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Research Article

Wireless Sensor Modeling Optimization Algorithm Based on Artificial Intelligence Neural Network

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With the development and progress of society, science and technology have entered the field of view of scholars at home and abroad. As the science and technology with the biggest potential in recent years, wireless sensor network has been involved in many scientific fields. This paper aims to study the wireless sensor modeling optimization algorithm of artificial intelligence neural network. In this paper, a WSN data fusion algorithm (DFRMP) based on regression model prediction is proposed, and the four algorithms of SLR, PAQ, TINA, and DFRMP are compared. The experimental results of this paper show that when the mean square error and mean absolute error are not much different, the data transmission rate of DFRMP algorithm is the smallest. When the absolute error threshold is 1, the data transfer rates of these four algorithms are 0.033, 0.0327, 0.035, and 0.017, respectively. This shows that the DFRMP algorithm proposed in this paper has superior performance.

1. Introduction

Different from traditional wireless communication networks, sensor networks can realize functions such as no equipment, unmanned operation, many nodes, and self-organizing multi-hop. Wireless sensors can be used in image recognition, communication, signal transmission, and other fields. The artificial neural network model has some shortcomings, such as weak stability, the result is easily affected by the initial value, and the speed is easily limited. Therefore, combined with new algorithms, different types of intelligent neural networks are formed, and they are used in the further optimization of wireless sensor modeling. This will be of great value to the advancement of wireless sensor networks.

In recent years, with the development of social science and technology, many network systems have spread in people's daily life, and wireless sensor network is one of them. Wireless sensor networks can realize various functions such as data perception, data collection, information processing, and information transmission. The network connects the information world and the real world and transforms the way of information exchange between people and nature, so it is widely used. The artificial neural network is an intelligent technology that simulates the human brain in recent years. Artificial neural network has strong nonlinear function and better learning ability. The functional relationship of its response can be adapted by adjusting the corresponding values in the network and does not need to be further expressed by functional expressions. This can well avoid the bias caused by improper selection of relevant parameters in the function. Therefore, the wireless sensor modeling optimization of artificial intelligence neural network has become one of the directions of future research, and its further exploration will have good theoretical and practical significance.

Driven by the demands of military technology, automation, and intelligence, artificial intelligence neural networks have received extensive attention from academia and industry, and, in recent years, many new theoretical and methodological advances have been made. Artificial neural network includes recurrent neural network, BP neural network, and convolutional neural network. However, in recent years, the artificial intelligence neural network has not paid much attention to the optimization of wireless sensor modeling but only talked about the advantages of artificial intelligence neural network in wireless sensor modeling from the side, which lacks specific concept research and practical exploration. Therefore, this paper explores the wireless sensor modeling optimization algorithm of artificial intelligence neural network, so as to promote the development of artificial intelligence neural network, which also provides reference for future related research on wireless sensor modeling.

2. Related Work

With the development of social science and technology, artificial intelligence neural network can have a significant influence in all walks of life. Brain-inspired photonic neural networks have attracted renewed interest in recent years. For many computing tasks, such as image recognition, speech processing, and deep learning, photonic neural networks have the potential to increase computing speed and energy efficiency by orders of magnitude compared to digital electronics. Bai summarized some important recent advances in silicon photonic neural networks, including multilayer artificial neural networks for artificial intelligence and brain-like neuromorphic systems, and he proposed a silicon photonic artificial intelligence processor prototype for ultrafast neural network computing [1]. Although his research is a breakthrough in artificial intelligence, it is still immature in the application of technology. At present, with the continuous development of artificial intelligence technology, neural networks have opened up new ways for corporate financial crisis early warning. Tian and Yue constructed and researched the early warning of enterprise financial crisis based on artificial intelligence. They used the neural network model to conduct empirical research on corporate financial crisis early warning, analyzed the prediction accuracy of the model, explored the method of determining the optimal solution, and enriched the research content and results of financial crisis early warning [2]. In recent years, many systems for development training have emerged, in which artificial neural networks occupy a considerable place. While artificial intelligence is increasingly used in educational settings, Zakaryan presents an example of the use of artificial neural networks that play an important role in developing educational systems [3]. Although his research is helpful for the development of educational systems, the computational process is too complex to be applied in practice. The field of optical measurement and inspection systems is increasingly applying artificial intelligence and machine learning systems through artificial neural networks. Heizmann et al. showed that the results obtained by this method are generally very promising and the associated development work requirements are reduced [4]. Due to the large volume of smears at cancer screening centers and the labor-intensive testing required, Sanyal et al. developed a software program to identify lesions of abnormal cells from routine smears. The convolutional neural network (CNN) model was chosen due to the significant power of image classification. There were 1838 photomicrographs from cervical smears, containing 1301 "normal" lesions and 537 "abnormal" lesions. The dataset is divided into training set, test set, and validation set. CNN showed a diagnostic accuracy of 95.46%, indicating a huge potential use in screening [5]. Targeted telemedicine is an essential support system for the clinical environment outside the hospital. Recently, the importance of the Telehealth Assessment Model (MAST) has been highlighted. Ohura et al. explored whether diabetic foot ulcer (DFU) and venous leg ulcer (VLU) wound segmentation can be performed by convolutional neural network (CNN) after education using the sacral pressure ulcer (PU) dataset. This method prepares CNNs with different algorithms and architectures, and the three architectures are SegNet, LinkNet, and U-Net. Each CNN learns from supervised data on sacral pressure ulcers (PU). The best results among the four architectures were obtained using U-Net [6]. To sum up, it cannot be seen that, in recent years, artificial intelligence neural networks have not only had relevant research in enterprises but also had very good application prospects in the fields of medical care and education. With the progress of scientific research, artificial intelligence neural network has become a new trend of research in various countries, but there are not many practical research studies on wireless sensor modeling optimization. Therefore, in order to further promote the advancement of wireless sensors, the research on the optimization of wireless sensor modeling of artificial intelligence neural networks is urgent.

3. Theory Related to Wireless Sensor Modeling and Optimization Algorithm of Artificial Intelligence Neural Network

3.1. Artificial Intelligence Neural Network. An artificial neural network system consists of a large number of neurons. Neural networks were originally discovered from studies of the animal visual system. Since the connections between neurons are very perfect, the system can handle complex logical operation problems. Artificial neural network combines the advantages of biological neural network, so it has strong associative ability, memory, high degree of parallelism and nonlinear global effect, and adaptive learning ability [7, 8]. However, it does not work well in all fields. Artificial neural network has the characteristics of parallel distributed processing, nonlinear mapping characteristics, good robustness, self-learning, self-organization, and self-adaptation. Because of this, neural network just meets the requirements of data fusion technology processing. In the stage of various activities and cognition and change of the real world, human beings are mainly through the learning and application of various knowledge and the ability to integrate various information. The principle of neural network fusion technology is to simulate the process of the human brain comprehensively processing various data or information. Figure 1 is an artificial neural network fusion

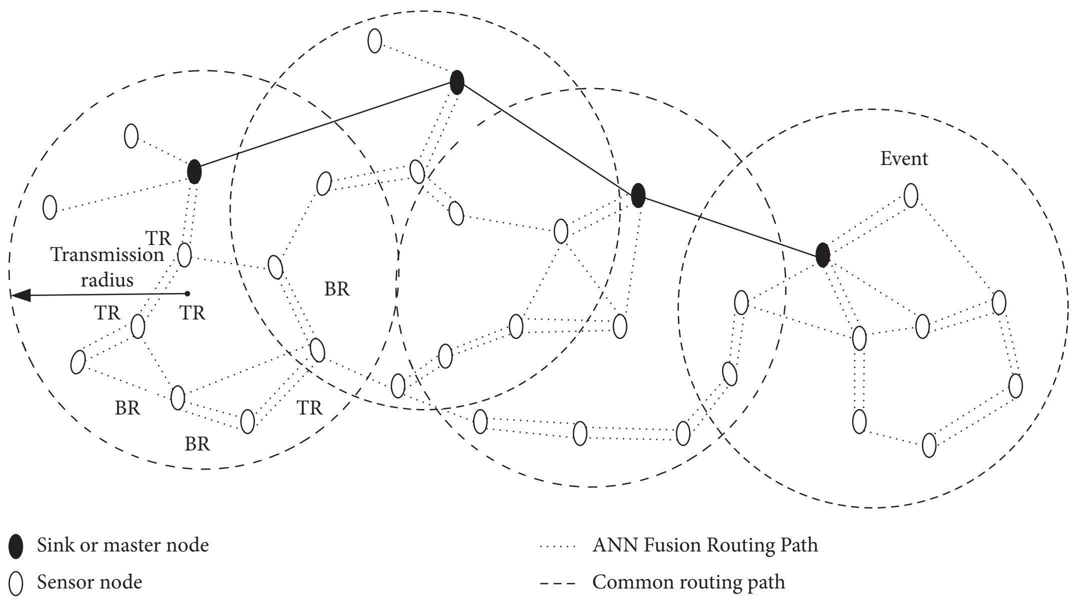

Figure 1: Artificial neural network data fusion model.

routing model. In the routing without the application of neural network fusion technology, there is a lot of redundant information transmission between sensor nodes in the network, which increases the work intensity of the nodes, the time for processing data, and the frequency of communication. In the data fusion, in the weight distribution of the neural network, the neural network mainly classifies the samples through a certain degree of similarity, and the neural network can further analyze the knowledge system according to the learning algorithm [9, 10].

3.2. Wireless Sensor Networks. Wireless sensor network is a self-organizing network system formed by placing many small sensors in a corresponding area through wireless communication [11, 12]. The network does not need to be connected through extensive infrastructure. The sensor nodes can be arranged in the corresponding area by manual, aircraft, or even artillery launch, and its deployment is very convenient. The sensor network structure consists of base station nodes, sensor nodes, management nodes, and other parts, as shown in Figure 2. Since RF can reduce the single-hop communication distance, in most applications, the transceiver module of the communication unit in the sensor node will take precedence over the RF module. Another reason why RF is the primary communication method for sensor networks is that RF uses the Industry, Science, and Medical (ISM) frequency band. ISM bands in most countries are publicly free [13, 14]. The radio waves are divided into segments according to different frequencies, such as low frequency, medium frequency, high frequency, and ultra-high frequency. Table 1 shows some of the available frequency bands for ISM applications.

Sensor nodes are usually scattered in a sensing area, and each sensor node has the ability to collect and route data to the sink node. Each node is a miniature embedded system, mainly including functional units: power supply unit, communication unit, sensing unit, and processing unit. Its structure is shown in Figure 3. As the name suggests, the wireless communication unit communicates with the sensor nodes; it is composed of transceivers, MAC, and other modules with low energy consumption and short distance [15, 16]. All nodes communicate with each other and work together in a system. The sensing unit is to acquire the information of the corresponding area and convert it into digital information, which is composed of sensors and digital conversion function equipment. The main job of the processing unit is to process the collected information and manage the internal operation of the network such as network protocols. Its processing unit consists of operating system, memory, and so on.

The base station node, also known as the sink node, mainly receives data and sends data collection commands to the sensor nodes; it monitors the entire network. The task management node means that the user publishes network monitoring tasks and collects monitoring data through the management node, so as to achieve the purpose of managing the entire network [17].

The wireless network topology is generally divided into star network, mesh network, and hybrid network, as shown in Figure 4.

The star network topology is relatively simple, and the terminal node and the sink node can communicate directly; there is no connection between end nodes. The mesh topology is to select a path for data transmission through a certain algorithm, and all terminal nodes can be connected. Hybrid network topology is a network structure that combines the advantages of simple and efficient star network with the advantages of strong repair ability of mesh topology. The typical one is the hierarchical structure [18], as shown in Figure 5.

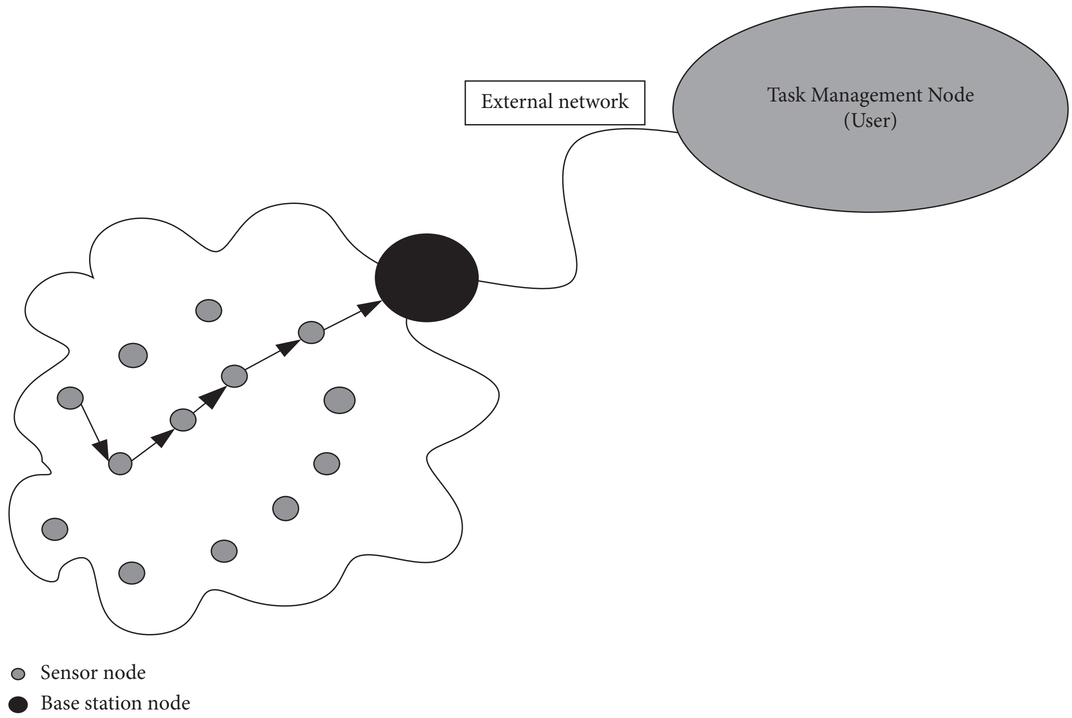

Figure 2: Wireless sensor architecture diagram.

Table 1: Available frequency bands for ISM.

Frequency band	Center frequency
13553–13567 kHz	13560 kHz
5725–5875 kHz	5800 MHz
433.05–434.79 kHz	433.92 MHz
61–61.5 GHz	61.25 GHz

The task of routing protocols is to establish routes between sensor nodes and base station nodes to transmit data reliably [19]. In order to be able to better analyze the transmission data, it is necessary to measure these indicators. Routing protocols in traditional networks cannot effectively reduce energy consumption, so there are routing protocols specially adapted for wireless sensor networks. The wireless sensor network routing protocol comparison is shown in Table 2.

3.3. Wireless Sensor Model of Artificial Intelligence Neural Network. For all sensors, the wireless sensor model based on artificial intelligence neural network refers to the following: Based on the information service system, it provides a standard interface and protocol through WEB for resource registration, discovery, and access of distributed sensors. Then, by specifying the processing algorithm in the sensor model, the processing and analysis of the sensor observation data can be realized on demand. It derives new observation data or products from existing observations through artificial intelligence neural networks. In a narrow sense, it is the sensor information model, including sensor and platform hardware information, sensor observation information, and sensor observation data processing information model [20].

For all sensors, they are modeled as one category, the sensor processing model. Each sensor processing model describes the basic metadata information model of the sensor and has an input and output model. The values of the output model are represented as phenomena or digitally quantified values corresponding to the input model values by defining a nonphysical (purely processing) model [21]. The processing-oriented modeling of artificial intelligence neural network is based on the description of sensor metadata, and the focus is on the application and processing of sensor observation data. According to the overall processing analysis of sensor observations, the processing level is divided. Its advantages lie in the fact that it focuses on the processing and analysis of sensor observation data and realizes the processing model of measurement and post-measurement data transformation by defining a unified interface. For the complex processing model, it can be described by the processing chain model, which can describe the sensor and the entire sensor system more clearly. The user can customize the processing level and customize the data type and processing method according to the divided processing level, which makes the processing execution more effective. The normal sensor modeling process is for the user to select the sensor platform. Then, according to the physical, geometric, measured characteristic values of the sensor and its platform and the information characteristics of the observation data, the relevant sensor modeling language is used to describe the sensor platform and data information selected by the user in a model way. The wireless sensor modeling of artificial intelligence neural network encapsulates one or more processing models into artificial intelligence neural network standard documents and

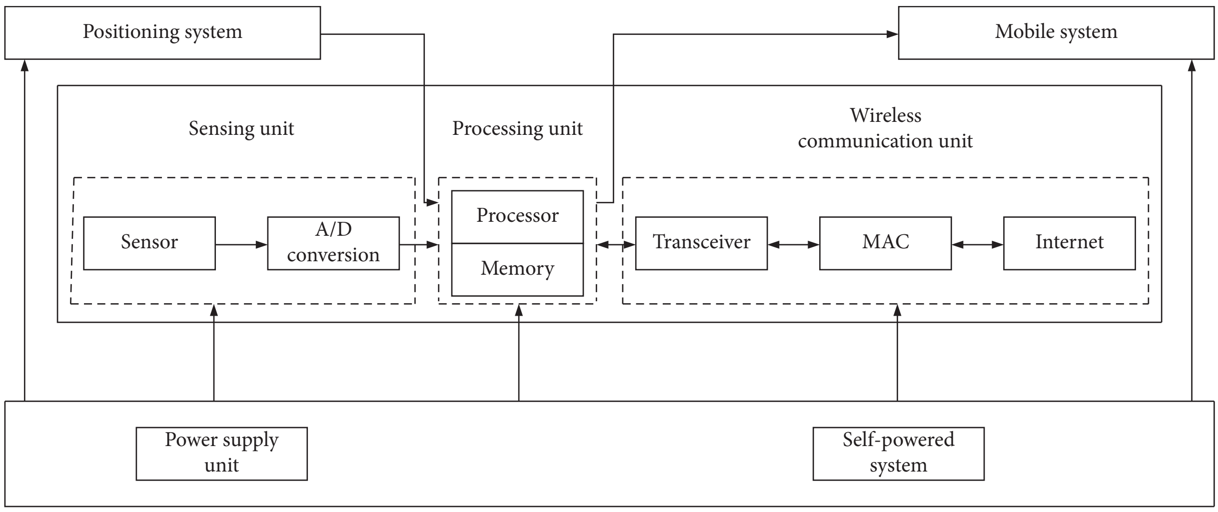

Figure 3: Wireless sensor node structure diagram.

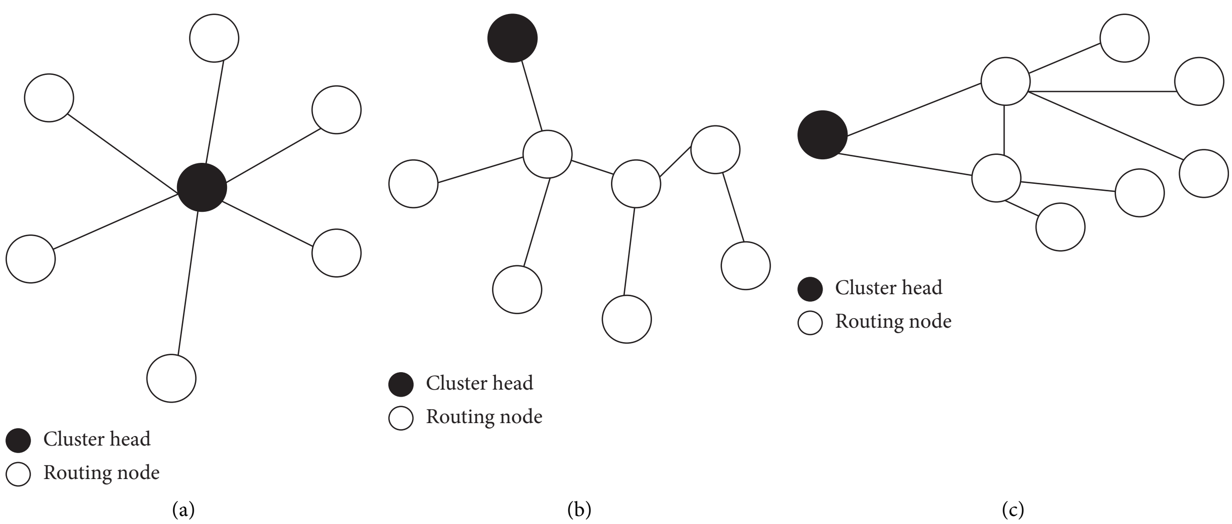

Figure 4: Common topology of wireless network. (a) Star topology. (b) Mesh topology. (c) Hybrid network topology.

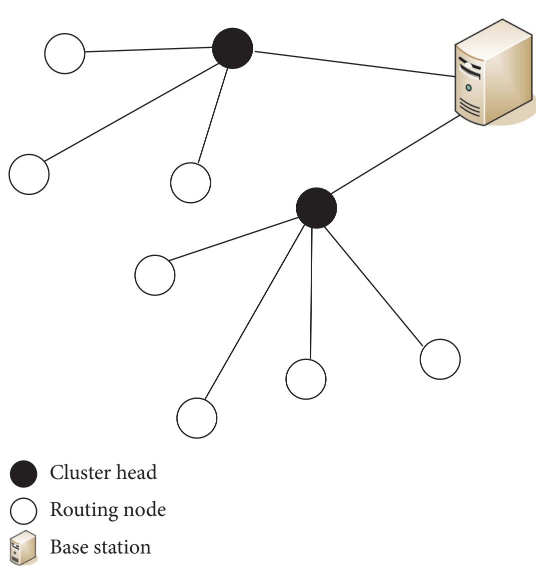

Figure 5: Hierarchical hybrid network topology.

Table 2: Comparison of wireless sensor network routing protocols.

Protocol name	Routing structure	Location based	Data-centric	Data fusion	Multipath	Energy saving	Network lifetime	Extensibility	Robustness	QoS support
DD	Flat	No	Yes	Yes	Yes	Level 1	Level 1	Secondary	Level 1	No
LEACH	Layered	No	No	Yes	No	Level 1	Level 1	Level 1	Level 1	No
SPIN	Flat	No	Yes	Yes	Yes	Level 1	Level 1	Secondary	Level 3	No
AODV	Flat	No	Yes	Yes	Yes	Level 1	Level 1	Level 1	Level 1	Yes

combines them into an artificial intelligence neural network sensor model instance. For a given sensor and platform, the modeling includes the following: platform system modeling, sensor analysis on the platform, and sensor standard selection. Afterwards, the overall processing and analysis of the observation data of each sensor are carried out, the processing modeling is carried out for the nonphysical and physical atoms, and the processing chain modeling is carried out for the nonphysical and physical composites [22]. Figure 6 is the artificial intelligence neural network wireless sensor information modeling process.

3.4. Data Fusion Algorithm. Data fusion technology refers to the information processing technology. In this paper, the neural network is used to realize data fusion. It uses the data fusion algorithm to obtain more complete data, less redundancy, and reduced data transmission, so as to improve the efficiency of data transmission and reception, reduce energy consumption, and prolong the life cycle of the sensor network. Although the algorithm has many advantages, its operation process is also very complicated. Common algorithms in data fusion include TINA, PAQ, and SLR.

TINA algorithm is a typical data fusion algorithm to reduce data redundancy in adjacent time periods. This algorithm uses time consistency tolerance to reduce node energy consumption in the data fusion process. The algorithm mainly compares the sensor data collected by sensor nodes with the sensor data collected last time and sends the collected data when the prediction error exceeds a given threshold [23]. When the detected environment changes slowly, the algorithm can reduce the amount of data transmission while ensuring the accuracy of the collected data. However, when the detected environment changes drastically, the algorithm will perform high-intensity operations on the sensor nodes. At this time, the algorithm cannot improve the energy utilization rate well.

PAQ is a low-level AR model time series data prediction algorithm. The method of time series prediction is to form a sequence of data sensed by WSN nodes in time order; it extracts useful information by analyzing sequence change trends [24]. The PAQ algorithm mainly realizes the network burden of WSN nodes. The sensor node stores the collected data in the queue, and when the queue is full, the node transmits the calculated model to the sink node. When the prediction error of the newly collected data is within the set error interval, the model is considered valid; on the contrary, it is considered that the new data may be abnormal data. When multiple consecutive data are considered abnormal data, the model has failed and the model should be reupdated.

The SLR algorithm uses a linear regression model for data fitting, which reduces the amount of data transmission [25]. The SLR algorithm is divided into two parts; one is the piecewise linear homotropic true line fitting. First, through the analysis of the collected sensory data sequence, it is concluded that, in the stable environment, the monitoring data exhibits a piecewise linear periodic change rule, and the piecewise straight line is used to fit the change trend of the monitored object. Second is to adjust the parameters of the regression model based on the confidence interval. It compares the actual sensing data with the set valid physical value interval and compares the absolute value between the predicted value and the sampled value with the confidence interval. Distinguish whether the data is abnormal according to the results to dynamically adjust the parameters of the regression model [26, 27].

This paper proposes a WSN data fusion algorithm (DFRMP) based on regression model prediction. The algorithm is that the WSN node uses its own computing power to analyze the data correlation of the collected data in adjacent time periods and a univariate linear regression model is established by analyzing the perception time series in the sliding window [28, 29]. It uses the Kalman filter method to solve the model parameters and introduces the sliding time window mechanism to segment the model to dynamically optimize the model parameters. Its calculation formula is shown in formulas (1) to (20).

$$y_t = Z_t\beta_t + d_t + \mu_t, \quad t = 1, 2 \ldots, T, \tag{1}$$

$$E(\mu_t) = 0, \tag{2}$$

$$\operatorname{var}(\mu_t) = H_t, \tag{3}$$

where

T indicates the sample length;

Z_t represents an $m \times n$-dimensional measurement matrix;

y_t is $m \times 1$-dimensional observable vector representing m variables;

β_t represents an $n \times 1$-dimensional state vector.

The state equation model represents the state of a dynamic system after a certain moment of transition under the action of input variables, which is

$$\beta_t = T_t\beta_{t-1} + c_t + R_t\varepsilon_t, \quad t = 1, 2, \ldots, T, \tag{4}$$

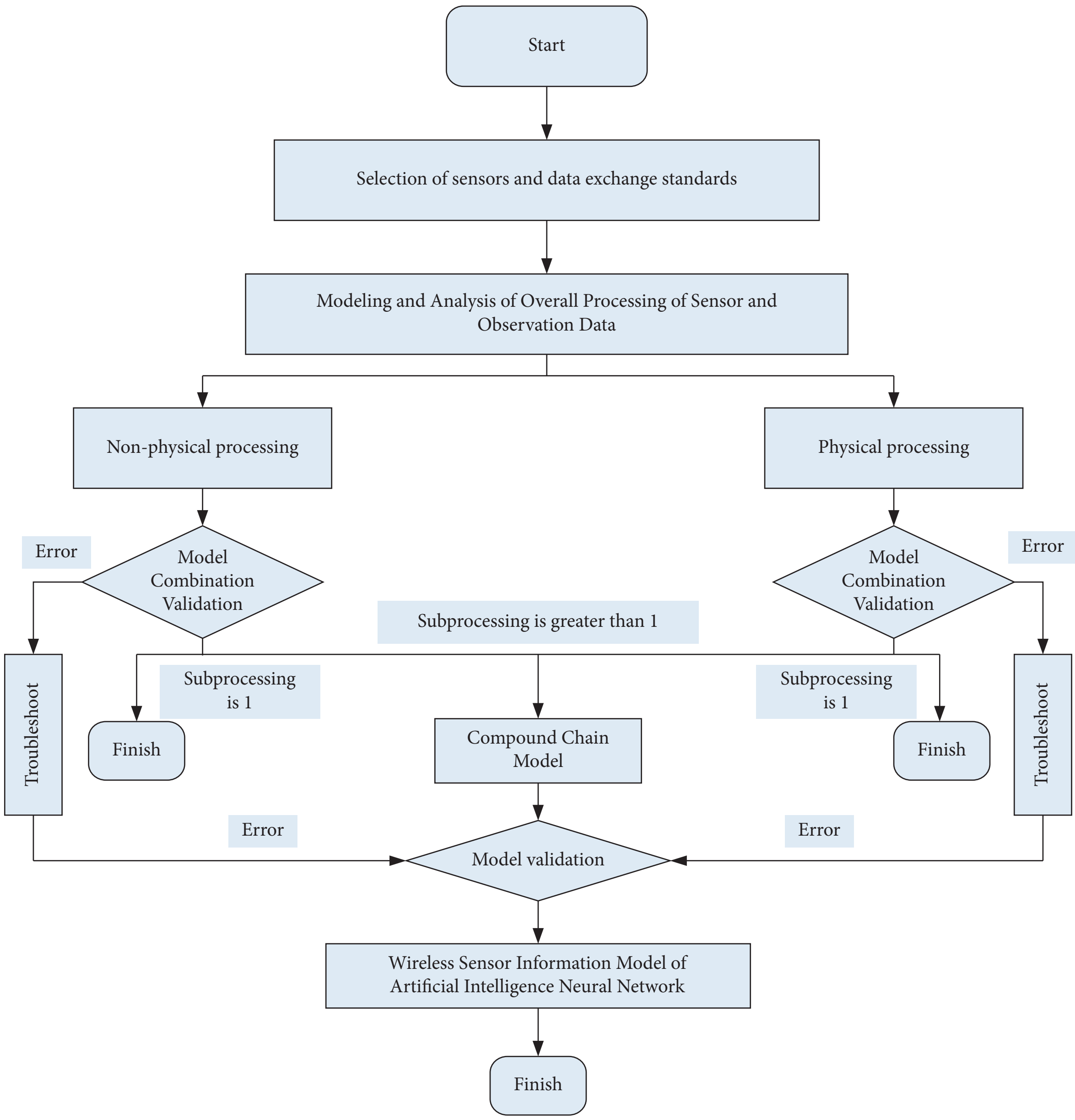

Figure 6: The wireless sensor information modeling process of artificial intelligence neural network.

where

T_t represents an $n \times n$ state matrix;

c_t is a vector representing $n \times 1$;

R_t is a matrix representing $n \times g$;

ε_t represents an error vector of $g \times 1$.

The mean is 0 and the covariance matrix is Q_t; that is,

$$E(\varepsilon_t) = 0, \tag{5}$$

$$\operatorname{var}(\varepsilon_t) = Q_t. \tag{6}$$

The covariance matrix of the measurement and the disturbance term of the equation of state is denoted by Ω:

$$\Omega = \operatorname{var}\begin{pmatrix} \mu_t \\ \varepsilon_t \end{pmatrix}, \tag{7}$$

$$\Omega = \begin{pmatrix} H_t & 0 \\ 0 & Q_t \end{pmatrix}. \tag{8}$$

Then the linear regression model is

$$y_t = x_t'\alpha + \mu_t, \quad t = 1, 2, \ldots, T, \tag{9}$$

where

x_t represents the explanatory variable vector;

y_t represents the dependent variable;

α represents the parameter vector to be estimated.

Invariant parameters are environmental data that cannot continuously monitor changes, so a variable parameter model is needed to reflect data changes; namely,

$$y_t = x_t'\alpha_t + \mu_t, \tag{10}$$

$$\alpha_t = T_t\alpha_{t-1} + \varepsilon_t, \tag{11}$$

$$(\mu_t, \varepsilon_t)' = N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} H_t & 0 \\ 0 & Q_t \end{pmatrix}\right), \quad t = 1, 2, \ldots, T. \tag{12}$$

In the above formulas, $x_t' = [\,1 \;\; t\,]'$, where $\alpha_t = [\,b_t \;\; k_t\,]$ and b_t and k_t correspond to the intercept and slope of the function, respectively, and the disturbance terms μ_t and ε_t are not related.

The parameters of the state space model are usually solved using Kalman filtering, but

$$a_{t|t-1} = E(a_t|Y_{t-1}), \tag{13}$$

$$P_{t|t-1} = \operatorname{var}(\alpha_t|Y_{t-1}), \tag{14}$$

where

$\alpha_{t|t-1}$ represents the conditional mean covariance matrix of state vector α_t based on information set Y_{t-1};

$P_{t|t-1}$ represents the conditional error covariance matrix of state vector α_t based on information set Y_{t-1}.

$$P_{t-1} = E[(\alpha_{t-1} - a_{t-1})(\alpha_{t-1} - a_{t-1})'], \tag{15}$$

$$\alpha_{t|t-1} = T_t\alpha_{t-1} + c_t. \tag{16}$$

The covariance matrix of the estimated error is

$$P_{t|t-1} = T_t P_{t-1} T_t' + R_t Q_t R_t', \tag{17}$$

$$\alpha_t = \alpha_{t|t-1} + P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1}, \tag{18}$$

$$P_t = P_{t|t-1} Z_t' F_t^{-1} Z_t P_{t|t-1}, \tag{19}$$

$$F_t = Z_t P_{t|t-1} Z_t' + H, \tag{20}$$

where

a_0 represents the mean of the known initial state vector α_t;

P_0 represents the initial value of the error covariance matrix;

P_{t-1} represents $m \times m$ matrix;

$\alpha_{t|t-1}$ represents the mean of the conditional distribution of α_t.

When all t observations have been processed, the Kalman filter generates the optimal estimate of the current model parameters α according to the sample sequence Y_t, and the model is successfully constructed.

Sliding windows can quickly represent a time series linearly and can learn online. Because of this, in order to better detect the accuracy of the prediction model, this paper applies this technique to the temporal correlation data fusion algorithm. Figure 7 shows the processing method of this technology.

4. Performance Analysis and Simulation

4.1. Experimental Parameters. In this paper, the performance of the WSN data fusion algorithm (DFRMP) based on regression model prediction is verified by simulation experiments. This paper mainly reflects the characteristics of the algorithm through the data processing of the WSN node and realizes the effect of the simulation experiment. The experimental data comes from the dataset. 56 wireless nodes are set up in the laboratory, and the environmental parameters in the laboratory are monitored through the data collection system. Because of the variation of the temperature difference between day and night, it will be beneficial to detect the adaptability of the prediction model to the dynamic change. Therefore, this paper selects 5000 pieces of temperature data collected by node 16 over several days as the experimental data, and the data time interval is 2 min after preprocessing.

Table 3 shows the parameters set in the simulation experiment.

4.2. Node Data Regression Model Effect. This paper will select 300 pieces of data of node 16 for data fitting, in order to further understand the effect of the DFRMP algorithm proposed in this paper. When the difference between the sampled value and the predicted value is not within the set error threshold, the model parameters will be adjusted to improve the accuracy of the model. Figure 8 shows the local effect diagram of 300 pieces of data fitting models. Figure 9 is a global effect diagram of 5000 pieces of data fitting models.

It is not difficult to see from Figure 8 that the two linear regression models of the actual sampled value and the predicted value can fit the time series of perceptual data well. Both linear regression models fit well the trend of temperature changes within 200 minutes, allowing users to obtain data information more directly. It can be seen from Figure 9 that the predicted value model fits the actual sampled value model well, and the fitting degree is very high.

4.3. Performance Comparison with Other Methods. This paper introduces three data fusion algorithms of TINA, PAQ, and SLR, but these three algorithms all have shortcomings. The idea of the TINA algorithm is to compare two adjacent sensing data samples. When the detected environment changes, the wireless sensor network nodes will process the sensing data at high speed. The PAQ algorithm based on time series forecasting does not contain more trend items in its model. It cannot filter smooth anomalies well and cannot avoid the influence of mutation sequences and abnormal data. However, the algorithm is very accurate and can perform high-precision operations. The linear regression

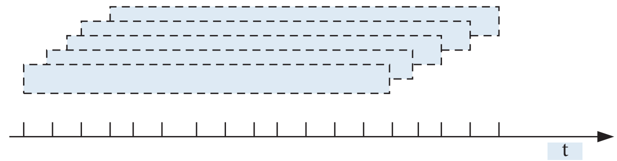

FIGURE 7: Sliding window processing method.

TABLE 3: Simulation parameter settings.

Simulation parameters	Value
Time series source	Node 16
Sampling period T	2 min
Absolute error threshold ε_v	0.2
Update threshold ε_T	5 times
Sliding window maximum L_{max}	25
Sliding window minimum L_{min}	6

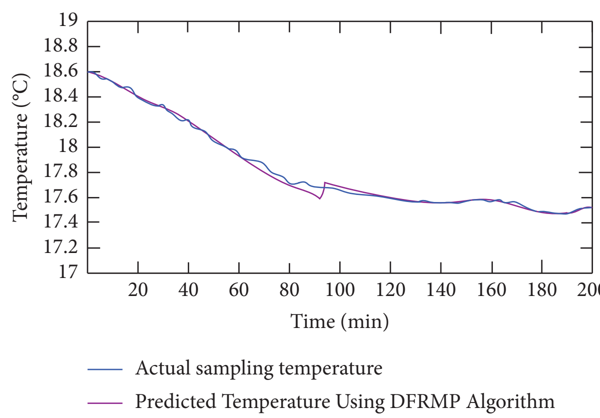

FIGURE 8: Model fitting local effect diagram.

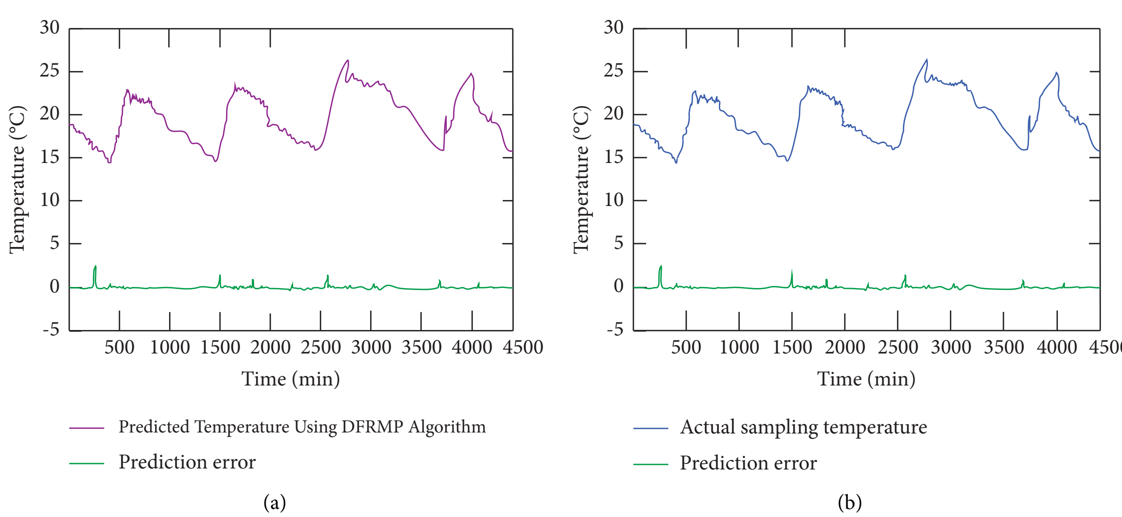

FIGURE 9: Model fitting global effect diagram. (a) The global effect diagram of the predicted value linear regression model fitting. (b) The global effect of fitting the sampled value linear regression model.

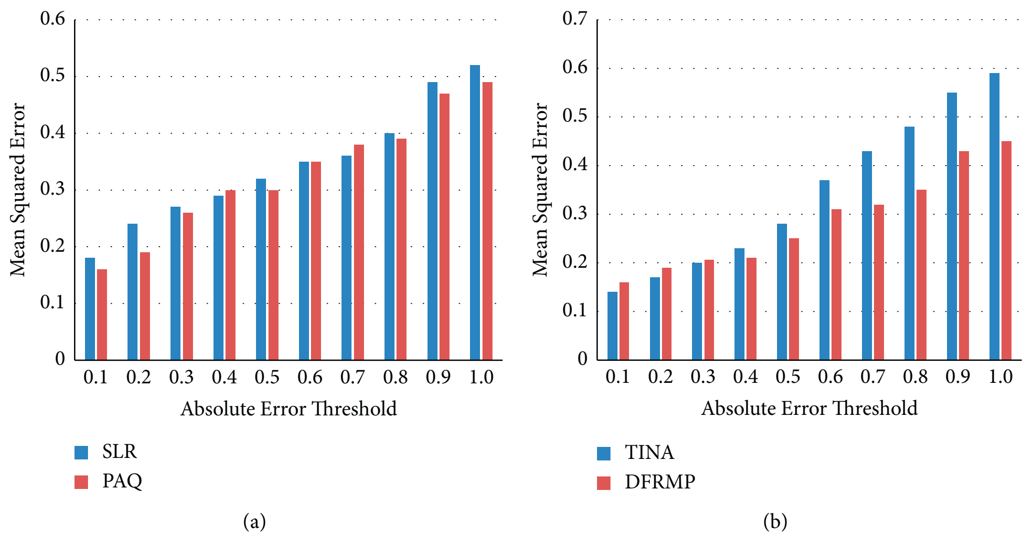

Figure 10: Comparison of mean square errors of different ε_v. (a) Comparison of mean square error between SLR algorithm and PAQ algorithm ε_v. (b) Comparison plot of mean square error of TINA algorithm and DFRMP algorithm ε_v.

SLR algorithm uses the frequent fluctuations of short-term data as the time series of model adjustment, resulting in a substantial increase in the number of model updates and the influence of abnormal points on it, which increases the consumption of network energy. The DFRMP proposed in this paper can solve these problems well. The paper analyzes and compares the four algorithms in terms of model accuracy and data transmission rate.

Model accuracy comparisons use mean square error E_{mse} and mean absolute error E_{mae}, as shown in the two following formulas:

$$E_{\text{mse}} = \sqrt{\frac{\sum_{t=1}^{n} \left(y^m(t) - y(t)\right)^2}{n}}, \quad (21)$$

$$E_{\text{mae}} = \frac{1}{n} \sum_{t=1}^{n} \left| y^m(t) - y(t) \right|. \quad (22)$$

We have the following:

$y^m(t)$ indicates the predicted value of the sensor node;

$y(t)$ indicates the actual collection value of the node.

4.3.1. Comparison of Model Accuracy. It is not difficult to find from Figures 10 and 11 that, through the comparison of the mean square error and the mean absolute error of different ε_v, the error trends of the four algorithms are similar. When the absolute error threshold is 1, the mean square errors of the four algorithms of SLR, PAQ, TINA, and DFRMP are 0.52, 0.49, 0.59, and 0.45, respectively. It is found that the mean square error and mean absolute error of different ε_v of the DFRMP algorithm are smaller than those of the other three algorithms, indicating that this method has the best model accuracy.

4.3.2. Comparison of Data Transfer Rates. It can be seen from Figure 12 that the data transmission rates of the four algorithms, SLR, PAQ, TINA, and DFRMP, gradually decrease as the error threshold ε_v increases gradually. When the absolute error threshold is 0.6, the data transfer rates of these four algorithms are 0.04, 0.04, 0.049, and 0.032, respectively.

5. Discussion

Through the fitting of the local effect map and the global effect map of the linear regression model of the sampled value and the predicted value, it is concluded that the predicted value model can accurately describe the dynamic changes of the experimental data and the fitting accuracy is high.

Through the comparison of the model accuracy and data transmission rates of the four algorithms of SLR, PAQ, TINA, and DFRMP, the results are obtained:

(1) Comparison of model accuracy. The error comparison trend of the four algorithms is basically the same, and the error evaluation parameters gradually increase with the increase of the absolute error threshold. If the error threshold is set larger, the accuracy of the model will be reduced. The data results show that when the threshold is small, the error of the DFRMP algorithm is higher than that of the TINA algorithm through the comparison of the mean square error and the mean absolute error of the algorithm. This is because the TINA algorithm compares the adjacent sensing data and transmits it to the sink node. However, with the increase of the threshold, the accuracy of the TINA algorithm begins to decrease, and the mean square error and mean absolute error of the DFRMP algorithm are generally smaller than those of the TINA, PAQ, and SLR algorithms.

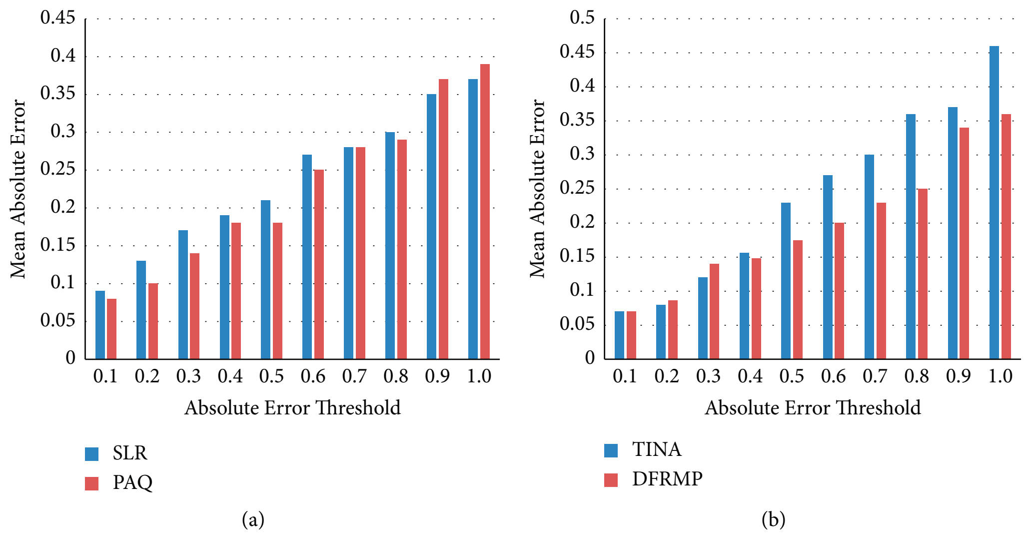

Figure 11: Comparison of the mean absolute errors of different ε_v. (a) Comparison of mean absolute error between SLR algorithm and PAQ algorithm ε_v. (b) Comparison plot of mean absolute error of TINA algorithm and DFRMP algorithm ε_v.

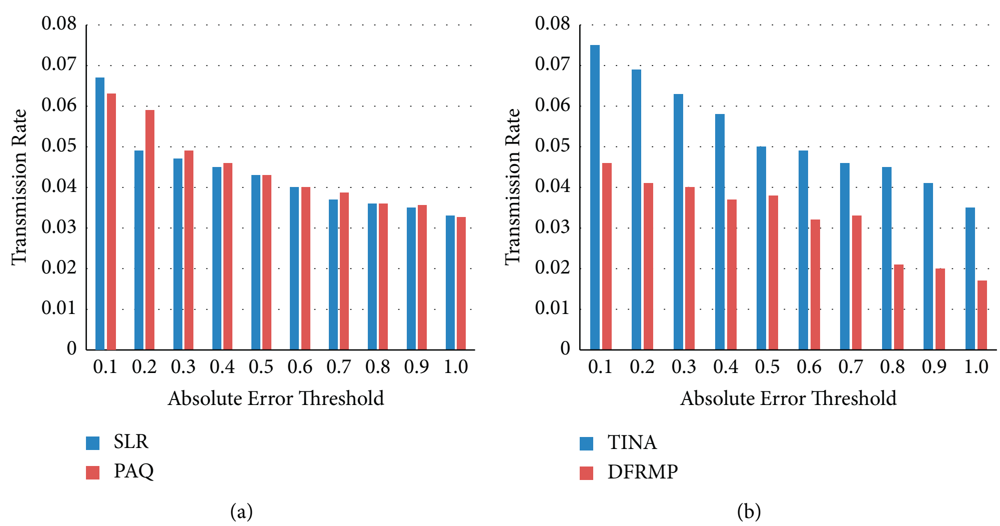

Figure 12: Comparison of data transfer rates for different ε_v. (a) Comparison of data transmission rates between SLR algorithm and PAQ algorithm ε_v. (b) Comparison of data transfer rates between TINA algorithm and DFRMP algorithm ε_v.

(2) Comparison of data transfer rates. Through the comparative analysis of the four algorithms, the errors of the four algorithms are similar; in this case, the data transmission rate of the DFRMP algorithm is the smallest. Compared with the PAQ and SLR algorithms, when the data transmission rates of the two algorithms are not much different, the two algorithms have better fit. This shows that the DFRMP algorithm has a good compression effect under the condition of high precision.

These four algorithms have their own advantages and disadvantages, so they should be used according to different actual situations.

6. Conclusion

Aiming at the problem of high redundancy of data collected by sensor nodes and the shortcomings of existing data fusion algorithms, this paper uses neural networks and makes full use of the limited computing power of WSN nodes, and, according to the correlation of sensing data in adjacent time periods of sensing nodes, the sliding window is analyzed, and a data fusion algorithm based on regression model prediction is proposed. The final experimental results show that the detected objects will change drastically in the short term but tend to be stable in the long term. Under the guarantee of certain data precision, DFRMP algorithm can reduce the amount of data transmission well. The sensory data transmitted by the algorithm to the sink node are no longer discrete but generalized model parameters. This feature effectively reduces the amount of data transmission, improves data processing efficiency, and reduces network energy consumption. It well optimizes the wireless sensor model of artificial intelligence neural network and has good use value. The wireless sensor modeling algorithm of artificial intelligence neural network is very complex and involves a wide range of areas. Due to our limited time and energy and the limitation of resources, this article has some shortcomings in writing, such as introducing other modeling algorithms for further optimization.

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Disclosure

The two authors Qiang Liu and Bohua Sun are co-corresponding authors of this article.

Conflicts of Interest

The authors state that this article has no conflicts of interest.

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