to the entire data set.

The genetic algorithm (GA) is a method to solve both constrained and unconstrained optimisation problems based on biological evolution [23]. It is usually applied to solve problems

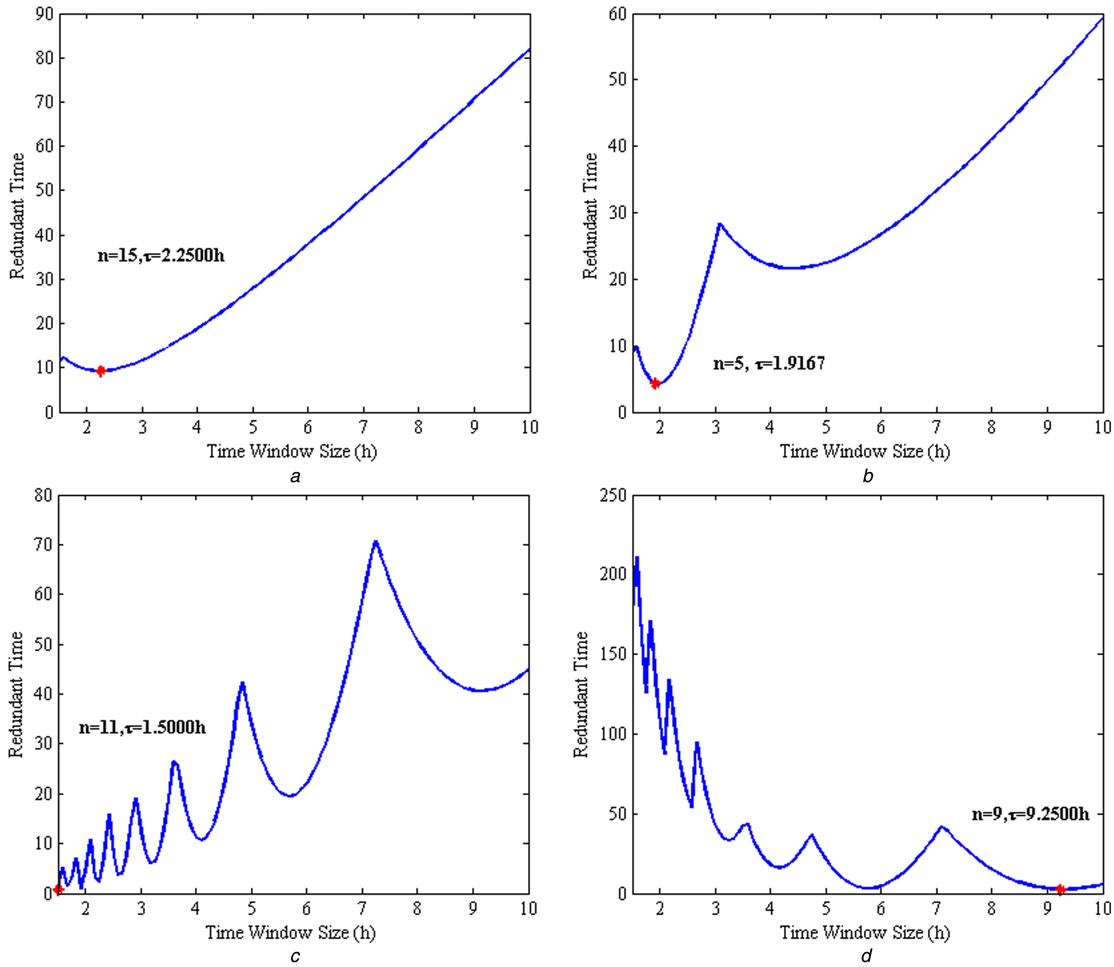

Fig. 5 *Variations of minimum non-ramp time*
(a) One case having the minimum non-ramp time when $n = 15$, $\tau = 2.2500$ h, ***(b)*** One case having the minimum non-ramp time when $n = 5$, $\tau = 1.9167$ h, ***(c)*** One case having the minimum non-ramp time when $n = 11$, $\tau = 1.5000$ h, ***(d)*** One case having the minimum non-ramp time when $n = 9$, $\tau = 9.2500$ h

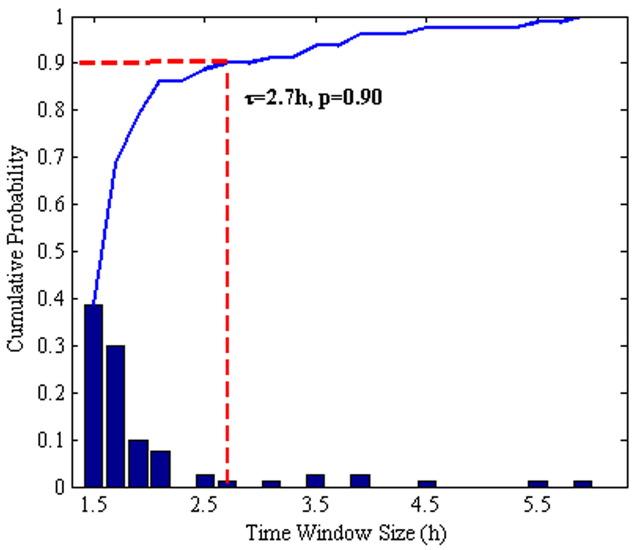

Fig. 6 *Probability distribution of different time window size*

that are not well suited for standard optimisation algorithms, such as discontinuous, non-differentiable, stochastic and highly non-linear problems. Thus it is feasible to solve the problem in selecting time window for WPREs. The process of GA contains three parts:

i. Initialisation. This process creates a random population.
ii. Evaluation. This process is to evaluate the results of objective function. For example, the evaluation is to judge whether the redundant information is the minimum in the paper.
iii. Genetic operation. This part is to produce the children for the next generation, it includes parts of mating, crossover, random production of offspring, mutation and reproduction.

Through the successive generations, the algorithm modifies the population of individual solutions and evolves to optimal results. By applying this algorithm in (5) and (7), the optimal time window for ramp prediction and analysis can be selected.

5 Case study and discussion

5.1 Selection of the optimal window size

The historical WPREs are obtained from the data of BPA area. Each ramp window is analysed individually in order to optimise non-ramp time for selecting time window size. The objective function about two variables n_i and τ is presented in (5), and the GA is used to solve the optimisation issue. Fig. 5 shows the graph of non-ramp time in different size of time window.

From Fig. 5, it shows four typical variations of minimum non-ramp time in different ramp events' analysis. The possible minimum time window size is restrained as 1.5 h by the parameter T_m. It is seen that different optimal time windows are obtained when different ramp events are studied in (5). The value of τ is not too large in most of cases (e.g. Figs. 5*a*–*c*), and a large window size is optimal only in a few cases (e.g. Fig. 5*d*). In order to analyse the possible time window sizes of each ramp events, (5) is applied to calculate the optimal time window size of all historical ramp events. Fig. 6 gives out the distribution of time window size.

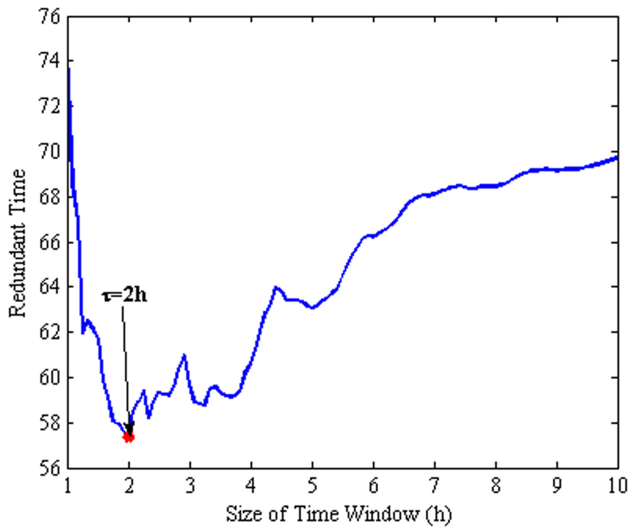

Fig. 7 *Optimal result of time window selection*

Table 1 Confusion matrix

	Observation		Total
	True	False	
prediction true	TP	FP	true prediction
false	FN	TN	false prediction
total	true observation	false observation	***N*** = TP + FP + TN + FN

Table 2 Prediction performance of ramp windows at different time window sizes

	Precise	Recall	Accuracy	Error
1.5 h	0.7976	0.8072	0.8166	0.1834
2.0 h	0.8059	0.8390	0.8747	0.1253
2.5 h	0.7857	0.7781	0.8047	0.1953
3.0 h	0.7619	0.7701	0.7811	0.2189
3.5 h	0.7571	0.7889	0.7757	0.2243

It is clear that the majority of time window size with the minimum non-ramp time is lesser than 2.5 h in Fig. 6. To calculate the probability of time window size, Fig. 6 also shows the cumulative distribution to analyse the range of time window size. 90% of ramp events have an optimal time window for ramp prediction in the range of 1.5 to 2.7 h. Therefore, if the final time window size for the whole data set is chosen in this range, it guarantees less non-ramp time as possible.

On the other hand, the model (7) is established to select the optimal time window based on the minimum non-ramp time of the whole data set. Similarly, the parameter of T_m and N are decided according to the above description. Since τ and n_i of N need to be calculated, traditional methods are not convenient to solve this issue, the GA algorithm is also applied in (7). The results of calculating the non-ramp time of the whole data set are shown in Fig. 7.

Fig. 7 shows the curve of non-ramp time with different time window size. It is seen that the minimum non-ramp time is obtained when the time window size is chosen as 2 h. Combined with the results in Fig. 6, it is concluded that a time window size of 2 h is suitable, it not only makes the whole data sets have the minimum non-ramp time in Fig. 7, but also guarantees each ramp event to be contained in a time window validly since it is in the range of [1.5 h, 2. 7 h]. As a result, the final size of time window for ramp prediction and analysis is decided as $\tau = 2.0$ h.

5.2 Evaluation and discussion

To evaluate the performance of the selected time window size, the confusion matrix of information retrieval field [24] is introduced as the criterion in ramp prediction and analysis, the detailed description of this matrix is defined in Table 1.

In Table 1, TP represents true positive events; FN represents false negative events; FP represents false positive events; TN represents true negative events. There are a series of indicators defined according to Table 1, such as recall (R), precision (P), accuracy (Acc), error (Err), F-measure, and so on [25]. The first four indicators are defined in (10), they are usually used to assess the performance of many research analysis, such as prediction, classification and so on.

$$\begin{cases} R = \dfrac{\text{TP}}{(\text{TP} + \text{FN})} \\ P = \dfrac{\text{TP}}{(\text{TP} + \text{FP})} \\ \text{Acc} = \dfrac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \\ \text{Err} = 1 - \text{Acc} \end{cases} \tag{10}$$

By using the selected time window, the hybrid models are utilised to predict wind power for ramp prediction. First, the time window size is used to divide the data, then the prediction of wind power in each window is regarded as a short-term prediction. By taking the support vector machine (SVM) as the prediction model [26] and utilising the data of NWPs as prediction input, the prediction model of wind power is established and trained. The model is used to predict wind power window by window, then the predicted wind power is used to detect ramp events by detection algorithms. In the process of ramp detection, increasing the number of ramp windows is helpful to predict ramps by allowing to lose a few points of a ramp in a time window. Therefore, an approximate definition of a ramp window is described in (11), where a ramp window is regarded to contain most wind power of a ramp.

$$\text{Rampwindows:}\{\text{ramps}|(trs \geq (n_i - 1)\tau - \eta)|(tre \leq n_i\tau + \eta)\} \tag{11}$$

where, it means the window containing 90% of ramp data as a true ramp window when $\eta = 10\% \cdot \tau$. This definition is more valid to detect a ramp event in a time window for actual system operators. In order to compare the prediction performance of different time window size, different time window sizes (e.g. 1.5, 2.0, 2.5, 3.0 and 3.5 h) are used in the proposed ramp prediction method.

Table 2 shows the prediction performance of ramp windows according to the four indicators presented in (10). It is seen that when the time window size is selected as $\tau = 2.0$ h, the value of recall, precision, accuracy exceed 80% and have the best performance than other window sizes. It also illustrates that WPREs will be captured effectively in the selected ramp windows, and that the method for selecting time window size is valid in ramp prediction and analysis.

Furthermore, the receiver operating characteristic (ROC) curve is a useful tool based on confusion matrix for performance analysis [27]. The window size $\tau = 1.5$ h and $\tau = 2.5$ h are chosen for comparison with 2.0 h, and the results of these three different time window sizes are shown in Fig. 8.

In Fig. 8, the vertical axis represents the value of true positive rate, namely the value of recall. The horizontal axis represents the value of false positive rate (FPR) defined in the following.

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{12}$$

Combining (10) and (12), the performance of a prediction system is expressed by ROC curve. In ROC space, the green diagonal line represents the random guess, and the best prediction system will yield a point in the upper left corner of the ROC space. Conversely, if the points are below the diagonal line, it means the prediction performance is bad. It is seen that the point representing 2.0 h time window locates more close to the left and up in Fig. 8, which means the 2.0 h time window has the best prediction performance. While 1.5 and 2.5 h time windows have more non-ramp time when

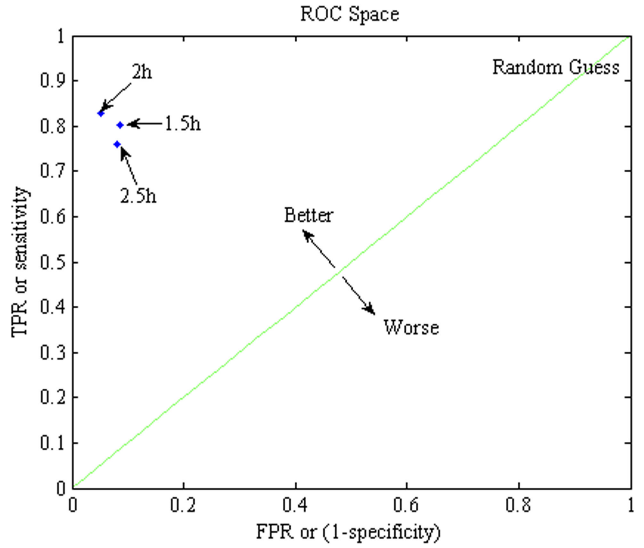

Fig. 8 *Prediction performance of ramp windows at three window sizes in ROC space*

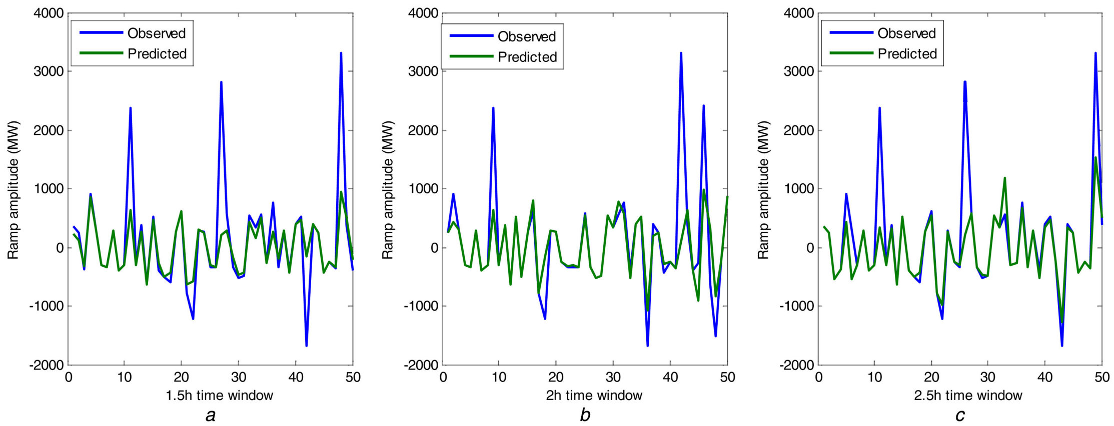

Fig. 9 *Prediction results of ramp amplitude at different time windows*

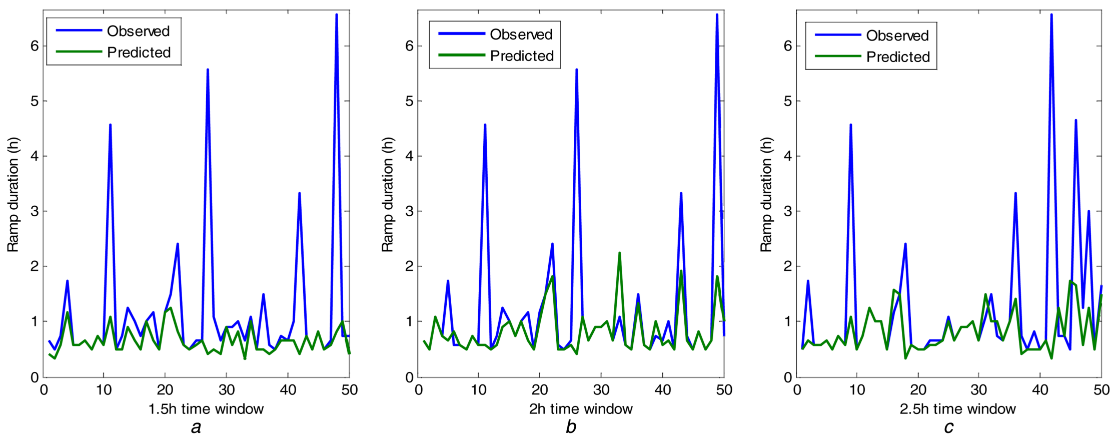

Fig. 10 *Prediction results of ramp duration at different time windows*

predicting a ramp event, which influences the accuracy of ramp detection and results in the smaller values in ROC space.

To verify the selected time window size is optimal in ramp prediction, ramp events are detected in the predicted ramp windows. According to (3), three main ramp characteristics are extracted from the predicted ramps, and used for performance analysis in Figs. 9–11.

By taking 50 true ramp windows as examples at different window sizes, Figs. 9–11 shows the prediction results of ramp amplitude, ramp duration and ramp rate, respectively. It is seen that there are some errors in prediction of ramp characteristics at different window sizes. To evaluate the performance, the mean (m) and standard deviation (σ) of ramp prediction are calculated in Table 3.

In Table 3, the statistical indicators of ramp prediction error are shown. In prediction of ramp amplitude and ramp duration, the time window of 2.0 h has the smallest mean and deviation. In prediction of ramp rate, 2.0 h time window also has smallest deviation and 2.5 h time window has the smallest mean. Combining the results of Fig. 11, the prediction of ramp rate at three window size are all good. Therefore, it is concluded from all results that the selected time window size (2.0 h) is optimal in ramp prediction, and the proposed approach is feasible to select the optimal time window.

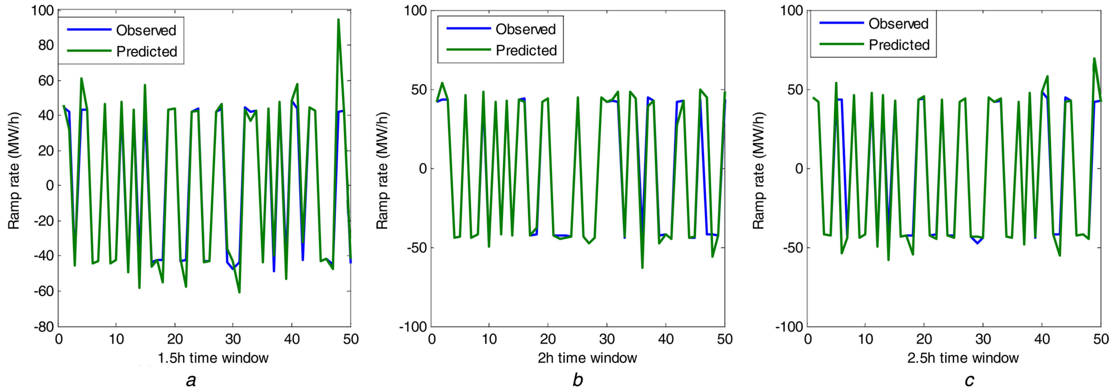

Fig. 11 *Prediction results of ramp rate at different time windows*

Table 3 Statistical indicators of ramp prediction errors at different window sizes

	Ramp amplitude, MW		Ramp duration, h		Ramp rate, MW/h	
	m	*σ*	*m*	*σ*	*m*	*σ*
1.5 h	60.8939	622.9557	6.7576	14.2376	−1.4726	14.2090
2.0 h	**45.6607**	**532.7516**	**4.2286**	**12.7053**	−1.0594	**12.5115**
2.5 h	82.1857	614.661	4.6429	13.9641	**0.1101**	16.9335

6 Conclusions

An optimisation model was proposed to select a suitable time window for the new ramp prediction approach improving accuracy. The non-ramp time was selected as the research object and required minimum in modelling. The minimum non-ramp time of a ramp window and that of all ramp windows were calculated. The final time window size based on actual data of BPA area was decided as 2.0 h. To analyse the validity of the selected time window, the prediction method based on the selected time window is proposed to predict ramp events. SVM model is regarded as the basic prediction model in this paper. The results of ramp prediction is good. To analyse the optimisation of 2 hours' time window, the window size of 1.5 and 2.5 h were also used to predict ramp events, the results of ROC curve verified that the time window size of 2.0 h has the minimum non-ramp time and also the better performance in ramp prediction.

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