International Journal of Innovative Computing, Information and Control
Volume **12**, Number **5**, October **2016**
 ISSN 1349-4198
pp. 1423–1438

OPTIMIZATION-BASED EXTREME LEARNING MACHINE FOR DATA FUSION IN MOBILE WIRELESS SENSOR NETWORKS

Yinggao Yue[1], Jianqing Li[1,*], Hehong Fan[2] and Qin Qin[1]

[1]School of Instrument Science and Engineering
[2]National Research Center for Optical Sensing/Communications Integrated Networking
Southeast University
No. 2, Sipailou, Xuanwu District, Nanjing 210096, P. R. China
*Corresponding author: ljq@seu.edu.cn

Received February 2016; revised June 2016

Abstract. *Energy-efficient and reliable transmission of sensory information is a key problem in mobile wireless sensor networks. The common sensor nodes can be easily disturbed by the external environment, which will affect the measuring results, and an appreciable quantity of redundant nodes will generally be deployed to resolve the problems like node failure and inaccuracy of measurement. However, the collected original data are highly redundant, and will consume too much energy during the transmission, which will shorten the life cycle of network. Data fusion is an effective way for mobile wireless sensor network to lessen data communication between sensor nodes, decrease energy consumption and extend network lifetime. In this paper, a new data fusion algorithm for mobile wireless sensor network based on the extreme learning machine algorithm is proposed, applying to realizing fusion of the collected original data based on the weights and threshold of extreme learning machine algorithm. Simulation results show that the algorithm proposed in this paper is capable of improving the efficiency of data fusion and data transmission reliability, reducing network flow and energy consumption, and extending the life cycle of network.*
Keywords: Data fusion, Mobile wireless sensor networks, Extreme learning machine, Efficiency, Reliability

1. **Introduction.** Internet of Things (IoT) is called the third wave of the world information industry after computer and Internet [1]. As the important carrier of IoT promotion and a key technology at the basement to extend the application of Internet and promote pervasive computing, mobile wireless sensor network (MWSN) has attracted wide attention from specialists and scholars. Due to the demand of application, the sensor node requires high-density deployment [2]. However, it determines that MWSN can hardly transmit a great number of perception data since the node only has limited computing power, restricted electric power supply, and small network transmission bandwidth. It has been the important topic of the research on wireless sensor network to effectively fuse the perception data to reduce network flow, improve use ratio of resources, improve fault tolerance, and extend life cycle of network [3,4].

The specialists and scholars have carried out many researches on data fusion of wireless sensor network, and progresses have been achieved [5-10]. Nevertheless, most of the algorithms of data fusion only consider the high efficiency of energy in the route, which will easily cause network congestion due to the concentration of data transmission on the route with minimum energy, and cause rapid consumption of energy on this route. Moreover, the algorithm complexity of the current data fusion algorithm will rapidly increase when the network scale increases, which is hard to meet the limitation requirements of network resource of wireless sensor network.

According to the conclusion of the previous researches, a novel data fusion algorithm based on swarm intelligence algorithm is established in this paper, which can carry out theoretical calculation of the network energy consumption under different intensities of fusion, and analyze network energy consumption and operation of network under different fusion algorithms. It proposes to apply the weight and threshold value of BP neural network optimized by firefly algorithm into the data fusion of MWSN, effectively extract a small quantity of characteristic data in the original data collected by sensor nodes during MWSN data fusion, and send to Sink, so as to improve the efficiency of data collection, enhance the data transmission credibility of network, and extend life cycle of network.

Based on these considerations, in this paper we develop optimization-based extreme learning machine for data fusion in large-scale mobile wireless sensor networks. The main contribution of our work in this paper can be summarized as follows.

1). Characterize the issues of data fusion for mobile wireless sensor networks. Formalize the problem of finding optimal mobile data fusion strategies as a network utility maximization problem with guaranteed network lifetime, latency and reliability.

2). Present a new data fusion algorithm based on extreme learning machine algorithm.

The rest of the paper is organized as follows. Section 2 discusses the related work. Section 3 describes the basic principles of extreme learning machine method. Section 4 applies to realizing fusion of the collected original data based on the weights and threshold of extreme learning machine algorithm. Section 5 provides the parameters setting and simulation results which validate the performance of our algorithm. Section 6 concludes the paper.

2. **Related Work.** Since data fusion technology has been a key point of research on energy saving of wireless sensor network, many scholars have studied the fusion of multiple sensor data. The typical LEACH (low energy adaptive clustering hierarchy) algorithm fuses by collecting data nosed at the adjacent cluster head through dynamic cluster, which has simplified the complexity of fusion algorithm to a certain extent [11]. In this algorithm, high cost of clustered control overhead and energy consumption, and relationship between the data dependency indicators and data volume after fusion is not analyzed in detail.

Cheng et al. presented a delay-aware network structure model for WSNs with in-network data fusion. The proposed network structure model can reduce delays in data aggregation processes [12]. Chou et al. proposed a computational efficient method to compute a weighted average of sensor measurements, which appropriately takes sensor faults and sensor noise into consideration [13]. Tan et al. studied the scaling laws between coverage, network density, and signal-to-noise ratio (SNR), and showed that data fusion can significantly improve sensing coverage by exploiting the collaboration among sensors when several physical properties of the target signal are known [14]. Luo et al. explored the problem of minimum energy reliable information gathering (MERIG) when performing data fusion. By adaptively using redundant transmission on fusion routes without acknowledgments, packets with more information are delivered with higher reliability [15]. Baccarelli et al. studied the most relevant aspects regarding the fusion, storage, transmission, and retrieval of sensors data, presented a power-efficient QoE sensors data fusion and clustering [9].

In recent years, with the popularization of the statistical learning method and the development of neural networks, the extreme learning machine method gets more and more attention. Miche et al. presented the optimally pruned extreme learning machine (OP-ELM) methodology. It is based on the original extreme learning machine (ELM) algorithm with additional steps to make it more robust and generic. The whole methodology is presented in detail and then applied to several regression and classification problems [16]. Yang et al. proposed a new learning bidirectional extreme learning machine (B-ELM) algorithm, faster than other incremental ELM algorithms [17]. Bazi et al. proposed an efficient classification method for hyperspectral images based on this machine learning approach. To address the model selection issue that is associated with the ELM, we develop an automatic-solution-based differential evolution [18]. Zhang et al. evaluated the multicategory classification performance of ELM on three benchmark microarray data sets for cancer diagnosis [19]. In [20], the authors proposed an image segmentation based on extreme learning machine algorithm, which can separate the image white blood cells from the complex background complete.

It can be seen that the data fusion algorithm in WSNs is not carefully addressed by most of the energy efficient routing protocols above. In fact, it has very important impact on many network metrics like energy consumption, routing overhead, and interference. As is mentioned in [15], the authors presented the MERIG data fusion algorithm; they mainly focus on theoretical study and proof of the optimal hop number. However, they treat every node equally which is not true for WSNs since source and intermediate node consume different amount of energy, as seen from energy model. Also, more simulation work is needed since the real sensor network may not have such sensor nodes which are corresponding to the optimal intermediate nodes. The authors in [9,13,14] only consider energy consumption, not consider the latency and network load balance in their environment and do not provide further analysis.

Different from the above approaches, our work in this paper focuses on performance optimization of data fusion and differs from the earlier work. The extreme learning machine algorithm is applied to the mobile wireless sensor network data fusion in this paper. Learning machine is provided with generalization performance and relatively less adjustable parameters because of the introduction of kernel learning, and its structure does not require tests for determination. Fusion method proposed in this article can improve the efficiency of data integration and data transmission reliability, reduce network traffic and network energy consumption and prolong network lifetime.

3. Extreme Learning Machine.

In 2006, Professor Guangbin Huang from Nanyang Technological University, proposed FFNN-ELM algorithm on the basis of MP-GIM theory [21,22]. ELM is a special type of single hidden layer feedforward neural network (SHL-FFNN), and only hidden layer nodes have extended it to the universal SHL-FFNN later. The algorithm determines output weight of learning network only by one step, and compared with iterative algorithm, ELM greatly improves the generalization ability and learning speed of the network.

Network training model of ELM uses the forward single hidden layer structure [23]. Supposed that m, M and n are network input layers, the hidden layer and the number of nodes in output layer respectively; $g(x)$ is the activation function of the hidden layer neurons; b_i is the threshold; assumed that there are N different samples (x_i, t_i), $1 \leqq i \leqq N$, and among it, $x_i = [x_{i1}, x_{i2}, \ldots, x_{im}]^{\mathrm{T}} \in R^m$, $t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]^{\mathrm{T}} \in R^n$, then the network training model of ELM is shown in Figure 1 [24].

Network model of ELM can be expressed mathematically as:

$$\sum_{i=1}^{L} \beta_i g(w_i \cdot x_i + b_i) = o_j, \quad j = 1, 2, \ldots, N \tag{1}$$

In the formula, $w_i = [w_{i1}, w_{i2}, \ldots, w_{im}]^{\mathrm{T}}$ indicates the input weight vector connecting the network input layer and the i-th hidden layer nodes; $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}]^{\mathrm{T}}$ indicates

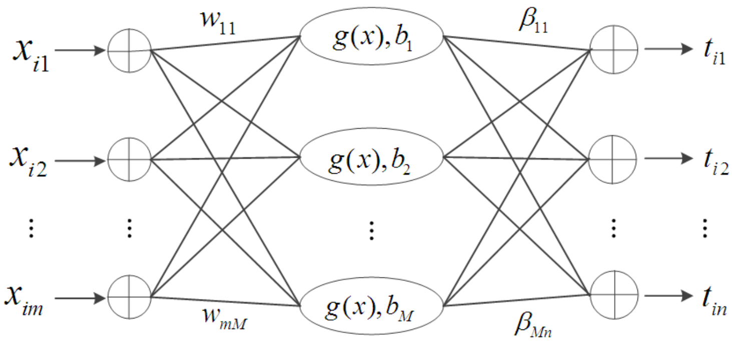

FIGURE 1. Network training model of extreme learning machine

the output weight vector connecting the i-th hidden layer nodes and network input layer nodes; $o_j = [o_{j1}, o_{j2}, \ldots, o_{jn}]^{\mathrm{T}}$ indicates network output value [25].

Cost function E of ELM is expressed as

$$E(S, \beta) = \sum_{j=1}^{N} \|o_j - t_j\| \tag{2}$$

In the formula, $S = (w_i, b_i, i = 1, 2, \ldots, M)$ includes network input weights and hidden layer node threshold. Professor Huang points out that training goal of ELM is to seek the best S and β to minimize the error between network output value and corresponding actual value, i.e., $\min(E(S, \beta))$. $\min(E(S, \beta))$ can be further expressed as

$$\min E(S, \beta) = \min_{w_i, b_i, \beta} \|H(w_1, w_2, \ldots, w_M, b_1, b_2, \ldots, b_M, x_1, x_2, \ldots, x_N)\beta - T\| \tag{3}$$

In the formula, H indicates that the network hidden layer output matrix on samples; β indicates output weight matrix; T represents the target matrix of sample set. H, β and T are defined as follows:

$$\begin{aligned} & H(w_1, w_2, \ldots, w_M, b_1, b_2, \ldots, b_M, x_1, x_2, \ldots, x_N) \\ = & \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \cdots & g(w_L \cdot x_1 + b_M) \\ \vdots & \cdots & \vdots \\ g(w_1 \cdot x_N + b_1) & \cdots & g(w_L \cdot x_N + b_M) \end{bmatrix}_{N \times M} \end{aligned} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_M^T \end{bmatrix}_{M \times n}, \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \times n} \tag{5}$$

Network training process of ELM can be attributed to a nonlinear optimization problem, and Formula (3) is the objective function. When activation function of hidden layer nodes is infinitely differentiable, the network input weights and hidden layer node threshold can be randomly allocated. Then the matrix H is a constant matrix, and the learning process of ELM can be equivalent to resolving of least square solution $\hat{\beta}$ for minimum norm of linear system $H \times \beta = T$, which is calculated as follows:

$$\hat{\beta} = H^{\dagger} T \tag{6}$$

In the formula, $H^{\dagger}$ is MP's generalized inverse of matrix H. After solving $\hat{\beta}$, network training process of ELM is completed.

4. **Data Fusion Based ELM for MWSN.** In this paper, the data fusion technology is applied to routing layer of mobile wireless sensor networks (MWSN), and ELM method is introduced based on hierarchical routing protocol to propose a new extreme learning machine data fusion (ELMDF). It can greatly reduce the feature dimensions of transmission data and improve the data fusion efficiency of MWSN.

Mobile wireless sensor network data fusion scene is shown in Figure 2. The MWSN has the following properties.

1) N sensor nodes are randomly distributed in the monitoring area, and the nodes are deployed to stop moving, and all the nodes are arranged in a unique ID number, which can confirm their position coordinates.

2) Each node has the same type, the initial energy and data processing capabilities. Limited node energy cannot add.

3) Sink moves at a constant speed, so as to collect the data on the cluster area.

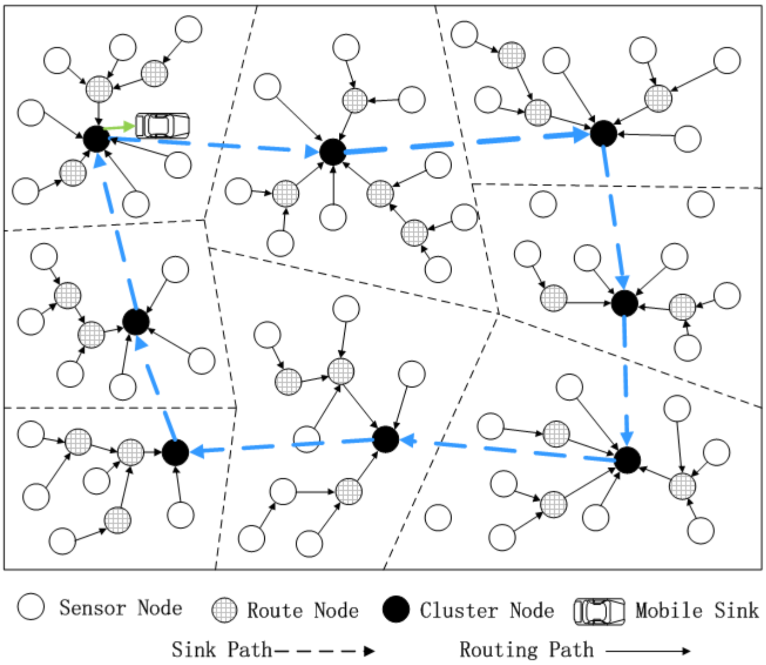

FIGURE 2. Example of mobile wireless sensor network data fusion

ELMDF algorithm is based on the improved LEACH clustering routing protocol for WSNs, and the optimal cluster-head is selected according to certain rules in entire wireless network to form a stable cluster structure. In each sub-cluster structure, sensor nodes within each cluster collect large amounts of raw data and transfer to the cluster-head nodes after the head after pretreatment, and then they are sent to Sink nodes after data fusion treatment inside cluster-head nodes. ELMDF algorithm is to handle the data between sensor nodes within each cluster and cluster-head nodes using ELM. Data fusion model diagram of ELMDF algorithm is shown in Figure 3.

When clustering structure of MWSN gets stable, before network enters into a stable state of autonomous operating, ELM network model needs to be trained, thereby obtaining corresponding network weights and threshold parameter values. Because MWSN has finite and unavailable node energy, in order to minimize the energy consumption of sensor nodes and to prolong the life of the wireless network, ELMDF will complete the training of the neural network model within Sink node of mobile WSNs. Figure 4 is a flowchart of implementation of ELMDF.

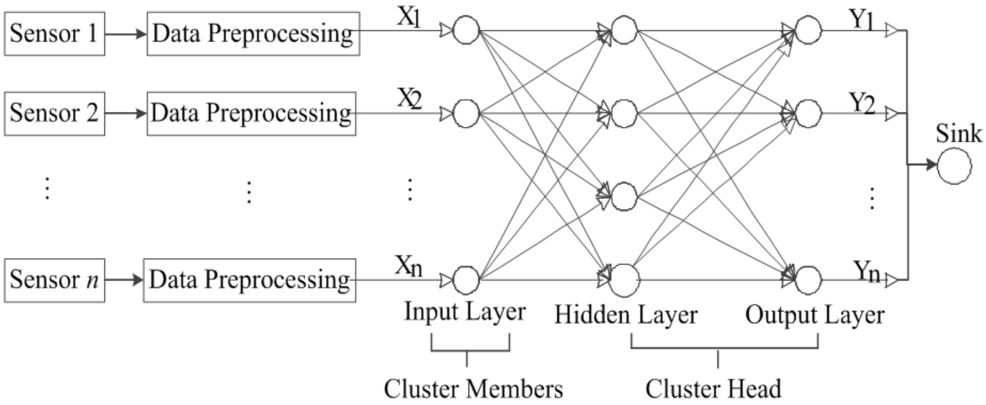

Figure 3. MWSN data fusion model based on ELM

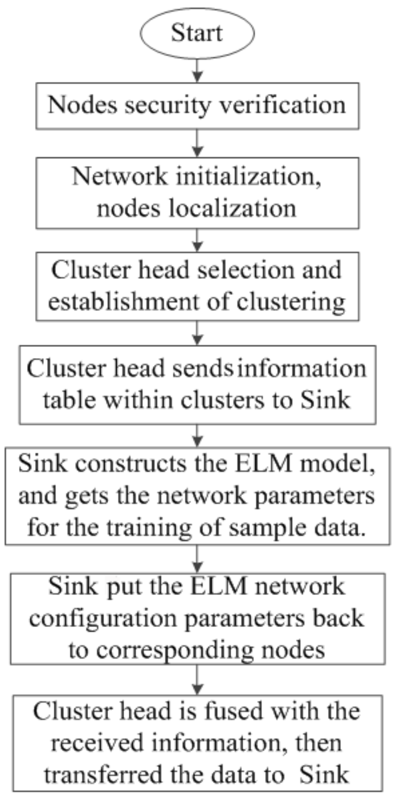

Figure 4. Implementation of data fusion based on ELMDF algorithm

After the initialization of the network, when the network node status is determined, WSNs start conducting selection of cluster-head and establishing clustering structure, then the cluster-head gets information of all cluster nodes, and after clustering structure is stable, the cluster-head node sends information about all nodes within clusters to Sink. Sink builds ELM network structure on the basis of the obtained network information, and collects the network with training samples matching node information within clusters in sample database, thereby getting relevant network parameters. Sink sends the parameters (weights and thresholds) of the network layers to the corresponding cluster nodes. In this way, WSN clustering structure can take advantage of the trained network model for data fusion, and finally the processed data are transferred to Sink along the shortest path.

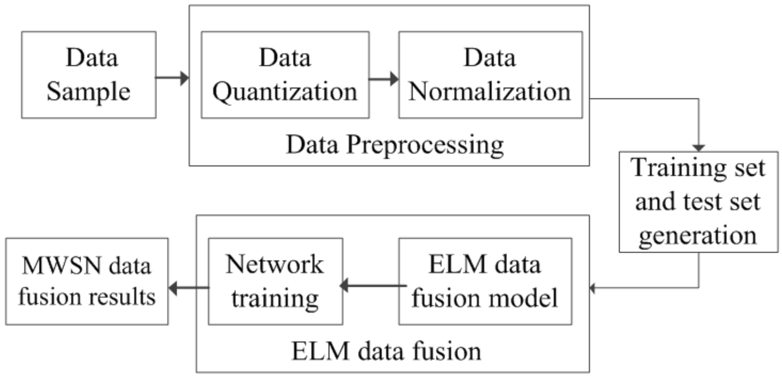

Figure 5. Data fusion process based on ELM

Table 1. The process of the proposed ELMDF model

Input: the sample data Output: the data fusion results of ELMDF
Step 1: The parameters are configured, such as the nodes security verification, network initialization, node localization and number of hidden node of ELM. Step 2: Data fusion model will be initialized under meeting the constraints of input weights and threshold. Step 3: Data fusion is assigned to initialize the ELM model, and the expected error is calculated as the fitness of data fusion. Step 4: Cluster head selection and the establishment of clustering region. Step 5: The cluster head sends the Sink to the cluster node information table. Step 6: Sink constructs the ELMDF model, training the sample data to get network parameters (weights and threshold). Step 7: The terminated condition is not reached, perform continuously. Step 8: Sink sends the ELM network structure parameters to the corresponding nodes. Step 9: Cluster head data fusion for the received information. Then transfer the fusion data to Sink.

Steps for ELM-based MWSN data fusion: firstly, the best MWSN data fusion model is constructed, and then the model is applied to MWSN to improve network fusion precision and to prolong network lifetime. ELMDF-based MWSN data fusion algorithm is shown in Figure 5.

The process for data fusion of mobile wireless sensor networks based on the extreme learning machine is shown in Table 1.

5. Performance Analysis.

5.1. **Simulation environment.** In order to test the performance of the data fusion algorithm proposed in this paper, we use MATLAB simulation software to analyze the performance of wireless sensor network. The simulation platform uses MATLAB 2010(a) simulation software, computer with win7 operating system, configurable processors Intel core i3 processor, memory 4G, 32-bit operating system. The nodes randomly distributed in the two-dimensional space of 1000×1000 m^2, the sensor nodes scale 300. The number of simulation round is 500, each sensor node has 10 packets from the source node to the mobile Sink transmission, the initial energy of each packet capacity 4 kb. Mobile

Sink is set to 50 J, Sink to 5 m/s speed uniform linear movement. The extreme learning machine parameters are set as follows: the initial hidden layer node number is 10, the number of hidden layer nodes is increased by 20, and the number of hidden layer nodes is reached to 300. The implicit layer activation function of ELM is chosen to study the hardlim function. In order to make the results more convincing, the results of this paper are the average results of the 100 experiments. The simulation environment parameters are shown in Table 2 [26].

Table 2. Simulation environment

Parameter	Value
Network size	1000×1000 m^2
Node number	300
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_{mp}	0.0013 pJ/bit/m^4
Data size	4000 bits
d_0	$\sqrt{E_{fs}/E_{mp}} = 87$ m

In this paper, LEACH protocol [27], BP neural network [28], RBF neural network [29] and extreme learning machine (ELM) of four kinds of data fusion algorithms are compared.

- LEACH protocol: Data fusion algorithm based on clustering for mobile wireless sensor network.
- BP neural network algorithm: Data fusion algorithm for mobile wireless sensor networks based on BP neural network.
- RBF neural network algorithm: Data fusion algorithm for mobile wireless sensor networks based on RBF neural network.
- Extreme learning machine algorithm: Our proposed algorithm.

5.2. **Performance analysis.**

5.2.1. *Network energy consumption.* The total energy consumption of the sensor network is defined as the energy consumption of the whole network sensor nodes. The total energy consumption of the network is smaller, which shows that the network data fusion efficiency is higher, the transmission data is less, and the network lifetime is longer. Taking total energy consumption as a measure, the total energy consumption of the four algorithms is shown in Figure 6.

From Figure 6 it can be seen that the energy consumption of the algorithm is less than the other three algorithms of energy consumption, the energy consumption of the LEACH protocol is the largest, the BP neural network is bigger, the RBF neural network is smaller, and the extreme learning machine algorithm is the smallest. This is because in the data transfer process, LEACH protocol does not carry out data fusion, with the extension of time, energy consumption is growing dramatically, BP neural network, RBF neural network and extreme learning machine algorithm using data fusion to reduce the amount of data transmission, so as to reduce the excessive consumption of energy consumption.

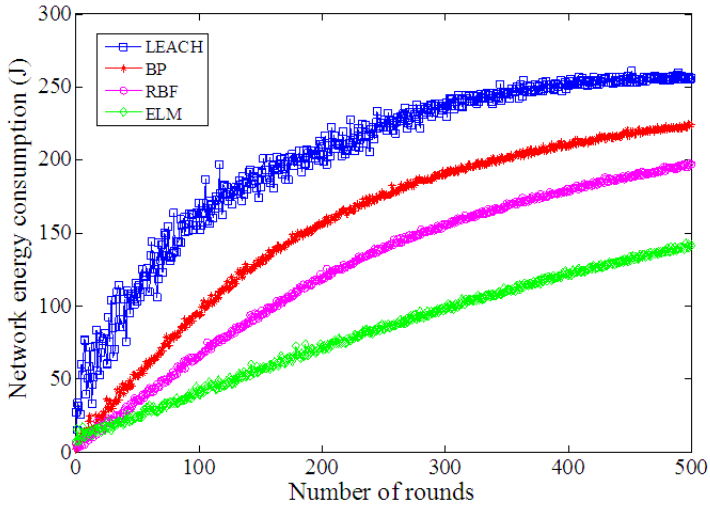

FIGURE 6. The total energy consumption

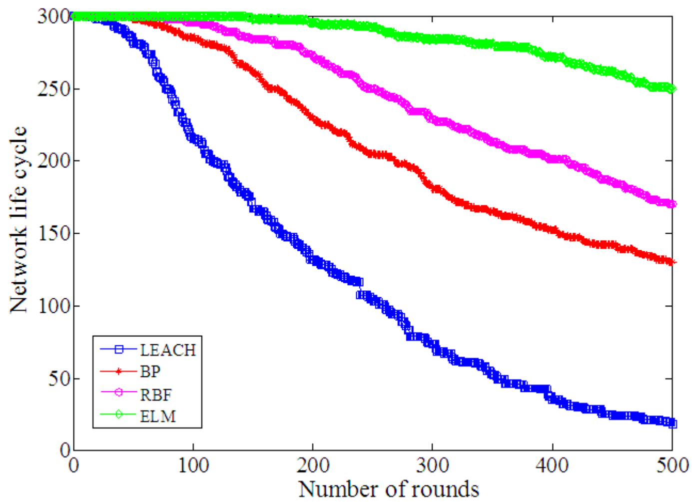

FIGURE 7. Network life cycle

5.2.2. *Network life cycle.* The life cycle of network is one of the important indexes to evaluate the performance of mobile wireless sensor networks. By comparing with other schemes, the performance of the proposed routing protocol is evaluated in Figure 7. The curve diagram of the main survival nodes on different routing protocols changed with the increase of rounds was compared.

From Figure 7 it can be seen that, in the LEACH protocol, the time of sensor nodes run out is 178th. In the data fusion of BP neural network, the time of sensor nodes run out by 50% is 402nd. RBF neural network algorithm in the network running 500 rounds, the node mortality rate is 43.3%, and the algorithm proposed in this paper is 16.7%. This is mainly because the proposed algorithm considers the residual energy of MWSN and the distance to Sink, and then passes the cluster head node to Sink, and the network energy consumption is small. Taking the 500 rounds as an example, the network life cycle is improved by 82.3%. Compared with the LEACH protocol, BP neural network algorithm and the RBF neural network algorithm improve 87.3%, 38.3% and 26.2%.

5.2.3. *Network load balancing.* Load balancing is an important basis for judging the network lifetime, and the load balance is essential to extend the life cycle of the entire WSNs.

Load balancing factor (LBF) provides a convenient and effective assessment method for network performance analysis. L_{LBF} is defined as the reciprocal of sensing nodes (including cluster head nodes) variance of members within the network, and among it, the greater L_{LBF} is, the better the performance of the network load balancing, specifically calculated as [25]:

$$L_{LBF} = \frac{n_c}{\sum_{i=1}^{n_c}(x_i - u)^2} \tag{7}$$

Among it, n_c is number of WSN sensor node; x_i is the number of sensor nodes of the i-th cluster head member; u is the average number of nodes in all cluster head nodes. The comparison in load balancing of three kinds of algorithms is shown in Figure 8.

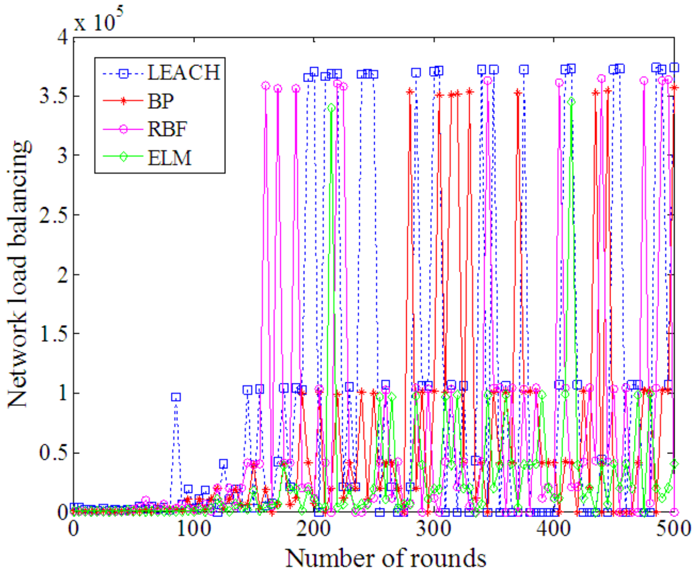

FIGURE 8. Network load balancing

In Figure 8, with the increase of the simulation round, network load balances of the four algorithms are increasing, and the load balance performance of the network is also better. In addition, it can be seen that the best load balancing performance is the data fusion algorithm of RBF neural network. Secondly, the BP neural network algorithm and the LEACH protocol are also better. However, in this paper, the load balancing performance is not satisfactory.

5.2.4. *Sink received the data packets number.* In the application of MWSN, the user receives the data from Sink to analyze and process the information to evaluate the monitoring area. Therefore, it is of great significance to analyze the number of packets received by Sink. The energy of sensor nodes is mainly consumed in data transmission, and the number of packets received reflects the performance of the algorithm. Comparison of the number of packets received for Sink is shown in Figure 9.

With the increase of the number of rounds, the number of received data packets of the four algorithms is increased. In the LEACH protocol, the number of Sink receive packets is reduced dramatically with the energy consumption of sensor nodes. BPNN and RBF neural network data fusion algorithm receive the number of packets more than the LEACH protocol. Data packets number received by proposed algorithm in this paper is maximum, which is 118.4%, 29.1% and 10.9% more than LEACH protocol, BP neural network and RBF neural network respectively.

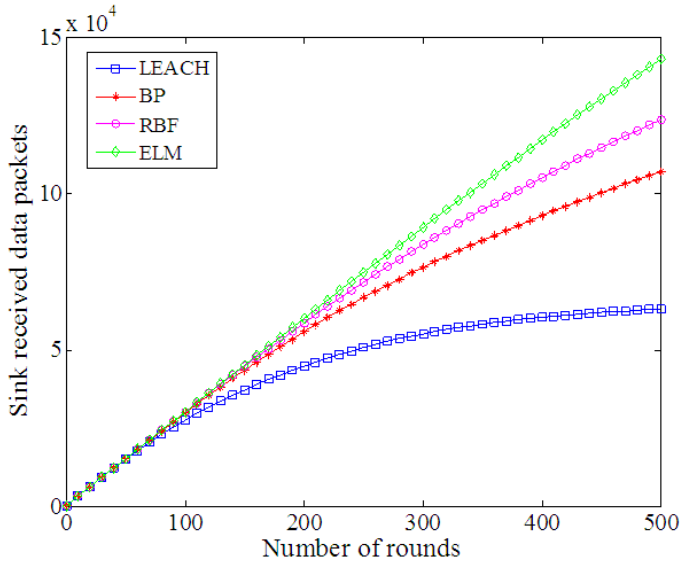

FIGURE 9. Sink received the data packets number

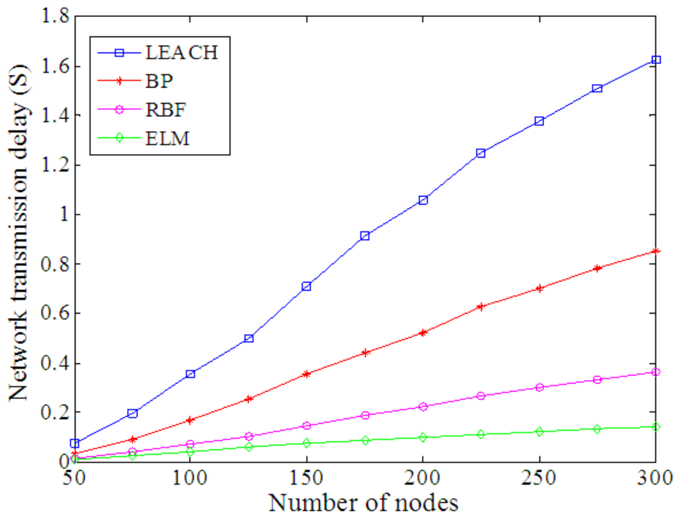

FIGURE 10. Network transmission latency

5.2.5. *Network transmission latency.* We use the transmission delay of successfully received data packet to measure real-time performance of protocol. Transmission time of data at source node is recorded as T_s, and the reception time at the Sink node is recorded as T_r. The average transmission delay is as follows:

$$T_{trans} = \frac{1}{N_r}\sum_{i=1}^{N_r}(T_{ri} - T_{si}) \tag{8}$$

Among it, N_r is the total number of successfully received packets. Network delay of four algorithms is shown in Figure 10.

It can be seen that from Figure 10, with the increase of the number of rounds simulation, data transmission latency increased significantly; this is mainly because with the operation of the algorithm, fewer and fewer residual energy, conflict and retransmission increase in the number, have greater transmission latency. However, transmission latency of data fusion algorithm is smaller than those of BP neural network and RBF neural network. LEACH protocol is not characterized in advance, the data transmission latency is the largest, and so the network transmission latency is the largest. Through statistical calculation, compared with that of LEACH protocol, BP neural network and RBF neural network method, the average transmission latency of ELM algorithm decreases by 88.9%, 39.8% and 12.5% respectively.

5.2.6. *Data fusion efficiency.* Data fusion efficiency reflects the performance of data fusion algorithm, the higher the efficiency, the less the amount of network data transmission, the less energy consumption, the higher the network lifetime and reliability. Therefore, the efficiency of data fusion is an important assessment of the performance of this paper. Data fusion efficiency comparison of our algorithms is shown in Figure 11.

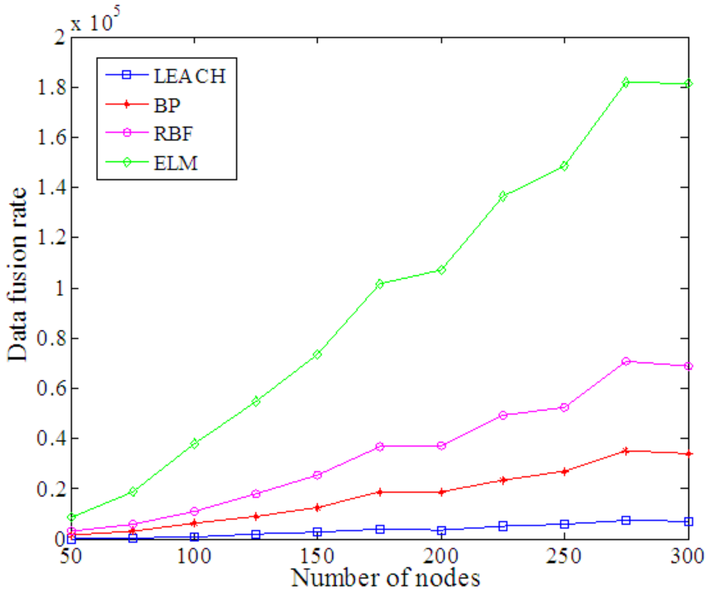

FIGURE 11. Data fusion efficiency

It can be seen that from Figure 11, with the increase of network size, the fusion data rate is gradually increased. This is due to the increase in the number of nodes, there will be more neighbor nodes, and these nodes are transferred to the base station after data fusion, which is caused by the increase of the fusion data, and can be seen from the graph, this increase and the number of nodes is almost linear upward trend. After calculation, data fusion rate ELM with LEACH protocol, BP neural network and RBF neural network algorithm compared increased by 94.4%, 79.1% and 64.6%.

5.2.7. *Network connectivity.* For mobile networks, generally, continuous motion discretization method is used to calculate the rate of network connectivity. For the network at a moment, the method of node traversal is used to calculate network connectivity. Node traversal method is to select an initial node, and directly connected nodes, binary-hop connected nodes and three jumps connected nodes are searched from it in sequence, until the node number connected to initial nodes is no further increased, and connectivity rate is calculated as:

$$N_{con} = \frac{N_l}{n} \tag{9}$$

wherein, N_l is the number of neighboring nodes in the communication range, n is the number of nodes in the network. Comparison in network connectivity of four algorithms is shown in Figure 12.

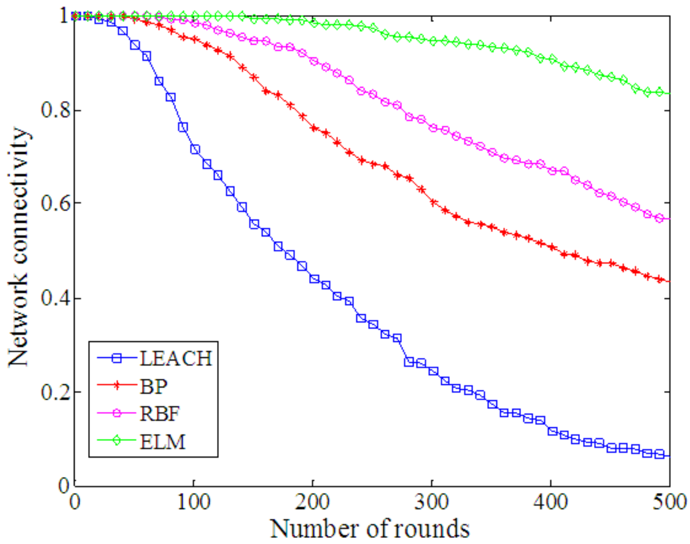

FIGURE 12. Network connectivity

As can be seen from Figure 12, with the increase of the simulation round number, the network connectivity of LEACH protocol is low, and the fluctuation is very large, the range is between 0.08∼1, and the average value is 0.41. The data fusion method of BP neural network is high, the range is between 0.42∼1, and the average value is 0.74. The data fusion method of RBF neural network is very high, and it is stable, and the range is between 0.6∼0.1, and the average value is 0.83. The proposed algorithm in this paper is the highest, the overall stability, the range is between 0.8∼1, and the average value is 0.95. Overall, the extreme learning machine data fusion algorithm has the best network connectivity.

5.2.8. *Network reliability.* Integrated network reliability of R_{net} is comprised of network node connectivity reliability I_1, network connectivity rate I_2 and network capacity I_3. The formula is:

$$R_{net} = 0.1667I_1 + 0.5I_2 + 0.3333I_3 \tag{10}$$

Network node connectivity reliability I_1 refers to the interconnected reliability of end-to-end nodes, and the reliability matrix is calculated in line with the distance between nodes particularly, and according to the reliability matrix and the random edge reliability matrix sample, and then on the basis of Monte Carlo analysis, node connectivity reliability value on average is obtained after 50 times. Network capacity I_3 is the network survival probability, and the network survival probability is usually obtained by dividing the surviving node of network nodes by the number of all network nodes. Network reliability comparison of four algorithms is shown in Figure 13.

As can be seen from Figure 13, the proposed algorithm is the best and the decrease amplitude is smallest. Taking the network reliability of 0.8 as a reference, the LEACH protocol of network reliability is reduced to 0.8 in the 150 round, the BP neural network algorithm in the 305 round, the RBF neural network algorithm in the 400 round, extreme learning machine algorithm proposed in 750 round, compared with the reliability of LEACH protocol, BP neural network and RBF neural network higher than 77.1%, 58.2% and 43.5%.

In order to make the advantage of our work clearer, and compare the methods by each metric, a summary on the comparison of performance comparison of different algorithms

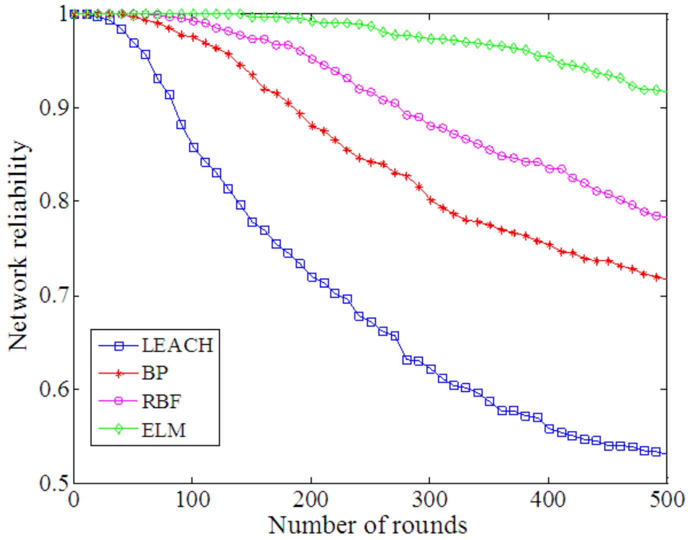

Figure 13. Network reliability

Table 3. Performance comparison of different algorithms

	LEACH	BP	RBF	ELM
Network energy consumption	poor	general	good	better
Network life cycle	poor	general	good	better
Network load balancing	good	good	good	general
Sink received the number of data packets	general	good	good	good
Network transmission latency	poor	general	good	good
Data fusion efficiency	poor	general	general	good
Network connectivity	poor	general	good	better
Network reliability	poor	general	good	better

is showed in Table 3. And we give four evaluation of the performance of the data fusion algorithm, "poor", "general", "good", "better".

Overall, although the extreme learning machine data fusion method increases the calculation, it significantly reduced the amount of data communication, so as to improve mobile wireless sensor networks life cycle and network reliability. In this paper, the proposed algorithm can reduce the amount of network traffic and network energy consumption, prolong the network lifetime and improve the efficiency of data fusion and data transmission reliability.

6. **Conclusion and Future Work.** In this paper, a new data fusion algorithm of mobile wireless sensor network based on extreme learning machine algorithm is proposed, applying the extreme learning machine method to realizing fusion of the collected original data. Simulation results show that the proposed algorithm in this paper is capable of improving the efficiency of data fusion, reducing network flow and energy consumption, enhancing network reliability. In the data transmission process, the first need to find efficient routing data fusion, as well as data fusion operation, is likely to result in transmission of data latency. Therefore, how to reduce the transmission delay caused by data fusion and enhance the reliability of network is an issue needing further research and solution.

Acknowledgments. This study was supported by International S&T Cooperation Program of China (2015DFA10490), the Natural Science Foundation of China (61571113, 61240032) and the Specialized Research Fund for the Doctoral Program of Higher Education (No. 20130092110060).

REFERENCES

[1] S. Rani, R. Talwar, J. Malhotra et al., A novel scheme for an energy efficient Internet of things based on wireless sensor networks, *Sensors*, vol.15, no.11, pp.28603-28626, 2015.

[2] G. Kortuem, F. Kawsar, D. Fitton and V. Sundramoorthy, Smart objects as building blocks for the Internet of things, *IEEE Internet Computing*, vol.14, no.1, pp.44-51, 2010.

[3] R. Velmani and B. Kaarthick, An efficient cluster-tree based data collection scheme for large mobile wireless sensor networks, *IEEE Sensors Journal*, vol.15, no.4, pp.2377-2390, 2015.

[4] Y. C. Wang and Y. C. Tseng, Distributed deployment schemes for mobile wireless sensor networks to ensure multilevel coverage, *IEEE Trans. Parallel and Distributed Systems*, vol.19, no.9, pp.1280-1294, 2008.

[5] V. W. Cheng and T. Y. Wang, Performance analysis of distributed decision fusion using a multi-level censoring scheme in wireless sensor networks, *IEEE Trans. Vehicular Technology*, vol.61, no.4, pp.1610-1619, 2012.

[6] H. T. Pai and Y. S. Han, Power-efficient direct-voting assurance for data fusion in wireless sensor networks, *IEEE Trans. Computers*, vol.57, no.2, pp.261-273, 2008.

[7] Z. J. Zhang, C. F. Lai and H. C. Chao, A green data transmission mechanism for wireless multimedia sensor networks using information fusion, *IEEE Wireless Communications*, vol.21, no.4, pp.14-19, 2014.

[8] P. A. C. S. Neves, J. J. P. C. Rodrigues and K. Lin, Data fusion on wireless sensor and actuator networks powered by the ZenSens system, *IET Communications*, vol.5, no.12, pp.1661-1668, 2011.

[9] E. Baccarelli, F. Chiti, N. Cordeschi, R. Fantacci and A. Uncini, Green multimedia wireless sensor networks: Distributed intelligent data fusion, in-network processing, and optimized resource management, *IEEE Wireless Communications*, vol.21, no.4, pp.20-26, 2014.

[10] D. F. Larios, J. Barbancho, G. Rodríguez and J. L. Sevillano, Energy efficient wireless sensor network communications based on computational intelligent data fusion for environmental monitoring, *IET Communications*, vol.6, no.14, pp.2189-2197, 2012.

[11] A. Kong and H. Yun, Energy efficient cooperative LEACH protocol for wireless sensor networks, *Journal of Communications and Networks*, vol.12, no.4, pp.358-365, 2010.

[12] C. T. Cheng, H. Leung and P. Maupin, A delay-aware network structure for wireless sensor networks with in-network data fusion, *IEEE Sensors Journal*, vol.13, no.5, pp.1622-1631, 2013.

[13] C. T. Chou, A. Ignjatovic and W. Hu, Efficient computation of robust average of compressive sensing data in wireless sensor networks in the presence of sensor faults, *IEEE Trans. Parallel and Distributed Systems*, vol.24, no.8, pp.1525-1534, 2013.

[14] R. Tan, G. L. Xing, B. Y. Liu, J. P. Wang and X. H. Jia, Exploiting data fusion to improve the coverage of wireless sensor networks, *IEEE/ACM Trans. Networking*, vol.20, no.2, pp.450-462, 2012.

[15] H. Luo, H. X. Tao, H. D. Ma and S. K. Das, Data fusion with desired reliability in wireless sensor networks, *IEEE Trans. Parallel and Distributed Systems*, vol.22, no.3, pp.501-513, 2011.

[16] Y. Miche, A. Sorjamaa, P. Bas, O. Simula, C. Jutten and A. Lendasse, OP-ELM: Optimally pruned extreme learning machine, *IEEE Trans. Neural Networks*, vol.21, no.1, pp.158-162, 2010.

[17] Y. M. Yang, Y. N. Wang and X. F. Yuan, Bidirectional extreme learning machine for regression problem and its learning effectiveness, *IEEE Trans. Neural Networks and Learning Systems*, vol.23, no.9, pp.1498-1505, 2012.

[18] Y. Bazi, N. Alajlan, F. Melgani, H. Alhichri, S. Malek and R. R. Yager, Differential evolution extreme learning machine for the classification of hyperspectral images, *IEEE Geoscience and Remote Sensing Letters*, vol.11, no.6, pp.1066-1070, 2014.

[19] R. X. Zhang, G. B. Huang, N. Sundararajan and P. Saratchandran, Multicategory classification using an extreme learning machine for microarray gene expression cancer diagnosis, *IEEE/ACM Trans. Computational Biology and Bioinformatics*, vol.4, no.3, pp.485-495, 2007.

[20] C. Pan, D. S. Park, Y. Yang et al., Leukocyte image segmentation by visual attention and extreme learning machine, *Neural Computing and Applications*, vol.21, no.6, pp.1217-1227, 2012.

[21] G. B. Huang, Q. Y. Zhu and C. K. Siew, Extreme learning machine: Theory and applications, *Neurocomputing*, vol.70, no.1, pp.489-501, 2006.

[22] G. B. Huang, H. Zhou, X. Ding et al., Extreme learning machine for regression and multiclass classification, *IEEE Trans. Systems, Man, and Cybernetics, Part B: Cybernetics*, vol.42, no.2, pp.513-529, 2012.

[23] Q. Y. Zhu, A. K. Qin, P. N. Suganthan et al., Evolutionary extreme learning machine, *Pattern Recognition*, vol.38, no.10, pp.1759-1763, 2005.

[24] G. B. Huang, X. Ding and H. Zhou, Optimization method based extreme learning machine for classification, *Neurocomputing*, vol.74, no.1, pp.155-163, 2010.

[25] G. Feng, G. B. Huang, Q. Lin et al., Error minimized extreme learning machine with growth of hidden nodes and incremental learning, *IEEE Trans. Neural Networks*, vol.20, no.8, pp.1352-1357, 2009.

[26] J. Wang, J. Cho, S. Lee, K. C. Chen and Y. K. Lee, Hop-based energy aware routing algorithm for wireless sensor networks, *IEICE Trans. Communication*, vol.93, no.2, pp.305-316, 2010.

[27] S. A. B. Awwad, C. K. Ng, N. K. Noordin et al., Cluster based routing protocol for mobile nodes in wireless sensor network, *Wireless Personal Communications*, vol.61, no.2, pp.251-281, 2011.

[28] S. Li, M. Y. Liu and L. Xia, WSN data fusion approach based on improved BP algorithm and clustering protocol, *The 27th Chinese Control and Decision Conference*, pp.1450-1454, 2015.

[29] W.-T. Sung and C.-H. Chen, Parallel data fusion for an industrial automatic monitoring system using radial basis function networks, *International Journal of Innovative Computing, Information and Control*, vol.6, no.6, pp.2523-2536, 2010.

[30] R. Geng, Z. Ning and N. Ye, A load-balancing and coding-aware multicast protocol for mobile ad hoc networks, *International Journal of Communication Systems*, 2015.