

Genetic Algorithm-based Fuzzy Optimization Neural Network Model for WSNs Performance Evaluation

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Abstract

In recent years, wireless sensor network is becoming the hottest research fields, which opens up a wealth of opportunities for many application domains. Comprehensive performance of WSNs is important for planning and management of a construction network. In order to deal with the deficiency of existing evaluation methods for WSNs performance, an intelligent evaluation model based on fuzzy optimization neural network model is proposed, which introduces genetic algorithm to optimize the connection weight of the neural network model to achieve approximate optimal solution. The weights are to be regarded as initial values for the next step that a neural network is tuned finely further. Fuzzy optimization model is as activation function of the neural network, therefore the model has explicit physical meanings. This model is applied to evaluate WSNs performance of some samples, and the comparative analysis with other models shows that the model improves evaluation precision and efficiency and is practical. The first part is the research status and related problems. The second part is the establishment of evaluation model. The last part is the experimental analysis and conclusion.

Keywords: *WSNs, fuzzy optimization, neural network model, Genetic algorithm*

1. Introduction

In recent years, wireless sensor network is becoming the hottest research fields concerning in the international community, involving cross multidisciplinary and highly integrated knowledge [1-2]. The wireless sensor network has very vast application prospect and potential utility value, opens up a wealth of opportunities for military management, industry and agriculture, city management, Bio Medical, environmental monitoring, emergency rescue and disaster relief, anti-terrorism, remote control of hazardous area and many other important areas [3-6]. There have been several large-scale sensor network deployments reported during the past years, including Vigil-Net for field surveillance [7], Mote lab that provides an indoor test bed [8], Sensor Scope for weather monitoring in the wild [9], and Trio which enables a large-scale solar-powered sensor network [10]. WSNs has been highly paid more attention by academic and industrial circles in many countries, and was regarded as one of the most shining technology which has the huge influence on twenty-first century.

The current research on WSNs mainly concentrated in the protocol stack development, network topology design, algorithms in each protocol layer, application prospects and other aspects[11-13]. There are few articles about performance rank in WSNs, we need a comprehensive guidance theory to evaluate the network performance of WSNs, which can be agreed by most researchers [14-15]. A number of empirical studies present network measurement results in many aspects, with emphasis on understanding the complex and non-ideal behavior of low power wireless communications[16-18]. In current researches,

according to the performance index of wireless sensor network, there is no uniform standard. There is some related research for ordinary IP nets, and two major international institutions research and analysis, set up the parameters of IP network performance, which are speed, accuracy, dependability, availability and so on[22-23]. On the one hand, WSNs performance indexes usually are separately considered [24-25], which neglects the crossover impact; on the other hand, weight is ignored [26]. At present, traditional network performance comprehensive evaluation models are regression analysis model, system analysis model, and gray theory model and so on [27-29]. However, the regression analysis model is insufficient to accurately characterize the complex connection between WSNs performance measured and expert evaluation results, human factors in the system analysis method is too heavy, grey theory model is too dependent on the evaluation experience range. Some aspects of the method in the prediction accuracy and efficiency have achieved gradual improvement, but how to make the physical meaning of the neural network model more clear, and easy to understand.

Therefore, with considering the intricate characters of WSNs in different applications, we integrate genetic algorithm and fuzzy optimization neural network (FONN) to build a full advantage WSNs performance evaluation model. In this paper, firstly, we build fuzzy optimization neural network model, which contains fuzzy optimization and neural network. Secondly, an improved fuzzy optimization neural network model based on the genetic algorithm is suggested to study the WSNs performance. Finally, we apply Open network simulation software to implement simulation experiments; the evaluation results show us that the proposed model is efficient and effective.

2. Fuzzy Optimization Neural Network Model

2.1. Fuzzy Optimization Model

Superiority and inferiority are two antithesis concepts, which have both difference and collective dimension in the two extreme points with intermediary transition. Therefore, it is called fuzzy optimization. Fuzzy optimization is carried out in the finite domain of non-dominated solution set. To a certain standard, this is relatively preferred. We assume that the system has a scheme set composing of n plans to meet the constraints, with m targets (evaluation index) on schemes for evaluation. The eigenvalue matrix is as following:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m1} & \cdots & x_{mn} \end{pmatrix} = (x_{ij}) \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n \quad (1)$$

In which x_{ij} is the eigenvalue of i th index in j th WSNs. There are two kinds of target eigenvalue, one type in which the bigger of the value the better, the other type in which the smaller of the value the better. The formulation of the former can be represented as follows:

$$r_{ij} = \begin{cases} 1; & x_{i \max} \\ x_{ij} / x_{i \max}; & \text{others} \\ 0; & 0 \end{cases} \quad (2)$$

And the formulation of the latter can be represented as follows:

$$r_{ij} = \begin{cases} 1; & x_{i \min} \\ x_{i \min} / x_{ij}; & \text{others} \end{cases} \quad (3)$$

Then we can transfer the eigenvalue matrix X into R

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{m1} & r_{m1} & \cdots & r_{mn} \end{pmatrix} = (r_{ij}) \quad (4)$$

According to the relative membership degree defined, inferior and superior are respectively in two little reference pole, and the objective vector of the inferior and superior schemes are respectively:

$$b = (0 \quad 0 \quad \cdots \quad 0) \quad (5)$$

$$g = (1 \quad 1 \quad \cdots \quad 1) \quad (6)$$

The weight matrix of i th index in j th WSNs is as following:

$$W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & r_{22} & \cdots & w_{2n} \\ \vdots & \vdots & & \vdots \\ w_{m1} & w_{m1} & \cdots & w_{mn} \end{pmatrix} = (w_{ij}) \quad (7)$$

In which w_{ij} is the weight of i th index in j th plan, given a random WSNs, $\sum_{i=1}^m w_{ij} = 1$.

However, the distance between j th WSNs and the superior or inferior schemes is:

$$d_{jg} = \sum_{i=1}^m w_{ij} (1 - r_{ij}) = 1 - \sum_{i=1}^m w_{ij} r_{ij} \quad (8)$$

$$d_{jb} = \sum_{i=1}^m w_{ij} (r_{ij} - 0) = \sum_{i=1}^m w_{ij} r_{ij} \quad (9)$$

Assume that relative membership degree of j th WSNs comparing to the superior and inferior schemes is u_j and u_j^c , and $u_j^c = 1 - u_j$. Defining membership degree as weight, we get the weight distance:

$$D_{jg} = u_j d_{jg}, \quad D_{jb} = u_j^c d_{jb} = (1 - u_j) d_{jb} \quad (10)$$

In order to solve the optimal value of relative membership degree of j th WSNs, minimize the square sum of weight distance away from the superior and inferior schemes, and the objective function is:

$$\min F(u_j) = D_{jb}^2 + D_{jg}^2 = u_j^2 \left(1 - \sum_{i=1}^m w_{ij} r_{ij} \right)^2 + (1 - u_j)^2 \left(\sum_{i=1}^m w_{ij} r_{ij} \right)^2 \quad (11)$$

If $d F(u_j) / u_j = 0$, we obtain the fuzzy optimization model:

$$u_j = \frac{1}{1 + \frac{1 - \sum_{i=1}^m w_{ij} r_{ij}}{\sum_{i=1}^m w_{ij} r_{ij}}} = \frac{1}{1 + \left(\frac{d_{jg}}{d_{jb}}\right)^2} \frac{1}{1 + \left(\frac{1 - d_{jb}}{d_{jb}}\right)^2} \quad (12)$$

The physical meaning is that the relative membership degree of j th WSNs $u_j > 0.5$, if $d_{jg} > d_{jb}$; if $d_{jg} < d_{jb}$, $u_j = 0.5$; and if $d_{jg} = 0$, the j th WSNs is the best scheme, $u_j = 1$; if $d_{jg} = 1$, then $u_j = 0$. Therefore, we can use fuzzy optimization model to describe the incentive function in neuron network system, make the incentive function of node neurons have distinct physical meaning, and optimization is the essence of the human brain.

2.2. Neural Network Model

In a given neuron network, the number of nodes in input layer nodes is m , hidden layer node is l , output layer nodes is g . To facilitate the representation, we take i as input layer node, k as hidden layer node, p as output layer node in Figure 1.

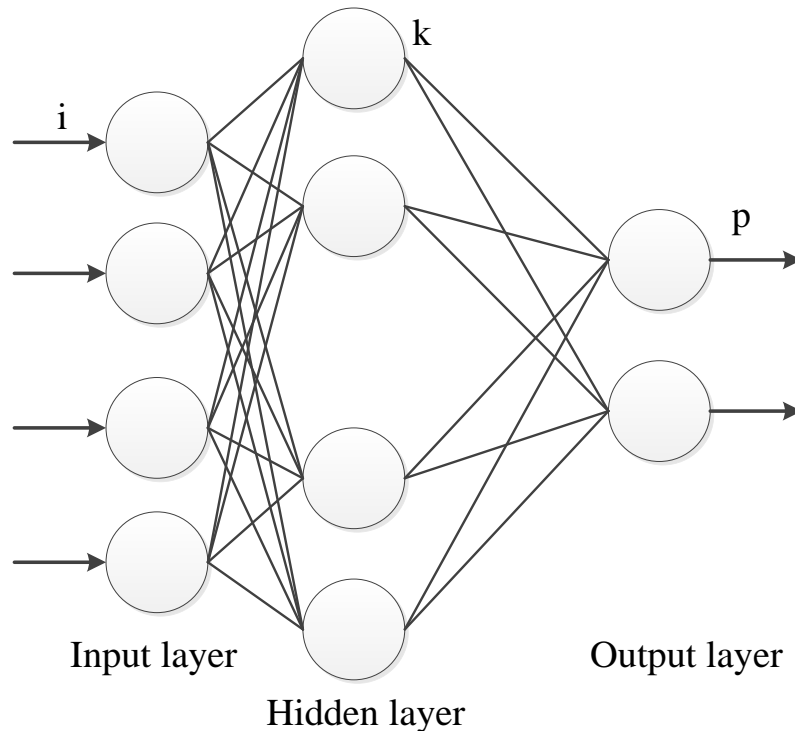


Figure 1. Neural Network Framework

There are m samples, the input value of i th sample is r_{ij} , $i = 1, 2, \dots, m$ $j = 1, 2, \dots, n$. Node i in input layer deliveries information to node k in hidden layer directly, and input value is equal to output value, $u_{ij} = r_{ij}$.

According to node k in hidden layer, the input value is $I_{kj} = \sum_{i=1}^m w_{ik} r_{ij}$, and its output value is:

$$u_{kj} = \frac{1}{1 + \left[\left(\sum_{i=1}^m w_{ik} r_{ij} \right)^{-1} - 1 \right]^2} = \frac{1}{1 + (I_{kj}^{-1} - 1)^2} \quad (13)$$

In the formula, w_{ik} is connection weight between node i and k .

According to node p in output layer, the input value is $r_{pj} = \sum_{k=1}^m w_{kp} r_{kj}$. And its output value is:

$$u_{pj} = \frac{1}{1 + \left[\left(\sum_{k=1}^m w_{kp} r_{kj} \right)^{-1} - 1 \right]^2} = \frac{1}{1 + (I_{pj}^{-1} - 1)^2} \quad (14)$$

In the formula, w_{ik} is connection weight between hidden layer and output layer.

The actual output value u_{pj} is responsive to input r_{ij} in fuzzy optimal selection of neural network. Assuming that the expected output value of the j th sample is $M(u_{pj})$, we can calculate the square error as follows:

$$E = \frac{1}{n} \sum_{j=1}^n E_j = \frac{1}{2n} \sum_{j=1}^n \sum_{p=1}^g (u_{pj} - M(u_{pj}))^2 \quad (15)$$

Then, the connection weight between nodes of the hidden layer and the output layer node is adjustment:

$$\Delta w_{kp} = \frac{2\eta}{n} \sum_{j=1}^n u_{pj}^2 u_{kj} \left[\frac{1 - \sum_{k=1}^m w_{kp} u_{kj}}{\left(\sum_{k=1}^m w_{kp} u_{kj} \right)^3} \right] \times \sum_{p=1}^g (M(u_{pj}) - u_{pj}) \quad (16)$$

In the formula, η is learning coefficient. The connection weight between the input layer nodes and the hidden layer nodes is also an adjustment:

$$\Delta w_{ik} = \frac{2\eta}{n} \sum_{j=1}^n r_{ij} w_{kp} u_{kj}^2 \left[\frac{1 - \sum_{k=1}^m w_{kp} u_{kj}}{\left(\sum_{k=1}^m w_{kp} u_{kj} \right)^3} \right] \times \delta_{pj} \quad (17)$$

The weight adjustment formula is as follow:

$$w_{ik}(t+1) = w_{ik}(t) + \Delta w_{ik}(t+1) + \alpha \Delta w_{ik}(t) \quad (18)$$

$$w_{kp}(t+1) = w_{kp}(t) + \Delta w_{kp}(t+1) + \alpha \Delta w_{kp}(t) \quad (19)$$

In which α is momentum coefficient, $0 < \alpha < 1$.

Using the model referred to above, we can determine the network connection weights, according to the training algorithm of neural network, and make the error between the actual output and the expected output error minimized.

3. Improved Fuzzy Optimization Neural Network Model based on Genetic Algorithm

The neural network model is easy to appear provincial minimum, and has the disadvantage of slow convergence rate. Therefore we integrate genetic algorithm which gets the

characteristic of global search and efficiency, with fuzzy optimization neural network algorithm together.

3.1. To Determine the Encoding Method

Floating point encoding method has lots of advantages, such as larger range of representation, high precision, large search space, and is easy to mix with other methods. Due to computational precision, efficiency and convenience, we build our model using floating point decoding method, which resolves our problem of encoding selection.

3.2. The Population Initialization

In the premise of guaranteeing the neural network sensitivity, the net input of each node is near to zero. In order to create more feasible solutions when we optimize FONN weight values using GA, we set the range of the initial population weights [2, -2].

3.3. Fitness calculation and set other parameters of GA

GA fitness is very good characterization of individual chromosomes, the larger the fitness is, the better the performance of chromosomes. We apply $f(E) = 1 / (1 + 10 \times E)$ as fitness function in the model, after FONN training 25 times and the output error is E which is the average relative error between the actual output and the expert scoring. Setting population size at 35, terminating conditions are $E \leq \varepsilon_1$ or to obtain the maximum number of iterations as 15. We employ selection operation by the roulette wheel method and crossover operation in uniform arithmetic crossover. The crossover probability is 0.6, and the mutation probability is 0.05.

3.4 The process of evaluation model

In this paper, we apply the Delphi program to realize the evaluation process, the concrete steps as showed in Figure 2.

(1) Firstly, determine the encoding method, terminating conditions, fitness function, other parameters of GA, initialization population size;

(2) Decoding to the solution space, after training 25 times, the output error is E , then we calculate the individual chromosome fitness $f(E) = 1 / (1 + 10 \times E)$;

(3) Judge whether to meet the termination conditions of genetic algorithm ($E \leq \varepsilon_1$ or to obtain the maximum number of iterations as 15), if to meet, then turn into (5), otherwise we continue step by step;

(4) Genetic operation such as selection operation, crossover operation and mutation operation, generate new population and turn to (2);

(5) Using BP network, we make slight adjustment of the approximate optimal solutions which is obtained by GA search, improve the accuracy of solutions until it reaches termination conditions, and then output results.

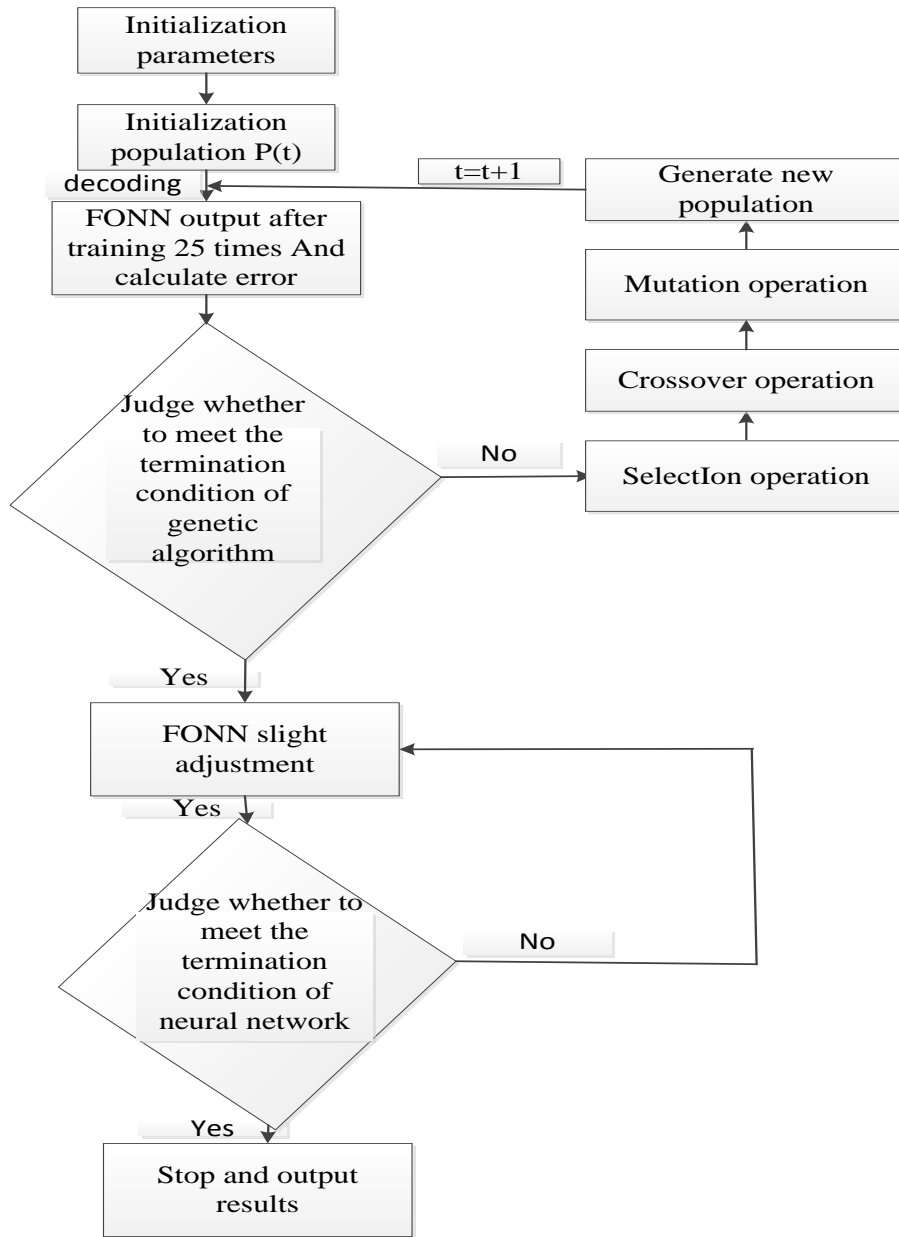


Figure 2. The Process of WSNs Performance Evaluation Model

4. A Numerical Example

To demonstrate the use of the singular metrics for wireless sensor network reliability and to explore the relationships between these metrics, a series of tests were conducted with a single radio transmitting to a receiver. Since many applications will require low data-rate communications, hardware was selected that conformed to the IEEE 802.15.4 standard for low-rate wireless personal area networks (2.4 GHz bands). In this paper, the performance evaluation of wireless sensor network is based on ZigBee technology, using network simulation software OPNET to build separate networks. Based on the simulated measurement, we collect network performance data, and evaluate the comprehensive performance of WSNs.

4.1. Select the Input and Output Parameters

Network performance reflects the quality of the network to provide communications services, is the embodiment of the characteristics of the network itself, can be composed of a series of index definitions and description. The three most commonly used indicators of network performance in networks are bandwidth, delay and packet loss rate. We select time delay, packet loss rate, and throughput as the model input parameters, and expert scoring as model output parameter.

4.1. Input and Output Data Preprocessing

We utilize the Sigmoid distribution transformation method to normalization process the input data in improved fuzzy optimization neural network model. In this paper, the Sigmoid distribution transformation formula is:

$$y_i = \frac{1}{1 + b e^{-ax_i}} \quad (20)$$

In the formula x_i is the initial value of evaluation index, y_i is the value of evaluation index after distribution transform, a, b is undetermined parameters, as show in Table 1.

Table 1. Parameters for Transformation WSNs Performance Evaluation Indices

Index	The original index optimal		The original index inferior		undetermined parameters	
	x_i	y_i	x_i	y_i	a	b
time delay	0.007453	0.75	0.092256	0.4	-0.156	0.054
packet loss rate	0.002754	0.75	0.066176	0.4	1.254	0.653
throughput	43753.45	0.75	24638.91	0.4	0.842	10.245

4.3 Analysis of the results

The generalization ability of the model is a very important aspect of our scientific evaluation model. For testing the generalization ability, we build the rank model using the 25 data sets collected by simulation, and divide it into 5 groups respectively, 4 groups as the training samples and the rest as testing samples(as shown in Table 2); In order to verify the stability, we carry out 5 times of consecutive training for each model; To test the effectiveness of the evaluation model, we compare results with other methods, such as regression analysis, BP neural network model and genetic neural network models.

Table 2. Statistical Table of Subjective Scores and Practica1data of WSNs

Number of WSNs	scores	time delay	packet loss rate	throughput
1	3.12	0.010150	0.013690	38095.49
2	4.25	0.070866	0.002560	29374.13
3	5.36	0.092256	0.001167	28449.55
4	5.02	0.011366	0.066176	43753.45

5	4.32	0.007456	0.002754	28027.18
6	3.62	0.008310	0.002895	28027.18
7	4.01	0.082839	0.002895	46038.35
8	2.98	0.008356	0.012486	40385.54
9	4.23	0.010455	0.003874	35548.68
10	5.16	0.007234	0.042158	35678.47

The training results of evaluation model is shown in Table 3, and terminating conditions of GA is $E \leq 0.04$, terminating conditions of neural network is $E \leq 0.02$, C_1 , C_2 , C_3 are correlation coefficient between the data of training samples, testing samples, expert scores and regression predict data. We can see clearly that the correlation coefficient achieve 0.95 above, absolute error basically is under 0.1. With the continuous training, the model often converges to the same value point.

Table 3. Training Results of Evaluation Model

Training sequence	Training times	Error	C_1	C_2	C_3
1	1954	0.06	0.972	0.941	0.968
2	1854	0.07	0.969	0.936	0.962
3	2000	0.08	0.975	0.946	0.958
4	2000	0.06	0.980	0.953	0.972
5	1689	0.05	0.973	0.924	0.963

As showed in Table 4, compared with GANN model, population size of is 50, iteration for more than 1200 generations to obtain ideal solution; and the population size of our model is 40, only 15 iterations to get the ideal solution.

Table 4. Comparison Between Evaluation Model and GANN Model

Model	Our model	GANN
Population size	40	50
Number of iterations	15	1205
Times of slight adjustment	<200	No
Correlation coefficient	>0.95	>0.92

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5. Conclusion

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research on WSNs mainly concentrated in the protocol stack development, network topology design, algorithms in each protocol layer, application prospects and other aspects. There are few articles about performance rank in WSNs. We need a comprehensive guidance theory to evaluate network performance of WSNs. In this paper, firstly, we build fuzzy optimization neural network model, which contains fuzzy optimization and the neural network. Secondly, an improved fuzzy optimization neural network model based on genetic algorithm is suggested to study the WSNs performance. Finally, we apply Open network simulation software to implement simulation experiments; the evaluation results show us that the proposed model is efficient and effective.

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