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Retraction

Retracted: Wireless Mobile Power Communication System Based on Artificial Intelligence Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Du and M. Guo, "Wireless Mobile Power Communication System Based on Artificial Intelligence Algorithm," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 1636033, 7 pages, 2022.

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Research Article

Wireless Mobile Power Communication System Based on Artificial Intelligence Algorithm

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In order to solve the problems of low-risk assessment accuracy and long time-consuming assessment of current wireless mobile communication systems, a wireless mobile communication system based on artificial intelligence algorithms is proposed. First, the research status of risk assessment of wireless mobile communication system at home and abroad is analyzed, and the risk assessment index system of wireless mobile communication system is established; then, the learning samples are collected according to the risk assessment index system of wireless mobile communication system, and artificial intelligence algorithm is used to optimize the neural network. Build the wireless mobile communication system risk assessment model; finally, carry out the wireless mobile communication system risk assessment simulation comparison test. The experimental results show that the accuracy rate of the risk assessment of the wireless mobile communication system by the artificial intelligence algorithm is over 95%, and the assessment error is smaller than in other models. The risk assessment time of the wireless mobile communication system is significantly reduced, the real-time performance is better, and it has a higher practical application value.

1. Introduction

With the development of the communication industry, the number of wireless users is increasing day by day. Now, the penetration rate of mobile phones has reached 64.4 units/100 people. Data show that the total number of mobile phone users in Beijing exceeded 25 million in 2011, an increase of 21.0% over 2010. The number of fixed telephone users in Beijing decreased by 0.2% over last year to 8.839 million [1]. The total number of mobile phone users was 25.76 million, an increase of 21.0% over last year. Users increasingly rely on wireless communication and are sensitive to voice quality and network coverage. Complaints about voice quality, wireless coverage, and other technical aspects are also increasing.

Wireless network refers to any form of radio computer network, which is combined with telecommunication network, and can communicate with each other between network nodes without cables. According to the coverage of the network, it can be divided into wireless body area network, wireless personal network, wireless local area network, wireless metropolitan area network, and wireless wide area network. Wireless personal networks and wireless LANs are the most exposed in daily life. Wireless networks formed by connecting several devices in a small range, such as Bluetooth devices, belong to wireless personal networks. The wireless network used to complete data exchange between network nodes or access the Internet in an area composed of wireless AP devices belongs to wireless LAN. Due to the rapid development and mutual promotion of wireless networks and mobile devices, wireless network coverage has been basically realized in public places and corporate offices [2]. Akpe, M. A. and others believe that wireless network terminal equipment and wired network terminal equipment have different characteristics, and wired network equipment will not be physically contacted by users or intruders, while the physical equipment of wireless network is likely to be contacted, so there may be intruders deploy fake APs. The computing power of wireless network terminal equipment is usually weak, and it is easier to lose and damage than wired network terminal equipment [3]. The use of the wireless network has greatly improved the efficiency of the office and information transmission, but at the same time, due to the openness of the wireless network, its security is fragile and vulnerable to monitoring or attack. Therefore, how to implement an effective security protection mechanism for wireless networks and enhance the security of wireless networks is an important issue facing wireless networks.

Huang, H. and others used the complex network to study the secondary derivative coupling law of disasters and constructed the dynamic network model and unconventional event chain model [4]. T d ü Zenli and others proposed the risk assessment model and calculation method for the wide area measurement system (WAMS) communication backbone network, calculated the probability of risk events by using the reliability analysis method, and built a comparison judgment matrix by using the analytic hierarchy process for reference to realize the quantitative calculation of the risk impact value, so as to obtain the comprehensive risk value of the communication backbone network [5]. Shang, Y. and others proposed a risk evaluation method combining the complex network theory and the risk characteristics of the power communication network. According to the edge importance, the threats and losses caused to the network after failure are considered. According to the typical structure and communication service characteristics of power communication network, the average service risk and service risk balance are used as the network reliability evaluation indicators. Balance is used as the evaluation index of network reliability. The failure probability between different levels of power communication network is analyzed, and the risk analysis model is established [6]. On the whole, at present, the risk assessment of urban public security in the special environment is still based on the risk assessment of a single disaster in various industries. There are few studies on the spatio-temporal risk interaction between special environment (such as major activities) and urban operation, especially the coupling of multidisaster and multiscale risks; in addition, the risk assessment process lacks the updating mechanism of the risk assessment method based on the special environment and is still in the qualitative and quantitative assessment stage. There is also a certain gap between the standardized research on risk assessment and emergency management and foreign countries [7, 8].

On the basis of this research, this paper proposes a research method of wireless mobile communication system based on an artificial intelligence algorithm. Aiming at the parameter optimization problem of BP neural network applied in the risk assessment of wireless mobile communication system, a risk assessment model of wireless mobile communication system based on artificial intelligence algorithm is designed, and the risk assessment model of wireless mobile communication system is compared with other wireless mobile communication system risk assessment models. The experimental results show that the risk assessment time of the wireless mobile communication system is significantly reduced, the real-time performance is better, and it has a higher practical application value.

2. Research Methods

2.1. Relevant Theories

2.1.1. BP Neural Network. The back-propagation algorithm is referred to as the BP algorithm, and the multilayer feedforward neural network using the BP algorithm is called the BP neural network. BP algorithm, also known as the negative gradient algorithm, adopts supervised delta learning. Its principle is to modify the connection weight between neurons in the network in the direction of gradient descent, so as to minimize the sum of square errors of network output to achieve the expected learning results. When the BP algorithm is used, the sigmoid function which can be continuously differentiable is often selected as the activation function in the neural network. Compared with a single neural network, the BP network composes simple nonlinear functions to realize highly nonlinear mapping of learning objectives. Therefore, BP neural network is widely used in nonlinear modeling in the fields of pattern recognition and adaptive control [9].

The internal calculation and learning of the BP neural network can generally be divided into two steps with different directions: the forward propagation of information and the reverse adjustment of error. The first is the forward propagation of information; that is, the information is propagated through the input layer to the hidden layer and finally output by the output layer. At this time, if the actual output is the same as the expected output, the learning and training are over, and the results are given; if it does not conform to the expected value, the error signal will return in the same way. By sequentially adjusting the weights of the release process and the hidden process, the error problem can be reduced in the negative gradient direction; that is, the error can be reduced by weight processing. After the above process, the final output of the network will gradually reach the expected output. Suppose that the input data of the BP neural network are $X = (X_1, X_2, \cdots, X_n)^T$, n represents the number of nodes of neurons in the input layer, the corresponding output data are $O = (O_1, O_2, \cdots, O_m)^T$, m represents the number of nodes of neurons in the output layer, and W_{ij} and W_{jk} are the connection weights of the hidden layer and the output layer, respectively. For the input component X_i of layer i, the corresponding outputs of the hidden layer and the output layer can be expressed as the following formula:

$$Y_o = f(X_i W). \tag{1}$$

The training steps of the BP neural network are as follows:

(1) The weights W_{ij} and W_{jk} are initialized randomly. Their values must not be the same. The range is usually $(-1.0, 1.0)$. For sample (X_p, Y_p), the output value is O_p.

(2) Calculate the error between O_p and Y_p, and adjust the weight matrix according to the error. For the p-th sample, the following formula (2) can be obtained:

$$E_p = \left(\frac{1}{2}\right)\sum_{j=1}^{m}\left(y_{pj} - o_{pj}\right)^2. \tag{2}$$

The neural network error calculation formula of all models is as follows (3):

$$E = \sum_{l=1}^{s} E_{pl}, \tag{3}$$

where s is the number of samples.

The process of reducing E can be thought of as an optimization problem. The weight matrix is processed by the steepest descent method: the following models (4) and (5) are used.

$$\begin{aligned} W_{jk} &= W_{jk} + \Delta W_{jk}, \\ &= W_{jk} + \alpha O\left(1.0 - O_k\right)\left(Y_k - O_k\right)O_j, \end{aligned} \tag{4}$$

$$\begin{aligned} W_{ij} &= W_{ij} + \Delta W_{ij}, \\ &= W_{ij} + \alpha O_j\left(1.0 - O_j\right)O_i \cdot \sum_{k_1=1}^{h}\sum_{k_2=1}^{m} W_{k_1k_2}O_{j+1,k_2}\left(1.0 - O_{j+1,k_2}\right)\left(Y_{j+1,k_2} - O_{j+1,k_2}\right), \end{aligned} \tag{5}$$

where α is the learning rate.

When the traditional BP algorithm adjusts the connection weight, it only operates according to the negative gradient direction at time K. When there is a large change in the learning and training process, the conventional BP algorithm is difficult to stabilize in a short time. As can be seen from the above formula, after adding the momentum term, the network can be adjusted according to the gradient value at time k and time k−1 at the same time, so that the network can converge better. In the process of learning, whether the learning rate is too large or too small, it is not conducive to training. However, the formula of learning rate cannot be deduced theoretically, so the learning rate is generally selected by empirical value, which will lead to the instability of the convergence rate. For this reason, a variable step size factor can be introduced to take the learning rate as a function of a certain variable. For example, the learning rate can change with the change in error gradient. At the beginning of training, it can be larger to increase the convergence speed. When the training tends to be stable, η can be smaller to maintain stability.

The selection of some activation functions may cause the gradient to disappear. When each node in a multilayer neural network uses sigmoid function as activation function, the gradient will be multiplied by a value less than 0.25 every time, and it passes through a sigmoid layer in the error backpropagation phase of BP learning. In order to solve the drawback of gradient disappearance, researchers proposed a method to change the activation function into an improved nonlinear function such as Relu. Take the Relu function as an example. When the parameter is greater than 0, the value of the Relu function is 0. When the parameter is less than 0, the output value of the Relu function is equal to the input value. The first values W_{ij} and W_{jk} of the traditional BP neural network are randomly determined, which makes the operation of the BP neural network unstable and cannot be solved effectively. Therefore, this paper introduces the particle swarm optimization algorithm into the intelligent algorithm to optimize the value between W_{ij} and W_{jk} [10, 11].

2.1.2. Artificial Intelligence Algorithm. The position vector of the i-th particle is $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, which represents a set of initial values of W_{ij} and W_{jk}, as well as a velocity vector $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. The particles adjust the flight direction by tracking the optimal position of individuals and groups, as shown in the following formulas:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1r_1\left(p_{id} - x_{id}(t)\right) + c_2r_2\left(p_{gd} - x_{id}(t)\right), \tag{6}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \tag{7}$$

where t is the number of iterations; ω is the inertia weight [12].

2.2. Risk Assessment of Wireless Mobile Phone Communication Based on Intelligent Algorithm

2.2.1. Risk Evaluation Index and Risk Level Setting of Wireless Mobile Power Communication System. The development of wireless mobile communication risks is based on the principles of research, usability, and functionality due to the increased risk of wireless mobile communication. First, the wireless mobile power communication system risk evaluation indicators are divided into two categories: artificial risk indicator system and technical risk indicator system [9, 13]. The technical risk indicator system is divided into hardware facilities, physical environment and guarantee, software facilities, and other risk subindicator systems, which can be subdivided into specific risk indicators. The human risk indicator system only includes the risk subindicator system

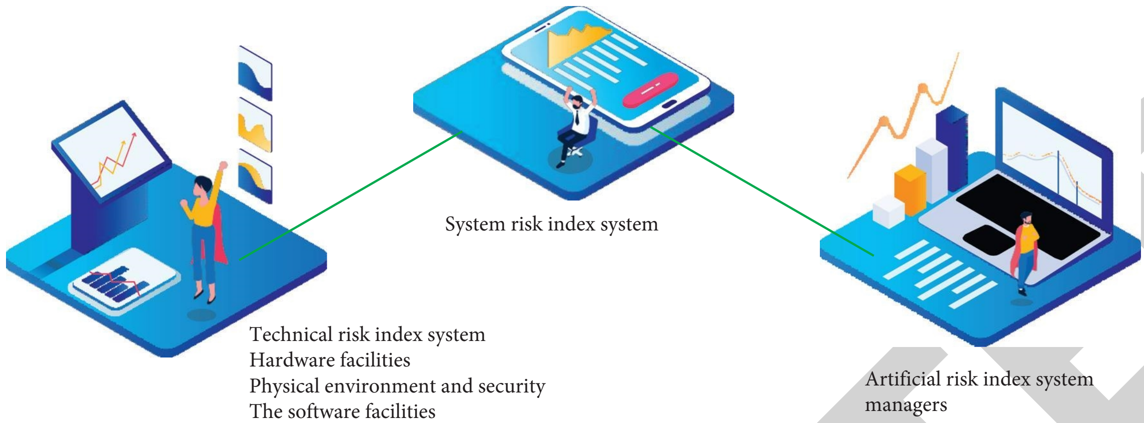

Figure 1: Hierarchical indicator structure.

of the manager, which can be refined. The established hierarchical indicator structure is shown in Figure 1.

According to the risk assessment specification for wireless mobile power communication system, the risk level can be set to level 5. The specific values and descriptions are shown in Table 1 [14].

2.2.2. Risk Assessment Steps of Wireless Mobile Power Communication System Based on Intelligent Algorithm

(1) According to the principles of scientificity, applicability, and operability, the risk indicators of the wireless mobile power communication system are selected
(2) Collect the corresponding wireless mobile power communication system risk assessment data according to the wireless mobile power communication system risk indicators
(3) Mark the risk level of wireless mobile power communication system by relevant experts [15]
(4) Since some indicators need to be quantified and some indicators need to be discretized, the corresponding pretreatment is performed on the indicators, and then, the preprocessed values are scaled, as shown in the following formula:

$$x_i' = \frac{(x_i - \max)}{(\max - \min)}, \tag{8}$$

where max and min, respectively, represent the maximum and minimum values of risk indicators of wireless mobile power communication system [16]
(5) Select some data to develop a training model for wireless mobile phone communication risk assessment, access the BP neural network, and activate the influence of the BP neural network, such as minimum error training and maximum algebraic training
(6) The intelligent particle swarm optimization algorithm is used to determine the initial connection of the BP neural network
(7) According to the initial connection weights and related parameters, the neural network is forward learning and error back propagation, and the weights are continuously adjusted through the gradient descent algorithm to make the training error meet the preset minimum training error range
(8) The risk assessment model of wireless mobile power communication system is established through the above steps, and the specific process is shown in Figure 2 [17]

2.3. Simulation Test

2.3.1. Risk Assessment Data Source of Wireless Mobile Power Communication System. In order to measure the performance of the wireless mobile power communication system risk measurement model based on the intelligent algorithm developed in this paper, the real-time nature of the wireless mobile communication risk data source culture is selected as the research material [18, 19]. Due to space limitations, only the risk cost of mobile communication is shown in Figure 3.

By analyzing the original value of wireless communication risk in Figure 3, it can be seen that the risk of mobile communication is different and has strong randomness, but there are also some constant changes. Finally, 50 pieces of data were selected as evidence, and additional data were used as training models for wireless communication risk assessment [20].

3. Result Analysis

3.1. Analysis of Risk Assessment Results of Wireless Mobile Power Communication System Based on this Model. The particle swarm optimization algorithm is used to determine the initial connection of the BP neural network, and then, the wireless communication risk assessment is performed on the receiving model, as shown in Figure 4 [21].

By analyzing the wireless communication risk assessment in Figure 4, it can be seen that the communication risk assessment of this form of mobile phone wireless model is very small and can be ignored. The evaluation results of

Table 1: Risk level of wireless mobile power communication system.

Wireless mobile communication system risk level number	Level	Value	Specific description
1	Very low	0~0.1	No impact
2	Low	0.1~0.3	Little impact
3	Middle	0.3~0.6	There is a certain impact, but the degree of impact is small
4	High	0.6~0.9	Have a great impact
5	Very high	0.9~1	Have a very serious impact

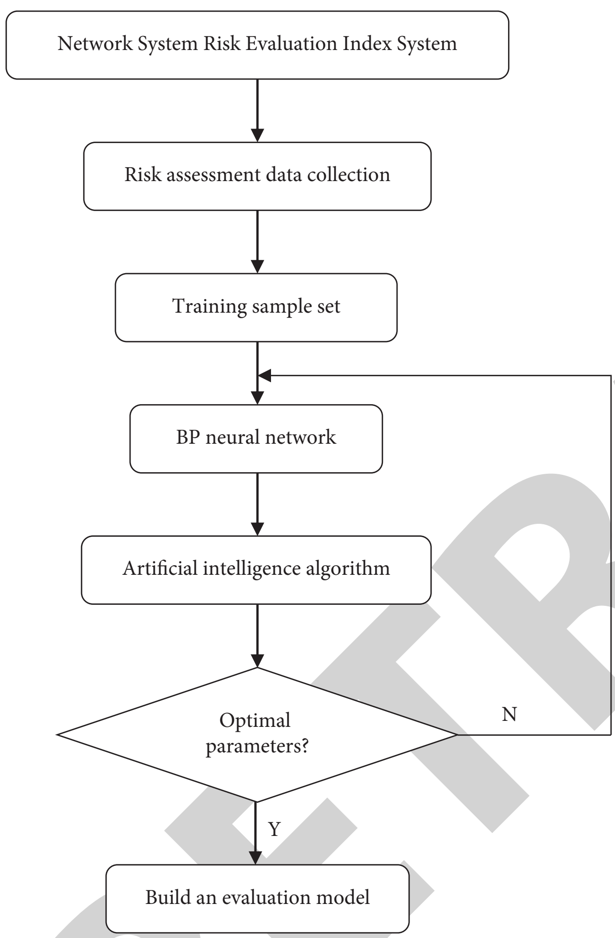

Figure 2: Risk assessment training process of wireless mobile power communication system.

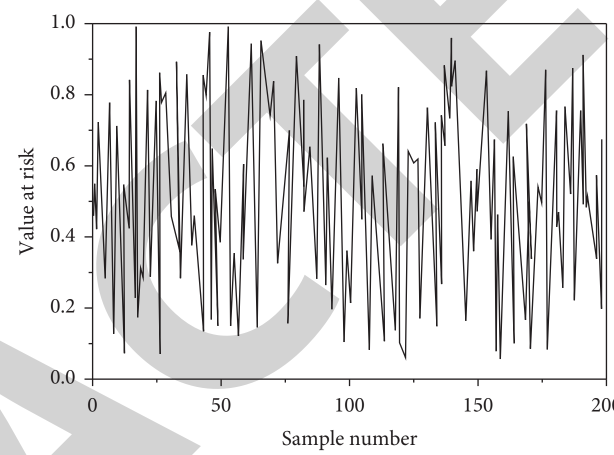

Figure 3: Risk value of wireless mobile power communication system risk assessment.

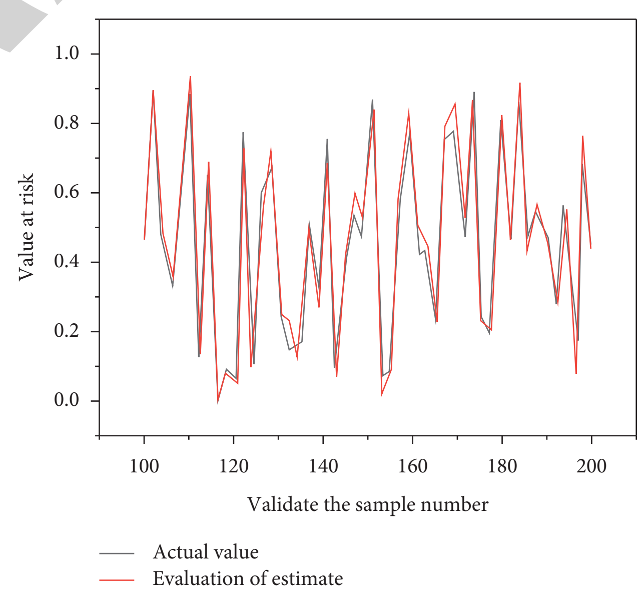

Figure 4: Risk assessment results of wireless mobile power communication system based on this model.

wireless mobile power communication system risk measurement are accurate and reliable. It is a measure of risk to wireless mobile communication performance.

3.2. Performance Comparison with Classical Wireless Mobile Power Communication System Risk Assessment Model. In order to measure the effectiveness of the risk measurement of mobile communication models based on intelligent algorithms, grayscale, group analysis, and BP neural network models are used to conduct comparative experiments under the same setting data and the same simulation environment. The correct rate of risk assessment and training time of wireless mobile communication system were counted. The specific testing and training times are shown in Table 2.

It can be seen from Table 2 that the accuracy of the wireless mobile communication risk measurement model based on the intelligent algorithm in this paper is above 95%, while the accuracy of the classic wireless mobile power communication system risk measurement standard is lower

Table 2: Comparison of risk assessment results of wireless mobile power communication system with classical model.

Risk assessment model of wireless mobile communication system	Evaluation accuracy rate/%	Training time/s
Gray model	88.84	11.51
Cluster analysis	86.62	12.27
Standard BP neural network	92.15	7.72
Paper model	95.67	4.67

than 95%. And the research time of this model is shorter than that of the classic wireless mobile power communication system risk measurement model, which improves the risk measurement speed of the wireless mobile power communication system [22, 23]. Therefore, the risk assessment results of wireless mobile communication system based on this model are more ideal.

4. Conclusion

The security of wireless mobile communication system is a hot research topic at present. In order to solve the problems existing in the risk assessment of the current wireless mobile communication system, a risk assessment model of wireless mobile communication system based on an artificial intelligence algorithm is designed. The results show that the accuracy rate of the risk assessment of the wireless mobile communication system by the artificial intelligence algorithm is more than 95%, and the training speed of the risk assessment of the wireless mobile communication system is fast. Evaluate modeling tools. In the era of rapid and dense information transfer, the communication network acts as a dynamic network. Due to uneven distribution of traffic density, tight frequency resources, suboptimal, and constantly changing network configuration, the service quality of the existing network is likely to be unsatisfactory. Reasonably adjust the parameters of the network, so that the network can reach the best operating state, and realize the guarantee of network quality in daily life.

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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