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A Novel Data Fusion Strategy Based on Extreme Learning Machine Optimized by Bat Algorithm for Mobile Heterogeneous Wireless Sensor Networks

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ABSTRACT In order to effectively reduce the redundant information transmission in the network, a data fusion algorithm based on extreme learning machine optimized by bat algorithm for mobile heterogeneous wireless sensor networks is proposed. In this paper, the data fusion process of mobile heterogeneous wireless sensor networks is mainly studied, and regards the nodes of wireless sensor networks as neurons in the neural network of extreme learning machines. The neural network of the extreme learning machine extracts the sensory data collected by mobile heterogeneous wireless sensor network and combines the collected sensor data with the clustering route to greatly reduce the amount of network data sent to the sink node. Aiming at the problem that the extreme learning machine randomly generates the input layer weight and the hidden layer threshold before training, the output result is unstable, affecting the data fusion efficiency and the long delay, a new method of data fusion for mobile heterogeneous wireless sensor networks based on extreme learning machine optimized by bat algorithm is proposed. Simulation experiments are carried out from two aspects: mobile heterogeneous wireless sensor networks and heterogeneous mobile heterogeneous wireless sensor networks. The simulation results show that compared with the traditional SEP algorithm, BP neural network algorithm and ELM algorithm, the proposed BAT-ELM-based data fusion algorithm can effectively reduce network traffic, save network energy, improve network work efficiency, and significantly prolong network's lifetime.

INDEX TERMS Mobile heterogeneous wireless sensor networks, data fusion, extreme learning machine, bat algorithm, energy efficient, reliability.

I. INTRODUCTION

At present, mobile heterogeneous wireless sensor networks (MHWSNs) have been widely used in various fields for the monitoring of various events, such as forest fire prevention, industrial environmental monitoring, and rehabilitation medical care [1], [2]. The sensor nodes in the deployment environment monitor the data in real time and then transmit the sensing to the base station [3]. The process of data transmission involves the problem of data fusion. Owe to the sensor node belongs to the micro node, and its energy and communication capabilities and computing power are limited. Therefore, the sensor nodes are usually deployed intensively to improve the accuracy of monitoring data. However, the intensive deployment nodes can cause multiple nodes to simultaneously perceive the same anomaly and form a large amount of data. In fact, there is some redundancy in these data. Moreover, some sensor nodes may also sense the erroneous data, which affect the performance of data fusion.

The sensor nodes layout in mobile heterogeneous wireless sensor networks (MHWSNs) has certain randomness and high density characteristics, so the collected data has redundancy, complementarity, real-time and originality. The data fusion algorithm is to make full use of these characteristics of data, eliminate part of data redundancy, improve data complementarity, improve data credibility, and enhance data fault tolerance. The definition of the data fusion technology

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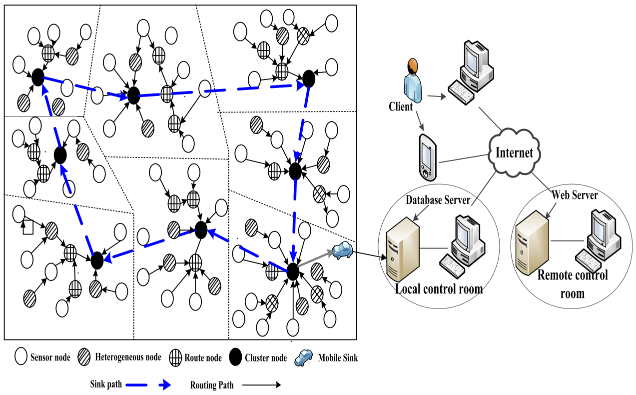


FIGURE 1. Data fusion scenario of mobile heterogeneous wireless sensor network.

that is now more recognized refers to the operations of comprehensive collection, data transmission, redundant filtering, association, analysis and synthesis through effective information sent by the multiple data sources. And the data fusion algorithm combines time and spatial correlation, eliminates redundant and erroneous information, and retains key and correct information components to form a set of multi-angle integrated, accurate and correct data descriptions of events. At the same time, it provides the decision-making body with situational judgment, planning or decision-making actions. The data fusion scenario of the mobile heterogeneous wireless sensor network (MHWSNs) is shown in Figure 1.

The role of data fusion technology is mainly reflected in the following four aspects: (1) Reducing energy consumption. In the process of processing redundant information in data fusion technology, the data of this node is processed firstly, such as removing redundant data, compressing data, hierarchical processing data, valuation operation, etc. The data to be forwarded is minimized under the condition that the content is not lost. (2) Enhance data security. If the user only collects a small amount of sensor node data, it is difficult to ensure the correctness of the information, and target data collection can be performed on multiple nodes to improve the reliability of the information. (3) Reduce the transmission delay of the network and improve the transmission efficiency. In the fusion design, the data is merged in the network first, which can reduce the size of the data packet to be transmitted, optimize the transmission route, and improve the overall efficiency of the entire network. (4) Optimize network resources and improve the overall performance of the network. The data fusion technology can reduce the energy consumption of network, at the same time, it can guarantee the balance of energy consumption of network nodes, avoid the phenomenon of energy holes, maximize the lifetime of a single node, thereby improving the overall performance of the entire network.

In the practical application of mobile heterogeneous wireless sensor networks, the data fusion technology is to process and fuse the data from the different sensor nodes to obtain data that the user meets the requirements. The main advantage of this method is to reduce the waste of communication bandwidth and energy. This is because there is a lot of redundancy in the monitored information. By filtering the redundant information, the transmission of information can be reduced. At the same time, it will increase the efficiency of information collection. Without the use of the information fusion technology, it will be more difficult for the link layer to schedule data from the different sensor nodes, and the collisions will increase, which reduces the efficiency of the communication and affects the timeliness of information collection.

A. PROBLEM STATEMENT AND MOTIVATE

Due to the small size and the limited resources of the sensor nodes, in the network coverage area, the sensor nodes tend to have high density and uneven distribution, which makes the data collected by the sensor nodes highly redundant. If they are sent to the Sink node, the perceived node energy consumption is too fast, which seriously shortens the service lifetime of the wireless sensor network. In order to avoid the above problems, the sensor network needs to use data fusion technology in the process of collecting data, which reduces the transmission amount of information in the network, and reduces the power consumption of the node while saving network communication bandwidth. The ultimate goal of data fusion is to take advantage of multi-sensor joint operation to improve the effectiveness of the system.

The model of the wireless sensor network (WSNs) is similar to the neural network. The sensor nodes in the WSNs used to collect the surrounding environment information are equivalent to the neurons in the neural network. The WSNs need to transmit information through certain connection rules, just as the neural network needs to realize information transmission through synapses. The whole process of wireless sensor network is to process a large amount of information collected, and obtain the characteristics of the data, which is the same as the function based on the neural network data fusion. Therefore, the neural networks can be applied to data fusion of wireless sensor networks. Each cluster of wireless sensor network constructs a neural network model. The cluster head merges the cluster member information, extracts the feature vector of the data in the cluster and transmits it to the aggregation node, which reduces the data transmission amount in the communication process, improves the data transmission efficiency, reduces the communication energy consumption, and prolongs the network's lifetime.

B. CONTRIBUTION

In this work, a new method of data fusion for mobile heterogeneous wireless sensor networks based on extreme learning machine optimized by bat algorithm is proposed. In comparison with the current general selection approaches, the main contributions of our work in this paper can be summarized as follows:

1. Characterize the issues of a data fusion method for the MHWSNs, and formulate the problem of the data fusion algorithm.

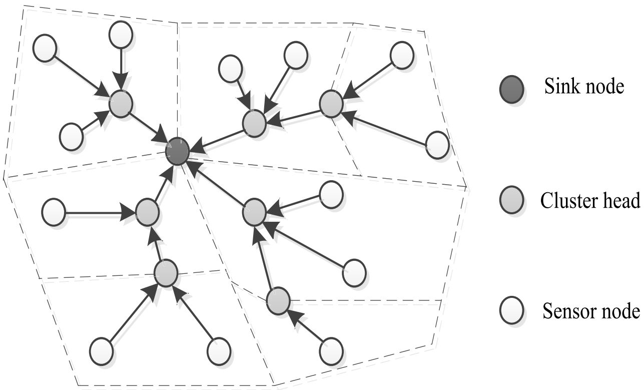


FIGURE 2. Cluster-based data fusion algorithm.

2. Present a new data fusion algorithm based on extreme learning machine optimized by the bat algorithm.
3. Provide extensive simulation results to demonstrate the use and efficiency of the proposed data fusion algorithm.
4. Evaluate the performance of the proposed algorithms by comparing them with the data fusion algorithms of SEP, BP and ELM.

The remainder of this paper is organized as follows: In section II, the related works associated with the data fusion method for MHWSNs are remarked. In section III, the basic principle and mathematical model of extreme learning machine is introduced. In section IV, the bat algorithm and the working process of extreme learning machine optimized by the bat algorithm. The application of BAT-ELM algorithm in data fusion of MHWSNs is given in Section V. In section VI, simulation analysis and discussions are presented. Conclusions are drawn in section VII.

II. RELATED WORK

The data fusion algorithms can be roughly divided into query-based and event-based responses. The query-based data fusion algorithm includes three aspects: clustering, interest diffusion and data transmission, and the responsiveness of the fusion mechanism sometimes has a large delay. Most of the current research work is responsive fusion algorithm. The data fusion path based on response can be divided into cluster hierarchy, tree fusion structure and plane fusion structure.

A. CLUSTER-BASED HIERARCHICAL DATA FUSION ALGORITHM

The cluster-based fusion algorithm first clusters all sensor nodes. The clustering data fusion method is generally used in a hierarchical cluster grid, as shown in Figure 2. The topological approach to data fusion divides the entire sensor network into a series of regions. It first selects one node in each region as the cluster head node, and other nodes will send the data to the cluster head after obtaining the monitoring data from the outside world. The cluster head node synthesizes the data collected from different nodes and sends the data to the gateway node. In each cluster, a cluster head is elected to send and forward the data packets, and the members in the cluster only need to send the data packets to the cluster head node. The cluster head node is additionally responsible for data forwarding and routing, its energy consumption will be higher than the other nodes. Therefore, the choice of cluster head and the periodic maintenance of the topology are the key points of the data fusion algorithm based on the cluster structure.

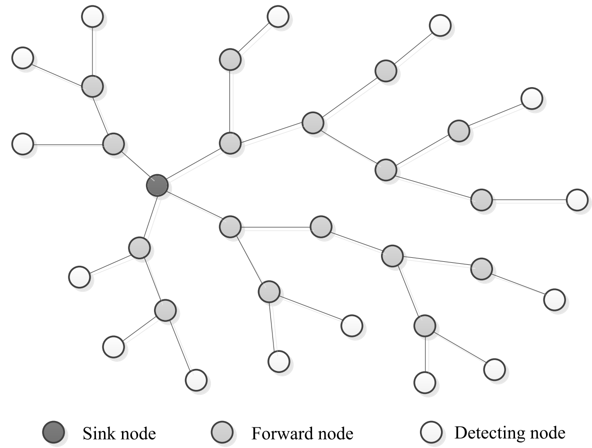


FIGURE 3. Tree-based data fusion algorithm.

The data fusion method is considered an essential process for preserving sensor energy, in [7], the author proposed an energy efficient method for clustering the nodes in wireless sensor network. Jan *et al.* [8] presented a novel technique by using a hybrid algorithm for clustering and cluster member selection in the wireless multi-sensor system, and the proposed scheme efficiently reduced the blind broadcast messages but also decreases the signal overhead as the result of cluster formation. To reduce the intensity of correlation for WSNs, in [9], the author proposed in-node data aggregation technique that eliminates redundancy in the sensed data in an energy-efficient manner, meanwhile adopted a novel data-driven approach to perform in-node data aggregation using an underlying cluster-based hierarchical network. In order to design both local and global data fusion rules based on the likelihood of ratio test statistics using a Neyman–Pearson lemma and Bayesian approach, Zhang *et al.* [10] proposed a novel mobile target detection algorithm (NMTDA) based on information theory.

B. TREE STRUCTURE-BASED DATA FUSION ALGORITHM

The data fusion method of tree-based WSNs is shown in Figure 3. After acquiring the data, the sensor node sends the data to the sink node through the reverse multicast fusion tree and multi-hop mode. In this topology, each intermediate node performs data fusion processing on the collected data. Firstly, it organizes a large number of clusters by itself, elects the cluster heads, and forms multicast trees among cluster heads. According to this way, the sensor nodes send data to cluster heads, after the cluster heads processing, then through reverse multicast tree fusion processing, it is finally sent to the Sink node.

The data fusion algorithm based on tree structure generally includes three stages: generation, maintenance and data transmission of tree structure. First, the algorithm organizes the sensor nodes into the tree structure. When the sensing node has a data packet to send, it only needs to forward it to its parent node. Then, combined with multi-hop mode, a reverse data collection tree from the information source node to the aggregation node is formed. During the data transfer phase, the sink node uses the generated reverse tree to collect data scattered throughout the network.

There are some works that take the benefits of both cluster-based and the tree-based techniques such as [10], [16], [17] and [18]. According to the particularity of the data in Internet of things, In [10], the author proposed a data fusion cluster-tree construction algorithm based on event-driven (DFCTA) and the data fusion architecture of fusion tree composed of fusion nodes. A data fusion enabled ensemble approach is proposed to work with medical data obtained from BSNs in a fog computing environment [11], the author obtained 98% accuracy when the tree depth is equal to 15, number of estimators is 40, and 8 features are considered for the prediction task. Considering the data has some relation and redundancy, Lin *et al.* [12] proposed an algorithm to achieve a high data generation rate for data-gathering trees based on data aggregation technology, improved the data generation rate in wireless networks. In order to improve energy efficiency at the node leveland to increase the network lifetime, In [13], the author proposed a routing model called energy-efficient clustering (ENEFC) based on a hierarchical routing scheme, the experimental results and analyses show that the ENEFC scheme is more effective in terms of energy efficiency than the others. Osamy *et al.* [14] proposed a new simulated annealing based tree construction algorithm (SATC) to aggregate data with a collision-free schedule for node transmissions, the SATC algorithm minimizes the time duration of delivering aggregated data to the sink. In order to query aggregation processing, and effective deduplication, Min *et al.* [15] proposed an approximate but effective aggregate query processing algorithm (DELCA), Improve the energy-efficient and the accuracy of data fusion. Spanning tree is considered as good topology control mechanism for sensor network, In [16], the author proposed a source based tree. Each of the source node generates a tree till sink, adopted an Energy aware tree creation to ascertain that all the intermediate nodes have maximum energy. In [17], the author proposed a new Cluster-Tree routing scheme for gathering data (CTRS-DG), the proposed scheme outperforms existing baseline algorithms in terms of stability period and network lifetime. In [18], the sensor nodes are organized in a tree structure, and the data aggregation are done in intermediate nodes at the junction of tree branches. One of the main characteristics of tree protocols is reduction of energy consumption through optimizing the structure of a data aggregation tree. For this, a swarm intelligent algorithm named river formation dynamics was proposed, greatly improve the lifetime of the network.

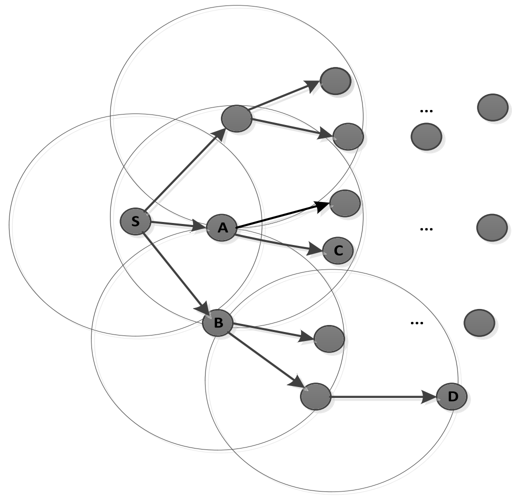


FIGURE 4. Planar structure-based data fusion algorithm.

C. PLANAR STRUCTURE-BASED DATA FUSION ALGORITHM

The classic flooding fusion path in the planar structure is shown in Figure 4. In Figure 4, the S node is the source node, the D node is the destination node, and the node C is the neighbor node of the node A and the node B at the same time. When using the flooding routing mechanism, the node C will receive multiple copies of the packets from the node A and the node B. The redundant data of ''implosion'' can be avoided by caching data packet mechanism of nodes. At the same time, because of its simplicity, effectiveness and high robustness, it is still used as an assistant of some algorithms. Routing with a planar structure is not conducive to setting filter points, and it is difficult to form an effective data filtering mechanism.

Recent research has asserted the superiority of serial structure-free approaches over serial structure-based ones, and over both parallel structure-free and parallel structure-based techniques. To resolve the evaluate the extent of data damage in presence of additive attacks, a resilient data aggregation method based on spatio-temporal correlation for wireless sensor networks is proposed, enhance the fusion efficiency of the network and the robustness against noise interference [19]. The Extreme machine learning technology provides a novel direction for data fusion and makes it more available and intelligent. Wang *et al.* [20] proposed an intelligent data gathering schema with data fusion (DGS-DF), and adopted a neural network to conduct data fusion to improve network performance, and the proposed algorithm could efficiently conserve energy and enhance the lifetime of the network. Owe to the serial structure-free approaches excel in large and medium-scale networks, their underlying path-construction algorithms are not optimal and can be improved by reducing the involved communications and further shortening the visiting path. To respond to this need, Merzoug *et al.* [21] proposed Geometric Serial Search (GSS), a new serial structure-free algorithm specifically designed to efficiently gather information from large wireless resource-constrained networks. The convergence efficiency and work efficiency of the network are improved.

However, these above algorithms do not take into account the authenticity of the data. In the actual environment, the sensing node may generate erroneous sensing data. For example, problems such as external noise or hardware failure may cause the sensor node to sense incorrect data. On the basis of summarizing the previous studies, in this paper, we analyze the network energy consumption and network operation under different data fusion algorithms, and propose a novel data fusion method for mobile heterogeneous wireless sensor network based on extreme learning machine optimized by bat algorithm. The data fusion algorithm first divides the network into multiple sub-areas, and each sub-area has different monitoring weights. The proposed algorithm uses the improved extreme learning machine to learn and optimize the weights and thresholds of the neural network, extracts the original data features collected by the nodes, and performs fusion processing. Then the cluster head sends the fused data to the Sink. In the data fusion process of WSNs, intra-network data fusion eliminates the transmission of redundant data and improves the accuracy of data fusion.

III. EXTREME LEARNING MACHINE

Different from the traditional neural network theory mentioned above, it is necessary to adjust all the parameters in the neural network. In 2006, Professor GuangBin Huang of Nanyang Technological University in Singapore proposed a new extreme learning machine (ELM) algorithm [22]. Extreme learning machine is a special type of single hidden layer feedforward neural network. Its biggest feature is that there is only one hidden node layer. Later, this structure is extended to the general single hidden layer feedforward neural network. Because the extreme learning machine randomly selects the number of hidden layer nodes of single hidden layer neural network, and calculates the output weights and thresholds of the neural network only through one step operation, the convergence speed is very fast, the training speed of the extreme learning machine method is very fast, and the generalization ability and learning speed of the extreme learning machine network are also improved. Therefore, compared with other BP neural networks, RBF neural networks and support vector machine SVM intelligent algorithms, the learning speed is increased by several thousand times [23]. This achievement has greatly stimulated the extensive use of extreme learning machine algorithms in the fields of system identification, face recognition, medical diagnosis, and image classification [24].

The ELM algorithm can obtain the good prediction results based on fewer training samples and are suitable for short-term load forecasting. The ELM algorithm randomly generates input layer weights and hidden layer thresholds before training. Assuming that the sample size of (x_i, t_i) $(i = 1, 2, \ldots, N)$ is a sample of the training set of N, the model is

$$\sum_{j=1}^{M} \beta_j g\left(\omega_j \times x_i + b_j\right) = o_i, \quad i = 1, 2, \cdots, N \tag{1}$$

The variable x_i is the input matrix, the variable t_i is the target output matrix, the variable M is the number of hidden layer nodes, the function $g(x)$ is the activation function; the parameter ω_j is the input layer weight. The variable b_j is the hidden layer threshold; β_j is the connection weight between the hidden layer and the output layer. The variable O_j is the output of the network [25].

If the ELM method satisfies the zero error approximation for all the samples (x_i, t_i), then the parameter β_j, ω_j, and b_j are considered to exist, so we can be obtained:

$$\sum_{j=1}^{M} \beta_j g\left(\omega_j \times x_i + b_j\right) = t_i, \quad i = 1, 2, \cdots, N \tag{2}$$

The formula (2) can also be expressed as:

$$H\beta = T \tag{3}$$

Wherein, $\beta = [\beta_1, \beta_2, \cdots, \beta_M]^T$, $T = [t_1, t_2, \cdots, t_N]^T$, the variable H is the hidden layer output matrix. In actual training, the number of neurons in the hidden layer is usually smaller than the number N of training samples, and ω_j and b_j are randomly formed during the training process, and the output weight can be obtained by finding the least squares solution of $H \times \beta = T$:

$$\beta^* = H^+ T \tag{4}$$

The parameter H^+ in the formula is the Moore-Penrose (MP) generalized inverse matrix of the matrix H.

Compared with traditional neural networks, ELM algorithm has the following advantages: 1) Short learning time. 2) The parameter setting is small and the algorithm is simple to implement. 3) The generalization ability is better. 4) The hidden layer mapping function of the extreme learning machine is more than the traditional BP network gradient method. The hidden layer mapping function can be changed without any change to the algorithm, just change the hidden layer mapping function. The traditional neural networks are mostly trained by the step-down method, while the ELM method randomly generates input layer weights and hidden layer thresholds. In the training process, there is no need for iterative adjustment, and the training speed is fast. The ELM method has the advantages of strong adaptive ability, good generalization performance and high prediction accuracy [26].

Aiming at the problem that the extreme learning machine randomly generates the input layer weight and the hidden layer threshold before training, which leads to unstable output, affecting data fusion efficiency and long delay, in this paper we propose a new method for mobile sensor network data fusion based on extreme learning machine optimized by bat algorithm.

IV. EXTREME LEARNING MACHINE OPTIMIZED BY BAT ALGORITHM

In this part, we first detail the basic principles, mathematical models and the flow chart of the bat algorithm. After that, it is applied to the weights and thresholds of the optimized extreme learning machine to improve the ability of the extreme learning machine algorithm.

A. THE BAT ALGORITHM

The bat algorithm is a meta-heuristic optimization algorithm based on pulse emissivity and loudness based on the bat echolocation behavior of X. S. Yang in 2010 [27]. By simulating the bat's echolocation ability, the solution of the group optimization problem is realized. The bat algorithm is an algorithm based on the bat-feeding behavior in nature. It is a novel intelligent search algorithm with certain advantages and characteristics in some aspects. They use a unique echolocation function to prey in the dark, avoid obstacles, and find their own habitat on the wall. They emit very high frequency sound waves and receive echoes that are reflected by surrounding objects. Different types of sound waves emit different characteristics, and even the same species emit sound waves of different characteristics according to different predation strategies. Their signal bandwidth also varies from one type to another, often using more harmonics to increase bandwidth [28].

As a novel intelligent search algorithm, the bat algorithm has been paid much attention by scholars and has been further improved and applied. The bat algorithm optimizes the target of the optimal function by echolocation behavior. The following bat populations are expressed in mathematical form during the flight update the speed, the loudness, the position and the pulse rate [29].

Suppose that the position of the *i-th* bat at time t is x_i^t and its speed is v_i^t, then the position x_i^{t+1} and the position v_i^{t+1} update formula at time $t+1$ are

$$Q_i = Q_{\min} + (Q_{\max} - Q_{\min})\beta \tag{5}$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*)Q_i \tag{6}$$

The speed update equation of the bat algorithm is

$$v_i^{t+1} = wv_i^t + (x_* - x_i^t)Q_i \tag{7}$$

In the formula (7), $\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times iter/\max it$, where the parameter w_{max} and the parameter w_{min} represent the maximum and minimum values of the flight inertia coefficient of the bat algorithm respectively, refer to the current number of iterations, and refer to the maximum number of iterations of the function. The parameters Q_1, Q_{max}, Q_{min} represent the maximum and minimum values of the acoustic wave frequency and frequency emitted by the *i-th* bat, respectively. The parameter β is the number produced between 0 and 1, and the parameter x_* is the current global optimal solution.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{8}$$

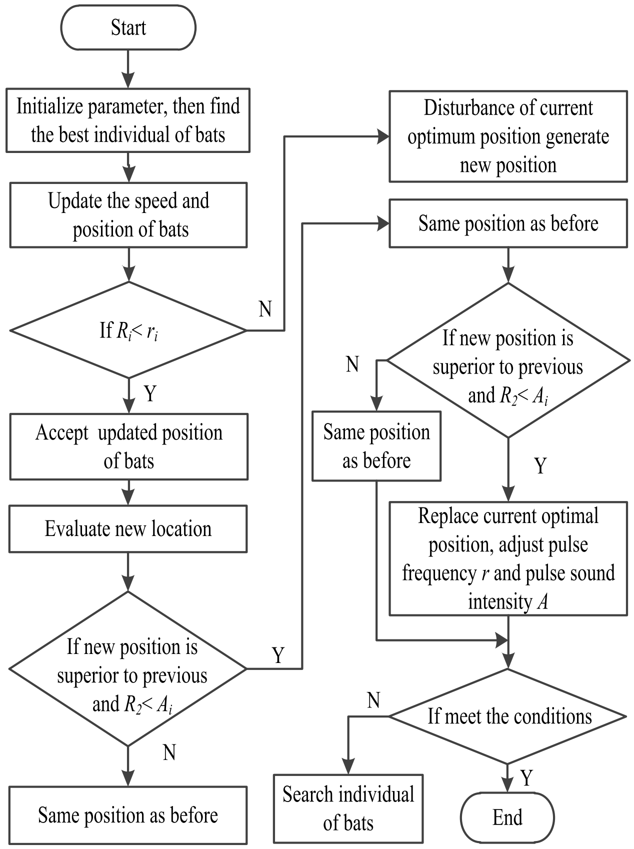


FIGURE 5. The flow chart of the bat algorithm.

Once the optimal solution is produced, the new position of the bat can be generated by the following formula

$$x''(i) = x' + \varepsilon AV^t \tag{9}$$

In the formula, the parameter x' is a random selection of the current optimal solution, the parameter AV^t represents the average value of the bat population loudness, and the parameter ε is a random vector between -1 and 1.

The loudness $A(i)$ and the launch rate $R(i)$ in the bat algorithm are updated as the iteration proceeds. Therefore, in the vicinity of the prey, the bat's loudness will gradually decrease, and the rate of pulse emission will increase. The specific update method is

$$A^{t+1}(i) = \alpha A^t(i) \tag{10}$$

$$R^{t+1}(i) = R_0(i) \times [1 - \exp(-\gamma t)] \tag{11}$$

In the formula, $0< \alpha <1$, $\gamma >0$, it is a constant. At the same time we define $t \to \infty, A^t(i) \to 0$, $R^{t+1}(i) \to R^0$.

Compared with other heuristic intelligent algorithms, the bat algorithm has frequency tuning and when the condition is satisfied, it will automatically switch from global search to local search, which can dynamically control the correlation between global and local search. The algorithm has the characteristics of simple model, fast convergence, parallel processing, simple operation and strong parallel robustness [30]. The bat algorithm work flow chart is shown in Figure 5.

The BAT algorithm has the advantages of simple calculation process, less need to set parameters, strong global search ability and good robustness. In this paper, the BAT algorithm is used to find the input layer weight and hidden layer threshold of the optimal ELM.

B. EXTREME LEARNING MACHINE OPTIMIZED BY BAT ALGORITHM

The extreme learning machine algorithm improves the learning speed of the algorithm by randomly selecting the hidden layer parameters and using the least norm least squares method to calculate the output weights. Although these features of the extreme learning machine overcome some of the shortcomings of the gradient descent algorithm, the number of hidden layer nodes is pre-allocated, the hidden layer parameters are randomly selected, and the parameters remain unchanged during the training process, resulting in the existence of many non-optimized nodes. These nodes contribute little to the cost function minimization process. Therefore, the extreme learning machine algorithm requires more hidden layer nodes than the traditional parameter-adjusted neural network algorithm. Too many hidden layer nodes not only make the network more complicated but also reduce the generalization ability of the algorithm. The bat algorithm is a new type of intelligent optimization algorithm with good global search ability. The bat algorithm is introduced into the optimization of the input learning weight and threshold of the extreme learning machine. Aiming at the above problems, this paper proposes a model based on bat algorithm to optimize the extreme learning machine. Using the global optimization ability of the bat algorithm, the input weight and the hidden layer threshold of the ELM are reasonably selected to obtain the optimal network model. In this paper, the extreme learning machine optimized by bat algorithm is proposed to optimize the weight and threshold for data fusion strategy of mobile heterogeneous wireless sensor networks. This method has the following advantages in large-scale sensor network data fusion. First, the bat algorithm is a global search algorithm that avoids local optimization. Secondly, compared with the traditional neural network which needs to optimize the weights of input layer, hidden layer and output layer, the proposed algorithm needs to optimize the weights of input layer and hidden layer of ELM, and then calculates the output weights by least square method. This method improves the training speed and has better generalization ability.

In this paper, we propose an improved extreme learning machine algorithm to optimize the data fusion problem for mobile heterogeneous wireless sensor networks. The proposed algorithm fully considers the remaining energy of the sensor node, the data transmission distance, the energy balance and the other factors, effectively increasing the network coverage area, expanding the network capacity, saving the network consumption, balancing the energy consumption distribution, and prolonging the network's lifetime. The proposed algorithm not only has the universality and adjustability, but also can improve network performance and efficiency.

V. APPLICATION OF BAT-ELM ALGORITHM IN DATA FUSION OF MHWSNS

A. THE DESIGN IDEA OF THE PROPOSED ALGORITHM

In this paper, according to the spatio-temporal correlation in the data collection process of the sensor nodes, the data fusion method is applied to the cluster layer of mobile heterogeneous wireless sensor network and the member nodes in the cluster for fusion [31]. An improved extreme learning machine data fusion method is introduced based on the routing clustering algorithm, and a data fusion method for mobile heterogeneous wireless sensor networks based on extreme learning machine optimized by bat algorithm (BAT-ELM) is proposed. The proposed algorithm comprehensively analyzes and processes the collected data, deletes the data with poor credibility, invalidity and redundancy, and improves the accuracy and accuracy of the data. In addition, it solves the problems of data fusion efficiency, network life cycle and data transmission reliability, reduces data transmission, reduces network energy consumption, and improves network work efficiency.

The BAT-ELM data fusion algorithm is based on the SEP clustering algorithm of mobile sensor networks. The classical clustered SEP routing protocol first clusters all the nodes in the detection area, and then randomly assigns values between 0 and 1. If it is less than a certain threshold, the sensor node becomes a cluster head, and the cluster head and the cluster member node in which it forms a stable cluster structure [32]. The member nodes in the cluster preprocess the collected data and then transmit it to the cluster head. The cluster head merges the collected data into data, removes redundant and useless information, and forwards it to the sink node. The BAT-ELM data fusion method uses a particle swarm optimization extreme learning machine method to process data between member nodes and cluster heads in a cluster. A schematic diagram of the data fusion model of the BAT-ELM data fusion algorithm is shown in Figure 6.

B. IMPLEMENTATION STEPS OF THE PROPOSED ALGORITHM

The BAT-ELM data fusion method combines an improved extreme learning machine with a SEP clustering routing protocol for mobile heterogeneous wireless sensor networks. In the cluster routing algorithm of mobile sensor networks, each round of loops needs to reconstruct the cluster and change its topology, and constructing clusters will increase the network energy overhead. Based on this consideration, the BAT-ELM data fusion algorithm proposed in this paper, and keeps its topology unchanged after clustering sensor nodes. When the cluster head is rotated, the highest energy of the sensor node is selected as the cluster head, which can reduce the energy consumption in clustering [33].

The data fusion process of mobile heterogeneous wireless sensor network based on BAT-ELM is as follows: First, initialize all components of the mobile heterogeneous wireless sensor network to determine the status of common nodes,

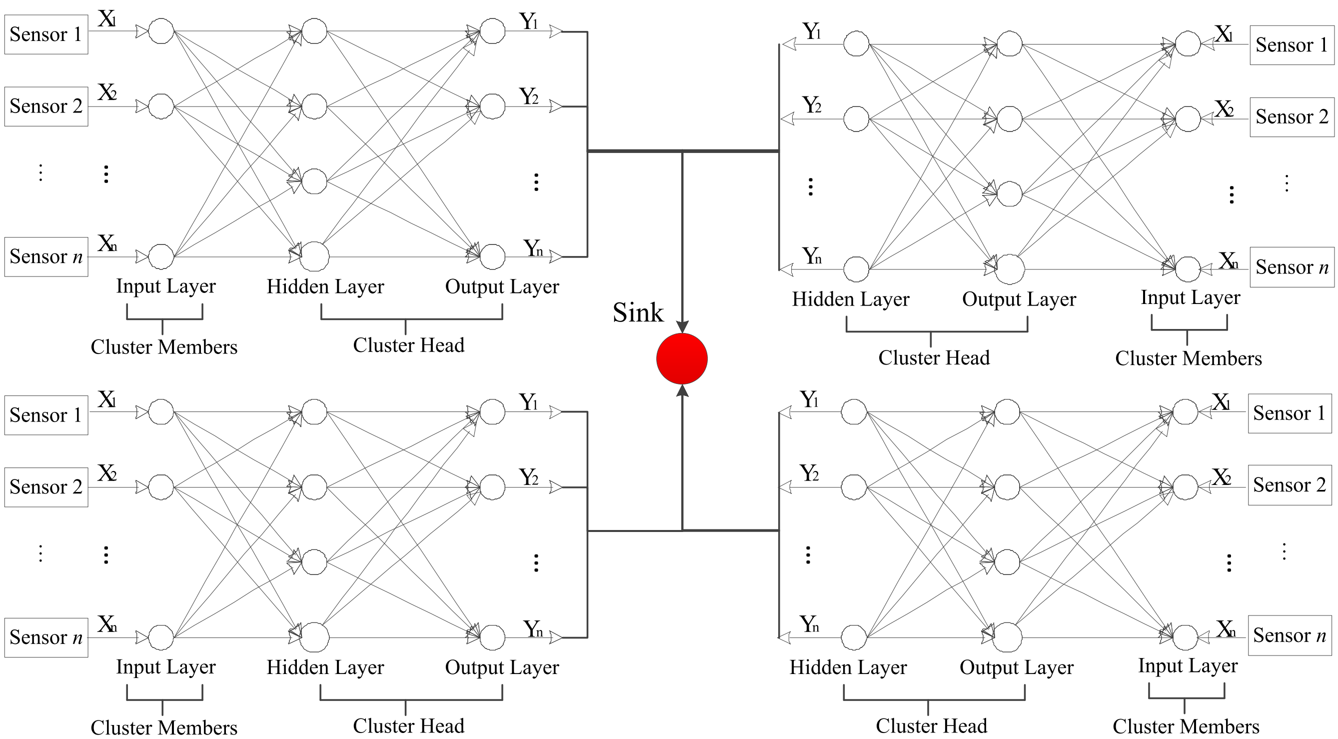


FIGURE 6. Data fusion model of MHWSNs based on improved extreme learning machine.

routing nodes, and cluster head nodes in the network. Then, according to the location of the sensing node, the clustering structure is established for the monitoring area, and the cluster head node is randomly selected in the cluster, and the cluster head node acquires all the information of the cluster member node. After the clustering of the WSNs is stabilized, a routing table of the common node to the sink is constructed, and the cluster head node forwards the information about the cluster member nodes to the sink node. After the network is stable, the WSNs data fusion model is first trained to obtain the number of nodes, weights and threshold parameters of the hidden learning network. Because the common sensor nodes of WSNs have limited energy, they must perform data sensing and the sending/receiving tasks. In order to reduce the energy consumption of the common nodes and prolong the network's lifetime, the training of the data fusion model based on the extreme learning machine is completed in the Sink node of the mobile heterogeneous wireless sensor network. The Sink node constructs the network structure of the extreme learning machine according to the received information, collects samples matching the information of the member nodes in the cluster head sample database for network training, and obtains relevant information of the relevant data fusion model after the training is completed. The Sink node then sends the data fusion model network parameters (the number of hidden layer nodes, the network weight and the threshold) to the corresponding cluster head node. The cluster head fuses the data sent by the member nodes in the cluster according to the trained data fusion model, extracts features, deletes redundant and useless information, temporarily stores the merged data, and sends it to the sink node. The flow chart of the data fusion algorithm for WSNs based on BAT-ELM is shown in Figure 7.

The data fusion steps of mobile heterogeneous wireless sensor networks based on BAT-ELM algorithm are as follows: Firstly, a data fusion model based on extreme learning machine optimized by artificial bee colony method is constructed, and then the fusion model is applied to mobile heterogeneous wireless sensor network clustering structure for data fusion, so as to improve the accuracy of network fusion, reduce the amount of data transmission and prolong the network's lifetime.

The implementation steps of data fusion in mobile heterogeneous wireless sensor networks based on BAT-ELM are shown in Table 1.

VI. PERFORMANCE EVALUATION AND RESULTS ANALYSIS

In order to better reflect the performance of the data fusion algorithm of MHWSNs proposed in this paper, we use MATLAB 2014b simulation software for experimental and performance comparison analysis. It is assumed that the sensor nodes of mobile heterogeneous wireless sensor networks are randomly and evenly distributed in a two-dimensional space of 600 × 600 m2, and the scale of the sensor nodes are 300 in size. The number of simulation round is set to 400. The sensor node has 10 data packets transmitted from the source node to the Sink. Each data packet has a capacity of 4 kb. The initial energy of Sink is set to 50J, and Sink moves linearly at a uniform speed of 5 m/s. The initial energy

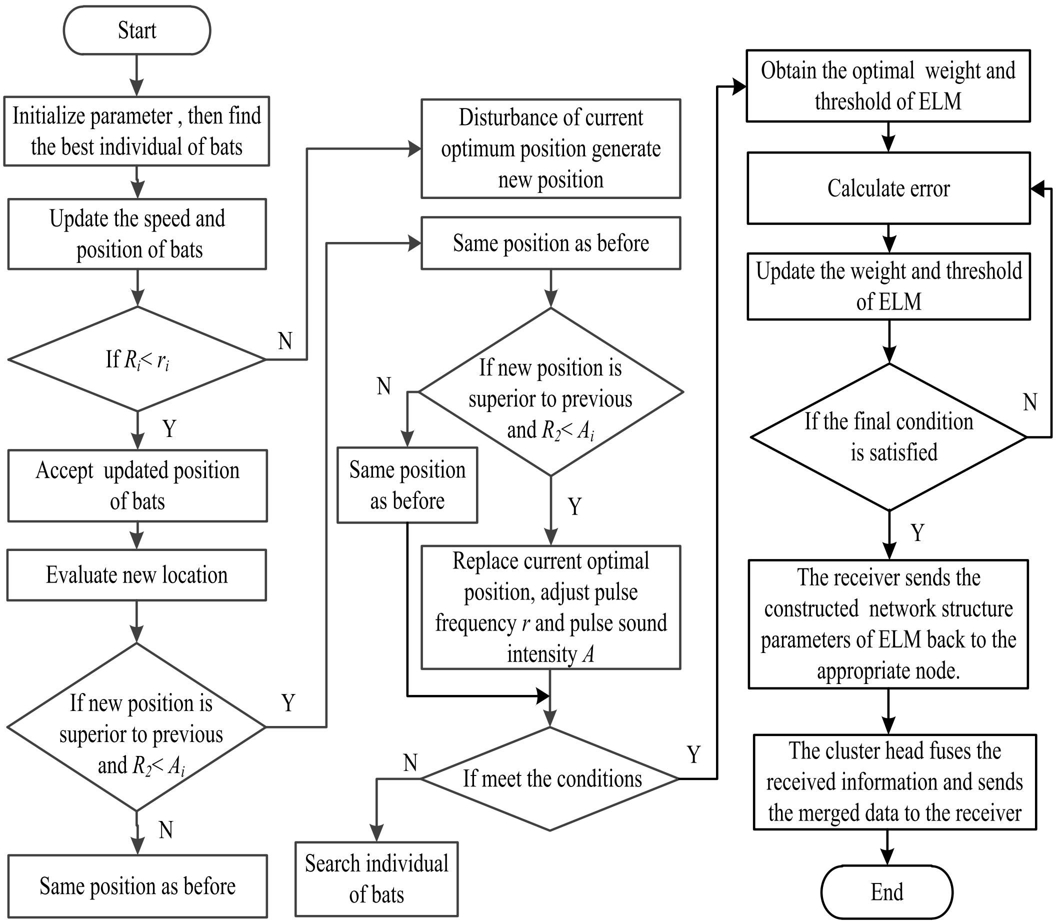


FIGURE 7. The flowchart of data fusion algorithm for WBCs based on BAT-ELM.

of the common node is 1J, and the initial energy of the heterogeneous node is 2J. E_{elec} is the energy consumption of a node sending or receiving unit length of data, E_{fs} is the energy consumption parameter of the amplifier in the free space data transmission model, and E_{elec} is the energy consumption parameter of the amplifier in the multipath attenuation data transmission model. The parameter l is the length of the transmitted data packet, and the parameter d_0 is the average distance between the transmitting end and the receiving end of the wireless sensor node. The limit learning machine parameter is set to: the number of initial hidden layer nodes of the selected network is 10, and the number of hidden layer nodes is increased by 20 cycles until the maximum set value 300 is reached. The implicit layer activation function of the ELM algorithm selects the hardlim function for learning. In order to make the results of the model more convincing, the results given in this paper are the average results of 100 experiments. The simulation environment parameter settings are shown in Table 2.

In order to better illustrate the superiority of the proposed algorithm, in this paper we compare four data fusion algorithms, such as the SEP (Stable Election Protocol) algorithm, BP (back propagation) neural network, extreme learning machine (ELM) algorithm and the proposed algorithm (BAT-ELM).

A. COMPARISON OF THE ENERGY CONSUMPTION

The average energy consumption of the network is one of the important indicators that reflect the performance of the network. With the increase of the number of simulation polls, the algorithm proposed in this paper gradually shows its superiority. The energy consumption of each polling is also reduced. Therefore, the smaller the total energy consumption of the network in the polling cycle, the higher the data fusion efficiency of the network and the longer the life cycle of the network. Taking the energy consumption of the sensor network as a measure, the network energy consumption of the four algorithms is shown in Figure 8.

As can be seen from Figure 8, the energy consumption per polling network of the BAT-ELM data fusion method proposed in this paper is much lower than that of the SEP method, and is lower than the method based on the BP neural network method and the ELM method. At the same time, as the number of polls increases, the network energy consumption per polling is gradually decreasing. At the same time, it can be seen that the network energy consumption

TABLE 1. Implementation steps of data fusion algorithm in MHWSNs.

Algorithm： Data fusion of MHWSNs based on BAT-ELM
Step 1: Initialization of the parameters of MHWSNs, such as the security verification of the sensor nodes, initialization of the network, location of sensing nodes, and the number of ELM hidden layer nodes, etc. meanwhile, the parameters such as population space, inertia weight and acceleration factor in the particle swarm optimization process are set, and the particle search space is defined.
Step 2: The data fusion model is initialized under the input weight and threshold constraints.
Step 3: For each particle in the population, the output weight matrix and output of extreme learning machine optimized by particle swarm optimization are calculated.
Step 3: The data fusion model is mapped to the BAT-ELM network model, and the calculated expected error is used as an optimization function of data fusion.
Step 4: The cluster heads are selected from the common nodes and the cluster head perception regions are established.
Step 5: The cluster head sends the cluster member node information table to the sink node.
Step 6: The Sink node constructs a BAT-ELM data fusion model and trains the sample data to obtain the extreme learning machine network parameters (weights and thresholds).
Step 7: If the termination condition of the network training setting is not reached, continue execution.
Step 8: The Sink node sends the trained BAT-ELM network structure parameters to the corresponding nodes.
Step 9：The cluster head node performs data fusion on the received data by the trained BAT-ELM network structure. The fused data is then sent to the Sink node.
Step 10: The data fusion algorithm of MHWSNs is over.

based on SEP data fusion method has decreased by nearly 93%, the BP neural network decreased by about 75%, and the ELM neural network decreased by about 66.7%. The BAT-ELM-based data fusion method has the lowest energy consumption. It can be seen that the proposed algorithm has the best stability, best performance and minimum network energy consumption.

B. COMPARISON OF THREE-DIMENSIONAL GRAPH OF NETWORK ENERGY CONSUMPTION

The overall energy consumption of the network is an important indicator for evaluating the performance of the network. To visually reflect the overall energy consumption of the network, the three-dimensional map of the overall energy consumption of the four algorithms is shown in Figure 9.

TABLE 2. Simulation environment parameter setting.

Parameter	Value
Network range	600×600 m^2
Number of nodes	300
Communication radius	80 m
V_{Sink}	5 m/s
Initial energy	1 J
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{amp}	0.0013 pJ/bit/m^4
l	4000 bits
d_0	$\sqrt{E_{fs}/E_{mp}}$=87 m

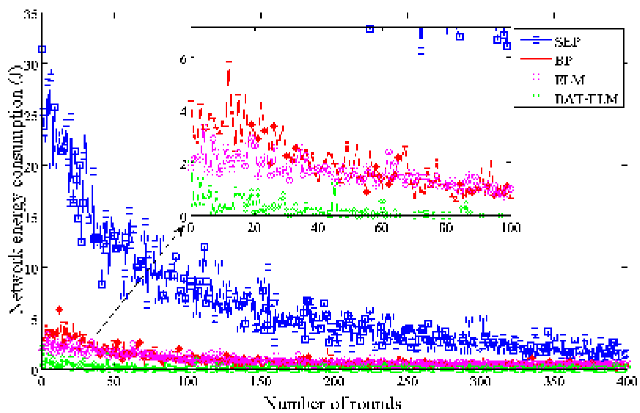
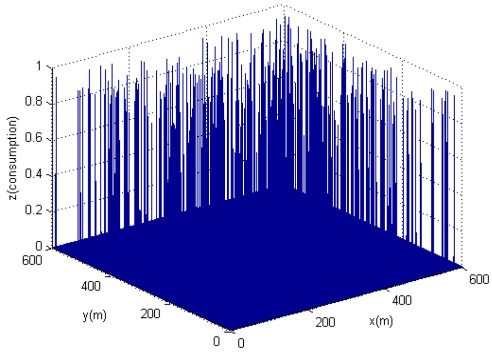


FIGURE 8. Comparison of average network energy consumption.

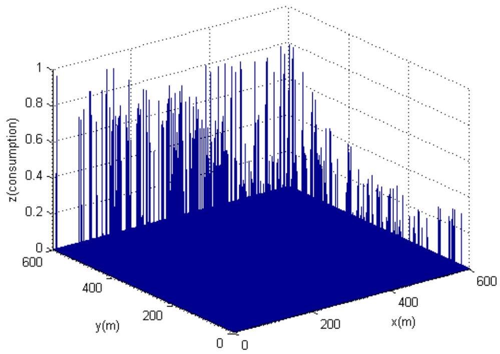
The three-dimensional diagram of Figure 9 shows the energy consumption of the sensor nodes in a mobile heterogeneous wireless sensor network within the simulated area in this paper. Among them, the SEP algorithm shows that the overall energy consumption of the network is about 0.9; the overall energy consumption of the RBF algorithm network is reduced by about 0.3 compared with the SEP algorithm, and the overall energy consumption of the ELM algorithm network is about 0.3. The overall energy consumption of the BAT-ELM algorithm proposed in this paper is only about 0.15, which is 83.3%, 75%, 50% lower than the SEP algorithm, RBF algorithm and ELM algorithm respectively. It can be seen that the sensor network for data fusion proposed in this paper has lower overall energy consumption, and the energy consumption fluctuation of the network sensor node is small.

C. COMPARISON OF THE NUMBER OF SURVIVING NODES

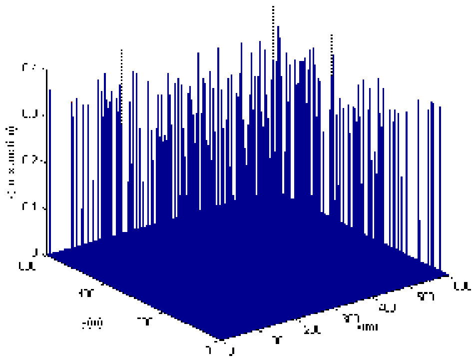
The number of network nodes surviving is one of the important indicators to reflect the performance of wireless sensor networks. The longer the network's lifetime, the better the sensor node can complete the monitoring task for a long time, and the stability of the sensing system. Figure 10 is mainly



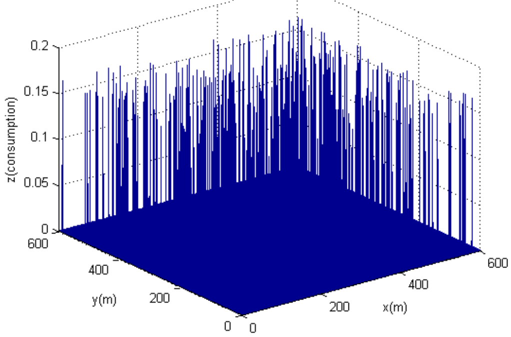
(a) SEP



(b) RBF



(c) ELM



(d) BAT-ELM

FIGURE 9. Comparison of 3D maps of network energy consumption.

a curve of the network surviving node changes of different data fusion algorithms as the number of simulation rounds increases.

As the number of rounds increases, the number of nodes that survive in the network node gradually decreases due to energy consumption. It can be seen from Figure 10 that in the SEP algorithm, the survival rate of the sensor nodes in the network around the 50th round is only 50%, and in the 400th round, the node survival number has been below 100, and the node mortality rate has reached 84%. In contrast, BP neural network, ELM neural network, and BAT-ELM algorithm have higher node survival rates. In the 400th round, the node survival rate of the BP neural network was 55%, and the node survival rate of the ELM neural network was 51.7%. Because the algorithm proposed in this paper improves and optimizes the ELM algorithm, the optimization efficiency of the ELM algorithm is improved, the data fusion efficiency is higher, and the transmission path is better. Therefore, the node survival rate of the BAT-ELM algorithm remains at 87% in the 400th round. Therefore, the node survival rate of the BAT-ELM algorithm remains at 87% in the 400th round. Compared with the other three algorithms, the mobile heterogeneous wireless sensor network based on BAT-ELM algorithm has more nodes, higher survival rate and longer network life cycle.

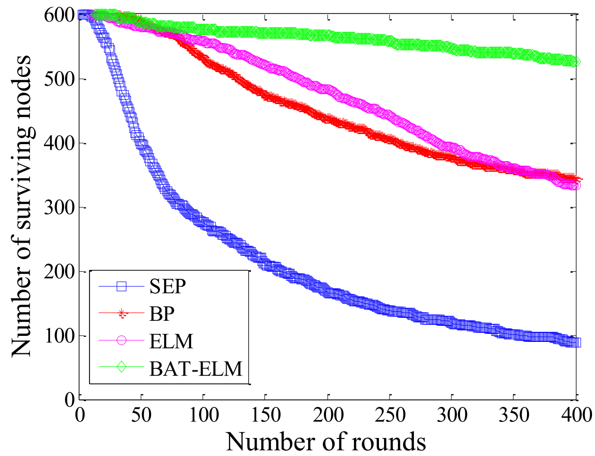


FIGURE 10. Comparison of node surviving numbers.

D. COMPARISON OF THE NUMBER OF NETWORK CLUSTER HEAD NODES

The number of cluster head nodes in the sensor network has an important impact on the energy consumption, stability and transmission efficiency of the sensor network. The network's optimal cluster head node number and its constant evaluation index can reflect the performance of the network to a certain extent. Generally, the number of cluster head nodes is controlled to be 6%-10% of the total number of sensor nodes. In this range, the number of cluster heads is larger, and the wireless sensor network with less change is better. The comparison of the number of network cluster head nodes of the four algorithms is shown in Figure 11.

As shown in Figure 11, the number of cluster head nodes of BAT-ELM algorithm proposed in this paper is about 10-35, and the number of SEP protocol cluster head nodes is between 1-32. The number of nodes fluctuates violently. In the life cycle after 250 rounds, they are all kept below 10. The number of cluster head nodes in BP neural network is

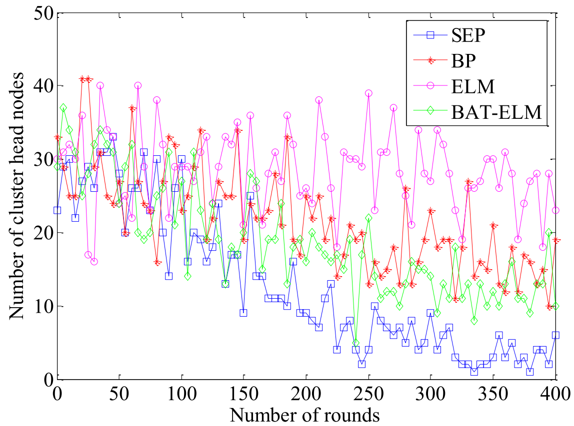


FIGURE 11. Comparison of network cluster head nodes.

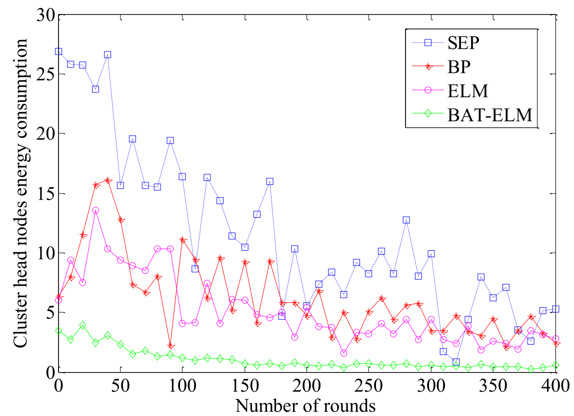


FIGURE 12. The energy consumption comparison of cluster head nodes.

between 10 and 42, and its fluctuation is also large. However, compared with the algorithm of this paper, the number of cluster head nodes is relatively close. The number of cluster head nodes in the ELM algorithm fluctuates between 18 and 40. It can be seen from Fig. 11 that the fluctuation range is relatively large as the number of the rounds increases. The optimal number of cluster head nodes and the stability of cluster head nodes are improved. It can be seen that the proposed algorithm performs best.

E. COMPARISON OF ENERGY CONSUMPTION OF CLUSTER HEAD NODES

In order to better reflect the superiority of the proposed algorithm, we increase the energy consumption of cluster head nodes, as shown in Figure 12.

It can be seen from Figure 12 that with the increase of the number of rounds, the average energy consumption of the cluster head node is gradually reduced, and the SEP algorithm has the largest reduction, which is about 81.5%. The BAT-ELM algorithm proposed in this paper has the smallest reduction. At the same time, the algorithm proposed in this paper has the lowest energy consumption, the ELM algorithm is smaller, the BP neural network is larger, and the energy consumption of the cluster head of the SEP routing protocol is relatively largest. Taking 400 rounds as

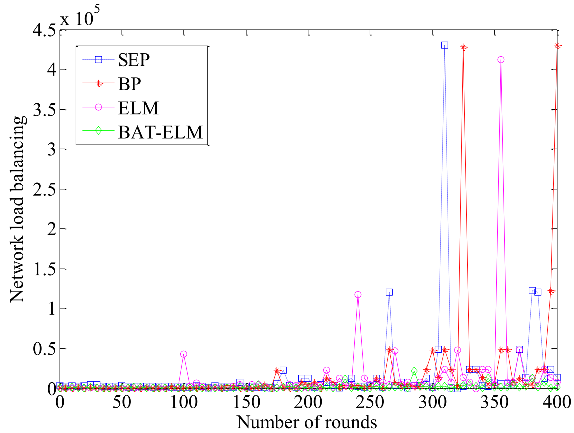


FIGURE 13. Comparison of network load balance.

a reference, the energy consumption of the BAT-ELM algorithm is reduced by 80%, 66.7%, and 66%, respectively, compared to the cluster head nodes of SEP algorithm, BP neural network algorithm, and the ELM algorithm. The energy consumption of the SEP algorithm is much higher than that of the other three algorithms mainly because the protocol does not perform data fusion, and the energy consumption of the cluster head node decreases drastically with the increase of the number of rounds. On the contrary, BP neural network, the ELM algorithm and the BAT-ELM algorithm use data fusion to reduce the transmission of data volume and optimize the transmission efficiency, so the average energy consumption of the sensor nodes is low. It can be seen from the comparison of the four algorithms that the proposed algorithm reduces the average energy consumption of the cluster head nodes due to the advantages of fewer optimization parameters and higher network learning efficiency.

F. COMPARISON OF NETWORK LOAD BALANCE

The load balancing of wireless sensor networks is an important indicator of the life cycle of the response network. The higher the network load balancing index, the longer the network's lifetime. The load balancing factor (F_{LBF}) is defined as the reciprocal of the variance of the variance of all cluster head members in the sensing area of the sensor network. The larger the value, the better the network load balance. As shown in the formula (12), it is a specific calculation formula. Wherein, the variable n_s is the total number of network sensor nodes; the variable x_jj is the number of nodes perceived by the j-th cluster head member; the variable w is the average number of nodes of all cluster heads. The network load balancing comparison of the four algorithms is shown in Figure 13.

$$F_{LBF} = n_s / \sum_{j=1}^{n_s} (x_j - w)^2 \tag{12}$$

In Figure 13, as the number of simulation rounds, the network load balancing factors of the four algorithms increase continuously, and the load balance of the network is also good. The simulation results show that the BP neural network data fusion algorithm has the best load balancing performance, followed by the ELM algorithm and the SEP protocol. Relatively speaking, the BAT-ELM data fusion method proposed in this paper has a general load balancing effect. The main reason is that network load balancing is mainly reflected in the energy consumption between clusters. In this paper, we mainly focus on data fusion within clusters and delete redundant data. Therefore, BAT-ELM algorithm cannot reflect its advantages in this performance.

G. DATA FUSION RATE COMPARISON OF NETWORK

The data fusion rate reflects the fusion performance of the data fusion algorithm. The higher the fusion rate, the higher the fusion efficiency, the lower the network energy consumption, the better the performance of the sensor network, and the packet loss rate. The data fusion rate of wireless sensor networks is one of the important evaluation performances of data fusion algorithms. The data fusion rate is calculated as follows: Assume that the sensor node i forwards the sensed data to the sensor node j. According to the time-space correlation of data collection, the data correlation coefficient $\rho(i, j)$ is calculated as:

$$\rho(i,j) = 1 - H(i\,|j)/H(i) \tag{13}$$

The parameter $H(i)$ represents the size of the data sent by the sensing node i. The parameter $H(i|j)$ indicates that the receiving node j removes the redundant information associated with the original data to obtain the size of the fused data according to the local data and the data spatial-temporal correlation during the data collection process. The data correlation system $\rho(i, j)$ reflects the degree of correlation between the data. The data correlation system $\rho(i, j)$ is inversely proportional to the distance between the sensor nodes. The calculation formula is

$$\rho(i,j) = 1/[1 + d(i,j)] \tag{14}$$

The data fusion rate λ_i consists of two parts, one part is forwarded by other nodes around the sensor node for data fusion. The other part is obtained by fusing the original data collected by the upstream node and the data collected by the cluster head itself. $\varphi(i, j)$ represents the fusion data from the node j to the downstream node i. The mathematical calculation formula for the data fusion rate λ_i is

$$\lambda_i = \sum_{i,j\in V,j\in S_i} [\lambda_j\varphi(i,j) + G_j(1 - \rho(i,j))] \tag{15}$$

The data fusion rate is mainly composed of two parts, one is the data forwarding fusion of other nodes around a certain cluster head node, and the other part is the fusion of the original data of the upstream cluster head node and the data of a cluster head node itself. The network data fusion rate comparison of the four algorithms is shown in Figure 14.

It can be seen from Figure 14 that with the increase of the number of the sensor nodes, the data fusion rate of SEP routing protocol, BP neural network, ELM algorithm and

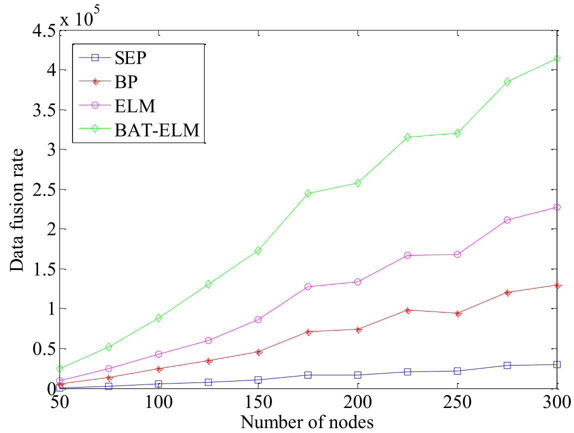


FIGURE 14. Comparison of the data fusion rate.

the algorithm is gradually improved. However, the algorithm proposed in this paper has the fastest growth rate and the largest increase. As the number of the sensor nodes increases, the number of neighbor nodes also increases significantly, and the data collected by the sensing nodes also passes through more neighbor nodes. Therefore, the number and frequency of data transmission between the sensing node and the neighboring nodes are greatly increased, and the probability of data fusion is also increased. Compared with the other three data fusion rate effects, this paper proposes 95.1%, 59.2%, and 46.3% higher than the SEP, BP, and ELM algorithms, respectively. Therefore, the above results show that the proposed algorithm has obvious advantages in network data fusion rate.

H. COMPARISON OF NETWORK TRANSMISSION DELAY

Wireless sensor networks have higher requirements for real-time and effectiveness of data transmission, which requires data to overcome path blocking, link failure, node energy consumption, data transmission rate and other problems in the process of transmission from the source node to the destination node, so as to ensure the transmission delay as low as possible. The transmission delay is usually indicated by the source node data transmission time T_s to the Sink node successfully receiving the data packet time Tr. The average transmission delay calculation formula is expressed as:

$$T_{trans} = \frac{1}{N_r}\sum_{i=1}^{N_r}(T_{ri} - T_{si}) \tag{16}$$

Wherein, the parameter N_r represents the total number of successfully received packets; the parameter T_{trans} is the average transmission delay of the sensor network. The comparison of network transmission delay is shown in Figure 15.

As shown in FIG. 15, as the number of sensing network nodes increases, the energy consumption of the network node increases, the remaining energy of the node decreases, and the number of data retransmissions and collisions increases, resulting in a significant increase in data transmission delay. Since the SEP algorithm does not extract the data

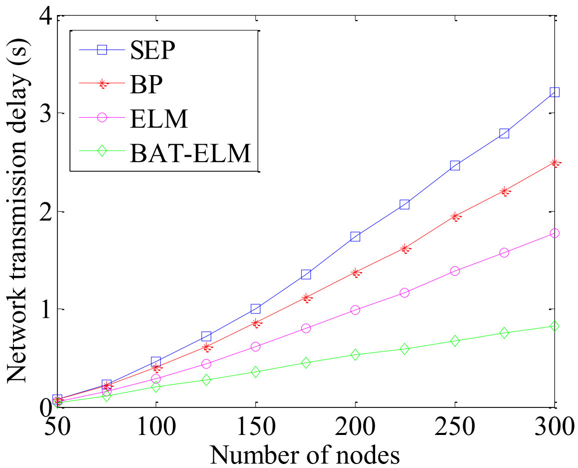


FIGURE 15. Comparison of the transmission delay.

feature values, the average network delay is significantly higher than the other three algorithms, and the maximum delay reaches nearly 3.2s. Then, the BP algorithm and ELM algorithm with the increase of the node delay are also significantly higher than the proposed algorithm achieved 2.5s and 1.8s respectively. The algorithm proposed in this paper optimizes the weight and threshold of neural network. After calculation, when the number of the sensor nodes reaches 300, the latency of this algorithm is about 0.8s. Compared with the SEP protocol and the BP neural network ELM algorithm, the proposed algorithm reduces the average delay by 73.4%, 68%, and 52.8%.

I. COMPARISON OF THE CONNECTIVITY OF THE NETWORK

The connectivity of mobile heterogeneous wireless sensor networks is an important way to ensure network fault tolerance. For a mobile heterogeneous wireless sensor network at a certain time, its connectivity calculation is determined by the perceptual node traversal method. Suppose that a sensing node is used as a reference, and the nodes connected from one hop, two hops and three hops are sequentially searched until the number of nodes connected with the initial sensing node no longer increases. The mathematical formula of the connectivity rate N_c is

$$N_c = N_1/n \tag{17}$$

Wherein, the parameter N_1 is the number of the neighboring nodes in the communication range of the sensor node, and the parameter n is the number of all nodes in the entire sensing network. A comparison of the network connectivity of the four data fusion methods is shown in Figure 16.

As can be seen from Figure 16, as the number of simulation rounds increases, the network connectivity of the SEP data collection method decreases rapidly. In the 300th round, the connectivity rate is only 0.2. The network connectivity between the BP neural network and the ELM neural network is relatively high and stable, both around 0.68. The algorithm proposed in this paper has the highest network

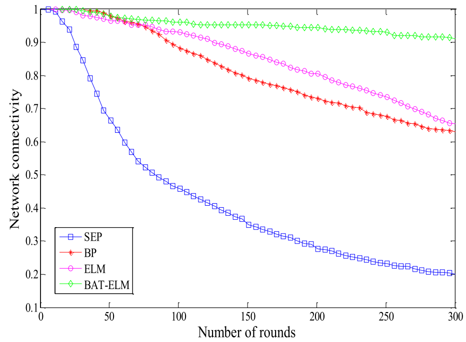


FIGURE 16. Connectivity comparison of the network.

connectivity and is stable overall. The connectivity value is 0.91 in the 300th round. Overall, the proposed algorithm has the best network connectivity. The stability of the BAT-ELM algorithm proposed in this paper is still higher than 0.95 in 300 rounds. Among these four algorithms, the BAT-ELM algorithm has the best network performance in the data fusion process of mobile heterogeneous wireless sensor networks.

VII. CONCLUSION

In order to effectively reduce the redundant information transmission in the network and improve the data fusion efficiency of the mobile heterogeneous wireless sensor network, the extreme learning machine method is used for data fusion. However, the number of hidden layer nodes that continue westward, the random selection of hidden layer parameters, and the parameters remain unchanged during the training process, resulting in the existence of many non-optimized nodes, reducing the generalization ability of the algorithm. Therefore, in view of the above problems, we propose a data fusion model based on the bat algorithm to optimize the extreme learning machine. At the same time, using the global optimization ability of the bat algorithm, the input weight and the hidden layer threshold of the ELM are reasonably selected to obtain the optimal network model. By using the above strategy, the energy load of the network is well balanced, and the network energy consumption is reduced, thereby achieving the effect of prolonging the lifetime of the network. Simulation experiments show that the proposed data fusion algorithm of mobile heterogeneous wireless sensor network based on BAT-ELM has higher performance improvement.

The following research focuses on the following two aspects: Firstly, comprehensive mobile heterogeneous wireless sensor network sensor node distance, residual energy and other factors, further improve and optimize the extreme learning machine algorithm, simplify the subsequent steps of data fusion, improve the network performance. Secondly, dynamically adding the new sensor nodes after a node dies can continuously maintain the communication capability of the network, and the strategy of injecting new nodes is worthy of further study.

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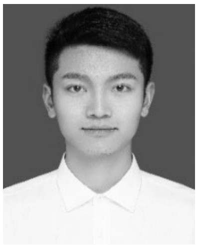

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