Wind power ramp detection algorithms based on slope point correction

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***Abstract*—Wind power ramp event refers to the large fluctuation of wind power in a short time interval, which will seriously affect the safe and stable operation of power grid system. In order to maintain the stable operation of power grid system, wind power ramp detection is extremely necessary. Therefore, how to improve the accuracy of wind power ramp detection is a problem worthy of study. In the existing wind power ramp detection algorithms, the accuracy of the ramp endpoint is not considered. Aiming at the problem of end-point accuracy in climbing section, this work proposes a wind power climbing detection algorithm RPCRD (ramp point correct climbing detection) based on ramp point correction, which considers the detection accuracy of wind power climbing point for the first time. In this algorithm, a merging method of climbing sections is proposed to solve the fracture problem, and a scoring mechanism for selecting climbing points is proposed to find the two extreme points that most conform to the climbing characteristics, and the climbing points at both ends of the climbing section of wind power are modified.**

***Index Terms*—Wind power ramp, Trend fitting, RPCRD algorithm**

I. Introduction

In recent years, wind energy has become the fastest growing new energy in the world due to its renewable, pollution-free, high energy and broad prospects. Wind power generation technology is developing rapidly, and it also faces many problems to overcome. Because wind is irregular and intermittent, the wind power connected to the grid may fluctuate greatly in a short time. This phenomenon of wind power fluctuation is called wind power ramp events (WPREs) [1].Wind power ramp detection, characterization and modeling is a new topic in the field of wind power statistical prediction.

The existing literature on wind power ramp event detection, such as kamath [2], Ren [3], Zareipo [4], Cutle [5], Bradfor [6], Yang [7], Ber [7] and Gallego [8], does not consider the accuracy of wind power ramp point (i.e. the start time and end time of ramp event). This work aims to solve the accuracy problem of wind power ramp point, and realize the wind power ramp detection algorithm based on ramp point correction. The algorithm has wider applicability and more accurate effect of climbing detection.

In the field of wind power ramp detection, this work proposes a wind power ramp detection algorithm RPCRD based on ramp point correction for the first time, which solves the accuracy problem of the start and end points of the ramp detection algorithm. In RPCRD algorithm, a scoring mechanism is proposed to select the optimal local extremum points for climbing segment correction, which can effectively improve the detection effect of existing algorithms.

The main contributions of this work are as follows.

This work proposes a wind power ramp detection algorithm RPCRD based on ramp point correction. Different from other existing researches, RPCRD mainly aims at the problem of inaccurate end points of the ramp section. RPCRD algorithm uses the way of merging climbing segments to solve the problem of climbing segment fracture. At the same time, considering the characteristics of the end points of the climbing section, the algorithm extracts the local extremum points of the wind power time series data, and selects the optimal extremum points through the scoring mechanism to modify the preliminary climbing detection results.

The structure of this work is as follows. Firstly, the research status of wind power ramp detection algorithm in recent years is described, and the advantages and disadvantages of different wind power ramp detection algorithms are summarized. Then the algorithm in this work is described in detail according to the flow order of the algorithm. Finally, the forth part summarizes the main work of this work.

II. Related work

This work summarizes the research status of wind power ramp detection algorithm in recent years and the advantages

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and disadvantages of different wind power ramp detection algorithms.

A. Research status of wind power ramp detection algorithm

Wind power climbing events are small probability events, that is, the proportion of wind power climbing section in historical wind power data is very small. If the original data is directly used for climbing detection, it will seriously affect the detection efficiency. Therefore, many researchers use trend fitting to preprocess the original data before climbing detection. Han et al. [9] [10] first proposed a more complete wind power ramp detection technology. Firstly, the L1 fitting algorithm [19] is used to fit the trend of the original data to reduce the interference of unimportant data points. Then, the scoring function related to the climbing rules is defined. Finally, all the climbing segments are identified by dynamic programming. Literature [6] [12] began to use revolving door algorithm to detect wind power ramp events. Zhou et al. [11] used the revolving door algorithm to extract slope events from the actual and predicted wind time series. Gallego et al. [8] developed an optimized revolving door algorithm OPSDA. Firstly, the wind power time series are segmented by SDA, and then the SDA segments are combined by dynamic programming algorithm, so as to improve the performance of climbing event detection. Li et al. [13] proposed a parameter and resolution adaptive algorithm PRAA to detect climbing events in power system databases with different data properties and resolutions. This method can process the original database of tens of millions of data points in seconds to merge the adjacent climbing segments [14] [15] uses feature selection technology in data mining to determine the slope of wind power generation.

B. Comparison and summary of the existing better algorithms

Ramp event detection can help predict wind power ramp events and improve the evaluation of power system flexibility for system planning [16] and setting ancillary service [17] requirements. On the one hand, ramp event detection can be used as a post-processing method in wind power prediction to detect ramp events in prediction database [14]. On the other hand, the prediction of wind power climbing events needs high-quality training set to improve its performance, and the detection of climbing events can make a regular sample set for statistical or machine learning prediction method [18]. The existing better climbing event detection algorithms are based on trend fitting for further climbing detection, such as l1-sw [19], OPSDA [8] and PRAA [10]. The comparison of their methods and corresponding defects is shown in Table 1.

L1-sw:The problems of l1-sw are as follows: firstly, although l1-sw can ensure that the climbing events meeting any rule set can not be missed by dynamic programming, it also leads to the calculation complexity and spatial complexity of climbing detection are very high. These defects have the problems of too much computation and low efficiency for the historical wind power data set with large data volume, and its storage capacity is required higher. Secondly, L1 trend fitting algorithm used in L1 SW algorithm is lower in accuracy and efficiency than spinning door transformation (SDT). Finally, l1-sw algorithm does not consider the accuracy of two endpoints of the climbing segment.

Opsda:The problems of OPSDA are as follows: firstly, because OPSDA adopts the same dynamic programming optimization method of l1-sw to detect wind power climbing, it also has the problems of high computational complexity and high spatial complexity. Secondly, OPSDA algorithm does not consider the accuracy of two endpoints of the climbing segment.

Praa:The problems of PRAA are as follows: Although PRAA improves the detection efficiency by merging climbing segments, it still does not consider the accuracy of two endpoints of the climbing segment. In conclusion, the existing wind power climbing detection methods based on trend fitting have the problem of accuracy of end-point detection in the climbing section except for the different detection efficiency problems.

III. RPCRD

RPCRD algorithm can solve the problem of accurate identification of wind power starting point and end point, and improve the existing climbing detection effect. RPCRD algorithm is mainly composed of three stages: data preprocessing stage, initial climbing detection stage and climbing correction stage. The algorithm framework is shown in Figure 1.

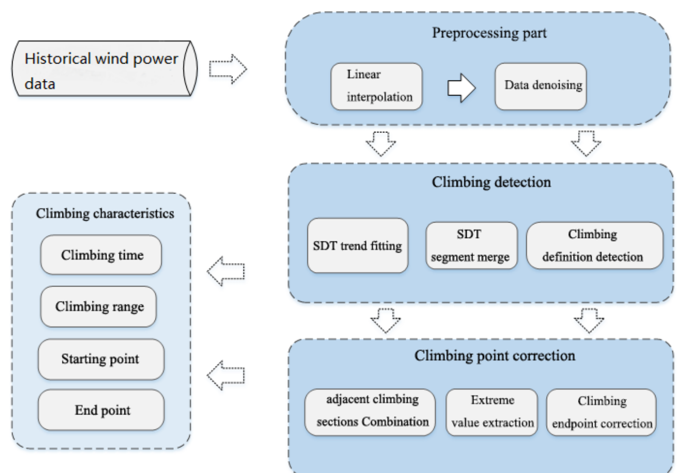

Fig. 1. algorithm framework

A. Climbing detection based on SDT trend fitting

Due to the uncertainty of wind power, wind power time series also has great volatility. It is necessary to eliminate the noise on an appropriate time scale to study the climbing events of time series data. In other words, it is necessary to eliminate data interference beyond the time scale of climbing events. Therefore, it is necessary to reduce the data amount of the original wind power time series data and retain the reasonable trend information of wind power data.

TABLE I
COMPARISON TABLE OF CLIMBING DETECTION ALGORITHM BASED ON TREND FITTING

algorithm	method	shortcoming
L1-SW	L1 trend fitting and dynamic programming	High time and space complexity, low detection accuracy of climbing endpoint
OpSDA	SDA trend fitting and dynamic programming	High time and space complexity, low detection accuracy of climbing endpoint
PRAA	SDA trend fitting and merging of adjacent climbing sections	The detection accuracy of climbing endpoint is low

Trend fitting just solves the above problems. According to the introduction of SDT algorithm in the second work, the only parameter of SDT algorithm is the width of revolving door. When the gate width is larger, the amount of data after fitting is less, and the time span of each SDT segment is larger; When the gate width is larger, the amount of data after fitting is larger, and the time span of each SDT segment is smaller.

After the trend fitting of the original wind power data is carried out by SDT algorithm, the work uses the definition of climbing to detect the initial slope. The definition of climb used in this work is as follows:

Definition 1:

$$|P_i - P_j| > 0.2P_{capacity} \tag{1}$$

Definition 2:

$$|P_i - P_j| > 0.2P_{capacity}, t_i - t_j < 4h \tag{2}$$

Definition 3:

$$P_i - P_j > 0.15P_{capacity}, t_i - t_j < 4h \tag{3}$$

$$P_i - P_j > -0.2P_{capacity}, t_i - t_j < 4h \tag{4}$$

The represents the rated capacity of the wind farm. According to the definition, if the wind power is reduced by 15% of the rated capacity within 4 hours, it means that the wind power downhill event is occurring; If the wind power increases by 20% of the rated capacity within 4 hours, it means that the wind power uphill event is occurring.

As shown in Figure 2, each SDT data segment is directly identified by using the climbing definition 1, and the corresponding climbing segment is detected.

B. Merge SDT segments

In order to solve the problem that many climbing segments are ignored due to improper parameter setting of SDT algorithm, this work considers using SDT segment merging method to capture those data segments that meet the definition of climbing, so as to improve the detection accuracy of wind power climbing detection in the number of climbing.

Given a wind power series after SDT fitting:$X = \{(T_1, P_1), (T_i, P_i), ..., (T_N, P_N)\}$, where T_m is the time index, P_i is the corresponding T_i wind power value, and N is the number of data points in the time series. The combined wind power time series data can be expressed as:$MS = \{(t_1, p_1), ..., (t_j, p_j), ..., (t_m, p_m)\}$ the time index of the combined SDT segment is the corresponding wind power value, and the number of time series data points is m. The process of SDT consolidation is as follows:

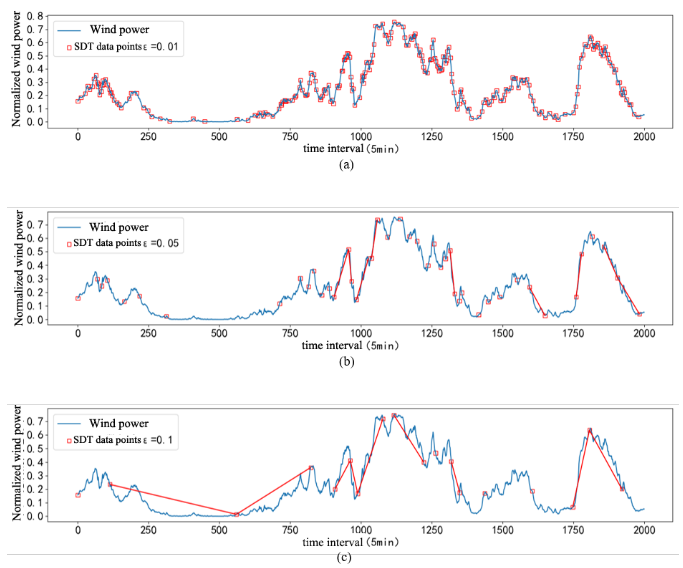

Fig. 2. climbing effect of different parameters under climbing definition 1

$$(P_i - P_{i-1}) \times (P_{i-1} - P_S) > 0 \tag{5}$$

$$\frac{|P_i - P_{i-1}|}{|T_i - T_{i-1}|} < \alpha \tag{6}$$

Formula (5) is the initial SDT data point of the current merge. Suppose $0 < i \leq N$ that if formula (5) and formula (6) hold simultaneously when combining SDT data points with serial number I, then $t_j = T_i$, $P_j = P_i$. And continue to merge forward.

Otherwise, it means that the change direction of the data segment formed by data point I and data point I-1 is inconsistent with the current merging direction, or the change slope is lower than the climbing rate defined by climbing, and the current merging is terminated. And the starting point of the next merge $t_{j+1} = T_{i+1}$, $P_{j+1} = P_{i+1}$. The pseudo code of SDT segment merging process is shown in Figure 3.

As shown in Figure 4, the parameter of SDT algorithm is set to 0.01, and SDT trend fitting is performed on the original data.

it can be concluded that SDT merging can help to extract more data segments with climbing and improve the quantitative accuracy of wind power climbing algorithm.

Algorithm 1 SDT segment merging

Input: the set of SDT segement points S

Output: the set of merged SDT points MS

$s \leftarrow 0$ //start point

$direct \leftarrow 0$ // -1 stands for down ; 1 stands for up

$L \leftarrow length(SDTSegements)$

for $i = 1 \rightarrow L$ **do**

  if $direct == 0$ **then**

    if $(S_p[i] - S_p[i-1])/(S_t[i] - S_t[i-1]) < \alpha$ **and** $(S_p[i] - S_p[i-1]) > 0$ **then**

      $direct \leftarrow 1$ //determine the merge direct

    else

      $direct \leftarrow -1$

    end if

  else if $((S_p[i] - S_p[i-1] > 0$ **and** $direct == 1)$ **or** $(S_p[i] - S_p[i-1] < 0$ **and** $direct == -1))$

    and $(S_p[i] - S_p[i-1])/(S_t[i] - S_t[i-1]) < \alpha$ **then**

    $i \leftarrow i + 1$

  else

    MS append S[s]

    s update to i

    direct reset to 0

  end if

end for

Fig. 3. pseudo code of SDT segment merging algorithm

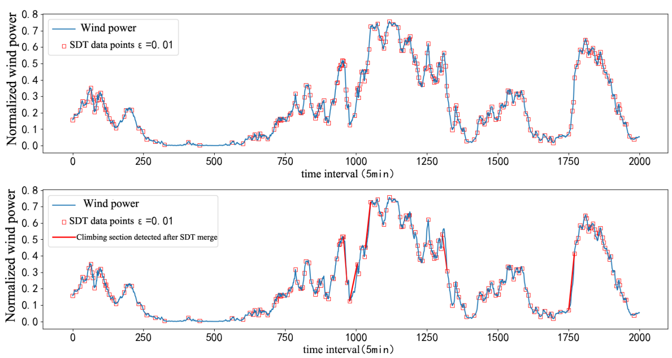

Fig. 4. Comparison of climbing effect between merged and unconsolidated SDT

C. Post processing of climbing correction – merging climbing sections

In the process of slope climbing detection, it is found that because of the existence of "bump section" in some climbing segments, SDT algorithm is divided into multiple SDT segments, and finally it is detected as multiple climbing sections, resulting in fracture problems. "Bump segment" refers to a small "bumpy section" between two adjacent and climbing segments in the same direction. As shown in the left circle in Figure 5.

Another problem in the process of climbing detection is that because the door width of SDT algorithm can not fit the definition of climbing section, a climbing segment is divided into two SDT segments, which eventually leads to the identification of two independent climbing segments and the fracture problem. As shown in the right circle in Figure 5. In view of the above two problems about segmentation in the process of climbing detection, this work adopts the method of merging adjacent climbing segments.

Given a wind power sequence:$X = \{(T_1, P_1), (T_i, P_i), ..., (T_N, P_N)\}$ where is the time index, is the corresponding wind power value, and N is the number of time series data points. The wind power ramp set detected in the early stage can be expressed as $R = \{(R_1, ...R_k, ..., R_L)\}$. The combined climbing segment set can be expressed as: $MR = \{(MR_1, ..., MR_j, ..., MR_m)\}$ the starting point of the j-th combined wind power climbing segment and the ending point of the j-th combined wind power climbing segment. The merging process of climbing section is as follows: For the k-th climbing segment $(0 < k \leq L)$, if the formulas (7) - (9) hold, then. Otherwise, it indicates the end of the current merging process and the starting point of the next merging segment $ms_j = s_k$.

$$|P_{s_k} - P_{e_{k-1}}| < \delta \times P_{capacity} \tag{7}$$

$$\forall s_k \leq \text{i} < e_{k-1}\text{: diff}(P_i, P_{i+1}) < \omega \tag{8}$$

$$|T_{s_k} - T_{e_{k-1}}| < \eta \times \min(T_{e_k} - T_{s_k}, T_{e_{k-1}} - T_{s_{k-1}}) \tag{9}$$

The pseudo code of the merging process of climbing section is shown in Figure 6. As shown in Figure 7, after merging the climbing segments corresponding to the climbing segment in Figure 5, two climbing segments with abscissa from 1000 to 1100 are merged into one climbing segment, and two climbing segments with abscissa from 1855 to 1982 are merged into one climbing segment.

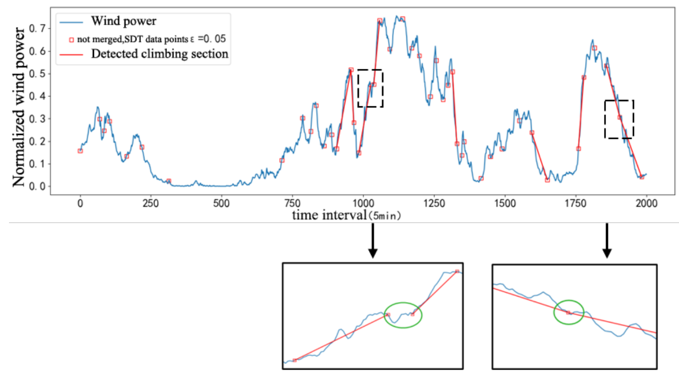

Fig. 5. segmentation of climbing section

D. Post processing of climbing correction – climbing endpoint correction

In the observation of the climbing detection results, it is found that there is a large error between the identified part of the climbing section and the actual climbing section. The error mainly shows that the two end points of the climbing section deviate from the actual end points. As shown in Figure 8, the error between the four climbing end points surrounded by four dotted circles and the actual climbing end points is obvious. In order to solve the problem of end-point error of climbing described above, this work proposes a method of end-point error correction based on extremum feature. Firstly, the set of local extremum points corresponding to each climbing segment is obtained based on the detected climbing segment set, and then the two endpoints of each climbing segment

```
Algorithm 2  Merging of climbing sections
Input:
  the sequence of wind power P;
  the set of ramping start points S;
  the set of ramping end points E;
Output:
  the set of merged ramping start points MS;
  the set of merged ramping end points ME;
  i ← 0
  j ← i + 1
  L ← length(RampSet)
  while j < L do
    if S_t[j] − E_t[j − 1] < η and |S_p[j] − E_p[j − 1]| < δ then
      for tt = S_t[j] → E_t[j − 1] do
        if |diff(P[tt], P[tt + 1])| > ω then
          B(S_t[j], E_t[j − 1]) ← 0
        end if
      end for
    end if
    if B(S_t[j], E_t[j − 1]) == 0 then
      j ← j + 1
    else
      (MS, ME) ← (i, j)
      i ← j + 1
      j ← i + 1
    end if
  end while
```

Fig. 6. merging pseudo code of climbing section

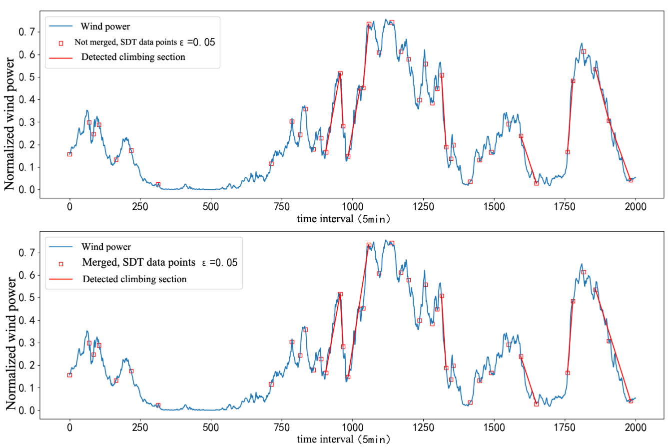

Fig. 7. Effect of merging climbing sections

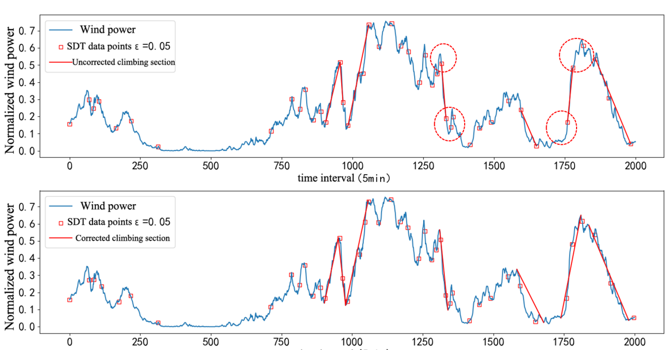

Fig. 8. uncorrected test results

are compared with the corresponding local extremum points; Then, whether the climbing endpoint needs to be modified and whether the modified climbing segment meets the climbing definition rules are judged; Finally, the final values of the two end points of the climbing segment are determined.

It is necessary to extract the extremum before modifying the climbing endpoint. According to the extremum characteristics, the rules of extremum extraction are as follows:

$$P_{i-1} < P_i > P_{i+1} \tag{10}$$

$$P_{i-1} > P_i < P_{i+1} \tag{11}$$

The extremum extraction effect is shown in Figure 9. The Red Cross indicates the local maximum, and the Blue Cross indicates the local minimum. Given a wind power sequence:$X =$

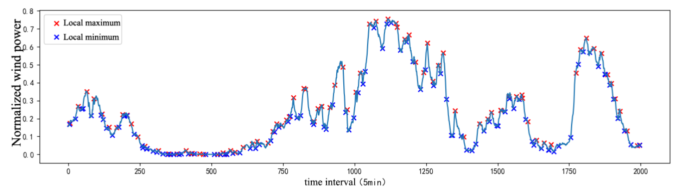

Fig. 9. effect of extremum extraction

$\{(T_1, P_1), (T_i, P_i), ..., (T_N, P_N)\}$ where is the time index, is the corresponding wind power value, and N is the number of time series data points. The peak set of wind power time series data can be expressed as $PK = \{pk_1, ..., pk_k, ...pk_L\}$, and the trough set of wind power time series data can be expressed as $TH = \{th_1, ..., th_k, ...th_L\}$.

$$S(i,j) = \frac{(P_j - P_i)^2}{T_j - T_i} \times D(i,j) \tag{12}$$

$$\begin{aligned} J(s_k, e_k) = \max(& \max_{a<i<b, c<j<d} S(i,j), \\ & S(s_k, e_k)), (a,b,c,d) \in (PK, TH) \end{aligned} \tag{13}$$

The goal of the end-point modification problem is to find the optimal two end points, so that the climbing segment is consistent with the climbing definition and complete enough. In order to find the optimal end point of the climbing segment, this work defines a scoring function for each data segment. See formula (11) for details. In formula (11), if the data segment in the range meets the climbing definition, the value of is 1; Otherwise, the value is 0. The scope must meet the climbing definition.

Specifically, for a climbing segment, the range of extreme points near the starting point of climbing is (a, b), and $a \in TH, b \in TH, a < s_k < b$. The range of extreme points near the starting point of climbing is (C, d), and $c \in PK, d \in PK, c < e_k < d$. As shown in formula (12), first calculate the maximum value of the scoring function within the extreme range near the two endpoints, and finally compare the optimal value with its own scoring function value, and select the larger one. The cost function value of climbing section is determined by its own score function value and the maximum score function value in the corresponding extreme range. The two end points corresponding to the final optimal cost function value will be used as the end points of the modified climbing section, as shown in formula (14) and formula (15).

$$CorS_k = i, CorE_k = j \tag{14}$$

$$J(s_k, e_k) = S(i, j) \tag{15}$$

The pseudo code of climbing endpoint correction is shown in Figure 10:

Algorithm 3 Climbing endpoint correction

Input:

the set of ramping end points R;

the set of peak pk;

Output: the set of corrected ramping points $CorR$;

$L \leftarrow length(RampSet)$

for $r = 0 \rightarrow L-1$ **do**

$J[r] = S[r_s, r_e]$

(a,b) selected near from r_s in pk

(c,d) selected near from r_e in pk

for $i = a \rightarrow b$ **do**

for $j = c \rightarrow d$ **do**

$S[i,j] = (R_p[i] - R_p[j])^2/(R_t[i] - R_t[j]) \times R(i,j)$

$J[r] = max(S[i,j], J[r])$

end for

end for

$CorR[r] \leftarrow corr \quad s.t.\ J[r] = S[corr]$

end for

Fig. 10. pseudo code correction of climbing end point

The effect of the climbing segment detected in Fig. 8 after the above correction is shown in Fig. 11. It can be clearly seen that the two end points of the two climbing segments, which are also in the black dotted circle box, are corrected to the extreme points, and conform to the climbing characteristics of wind power.

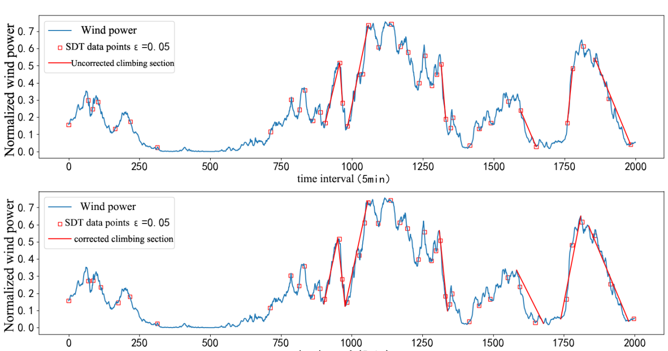

Fig. 11. effect picture after correction

IV. CONCLUSION

This work introduces a new algorithm RPCRD based on the modification of climbing points,and introduces its accuracy in wind power power climbing detection. Firstly, this work analyzes the accuracy of climbing endpoint in wind power climbing detection. Then, this work describes the basic framework of RPCRD algorithm. Then, this work describes the data preprocessing module, SDT segment merging stage, climbing segment merging stage and climbing endpoint correction module in RPCRD algorithm framework step by step. According to the analysis of the basic framework, the RPCRD algorithm considers the accuracy of the climbing endpoint, and uses the extremum feature to modify the identified climbing segment, which significantly improves the accuracy of the climbing detection.

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