Data Fusion Algorithms for Wireless Sensor Networks Based on BP Neural Network with Improved Particle Swarm Optimization

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***Abstract*—Data fusion algorithm of wireless sensor network based on Improved Particle Swarm Optimization BP neural network Aiming at the problem of slow convergence speed, sensitive to initial value and easy to fall into local optimal solution of traditional back propagation (BP) neural network in data fusion algorithm of wireless sensor network, this patent proposes WSN data fusion algorithm of improved particle swarm optimization BP neural network. Law. The particle swarm optimization (PSO) algorithm is improved by Beetle Antennae Search algorithm (BAS). The improved PSO algorithm is used to optimize the weights and thresholds of BP neural network. In WSN data fusion, the cluster head node extracts the features of the data through the optimized BP neural network and sends the fused features. Information to the sink node reduces redundant data transmission and prolongs the network life cycle.**

Keywords-Clustering routing; Data fusion; BP neural network; Beetle antennae search

I. INTRODUCTION

Due to the self-organization of WSN, low power consumption, etc., WSN is widely used in industrial, medical, Internet of things and other fields, but WSN sensor node resources and energy are limited, so it is necessary to design an efficient WSN network protocol to improve energy resource utilization efficiency [1].

The concept of data fusion was originally proposed in the 1970s. It was originally applied only to the military field. For example, the command-and-control communication system uses data fusion technology to process war information to successfully obtain accurate information about war. With the advancement of science and technology, the research on data fusion technology has attracted the attention of scholars and scientific research personnel from all over the world. It has research results in the field of data fusion technology in various academic conferences and academic journals.

The traditional BP neural network is applied to wireless sensor networks, which has the difficulty of training and is easy to fall into the local optimal solution. The optimization effect of GABP (Data fusion model based on genetic algorithm and BP neural network) algorithm is greatly affected by the initial distribution of the population, and the solution speed is slow. The PSO-BP algorithm lacks diversity of particle swarms and has a large optimization space. In this paper, aiming at the optimization of optimization performance and fusion precision, this paper proposes a WSN data fusion algorithm based on the improved particle swarm optimization algorithm of the Beetle antennae search operator, the BSOBP algorithm, which is optimized by the Beetle antennae search operator optimization particle swarm optimization algorithm. The particle swarm algorithm searches for spatial diversity and avoids falling into local optimal solutions.

II. RESEARCH STATUS

BP neural network is a typical multi-layer forward neural network. BP neural network is composed of input layer, hidden layer and output layer. It uses learning mechanism to store the mapping relationship between input and output. Its weights and threshold parameters usually adopt back propagation strategy. With the help of the steepest gradient information, the parameter combination that minimizes the network error can be obtained. It has strong non-linear mapping ability, self-learning ability, ability to learn and adapt, generalization and fault tolerance.

Data fusion algorithm based on BP neural network applies BP neural network to cluster routing protocol for feature extraction [2], thus reducing redundant data and slowing down node death time. However, BP neural network is sensitive to initial weights and thresholds, and easy to fall into local minimum.

The data fusion algorithm of BP neural network based on genetic algorithm (GA) uses genetic algorithm to optimize the weights and threshold parameters of BP neural network, which can effectively reduce redundant data and prolong the network life cycle. However, genetic algorithm has the shortcomings of poor search ability and slow solving speed.

The WSN data fusion algorithm PSO-BP [4] based on particle swarm optimization BP neural network is used to optimize the parameters of BP neural network. The optimized BP neural network and clustering routing protocol of sensor network are combined organically, which can effectively improve the efficiency of data fusion and balance network energy consumption. However, due to the loss of diversity in the search space, particle swarm optimization (PSO) has the disadvantage of easily falling into local optimal solution.

In summary, the traditional BP neural network used in wireless sensor networks is difficult to train and easy to fall into the defects of local optimal solution. The optimization effect of GABP algorithm is greatly affected by the initial distribution of population, and the solving speed is slow. Particle swarm in PSO-BP algorithm is lack of diversity, and there is a large optimization space.

III. TECHNICAL SCHEME

A. BP Neural Network Structural Data Fusion Algorithms

Based on the optimization of optimization performance and fusion precision, this paper proposes a BP neural network wireless sensor network data fusion algorithm based on improved particle swarm optimization. The optimized particle swarm optimization algorithm is used to optimize the initial weight and threshold parameters of BP neural network. The global optimal solution is used as the initial value of BP neural network structural parameters and further optimized training, thereby overcoming the shortcomings of BP neural network training which is easy to fall into the local optimal solution, avoiding the network oscillation caused by the random selection of the initial weight and threshold parameters of traditional BP neural network, and improving the generalization ability and convergence ability of BP neural network.

The particle swarm optimization (PSO) algorithm is a group optimization algorithm based on the social behavior of the bird population [5]. The group information sharing mechanism is used to find the current optimal value to obtain the global optimal value. The behavior of each particle mimics the flight of birds. The particle position is optimized according to its own inertia speed, historical experience and group social experience. The optimization formula is as follows:

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 \left(pbest_{id}^{k} - \mathrm{x}_{\mathrm{id}}^{\mathrm{k}} \right) + c_2 r_2 \left(gbest_{id}^{k} - \mathrm{x}_{\mathrm{id}}^{\mathrm{k}} \right)$$

$$x_{\mathrm{ild}}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{1}$$

where d = 1,2,..., D (D denotes the total dimension of particles), i = 1,2,...,N (N is the number of particle swarm), K is the current iteration number, v_{id}^{k} is the d-dimensional position vector of particle i at the k-th iteration, x_{id}^{k} is the d-dimensional position vector of particle i at the k-th iteration, w is the inertial weight, c_1 and c_2 are the acceleration constants, r_1 and r_2 are two random functions with values ranging from [0,1]. $pbest_{id}^{k}$ denotes the d-dimensional position of the historical optimum fitness of particle i in the k-th iteration, and $\mathrm{gbest}_{\mathrm{id}}^{\mathrm{k}}$ denotes the d-dimensional position vector of the historical optimum fitness of population particles in the k-th iteration.

The search behavior of beetle antennae search algorithm plays an important role in PSO algorithm. Given the characteristics of particle longicorn search behavior in PSO algorithm, it can effectively increase the diversity of particle population changes and overcome the problem of easily falling into local optimum in the process of PSO optimization. According to the roulette algorithm based on fitness value, this patent selects several particles for longicorn whisker search. In the initial stage of particle swarm search, the particles with longicorn search behavior can make the population more diverse, expand the scope of searching for the optimal solution, and avoid falling into local optimal solution. With the increase of iteration times, the particle swarm converges more and more. At this time, the number of particles with longicorn search behavior should be reduced, which is conducive to reducing the amount of calculation and fast convergence. The increment of longicorn whisker search behavior is added to the optimization calculation of particle swarm optimization.

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 (pbest_{id}^{k} - x_{id}^{k}) + c_2 r_r (gbest_{id}^{k} - x_{id}^{k})$$

$$x_{id}^{k+1} = x_{id}^{k} + (1-\lambda) v_{id}^{k+1} + \lambda \xi_{id}^{k+1} \tag{2}$$

Among them, w is the inertia weight reflecting the particle's exercise habit. In theory, when the value of w is small, the local search ability is strong, and the larger w value can enhance the global search ability. In this patent, the inertia weight w is a convex function decrement method. The number of reductions, beetle antennae search behavior incremental weight should also be reduced, so the search behavior incremental weighting factor λ is assigned as follows:

$$\lambda = (\lambda\mathrm{max} - \lambda\mathrm{min})(1 - \mathrm{iter/maxgen}) + \lambda\mathrm{min} \tag{3}$$

In WSN clustering routing algorithm, cluster heads need to be updated regularly to balance energy consumption, and corresponding clusters need to be updated dynamically. The change of cluster heads will lead to the change of BP neural network structure in clusters. The weight and threshold parameters are needed for data fusion of BP neural network. The threshold parameter, therefore, after the cluster head is updated, the parameters of the BP neural network also need to be updated and replaced before the WSN enters the autonomous working state. The sensor nodes in the WSN have limited computing power, node capabilities, and storage capabilities, so the training update of the parameters is performed at the base station node. The improved particle swarm optimization algorithm is applied to WSN clustering routing BP neural network data fusion. The overall steps of the algorithm are as follows:

Step 1: Each cluster of cluster head nodes is updated. After the clustering is formed, the cluster head records the node information in the cluster and transmits it to the base station node.

Step 2: The base station determines the BP neural network structure based on the cluster information.

Step 3: The base station selects the sample data set matching the cluster, and combines the improved PSO algorithm to train and optimize the BP neural network to obtain the BP neural network connection weight and threshold parameters of the corresponding cluster.

Step 4: The base station sends the BP neural network connection weight and the threshold parameter of the corresponding cluster to each cluster node, and stores the parameters for the next use.

Step 5: Each cluster set constructs a corresponding BP neural network according to the received parameter message, and the cluster head node performs fusion processing on the data uploaded by the member nodes in the cluster and transmits the result to the base station node. So far, complete a round of cluster routing communication process.

The purpose of the improved PSO algorithm in the above step 3 is to optimize the BP neural network algorithm to optimize the weight threshold parameters of the BP neural network and obtain a global optimization solution. The global optimization solution is taken as the initial weight and threshold parameters of the BP neural network, and the BP neural network is further trained and optimized to obtain the global optimal parameters. In this way, the BP neural network overcomes the shortcomings caused by the randomness of the initial weight selection, the training time is long, and it is easy to fall into the local optimal solution, which improves the convergence ability and the accuracy of the BP neural network.

B. Improved PSO algorithm optimization BP neural network algorithm

Improved PSO algorithm optimization BP neural network algorithm implementation steps are as follows:

Step 1: Determine the search space dimension. After the WSN clustering is formed, the number of member nodes in each cluster is the number M of the input layer neurons, the number of neurons in the hidden layer is N, and the number of neurons in the output layer is 1. Therefore, the search space dimension $D = M*N + N*1 + N + 1$.

Step 2: Initialize the settings. Initializing the initial position vector of n particles x_i (i=1,2,...,n), where $\mathrm{x}_i = (x_{i1}, x_{i2}, ..., x_{iD})$ is the D-dimensional search vector of the i-th particle, including the weights of the input layer and the hidden layer in the BP neural network, and The threshold of the hidden layer and the input layer; the velocity vector $\mathrm{v}_i(i = 1, 2, ..., n)$ of the n particles is initialized, where $v_i(v_{i1}, v_{i2}, ..., v_{iD})$ is the velocity vector of the i-th particle; the initialization speed variation range $[\text{-V}_{\max}, V_{\max}]$; and initialize the maximum number of iterations K.

Step 3: Define the fitness function. The sample data is fused, and the root mean square error (RMSE) of the sample data is used as the fitness function:

$$f(x_i) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(train_i\text{-}\mathrm{y}_i)^2} \tag{4}$$

where m is the number of training items for the sample data, train_i is the fusion prediction result of the i-th sample data, y_i is the measured value of the i-th sample data.

Step 4: Calculate the fitness function value of the particle. Each particle individual needs to remember the best position for his own search. The best position that the i-th particle has searched for is recorded as $pbest_{id} = (p_{i1}, p_{i2}, ..., p_{iD})$, and the best position that the group searches for is recorded as $\mathrm{g}best_d = (g_1, g_2, ..., g_D)$.

Step 5: By using the formula

$$\begin{aligned} \mathrm{x}_{ird}^k &= x_{id}^k + v_{id}^k * d^k / 2 \\ \mathrm{x}_{ild}^k &= x_{id}^k \text{-} v_{id}^k * d^k / 2 \end{aligned} \tag{5}$$

to update the beetle's left and right antennae to search for the spatial position and calculate $f(x_l)$ and $f(x_r)$ respectively.

Step 6: By using the formula

$$\xi_{\mathrm{id}}^{k+1} = \delta^k * v_{id}^k * sign(f(x_{ird}^k)\text{-}\mathrm{f}(\mathrm{x}_{\mathrm{ild}}^{\mathrm{k}})) \tag{6}$$

to calculate the search behavior increment.

Step 5: By using the formula

$$v_{id}^{k+1} = wv_{id}^k + c_1 r_1 (pbest_{id}^k \text{-} \mathrm{x}_{\mathrm{id}}^{\mathrm{k}}) + c_2 r_2 (gbest_{id}^k \text{-} \mathrm{x}_{\mathrm{id}}^{\mathrm{k}}) \tag{7}$$

and formula

$$x_{id}^{k+1} = x_{id}^k + (1\text{-}\lambda) v_{id}^{k+1} + \lambda \xi_{id}^{k+1} \tag{8}$$

to update particle speed and position.

Step 8: Iterative control. To determine whether the fitness function value of the number of iterations or the current position reaches the ideal value, if the iteration stopping condition is satisfied, the next step will be taken, otherwise the step 4 iteration parameter will continue to determine. The inertia weight w, learning factor c_1, c_2 and weight factor λ of beetle antennae search behavior increment are updated according to the formula

$$\begin{aligned} w &= (w_{\max} \text{-} w_{\min})(1\text{-}\frac{\mathrm{iter}}{\mathrm{maxgen}})^3 + w_{\min} \\ c_1 &= c_m + \frac{iter}{\max gen}(c_n \text{-} \mathrm{c_m}) \\ c_2 &= c_n + \frac{iter}{\max gen}(c_m \text{-} \mathrm{c_n}) \end{aligned} \tag{9}$$

Step9: Train the BP neural network. The optimal position of the population $\mathrm{g}best_d$ is the optimal initial weight and threshold of the BP neural network. The BP neural network uses $\mathrm{g}best_d$ as an initial parameter for training learning until the weight and threshold parameters are determined.

The workflow of the BSO-BP algorithm is shown in Figure 1.

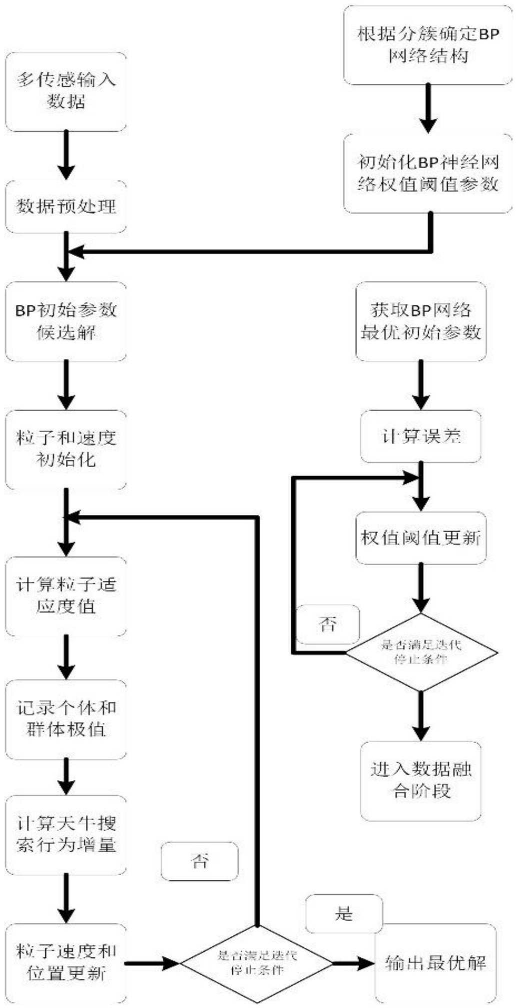

Figure 1. BSO-BP algorithm work flow chart

IV. SIMULATION VERIFICATION

In order to verify the data fusion performance of the algorithm, this patent uses forest fire area data set as the research sample [5-7]. The data set provides a number of meteorological data including temperature, humidity, wind speed, rainfall and the corresponding forest fire area data. WSN can effectively monitor small fires by collecting meteorological data, which is of great significance to forest safety. In the patent embodiment, the BP neural network model is a single hidden layer structure with 4 inputs and 1 outputs. Four meteorological data (temperature, humidity, wind speed and rainfall) monitored by sensors in the data set are selected as input layer parameters of BP and forest fire area data as output layer parameters. The number of hidden layer neurons is related to the ability of learning and information processing and the complexity of the network structure, so it is necessary to select the appropriate number of hidden layer neurons. Reference empirical formula:

$$k= \text{，} \quad a=1,2,3,\cdots,10 \tag{10}$$

The number of neurons in the hidden layer ranges from [4,12]. Table I shows the comparison of MSE values of fusion errors under different numbers of neurons. Comparing the MSE values of fusion errors with the number of neurons in different hidden layers, when the number of hidden layer neurons is set to 7, the MSE value of fusion error is the smallest. Therefore, in this patent, the single hidden layer structure of BP neural network is determined to be 4-7-1, and the number of parameters to be optimized is 4*7+7*1+1=43.

TABLE I. NUMBER OF HIDDEN LAYER NEURONS AND MSE VALUE

Number of Hidden Layer Neurons	Error MSE Value
4	0.5439
5	0.5149
6	0.4180
7	0.3598
8	0.4072
9	0.4577
10	0.5657
11	0.5814
12	0.6057

A. Fusion Accuracy

The fusion accuracy use Average Relative Error (AvRE), Root Mean Squared Error (RmSE) and Goodness of Fit (R2) as evaluation index. This patent synthetically compares the fusion accuracy of BSO-BP algorithm and BP algorithm, GA-BP algorithm and PSO-BP algorithm through experiments, Figure 2 is a comparison of the fusion results of the four algorithms, from the figure, the fusion result of BSO-BP algorithm is obviously better than that of traditional BP data fusion algorithm. The fitting degree of curve and actual value curve is better, the difference between fusion result and actual value is smaller, and the fusion result is less turbulent. Compared with GA-BP algorithm and PSO-BP algorithm, the fusion result is also greatly improved.

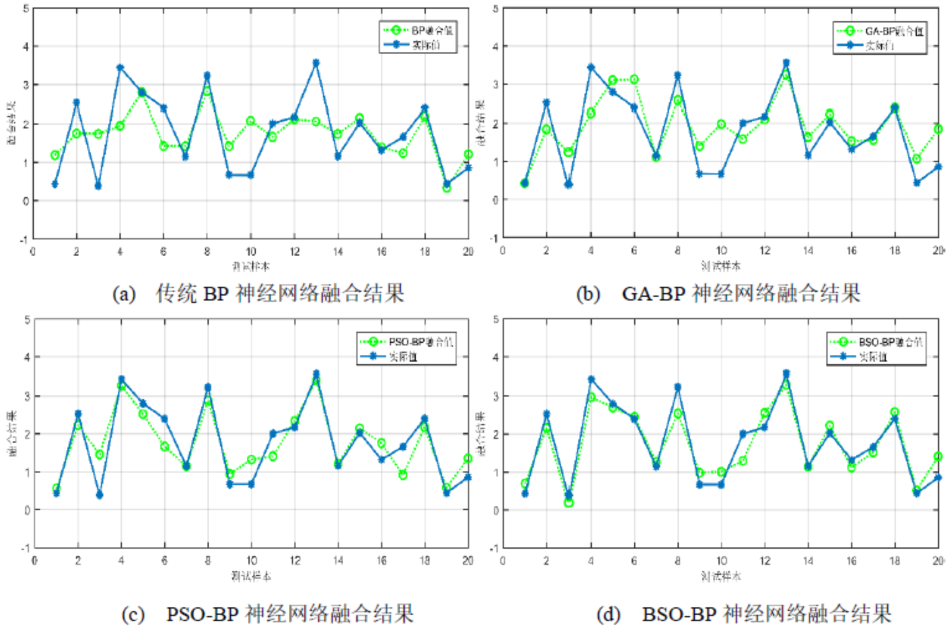

Figure 2. Comparison of the fusion results of the four algorithms

The detailed evaluation indexes of the four algorithms are compared as shown in Table II. From Table II, we can see that BSO-BP algorithm is superior to other three algorithms in average relative error, root mean square error and goodness of fit. Compared with traditional BP algorithm, the average relative error and root mean square error of BSO-BP algorithm are reduced by 12.89% and 15.79%, respectively. Compared with PSO-BP algorithm, the average relative error and root mean square error of BSO-BP algorithm are reduced by 4.11% and 5.84%. BSO-BP algorithm overcomes the shortcoming that BP neural network is easy to fall into local optimal solution, increases the diversity of population search space of particle swarm optimization algorithm, and solves the premature convergence problem of particle swarm optimization algorithm, so BSO-BP algorithm has better data fusion effect than other algorithms.

TABLE II. COMPARISON OF FUSION ERRORS

Evaluation Index	BP	GA-BP	PSO-BP	BSO-BP
$AvRE$	0.4603	0.4407	0.3725	0.3314
$RmSE$	0.5782	0.5011	0.4203	0.3619
R^2	0.7883	0.8359	0.8976	0.9176

B. Iterative Convergence Contrast

In order to test the convergence performance of BSO-BP algorithm, it is compared with GA-BP algorithm and PSO-BP algorithm by simulation. Figure 3 is the comparison result of iterative convergence optimization. It can be seen from the graph that GA-BP algorithm converges to the optimal fitness value after about 55 generations of iteration, PSO-BP algorithm converges to the global optimal solution after 46 generations, and BSO-BP algorithm converges at about the 35th iteration. Compared with GA-BP and PSO-BP algorithm, the convergence speed is faster, and can find the best fitness value. The results show that adding the beetle antennae search behavior of Longhorn whisker search algorithm to the particle characteristics of particle swarm optimization algorithm can effectively increase the search space, avoid falling into local optimum, improve the convergence speed and search performance, and effectively optimize the initial parameters of BP neural network.

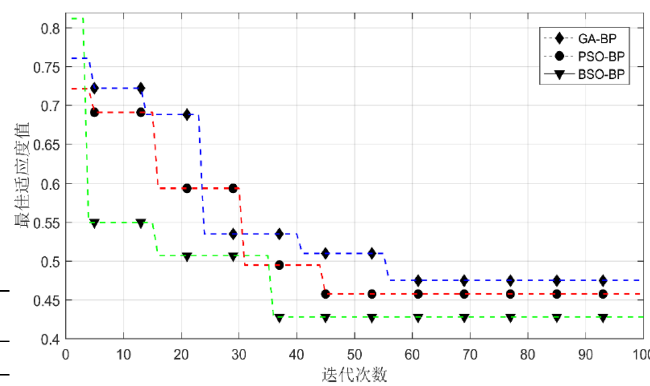

Figure 3. Iterative Convergence Comparison of Algorithms

C. Network Life Cycle

The WSN life cycle is defined as the time when coverage reaches the tolerance lower limit in the target monitoring area. When the surviving node of the network is less than 85%, the coverage rate reaches the tolerance value. At this time, the reliability of the data decreases and the energy of the sensor node needs to be supplemented. Figure 4 is the comparison result of network life cycle of each algorithm. From Figure 3, it can be seen that when the surviving node reaches the threshold of 85%, LEACH protocol network runs to about 700 rounds, BSO-BP algorithm and BP algorithm network runs to about 830 rounds, which is 18.5% longer than LEACH protocol, this is because BSO-BP algorithm and BP algorithm fuse monitoring data, reduce data transmission, reduce node energy consumption, and effectively extend the network life cycle.

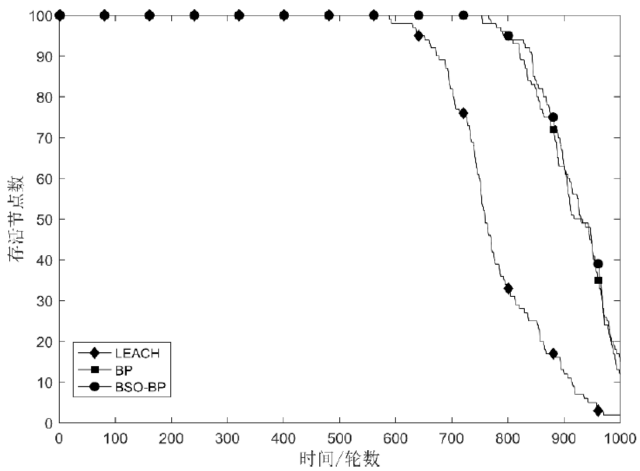

Figure 4. Number of Network Survival Nodes

V. CONCLUSION

In this paper, an improved particle swarm optimization BP neural network WSN data fusion algorithm is proposed. The particle swarm optimization algorithm is improved by Beetle Antennae Search algorithm (BAS). The improved particle swarm optimization algorithm is used to optimize the weights and thresholds of BP neural network, and WSN data fusion is introduced. The cluster head node extracts data features through optimized BP neural network, sends fused feature information to sink node, reduces redundant data transmission and prolongs network life cycle.

VI. ACKNOWLEDGEMENT

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