Research Article
Optimization of Computer Communication Monitoring System for Wind Turbine Speed

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This article first studies the operating principles of wind turbines, focusing on the analysis of the structure and working principles of permanent magnet direct-drive wind turbines. According to the actual needs of the wind power system, the monitoring objects of the monitoring system are determined, and the overall monitoring plan for wind power generation is proposed to realize real-time analysis of the operating characteristics of the wind power system. At the same time, it pointed out the great significance of the wind power generation simulation experiment system and focused on the wind speed modeling. In terms of hardware research and analysis, relevant sensors, high-speed data acquisition cards, etc., were selected, and relevant signal conditioning circuits were designed, and a permanent magnet direct-drive wind power generation system simulation monitoring platform was constructed. In terms of software, LabVIEW was chosen as the design language of the monitoring system, and it pointed out the advantages of using LabVIEW in this monitoring system. Finally, the system uses the laboratory permanent magnet direct-drive wind turbine as the monitoring object. The practicality and accuracy of the system are verified through experiments such as permanent magnet motor power test, motor speed test, database system test, and remote monitoring test. The experimental results show that the monitoring system has a friendly interface and perfect functions and has important practicability and reference in the field of wind power monitoring.

1. Introduction

In the current society, with the continuous deterioration of the human living environment and the ever-increasing energy crisis, the development and utilization of renewable energy has attracted more and more attention from all countries in the world [1]. Wind energy is a clean renewable resource, and the development of wind energy is conducive to alleviating the current tension of energy shortage. Now that the installed capacity and power generation capacity of wind power are getting larger and larger, wind power is developing in the direction of expanding single-unit capacity, developing offshore wind power, and intelligent monitoring of wind farms [2]. There are two main measurement methods for speed measurement in the current industry: one is to convert the speed into an analog signal and measure the analog signal [3]. For example, a tachogenerator directly converts the speed into a voltage signal and then measures its voltage. The other is to use a sensor to detect periodic signals related to the rotational speed, convert this electrical signal into a pulse signal, and obtain the rotational speed pupil 1 by calculating the number of pulses within a specific time or calculating the time required for a fixed number of pulses. Finally, the speed is displayed, analyzed, and judged [4].

In rotating machinery, the measurement of engine speed is often involved, and the real-time and correctness of the speed measurement is required. Rotation speed detection and control also occupies a large proportion in the real-time control of industrial processes [5]. It has a vital influence on the stability of the system. In the application of generators, the motor speed is one of the important signs to judge the operation status of the motor. In the measurement and control of many motion systems, it is necessary to detect and control the speed of the motor to improve the performance of the control system and increase the accuracy of the system [6]. The accuracy of measurement directly affects the control status of the system, and only the high accuracy of the speed
can obtain a high-precision control system. Traditional methods for measuring speed include mechanical speed measurement method, magnetoelectric method, vibration speed measurement method, and photoelectric method. However, they are all based on single-chip microcomputer and sensors, which makes the user interface not friendly enough. Moreover, the speed measuring instruments using these measurement methods are not easy to communicate with the computer and are limited by the number of computer communication ports [7].

This article uses LabVIEW to structure the monitoring system and designs the system startup module, user login module, parameter configuration module, acquisition and display module, file I/O module, database system module, alarm system module, temperature system module, and signal analysis system module. Different from the conventional monitoring system, this system has better functions. It uses TDMS files and SQL server mixed programming to centrally manage system login, data storage, and data playback, which can realize real-time analysis of large amounts of data. From a theoretical point of view, because the CUSUM control chart considers the data of historical observation points, the detection effect of small drift with a trend is obviously better than that of the chart, which is the result of the further development of the control chart. This paper presents a wind turbine status monitoring method based on the CUSUM control chart. For the research on the overall condition monitoring of wind turbines, firstly, the method is used to obtain the power characteristics of the unit, and then the output power is monitored by the CUSUM control chart, so as to realize the condition monitoring of the whole machine. For the monitoring research of wind turbine operating conditions, firstly, the robust least-squares regression is used to establish the wheel speed prediction model under the normal operating mode. Finally, the standardized residual is used as the test statistic, and a CUSUM control chart based on the residual is established to monitor the operation status of the wind turbine, so as to realize the failure prediction. At the same time, the multitechnology integration of Data Socket and Remote Panels is used to realize remote monitoring of the system. Finally, the system uses the laboratory permanent magnet direct-drive wind turbine as the monitoring object. The practicality and accuracy of the system are verified through experiments such as permanent magnet motor power test, motor speed test, database system test, and remote monitoring test. PLC communication realizes real-time control of the motor. The experimental results show that the monitoring system has a friendly interface and perfect functions and has important practicability and reference in the field of wind power monitoring.

2. Related Work

Since the country’s wind power industry started relatively late, the existing research results are mainly focused on the design of wind power generation units and large-scale power generation. The research in the field of wind turbine equipment status monitoring and fault diagnosis is still in its infancy, and the existing research results are relatively limited, mainly based on data-driven methods.

By analyzing the recorded index data, such as pressure, temperature, vibration, speed, power, etc., we predict the operating status of the wind turbine. For the evaluation of the operating status of the whole machine and the prediction of faults, Ali et al. [8] proposed a Gaussian mixture model parameter estimation to evaluate the health status of the operating wind turbine in real time. Herbert [9] applied fuzzy mathematics theory to establish a comprehensive evaluation model of unit operating status and used matter-element analysis to establish an evaluation method of grid-connected wind turbine operating status. Literature [10] uses the unit power curve obtained by the method to study unit performance. For units of the same configuration, according to the characteristics of installation and fault data, they construct random ending data of failure shutdown and use the Kaplan–Meier method to estimate the reliability of wind turbines by further fitting the Weibull distribution to get the mean time between failures. Neyja et al. [11] used the maintenance times of the unit to obey the nonhomogeneous Poison process to obtain the future failure time distribution, thereby predicting the failure time. Based on the alarm control chart of SPC, the wind turbine was researched on the failure of the wind turbine, which can detect the early failure of the equipment, but it is only effective for large drift detection, and is not suitable for the detection of small and medium drifts. It is difficult to find the failure trend of equipment earlier. For the research on the failure prediction of the key components of wind turbines, the existing research mainly includes support vector machines, neural networks, and multiple linear regression. Most of the basic ideas are to analyze the trend of residuals, so as to achieve the purpose of predicting failures. The online monitoring technology for judging whether the wind wheel is damaged mainly includes ultrasonic, vibration analysis, and acoustic emission. Among them, acoustic emission has good sensitivity to blade aging and damage, and you can find the location of abnormal areas. Yang et al. [12] extracted the sound source signal to obtain the initial crack characteristics and used the optimized wavelet redistribution scale spectrum analysis method to identify the crack initiation and re-expansion. The monitoring research on the balance of the wind wheel is mainly based on the electrical data of the generator. Dalala et al. [13] studied the impact of unbalanced faults on the power of a wind turbine, established a simulation model, and predicted the operating state of the wind turbine through spectrum analysis of the effective output power.

Developed countries in wind power generation, the United States, Denmark, Germany, etc., have achieved many results in unit design, condition monitoring, and failure prediction and maintenance. Merabet et al. [14] proposed using the Copula function to obtain the unit power curve probability model to effectively detect early faults and use the Hotelling statistical method to identify the operating status of the whole unit. Some scholars monitor and evaluate the status of wind turbines based on the artificial neural network of multiparameter fusion. For the key components of wind
turbines, there are mainly vibration analysis, lubrication analysis, thermal imaging, temperature, pressure, flow, oil, etc. Some researchers have proposed to use acoustic emission to monitor the position of the weakened area of the blade, monitor the running state of the wind wheel, use the spectral kurtosis to analyze the impact part of the vibration signal, and diagnose the fault. Other researchers use generator power to predict faults and use continuous wavelet transform to extract the effective output power of generators for further condition monitoring and fault diagnosis. Many developed countries have accumulated a certain amount in the field of wind power monitoring. In contrast, the country’s wind power monitoring system is still in the exploratory stage at the technical level. Although the current imported monitoring system can also monitor the wind power production process, because domestic technicians have not mastered its core technology, once a problem occurs in the monitoring system, it cannot be solved in time and must rely on foreign technicians to troubleshoot the problem. This not only delays production but also requires high costs for hiring foreign maintenance personnel, which will increase the burden on wind farms. In the event of a more serious situation, if foreign technical support is not available, the failure of the wind power equipment or system will directly lead to the paralysis of the wind farm. The backwardness of domestic monitoring technology will constrain the development of China’s wind power and make the entire wind power industry vulnerable. Nowadays, the management of wind power is gradually evolving towards digital operation, management information, and data centralization. Many wind farms have multiple types of wind turbines. Due to different wind power management indicators, wind farms must be equipped with multiple sets of wind power monitoring systems, and staff must learn different systems, which directly increases the difficulty of maintenance and increases the cost of operation and maintenance.

3. Model Construction of Computer Monitoring System for Wind Power Generator Rotation Speed

3.1. Wind Energy Power Generation System Architecture. Wind turbine is a complex electromechanical equipment, which converts the wind energy passing through the turbine into electrical energy, and implements grid-connected power generation. The power generation process is mainly composed of the following three links: 1. primary energy conversion. A certain wind speed corresponds to the corresponding average power of wind energy. According to the knowledge of physics, the relationship between average power of wind energy and wind speed is as follows:

\[
\frac{v(x)}{r(i)} + \frac{v(y)}{r(i)} + \frac{v(z)}{r(i)} = u(i).
\]

The wind blown into the fan drives the wind wheel to rotate, which converts part of the wind energy into mechanical energy to generate mechanical power, where \(v\) is the wind energy utilization coefficient. 2. Mechanical energy transfer: the low-speed shaft drives the high-speed shaft to rotate, which is converted into the mechanical power of the high-speed shaft.

\[
\gamma \sim N\left(\mu - \mu \left(1 - \frac{\alpha}{2}\right), \frac{\sigma}{\sqrt{n}}\right). \tag{2}
\]

For the needs of subsequent research, this article is based on the real-time measurement data of the SCADA system, according to the measurement method of the power characteristics of wind turbines provided by the International Electrotechnical Commission’s IEC 61400-12 standard, using the method to estimate the mean and standard deviation.

The electrical power output by the wind turbine is closely related to the wind speed cut in during the operation of the wind turbine. Figure 1 shows the wind energy power generation system architecture. Therefore, by detecting and analyzing the output effective power and wind speed, the overall operating state of the wind turbine can be effectively monitored for potential faults. We select the SCADA monitoring data under the normal operation of the wind turbine, find the average value \(V\) of the environmental wind speed in each time \(t\), where \(M\) is the amount of data monitored by SCADA in the time \(t\),

\[
\begin{bmatrix}
  x \\
  y 
\end{bmatrix} = \begin{bmatrix}
  r_1 & 0 \\
  0 & r_n
\end{bmatrix} \times \begin{bmatrix}
  i \\
  j
\end{bmatrix} + p' \times \begin{bmatrix}
  \alpha \\
  \beta
\end{bmatrix}, \tag{3}
\]

\[
u(x) = p \cdot (i, j) \cdot \sin(x) \cdot \cos(x), \tag{4}
\]

\[
\begin{cases}
  s(i) = r(i) + p' \sin(i), \\
  t(j) = r(j) + p' \cos(j).
\end{cases} \tag{5}
\]

Since the effective output power of a wind turbine under normal operating conditions changes with the wind speed, the normal fluctuation range of the output power will be different under different wind speeds. Therefore, the traditional statistical process control technology is used. Simple single fixed value control can not effectively identify the moment of abnormal working state.

\[
C(n) = \min(0, C(N - 1) + k - \mu), \tag{6}
\]

\[
\begin{cases}
  C(n, 0) = 0, \\
  C(n) = \min(0, p - \mu + k + C(n - 1)) < 0. \tag{7}
\end{cases}
\]

Since the wind speed in each bin has little difference, the influence of wind speed in the same interval on the output power is ignored. When the wind turbine is in normal operation, its output electric power will fluctuate within a certain range. If there is an abnormal state or failure, the output power change will exceed the control line. Here, we use the gradient descent method to perform linear regression on the 123 groups of rotation speed sample curves in the normal startup state. Through observation, the curve of speed and time satisfies a polynomial.
The operation of the wind turbine

The wind speed cut in during

The operation of the wind turbine

Data

Practicality

Data flow

v

Rotating

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speed

objective function is set to the following:

Using the principle of minimum mean square error, the respective; ,

, we will fit the speed-time curve with a fifth-order polynomial. It can be seen that the speed tends to stabilize after 50 s, so we focus on the range where the guide vane opening starts to increase until the unit speed reaches a stable value, that is, 5 to 50 s. We convert these samples into sample data, a better fitting effect can be obtained when at least 5, and we will fit the speed-time curve with a fifth-order polynomial. According to the analysis of sample data, a better fitting effect can be obtained when is at least 5, and we will fit the speed-time curve with a fifth-order polynomial. It can be seen that the speed tends to stabilize after 50 s, so we focus on the range where the guide vane opening starts to increase until the unit speed reaches a stable value, that is, 5 to 50 s. We convert these samples into data sample points, a total of \( M = 123 \times (50 - 5 + 1) \). Using the principle of minimum mean square error, the objective function is set to the following:

\[
f(i, j) = \frac{1}{N} \sum_{j=1}^{N} p(j) = \frac{1}{N(i, j)} \times p. \tag{8}
\]

In the formula, \( v \) and \( p \) are the estimated speed and time, respectively; \( f \) is the coefficient of the power of \( i \); \( N \) is the highest order of the polynomial. According to the analysis of sample data, a better fitting effect can be obtained when \( N \) is at least 5, and we will fit the speed-time curve with a fifth-order polynomial. It can be seen that the speed tends to stabilize after 50 s, so we focus on the range where the guide vane opening starts to increase until the unit speed reaches a stable value, that is, 5 to 50 s. We convert these samples into data sample points, a total of \( M = 123 \times (50 - 5 + 1) \). Using the principle of minimum mean square error, the objective function is set to the following:

\[
\frac{\partial g(x)}{\partial x} = -2 \times (v - v(x)) \times \sum_{i=0}^{N} x_i. \tag{9}
\]

Among them, \( x \) and \( g(x) \) are the actual value and estimated value of the unit speed, respectively. Our goal is to find a set of \( f \) so that \( L \) takes the minimum value. Using the principle of the gradient descent method, \( L \) calculates the partial derivative of \( a0, \ldots, a5 \), respectively, we can find the direction of the gradient descent, and use the gradient to iterate out the coefficient of the next cycle.

3.2. Computer Speed Monitoring Algorithm. This paper adopts robust regression, that is, adopts a robust estimation method in the regression model, which is intended to fit the structure of most of the data in the training data and accurately grasp the basic trend of the data. At the same time, we can also identify potential strong influence points, outliers, and structures that deviate from the model assumptions. In the range of use, robust estimation is more extensive. When the error of the variable obeys the normal distribution, the effect of the robust estimation is as good as the least square estimation. When there is a non-normal distribution and the least square estimation condition is not satisfied, the result of robust estimation will be far better than the least square estimation for defining different objective functions corresponding to different robust regression methods. The LAR method finds a curve that minimizes the absolute difference of the residuals, rather than the squared difference. Therefore, outliers have less influence on the fitting.

Then the Bellman equation shown can be used to obtain the optimal solution of the problem P1 through the classical value iteration algorithm or the strategy iteration algorithm. The bisquare weighting method is to minimize the weighted sum of squares, in which the weight assigned to each data point depends on the distance of the point from the fitted line. The points near the fitted line get all the weights. The weights of points that are farther offline gradually decrease. If the distance from the fitting line exceeds the preset range, its weight coefficient is zero. In most cases, the bisquare weighting method is better than LAR because it can identify outliers and minimize the influence of outliers while using most of the data to fit the curve. In fact, it is a robust least square method. Therefore, this paper adopts a robust regression based on bisquare to establish a model for predicting the rotation speed of the wheel. Figure 2 shows the computer speed monitoring algorithm flow.

Therefore, the study of whether the wind wheel fails or there is a potential failure is converted to the determination of the relationship between the wind speed and the hub speed, and the prediction model of the hub speed is established. By calculating the residual error between the predicted value and the actual measured value, and using it as a statistic, the CUSUM control chart is constructed.

These are perfect prior knowledge about renewable energy, computing tasks, channel status, etc. By judging whether the rotation speed of the hub is within the normal range under the wind speed of the environment where the wind turbine is located, the operation status of the wind turbine can be
detected, and then potential faults can be found. It can be seen that there is a functional relationship between wind speed and hub speed. According to the expression, the relationship should be a polynomial. We consider using the SCADA data of wind speed and hub speed under normal operation of wind turbines to conduct regression analysis and establish a prediction model for hub speed.

3.3. System Model Index Optimization. For analysis, this paper collected 125 sets of power generation start-up data for Unit 4 of Storage Power Station, including 2 sets of abnormal speed increase data caused by the damage of the guide vane opening feedback sensor and 123 sets of normal start-up data (including 2 sets of unit boot data under low head and 2 sets of boot data under high head). Through numerical analysis of the change law of unit speed with guide vane opening, time, and wind head, the curve fitting method is finally used to find the speed fitting curve with time as the independent variable and further use the idea of probability statistics to set a reasonable confidence interval to get the upper and lower thresholds.

However, in the real network environment, it is difficult to obtain as the main user of the agent. When the unit speed exceeds the threshold, it is determined that the guide vane opening feedback is faulty. This solution can detect the abnormal speed-up process of the unit caused by the damage of the guide vane opening feedback sensor in time, reduce the abnormal speed-up time of the unit, avoid the overspeed of the unit, and ensure the safe operation of the unit.

In normal operation, the speed of the hub of the same type of wind wheel is mainly affected by the intensity of the surrounding wind. The wheel speed value will be different under the same wind speed, and this fluctuation is mainly affected by random factors. If the wind wheel does not fail, the speed of the hub should fluctuate within the normal range. Once the wind wheel is icing, damaged, loose, and other faults, it will definitely affect the balance, the rotation of the wind wheel is affected, and the speed of the hub will become abnormal. Figure 3 shows the bar graph of residual speed of wind turbine generator. Therefore, it is only necessary to judge whether the fluctuation of the hub speed is within the normal range.

In order to facilitate the construction of CUSUM control charts, the statistical variables are standardized. Due to standardization, the wind wheel begs under normal conditions. Figure 4 shows the model framework of the wind power generator speed computer monitoring system. It should obey the standard normal distribution $t(0,1)$. For the wind turbine, when its operation is abnormal or malfunctions, the speed of the hub will slow down, which will affect the performance of the entire wind turbine. According to the central limit theorem, the residual error between the predicted value of the wheel speed under normal conditions and the real measured value should obey the normal distribution under the influence of random factors.

According to the classic sample estimation method, the residual mean $s$ and standard deviation of the sample data when the wind turbine is operating normally are obtained. We use MATLAB’s Distribution Fitting Tool to test the normal distribution of the sample residuals and estimate that the mean value and the standard deviation as the overall mean and standard deviation account for them to predict the speed of the hub at the ambient wind speed at time $f$ to get it. Therefore, the standardized residuals are used as statistics to construct a CUSUM control chart, and only the upward drift situation needs to be considered to construct a CUSUM control chart for judging upward drift.

4. Application and Analysis of Wind Power Generator Speed Computer Monitoring System Model

4.1. Wind Energy Generator Data Collection. In order to facilitate the understanding of the internal logic relationship, first simply qualitatively analyze the influence of the guide
vane opening, wind head, and time on the speed of the unit. First of all, from the perspective of wind head, we compared 4 sets of engine speed data under different heads, which are the two highest wind heads and the two lowest wind heads in the 125 sets of data. It can be seen from the comparison results that the high head reaches the rated speed faster than the low head, and the arrival time is about 48 s and 50 s, respectively. However, the difference between the two sets of curves is small, even lower than the amount of sudden change caused by random disturbance. Therefore, under the high and low heads reached in our actual production, the change trend of the unit speed is basically the same. Next, we analyze the opening of the guide vanes. For the convenience of observation, we averaged the speed data of the 123 groups of units under the normal start-up state. Figure 5 shows the histogram of the average value of unit speed data.

In order to make the system run more stably and prevent contact malfunctions, the intermediate relay control method is used in the PLC program processing instead of directly controlling the PLC output, and then the output of QB0 is judged by the judgment instruction. Through the analysis of the system, we establish the switch value contact action truth table. According to the requirements of fan control, the switch will be performed only when the output of QB0 meets the following truth table, so that the program has a strong software protection capability, and the system is more safe and secure.

4.2. Computer Monitoring Performance Simulation. This paper selects a wind power generator set of a wind farm as the research object. Its SCADA system records the parameter data (ambient wind speed, wheel speed, effective output power, generator temperature, etc.) of the generator every 1 s and records that the wind turbine is in abnormal operation status information. On the one hand, in order to improve the accuracy, on the other hand to avoid unnecessary tedious calculations, the SCADA data of this type of unit with a sampling time of 1 s in one month in 2019 were selected in a total of 2592,000 groups. According to the wind turbine fault record table of the SCADA system, the typhoon motor operated abnormally due to heavy rain in the early morning on September 13 of a certain year, and the wind leaves were not covered by a large amount of water droplets. The time when the company's monitoring system detects the fault is t. From the above comparison, we can get the alarm by using the CUSUM control chart, which is 20 minutes earlier than the control chart. It can be seen that in the event of a wind turbine operating failure, the CUSUM control diagram can detect abnormal operating conditions earlier than the diagram, predict potential failures earlier, and facilitate further
maintenance. In order to avoid accidental calculation of a single set of data, the SCADA data of this type of wind turbine before two failures were selected for calculation and obtained separately.

According to the unit setting, the guide vane opening change process is divided into four stages. In the first stage, the guide vane opening rapidly opens to 14%, which corresponds to between 0 and 7s. The unit speed increases and the acceleration gradually increases. Then it enters the holding phase of about 30s. The speed of the unit continues to increase, but the acceleration gradually decreases. At about 40s, the guide vane opening increased to about 21% again in a short time.

Finally, the opening of the guide vane dropped back and remained at 17%, and the speed of the unit no longer increased and remained at about 100%. Figure 7 shows the line graph of change of correlation coefficient of unit speed with time. Therefore, the guide vane opening degree determines the final stable value of the speed. It can be seen that the change curve of the speed of 125 sets of units with time includes 2 sets of fault data. It can be seen from the figure that there is a continuous functional relationship between the speed and time, and the downward trend of different heads is consistent. The guide vane opening of the system is set fixed, and the actual applied head range has little

Figure 4: The model framework of the wind power generator speed computer monitoring system.
influence on the trend of the speed curve. Therefore, fitting the function of the speed with time can effectively reflect the trend of the current system speed. For the SCADA data of the selected one-month wind turbine in normal operation, after the first step of the process, the wind speed is classified by 0.5 m/s, and the average value of the wind speed and output power in each interval is calculated.

4.3. Example Results and Analysis. We select the data recorded by the SCADA system of the same type of wind turbine for two consecutive weeks, and process the data stream according to the aforementioned process to obtain the value, and plot the last calculated 2019 data in the paper to obtain the CUSUM control chart. The upper and lower thresholds can completely cover the speed curves of 123 units under normal conditions without misjudgment.

Based on the above analysis, the main user has prior knowledge of the network environment. At the same time, we can also observe two sets of fault curves, which exceed the upper threshold and can be distinguished. And the speed is less than 60% of the rated speed when the boundary is exceeded for the first time. Figure 8 shows the deviation threshold curve for abnormal changes in unit speed. Therefore, real-time comparison between the current speed and the upper and lower speed threshold curves given by equations can quickly identify the abnormal speed increase of the unit in 99.99% of the cases.

In practical applications, a set of antioverspeed logic can be set in the monitoring system: during the speed-up phase of the unit, when the speed of the unit exceeds the range of the upper and lower speed threshold curves given by formulas, the output of the monitoring system increases abnormally. Speed alarm: this alarm can trigger an accident shutdown when the alarm is maintained for 2 s without reset, and it can identify and prevent the abnormal speed increase of the unit in time to avoid overspeed.

In order to prove that the CUSUM diagram can find that the wind turbine is in an abnormal operating state before the failure occurs, we select the data recorded by the SCADA system in the previous period of time when the failure occurred, calculate the CUSUM control chart, respectively, and compare it with the commonly used control chart and company monitoring system. Figure 9 shows the histogram of the fluctuation interval of the fan operating state. According to that, it can be seen that there was a small range of downward fluctuations before, but it quickly returned to the positive direction, indicating that the fan is operating in good condition, and it was always below the control line. According to the corresponding judgment criteria, the wind turbine was abnormal at 10 times. It can be seen that the CUSUM control chart is 5.12, and the exceeding control line is 5. It is at 50 minutes and keeps drifting high; it means that the wind turbine is malfunctioning. According to the aforementioned judgment principle, the moment when the wind turbine fails is the point closest to C; that is, the wind turbine starts to be abnormal.

During the collection process, according to the Kafka and incremental data transmission scheme, production data needs to be collected at regular intervals. Figure 10 shows the simulation results of the feedback signal value of the fan with the number of data acquisitions. First, we set the time interval for data collection.
Due to the consideration of the number of digits in the number, the number is encoded in a cyclic processing method, and the threshold of the number of acquisitions is set. If the number of acquisitions reaches the threshold, the number of acquisitions will be cleared and counted again; according to the number of production data collected each time, the data items of each production data are numbered. The numbered group production data format is shown in the paper. By comparing the difference between the set value and the feedback signal, the error is obtained, and then the error is transmitted to the controller. The controller uses a certain algorithm for calculation and analysis, and outputs control commands, adjusts the controlled object, and realizes the control of the speed. The speed can track the set value well, work in the best performance area, and realize the maximum wind energy capture by monitoring the speed.

5. Conclusion

This article focuses on the method of turning angle measurement. In order to measure the rotation angle, the relationship of the rotating body in the space coordinate system was studied, and a rotating machine speed measurement model was established. It is no longer a problem in modern science to measure small angles, but this is all at the expense of complex and precise mechanical structures, and these angles have no directionality at all. This article uses a USB camera and a PC to collect and process images and use the geometric vector method to obtain the rotation angle between two frames. The noncontact detection method in this paper avoids the errors caused by the traditional contact method due to mechanical wear, slippage, and vibration. At the advantage of no pollution or damage, they can be used in electronic detection and industrial control for rapid and accurate measurement of speed and rotation angle. With the further development of CCD technology, the influence of this limiting factor will inevitably become smaller and smaller. The upper limit of the measurement speed is 1200 r/min, and they can obtain accurate measurement results. Experiments show that the method used to measure the rotational speed of the analysis object has high accuracy, strong anti-interference ability, high cost performance, and simple system structure. Finally, this paper takes the actual operation monitoring data of a certain wind farm as an example for empirical analysis and compares it with the control chart. The empirical analysis results show that theCUSUM control chart based on SCADA data is an improvement of the alum chart, which can realize the detection of the operation status of the wind turbine and find the abnormality of the whole machine and the wind turbine. Through the research in this paper, the process of maintenance can be accelerated, equipment damage accidents can be avoided, and the safe and efficient operation of wind farms is beneficial.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.
Conflicts of Interest

The authors declare that they have no conflicts of interest.

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