Light & Engineering
Vol. 26, No. 4, pp. 130–136, 2018

SOLAR PHOTOVOLTAIC POWER GENERATION WIRELESS MONITORING SYSTEM BASED ON IOT TECHNOLOGY

Erhua SUN

Chongqing Real Estate Career Academy, Chongqing, 400035 China
E-mail: cydwmc52@sina.com

ABSTRACT

In order to further improve the real-time detection of power generation, a wireless monitoring model of solar photovoltaic power generation based on Internet of things (IoT) technology is proposed. Firstly, the application of remote monitoring in power generation technology is introduced, and the monitoring model of solar power equipment is constructed by wireless network, and the corresponding feedback mechanism is established by means of the (IoT) algorithm. Finally, the data processing ability and analysis effect of the wireless monitoring model are tested and studied. The test results show that the monitoring model can record and optimize the solar power generation data in real time, which greatly reduces the failure rate in power generation. It is proved that the monitoring model used in this paper has good feedback effect.

Keywords: Internet of things (IoT) technology, solar photovoltaic power generation, wireless monitoring

1. INTRODUCTION

The development of the national economy inevitably requires the use of a large amount of photovoltaic power generation, and the increasing use of photovoltaic power generation has driven the frequency of use of solar photovoltaic power generation equipment [1]. It is known that power generation equipment will have various faults in the process of use, but it can't be monitored 24 hours a day. Therefore, research on a remote control and wireless monitoring model for solar photovoltaic power generation equipment is getting louder and louder [2]. In response to this requirement, a remote control and wireless monitoring model of solar photovoltaic power generation equipment is established based on IoT technology through the combination of IoT technology. Real-time monitoring of solar photovoltaic power generation equipment and real-time monitoring of faults is achieved by using a computer wireless monitoring model [3]. However, the establishment of this detection model requires a comprehensive understanding of the performance of computers and photovoltaic power generation. This kind of interdisciplinary research is quite difficult. In this paper, the research on remote control and wireless monitoring model of solar photovoltaic power generation equipment is firstly an in-depth understanding and research on the IoT technology, and the optimization process of the calculation process and calculation formula of the IoT technology is given to the following wireless monitoring model. The establishment provides a basis for calculations. Then certain analysis and research on the performance of solar photovoltaic power generation equipment are conducted, and then the IoT technology is combined to establish the final remote control and wireless monitoring model of solar photovoltaic power generation equipment based on IoT technology. Through the use of this wireless monitoring model, the use of solar photovoltaic power generation equipment has been greatly improved, and at the same time, the revenue of the enterprise has been increased to reduce expenses and maximize the benefits of solar photovoltaic power generation equipment.

2. STATE OF THE ART

The use of power generation equipment was a product of the industrial revolution, dating back to the first industrial revolution in the UK in 1860 [4]. In the past two hundred years, the problem of solar photovoltaic power generation equipment has always been the focus and difficulty of our research. Because the failure of photovoltaic power generation is not regularly found, there is always the possibility of failure [5]. The improvement of the use of equipment has always been developed in two aspects. The first is to improve the performance of the equipment, and the second is to improve the detection effect [6]. With the rapid development of computer technology since the 1950s, we have gradually entered the information age, which facilitates the wireless monitoring of solar photovoltaic power generation equipment, and can remotely monitor solar photovoltaic power generation equipment by using computer computing models. And wireless monitoring is used for research. In particular, the IoT technology that emerged in the 1990s has brought convenience to wireless monitoring of photovoltaic power generation [7]. This new type of computer algorithm has a strong ability in information processing to classify and summarize information [8]. Through the research of IoT technology, it is not difficult to realize remote monitoring and wireless monitoring of solar photovoltaic power generation equipment [9]. In addition, after several decades of computational research and development of various forms of computing, the IoT technology gives us the use of great convenience has come, and the computational research in this paper is based on this [10].

3. METHODOLOGY

3.1. Research on the Computing Form of IoT Technology

In a strict sense, the IoT technology is a new form of computing that combines other computer algorithms. The computational research in this paper uses a combination of neural network algorithms for computational analysis. The neural network algorithm has a special property, that is, it can have multiple synapses for collecting information, and has multiple information export modes. In the wireless monitoring and remote monitoring of solar photovoltaic power generation equipment, it is needed to monitor and analyze multiple information of the equipment, which requires us to use computer algorithms with information collection points, and the neural network algorithm just meets this requirement. And combined with the IoT technology, in-depth learning and mining of the collected information can be carried out. This combination also has an important advantage, that is, the algorithm can be called by the data recorded by the previous deep learning process when performing similar calculations, reducing the calculation time of the algorithm and greatly increasing the computational efficiency of the algorithm. From a variety of perspectives, it is found that using this kind of IoT technology combined with neural network algorithm will bring us the best computing experience, and also provide a strong theoretical calculation basis for the establishment of later computational models.

The neuron node serves as the basic arithmetic unit of the neural network, and its unit model is shown in Fig. 1. $x_1, x_2, \cdots x_n$ is the input of neurons, simulating the output signals from other neurons, $w_{1j}, w_{2j}, \cdots w_{nj}$ is the connection weight of the neurons and other neurons, simulating the strength of signal transmission, θ is the Min value of neurons, and the function f represents the activation function of the neuron, and O is the output value of the neuron.

Among them, for the activation function of the IoT technology, the Sigmoid function is used. The function formula is as follows:

$$f(u) = \frac{1}{1+e^{-u}}. \tag{1}$$

Among:

$$u = \sum_i w_i x_i + \theta. \tag{2}$$

In addition, the neuron output value is:

$$o = f\left(\sum_i w_i x_i + \theta\right). \tag{3}$$

The neural network used in this paper has multiple layers of hidden layers. This is because different goals are had in remote monitoring and fault detection of solar photovoltaic power generation equipment. If only one hidden layer is used, not only the efficiency of calculation, but also the efficiency of calculation will be greatly reduced, the calculation accuracy cannot meet our use requirements. The special hidden layer calculation of special data is used in order to meet the calculation needs of this article. For example, an *n*-layer neural network, the first layer is the input layer, the last layer is the output layer, and the middle layer is all hidden layer. In the forward propagation process of the network, all the activation values of all the neurons of the layer *1* are calculated first, and then as the input to the next layer, calculate the activation value of all neurons in this layer, and so on, until the last layer.

The information transfer process of the IoT technology used in this paper is different from the transmission of neural network algorithms. In addition, certain deviations and noises sometimes appear in the process of information transmission. In order to increase the computational accuracy of this new type of computer algorithm, in the process of information transmission, the calculation form of the back propagation algorithm is combined. By using the reverse, the calculation of the propagation algorithm reduces the error in the algorithm calculation information transfer to a minimum. Since the neural network used in this paper uses the sigmoid function as the activation function, the Sigmoid function has a good computational advantage, and its derivative can be expressed by its output value:

$$\frac{df(o)}{do} = f(o)(1 - f(o)). \tag{4}$$

In fact, when performing network training, the error function is usually calculated using the mean square error. For a multi-class problem with *s* categories and *N* training samples, the error function is defined as follows

$$E = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{s}\left(y_k^n - o_k^n\right)^2. \tag{5}$$

Where y_k^n represents the *k-th* note value and o_k^n represents the *k-th* output value.

The error for a single sample can be expressed as:

$$E^n = \frac{1}{2}\sum_{k=1}^{s}\left(y_k^n - o_k^n\right)^2 = \frac{1}{2}\left\| y^n - o^n \right\|_2^2. \tag{6}$$

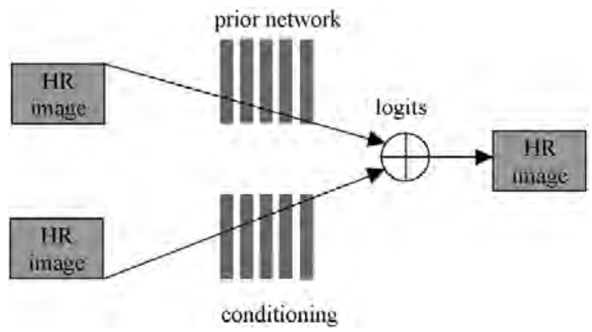

Fig.1. Artificial neuron unit model

According to the above method, the computational optimization research of the IoT technology is finally realized. Through the optimization research of the IoT technology, it provides a theoretical basis for the establishment of the following wireless monitoring model. Through our optimization analysis, the IoT technology can analyze different information without affecting the efficiency and accuracy of the algorithm calculation.

3.2. Solar Photovoltaic Power Generation Wireless Monitoring Model Based on IoT Technology

In the above research, the calculation form and calculation steps of the IoT technology is optimized. The remote control and wireless monitoring model of solar photovoltaic power generation equipment is analyzed based on IoT technology. First, the coding form of the model is studied. Nowadays, the rapid development of computer technology has brought many coding forms. Different coding forms have different features and functions. The model coding of this paper adopts the sparse de-noising automatic encoder. The sparse auto-coder implemented by the unsupervised feature learning algorithm completes the initialization of the deep neural network, and then uses the sparse feature expression learned by the encoder to train the last layer of neural network classifier, and finally completes the training and fine tuning of the entire deep neural network. In fact, this sparse de-noising auto-encoder is also the encoder after optimization. The traditional sparse de-noising auto-encoder cannot automatically reduce noise. In order to show the most realistic computing power of the computation model established in this paper, noise reduction processing is an indispensable form. An encoder incorporating noise reduction processing can minimize the noise impact of the model calculation data. The calculation model established in this paper can make more accurate judgments on fault handling, which is also determined by the use function of this paper. When the solar photovoltaic power generation equipment fails, many faults are not independent. It is likely, some information different and fault would appear at the same time. These fault information are interlaced, which brings huge impact on the wireless monitoring and remote control of the model. Challenge, although this paper uses different hidden layers for computational analysis in the optimization of model calculation algorithms, there will be some data cross-impact. Since the sparse de-noising auto-encoder is an unsupervised feature learning method, the deep neural network constructed by it can mine the intrinsic characteristics of the data from a large number of unlabeled data during the training process, greatly expanding the number of training samples, and is very suitable. The realization of big data mining of induction motor equipment is of great significance for the condition monitoring and fault diagnosis of induction motors.

After the analysis of the advantages of using this form of coding, it is also needed to study the coding process. According to the calculation form of this paper, the coding steps are mainly divided into three major steps, which are analyzed one by one below.

The first step is to use the data XI for coding training studies. Before coding the model in this paper, an automatic encoder model needs to be built in advance for encoding. Here, various parameters used in the encoding need to be set, the learning rate is represented by ε; the sparse parameter is ρ; the connection weight is *W*; and the offset is *b*. After setting these parameters, the various training numbers, iterations are analyzed, and the average activation amount ρ_j is calculated. And the sparse cost function of this paper is established:

$$C(W,b)=\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{2}\left\|h\left(x(i)-y(i)\right)\right\|^2\right)\right]+ +\beta\sum_{j=1}^{32}KL\left(\rho|\rho_J\right) \quad . \quad (7)$$

This completes the preparatory work for the coding form. The next step is to construct a deep neural network corresponding to the hierarchy, and use the parameters such as the sparse de-noising encoder weight ring and the offset *b* obtained in the previous step to initialize the first layer parameters of the deep neural network; learning rate, batch training number and iteration number, dropout parameter, etc., training network, extracting features and classifying; calculating the cost function and mean square error of deep neural network according to formula 7; performing the same back-propagation algorithm process as before (only the sparse item is set to zero). The network iteratively updates the weight once and fine-tunes the entire network. The model parameters of the remote control and wireless monitoring model of solar photovoltaic power generation equipment based on the IoT technology established in this paper are shown in Table 1.

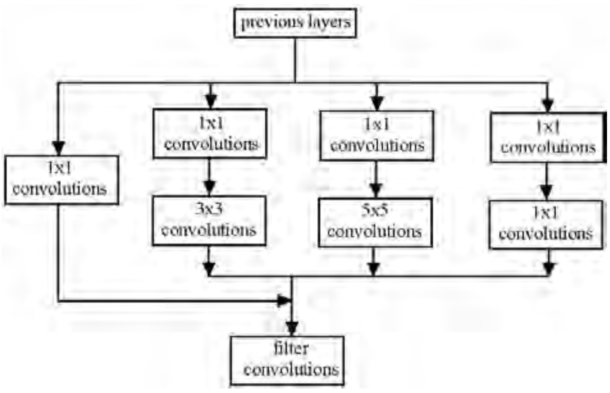

Fig.2. Steps for calculating the remote monitoring and fault detection model of machinery manufacturing equipment based on deep learning algorithm

According to the coding form above and the optimization of the IoT technology, the calculation steps of the remote control and wireless monitoring model of the solar photovoltaic power generation equipment based on the IoT technology are as shown in Fig. 2.

4. RESULT ANALYSIS AND DISCUSSION

In order to verify the detection effect of the remote control and wireless monitoring model of the solar photovoltaic power generation equipment based on the IoT technology established in this paper, a set of tests are established to prove the practicability of the test model established by testing the calculation effect of the model. The NI-PCI6259 data acquisition system is used to collect the vibration signals of the induction motor in six different operating states. The signal sampling frequency is 20 kHz. The vibration signal of the motor in the *Y*-axis direction at the SOHz speed is selected as the experimental processing signal. The types

Table 1. Model Parameters of Remote Monitoring and Fault Detection Model of Mechanical Manufacturing Equipment Based on Deep Learning Algorithm

Tpe	Patch size/stride	Output size	Depth
Convolution	7×7/2	112×112×64	1
Max pool	3×3/2	56×56×64	0
Convolution	3×3/1	56×56×192	2
Max pool	3×3/2	28×28×192	0
Max pool	3×3/2	14×14×480	1
Max pool	3×3/2	7×7×832	0
Avg pool	7×7/2	1×1×1024	0

Table 2. Types of Faults Involved in the Induction Motor in the Experiment

	Species	Description
HEA	Normal motor	Health status, no failure
SSTM	Stator winding failure	Short circuit of stator winding
UBM	Rotor imbalance	3 washers on the rotor cause imbalance
RMAM	Bearing failure	Fault in the bearing inner ring of the shaft end
BRB	Rotor broken bar	Rotor 3 spoke breaks
BRM	Spindle deflection	Spindle centre bend 0.01"

Table 3. Parameter Settings Used in the Calculation

DSAE			DNN		
M	2000	The number of input layer nodes	M	2000	The number of input layer nodes
Sz	600	Hidden layer nodes	S	600	Hidden layer nodes
out	2000	Output layer node number	out	6	Output layer node number
ρ	0.08	Sparse target	Dropout	0.3	Dropout rate
β	0.4	Sparse weight	ε	1	Learning rate

of faults included in the induction motor are shown in Table 2.

The wireless monitoring model for power generation based on sparse denoising auto-encoder proposed in this chapter, the input layer, the hidden layer and the output layer of the encoder are set to 2000, 600 and 2000 respectively, because the effect of one layer of encoder is mainly studied, and there are 6 kinds of motor running states to be classified, so the corresponding deep neural network structure is 2000–600–6. Through the test of this paper, it is hoped to analyze the denoising parameters and dropout rate of the model to achieve the test purpose of this paper. The parameter settings used in the calculation are shown in Table 3.

Through the preparation of the above data, the wireless monitoring model established in this paper can be tested. First of all, the calculation dispersion of the data in the calculation is analyzed. For the analysis of the dispersion, the calculated data is divided into five nodes for research, and the relationship between the data points of the model analysis and the actual curve is established, which is shown in Fig. 3.

As can be seen from the analysis of the model calculation dispersion in the above figure, the cal-

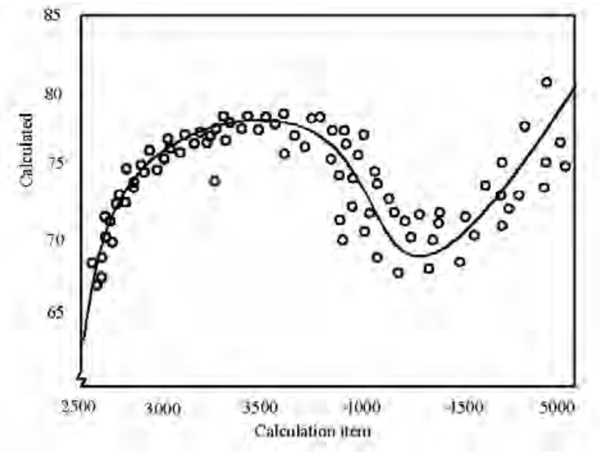

Fig.3. Dispersion analysis diagram of fault detection model

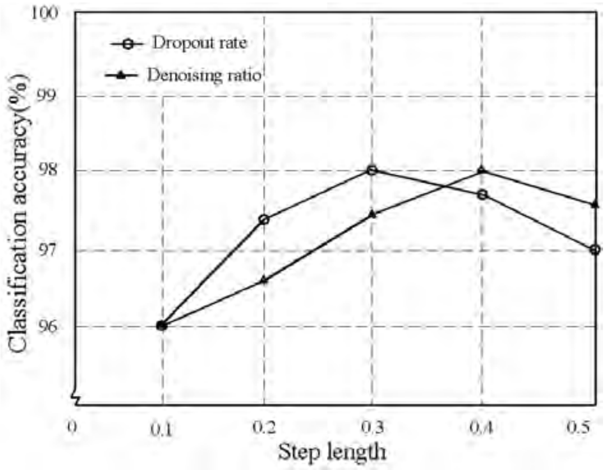

Fig.4. The model's de-noising ratio and model's dropout rate

culation of the model increases with the increase of the calculation items, and the dispersion of the model is the highest when the calculation term is between 4500 and 5000, which can be analyzed from the distance between the calculated data point and the actual curve. However, in terms of overall dispersion, the data analysis capability of the wireless monitoring model established in this paper is strong, which indicates that the model has higher calculation accuracy for the wireless monitoring model of solar photovoltaic power generation equipment, and the calculation results meet the requirements of this paper. The relationship between the calculation result and the exact value is relatively close.

Next, the model test is based on the de-noising ratio of the model and the dropout rate of the model. In the overall model calculation, the calculation ratio is used as the calculation variable in the test, and then the classification accuracy of the two ratios is tested and analyzed. The test results are shown in Fig. 4 below.

The experimental results directly prove the excellent performance of the wireless monitoring model established in this paper. Among the tests for dropout rate, in the range of 0~0.5, the classification accuracy rate of the model is increasing before 0.3, and it reaches 98 % correctly at 0.3, and the initial classification accuracy is 96 %. It can be seen that the dropout rate is well calculated in the detection model established in this paper. The calculation of the model is not calculation for the single information, so the increase of the classification accuracy rate is of great significance to the accuracy of the magic calculation. In addition, the calculation accuracy of the model for the de-noising ratio is also gradually increased from 0 to 0.5, reaching the apex at 0.4, and also achieving 98 % of the calculation accuracy. The test from these two aspects proves that the remote control and wireless monitoring model of solar photovoltaic power generation equipment based on IoT technology is in full compliance with the calculation requirements of this paper, and the calculation accuracy has been above 96 %. And the calculation of multiple hidden layers also ensures the computational efficiency.

5. CONCLUSION

With the gradual deepening of the application of computer technology, the detection and monitoring of power plant equipment failures are gradually using computers for research. A remote control and wireless monitoring model of solar photovoltaic power generation equipment based on IoT technology is established by studying computer technology. Through the test research of the model in this paper, it is found that the wireless monitoring model has low dispersion of data calculation when calculating and analyzing the data, and basically the calculated data is near the exact value. In addition, the de-noising ratio and the dropout rate of the model is also tested and analyzed. It is found that the classification accuracy of the model and the calculation accuracy of the model are all stable above 96 %. This kind of precision calculation can already meet the monitoring and wireless monitoring of solar photovoltaic power generation equipment at this stage. In addition, the model of this paper draws on the calculation of neural network algorithm, and uses a variety of hidden layers to classify and calculate the data. The calculation accuracy is improved and the calculation efficiency is also high. This parallel form of computational model has great advantages for the calculation and analysis of multiple data. The research in this paper will further improve the application in the future progress of solar power generation technology.

REFERENCES

1. Zabidi A., Yassin I M., Hassan H A. Detection of asphyxia in infants using deep learning convolutional neural network (CNN) trained on Mel frequency cepstrum coefficient (MFCC) features extracted from cry sounds. Journal of Fundamental and Applied Sciences, 2017, V9, #3S, pp.768–778.

2. Sirinukunwattana K., Raza S., Tsang Y W. Locality Sensitive Deep Learning for Detection and Classification of Nuclei in Routine Colon Cancer Histology Images. IEEE Transactions on Medical Imaging, 2016, V35, #5, pp.1196–1206.

3. Chang, C., Qiang, Z., Zhongjian, L. Design of wireless power supply optimized structure for capsule endoscopes. Journal of Power Technologies, 2016, V96, #2, pp.101–109.

4. Gan M., Wang C., Zhu C. Construction of hierarchical diagnosis network based on deep learning and its application in the fault pattern recognition of rolling element bearings. Mechanical Systems & Signal Processing, 2016, V72, #2, pp.92–104.

5. Weinan E., Han J., Jentzen A. Deep Learning-Based Numerical Methods for High-Dimensional Parabolic Partial Differential Equations and Backward Stochastic Differential Equations. Communications in Mathematics & Statistics, 2017, V5, #4, pp.349–380.

6. Abràmoff M D., Lou Y., Erginay A. Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning. Investigative Ophthalmology & Visual Science, 2016, V57, #13, p.5200.

7. Cocos A., Fiks A G., Masino A J. Deep learning for pharmacovigilance: recurrent neural network architectures for labelling adverse drug reactions in Twitter posts. Journal of the American Medical Informatics Association, 2017, V24, #4, pp.813–821.

8. Wang C., Cunefare D., Fang L. Automatic segmentation of nine retinal layer boundaries in OCT images of non-exudative AMD patients using deep learning and graph search. Biomedical Optics Express, 2017, V8, #5, pp.2732–2744.

9. Weiping Zhang., Akbar Maleki., Marc A. Rosen., Jingqing Liu. Optimization with a simulated annealing algorithm of a hybrid system for renewable energy including battery and hydrogen storage, Energy, 2018, V163, pp. 191–207.

10. Kumar, M., Mao, YH., Wang, YH., Qiu, TR., Yang, C., Zhang, WP. Fuzzy theoretic approach to signals and systems: Static systems, Information Sciences, 2017, V418, pp.668–702.

Erhua SUN, Master of Business Administration, Associate Professor. Graduated from the Chongqing communication college in 2001. Worked in Chongqing real estate college. Her research interests are data analysis and data mining