Evolutionary Algorithms for the Complex Network Based on Granular Neural Network

Yongqin Tao[1]

[1]College of Engineering, Xi'an International University

Xi'an, China

*[1]tyq_123@126.com

***Abstract-* To deal with the evolutionary of complex network, a new evolutionary method using granular neural network (GNN) is proposed based on Yin Yang methodology. The theory of the granular quotient space is introduced to the neural network. At first input variables of the neural network are granulated to equivalence classes, so that the input variables of the network structure can be simplified and have certain clustering characteristics and strong diversity. And then the network parameters and the weights are optimized using evolutionary algorithms. Not only can the algorithm converge to globally optimal solution, but also it solves premature convergence problem efficiently. The simulation results show that the algorithm effectively narrows the search space and accelerates the speed of convergence.**

Keywords- Complex Network; Granular Computing; Genetic Algorithm; Neural Network

I. INTRODUCTION

With the rapid development of computer technology and network theory, complex networks are an active area of scientific research, which have been extensively studied in many fields. Complex networks exist widely in nature, biology, engineering and human society Examples include Internet, social network, traffic network[1]. Further research on evolution of complex networks can reveal the community law and properties hidden in the network, which reveals the general law of macroscopic characteristics of complex networks[2].It is of great significance to adjust the dynamical behaviours of complex networks. For that reason, the paper has studied the characteristics of genetic algorithms, granular computing and neural network and has proposed GNN algorithms to deal with evolutionary problem of the complex network. Artificial neural network is a simulation of neural system of biology. It is a paralleled information processing system made up of many nonlinear units which are connected tightly with each other[3]. GNN algorithms uses a hierarchical granular quotient space to process data of the neural network and to improve network comstructure . For improving the network performance, the genetic algorithms is used to optimize the network weights and threshold. The experimental results show that the method makes the network more scientific, reasonable, economical and easy to operate and is effective and feasible.

The rest of this paper is organized as follows. Section II introduces the basic concept and principle of the granular neural network. Section III presents the concept and the measure mode of the complex network. Section IV shows the model design of granular evolutionary neural network algorithms. Section V describes simulations and discussion. Section VI gives a brief conclusion.

II. THE BASIC CONCEPT AND PRINCIPLE OF THE GRANULAR NURAL NETWORK

A. Topology Structure of Granular Computing

Definition 1: If each granule is regarded as abstract point, the set between granule and granule are regarded as the relationship between point and point [4]. This granular structure G (E) is called the quotient space. The semi-group set is generated by the following rules:

If $E(q)=E(p)$, $E(q)\bigcap E(p)=E(p)$,

Otherwise,

$$E(q)\bigcap E(p)=\phi$$

B. The Granulating of the Domain Attribute

It is known that the knowledge expression system can only be expressed by the limited attribute. This explains that humanity's knowledge is limited. Therefore, if we want to process the knowledge of the domain effectively, we must carry on the granulating to the domain attribute. However, the literature pointed out that the attribute granulating is not random. It will enormously affect the validity of the solution question. The following Figure 1 is the relation chart of validity and complexity

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about attribute granulating.

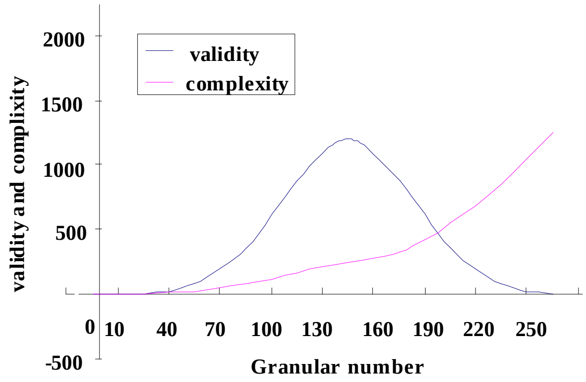

Fig. 1 The relation chart of the validity and complexity about granulating

From the above Fig. 1 it can be shown that along with the attributer granulating increase, when the validity of attribute increases continuously until some value, it will start to drop slowly. This explains that when we granulate attribute, we need to choose an appropriate granularity value. Only doing these can the validity of attribute be best. This paper adopts the binary bit granulating matrix to carry on the attribute granulating below. The experiment has proved that it is effective and feasible

C. The Expression of Granular Structure

Definition 2: Each granular with knowledge r is defined by a binary string with length l [5]. The corresponding ith position in the string is 1 if $u_i \in [X]_{IND(r)}$, otherwise, it is 0. 1 is the cardinal number of the universe U. Suppose there are l elements: u_1, u_2, …, u_k, …, u_l,(1≤k≤l) in universe U, the coding space is then defined as a mapping function from integer domain to binary space: $f: Z^+ \to \{0,1\}^l$, and binary strings of granular Y_i, and X_j, (1≤i≤m), (1≤j≤n)can be respectively expressed a*s*

$$Y_i = \{a_{i1}, a_{i2}, ..., a_{ik}, ..., a_{il}\} \tag{1}$$

$$a_{ik} = \begin{cases} 1 & u_k \in Y_i \\ 0 & u_k \notin Y_i \end{cases} \qquad 1 \le k \le l \tag{2}$$

$$X_j = \{b_{j1}, b_{j2}, ..., b_{jk}, ..., b_{jl}\} \tag{3}$$

$$b_{jk} = \begin{cases} 1 & u_k \in Y_i \\ 0 & u_k \notin Y_i \end{cases} \qquad 1 \le k \le l \tag{4}$$

Definition 3: The attribute granulating of decision system, namely, bit granular matrix is defined as follows: Every attribute granulation Y_i and X_i carries on binary coding [5]. Where U|IND（C）=Y，U|IND(D)=X. If the binary granular matrix expresses X, Y. Y, X will be as follows:

$$Y_{m\times l} \triangleq \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_m \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1l} \\ a_{21} & a_{22} & \dots & a_{2l} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \dots & a_{ml} \end{bmatrix} \tag{5}$$

$$X_{n\times l} \triangleq \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1l} \\ b_{21} & b_{22} & \dots & b_{2l} \\ \vdots & \vdots & & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nl} \end{bmatrix} \tag{6}$$

$$C_{m\times n} = C_{YX} \triangleq Y \times X' \tag{7}$$

$$C_{ij} = \sum_{k=1}^{l} (a_{ik} b_{kj}) \qquad i = 1, 2, ..., m \quad j = 1, 2, ..., n \tag{8}$$

The $\mathrm{C_{ij}}$ clearly shows the subordinative relation between Y_i and X_j, and its value represents the element number that Y_i includes X_j.

NE (i) reveals the element number of not zero in $\mathrm{C_i}$, and $\mathrm{C_i}$ is the element of ith row in matrix $\mathrm{C_{m\times n}}$.

When NE(i)=1 and $\mathrm{C_{ij}} \neq 0$, $\mathrm{Y_i} \subseteq \mathrm{X_j}$.When $\mathrm{C_{ij}} \neq 0$ $\mathrm{Y_i} \cap \mathrm{X_j} \neq \varnothing$

$$\mathrm{R\_X}=\{\bigcup \mathrm{Y_i} \mid \mathrm{NE(i)}=1\}$$

$$\mathrm{cardR\_X}=\sum_{\mathrm{NE(i)=1}} \mathrm{C_{ij}}$$

$$\mathrm{R^{-}X}=\{\bigcup \mathrm{Y_i} \mid \mathrm{C_{ij}} \neq 0\}$$

$$\mathrm{cardR^{-}X}=\sum \mathrm{C_{ij}}$$

D. Mathematical Model of Quotient Fuzzy Cognitive Map

Definition 4: Mathematical model of quotient fuzzy cognitive map: supposing $U=(V,E,W)$ is a FCM[6]. $\mathrm{V}_D=\{V_1,V_2,...,V_m\}$ is the partition of node sets in the D subsystem{ V_D , E_{D} , W_D }. $FCM \bigcup D=\{V_D,E_D,W_D\}$ is a quotient FCM of U. $E_D=\{<v_i,v_j> \mid v_i \in V_i, i \neq j, <v_i,v_j> \in E\}$ shows the directed arc of causal association between nodes. $W_{D_{ij}}$ shows that the node V_i is associated with or affected by the degree. If $W_{D_{ij}}$ >0, it expressed to have a positive effect. Namely, the increase (decrease) of V_i state values will cause the state value increase (decrease) of the V_j state value, conversely will have the negative influence. If $W_{D_{ij}}$ =0, it will not have influence to V_j .

Among them, $V_{DV_i}(t)$ and $W_{DV_{ij}}$ take the arithmetic mean value:

$$V_{DV_i}(t)=(\sum\nolimits_{v_{ik\in V_i}} v_{ik}(t))/|V_i| \tag{9}$$

$$W_{D_{ij}}(t)=(\sum\nolimits_{(v_i,v_j)\in E_D} w_{ij})/|E_D| \tag{10}$$

Fig. 2 is a weight matrix of $n\times n$ weight relationship. Fig 3 is a simple FCM.

$$\mathrm{W}=\begin{array}{c} \begin{array}{cccc} V_1 & V_2 & \cdots & V_n \end{array} \\ \left[\begin{array}{cccc} 0 & W_{12} & \cdots & W_{1n} \\ W_{21} & 0 & \cdots & W_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ W_{(n-1)1} & \cdots & 0 & W_{(n-1)n} \\ W_{n1} & \cdots & W_{n(n-1)} & W_{nn} \end{array}\right] \begin{array}{c} V_1 \\ V_2 \\ \vdots \\ V_{(n-1)} \\ V_n \end{array} \end{array}$$

Fig. 2 The border and power matrix of FCM

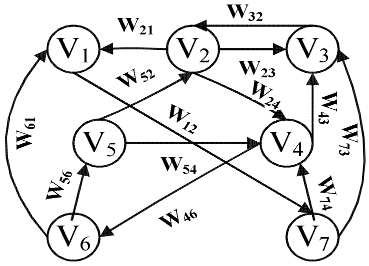

Fig. 3 A simple FCM

E. ANN and Hybrid Algorithm

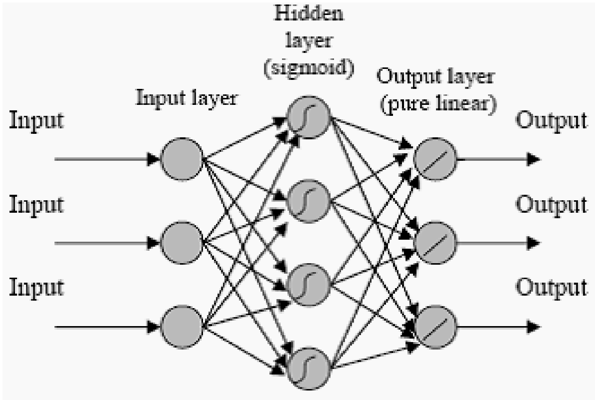

Fig. 4 ANN architecture

Artificial Neural Networks (ANN) is a computational structure, consisting of highly interconnected processing units called neurons [7]. The architecture network is multilayered (Fig.4), consisting of three layers that can complete the approximation tasks of any non-linear function. The transfer functions in the hidden and output layers are tan-sigmoid and pure-linear, respectively. Stopping criteria for ANN is to check the effective number of parameters. If this value reaches the total number of network parameters, the number of neurons in the hidden layer should be increased, to avoid under-fitting the networks. The second check is to estimate the consistency of evolutionary weight or setting up a target for evolutionary parameters

F. The Granular Neural Network

A new granular neural network (GNN) with a new high-speed evolutionary learning is designed to solve the efficiency problem, Such as granular data, granular information, granular knowledge and granular decisions[8]. Granules may be a class of numbers, a cluster of images, a set of concepts, a group of decisions, a category of information, etc. These granules are inputs and outputs as the attribute data are inputs and outputs of biological neural networks in the human brain.

A basic architecture of a granular neural network consists of granular neurons with intelligent functions such as a nonlinear mapping function and a fuzzy mapping function. These granular neurons are connected via links to perform special functionality. Learning algorithms is used to optimize a granular neural network with supervised learning functionality.self-organized granular neural network do not need supervised learning.

III. THE CONCEPT AND MEASURE METHOD OF THE COMPLEX NETWORK

A. The Concept of the Complex Network

Complex networks are composed of many nodes and edges of a connection between two nodes. The node is used to represent the individual real systems, and the edge is used to express the relationship between individuals. If the individuals have certain relationship between two nodes which are connected to an edge, the reverse is not even. Two nodes side connected in a network are regarded as the adjacent, so as to form a complex network. The complexity of the complex network is reflected in three aspects [8]: 1) node complexity: the nodes in the network may be dynamical systems with bifurcation and chaos of nonlinear behavior. 2) the structural complexity: the structure of network connection is the intricate and complex, contains the massive node. 3) various complicated factors affecting each other: real complex network can be affected by a variety of factors and effects, are also closely linked between various networks, which makes the analysis of complex networks become more difficult. Dynamical behaviors of complex networks usually rely on its topological structure, can be understood as the external manifestation of the intrinsic nature, because complex network has a scale-free properties. It is important to study scale-free properties of complex network for the transmission of the knowledge, information and virus. The scale-free properties are: 1) complex network leads to only a small number of nodes connected edges; 2) a handful of Hub nodes are connected with the number of edges in a complex network, very few Hub nodes compose the communications center of complex network, therefore, the efficiency of the complex network of information dissemination is very high, and the cost of the repair is low; 3) the negative effect of the complex network for the dissemination of information is that the spread of the virus cannot resist, as long as there is virus of nodes. The nodes could be close to Hub nodes quickly and result in the spread in a large area. Therefore, in the evolution of complex network we should control and take advantage of the Hub nodes.

B. The Measure Method of the Complex Network

Rule 1: Abstract the solid elements into nodes, the relationship between elements into sides, regardless of individual differences and the size of the side weights[9].

Rule 2: As long as there is information flow between any two nodes, connect the two nodes with undirected edge. In complex network model, nodes are defined as elements such as sensors, deciders, influencers, targets, human society, and edges are defined as relationship or exchange of material, energy and information, attack, detection, and so on[9].

The relations between nodes are more evident in a different type of network representation, the adjacency matrix, shown in Equation (1). M is an N*N matrix, N is the number of network nodes. If there is a link between node i and node j, $M_{ij}=1$, otherwise $M_{ij}=0$.

$$M=\begin{bmatrix}0&1&1&0\\1&0&0&0\\1&0&1&1\\0&1&1&0\end{bmatrix}$$

1) Degree Distribution:

In complex networks, the degree *k* of node *i* is defined as the number of other nodes connected to the node. Generally, the degree is much greater, the node in the network is more important. In the network the average value of degree about all nodes is called the average degree of the network. It is expressed as $<k>$[9]:

$$<k>=\sum_{k=0}^{\infty}kP(k) \tag{11}$$

The degree distribution of the nodes indicates that the node whose degree is k appears the probability in the network. It can be expressed by a random variable k and the distribution function P(k), this distribution function shows exactly random probability of occurrence of the node with the degree k, the degree distribution is an important parameter to describe the topological characteristics of the network. In order to better show the node degree distribution characteristics, sometimes it is also represented by the cumulative distribution function. That is

$$P(k)=\sum_{k'=k}^{\infty}P(k') \tag{12}$$

The meaning of the nodes in the network is greater than the probability of k, using the cumulative distribution function to represent the distribution of frequency or probability, can keep the effect of single point mutations phenomenon and weaken the noise.

2) *Betweenness Number Distribution:*

Assuming the number of the shortest path is $B(i,j)$ between nodes v_i and v_j, $B(i,m,j)$ is the number of shortest path through the node m. Wherein, the ratio $B(i,m,j)/B(i,j)$ represents the importance of the node m which connects v_i and v_j. If there is no shortest path through the node m, the contribution of node m is 0 to connect v_i and v_j. If there is all the shortest path through the m, the role of the node m is very large, it controls the shortest path between v_i and v_j, and the number of the betweenness distribution of the node m is defined as follows:

$$\sigma(m)=\sum_{i\neq j}\frac{B(i,m,j)}{B(i,j)} \tag{13}$$

Where the summation operation is the summation of all the different nodes. Of course, this node must have at least one shortest path, which is required to $B(i,j)>0$ .The same method can also define the betweenness number of the side. The side number of the shortest path in the network is defined by the edge betweenness number.

3) Average Path Length:

The distance between two nodes v_i and v_j in the network is d_{ij}. It is defined as the number of edges of the shortest path which connects these two nodes. The average path length of network L is defined as the mean length of the shortest paths between all pairs of nodes, that is

$$D=\max d_{ij}$$

The average path length of network is known as the characteristic path length of network.that is

$$L = \frac{2}{N(N+1)} \sum_{i \geq j} d_{ij} \tag{14}$$

In the above equation, N is the number of network nodes.

4) Clustering Coefficient:

Clustering coefficient *C* is used to describe how close the network is. Suppose there is a node i in the network and it has n_i edges which connect it to other nodes, here these n_i nodes are called neighbors of node j Clearly, the maximum number of edges between n_i nodes is n_i （n_i-1）/2, actually the number of edges between n_i nodes is E_i. Clustering coefficient of node i is defined as following:

$$C_i = \frac{2E}{n_i(n_i - 1)} \tag{15}$$

If the clustering coefficient of a node is greater, it proves that there are many edges connected to the node in complex network. The clustering coefficient of the entire network C is the average clustering coefficient of all nodes. If C is greater, it has better capacity of coordination between the various operational units when completing a combat mission.

5) Topology Potential:

This paper makes the describing e method of interaction between material granular and field be introduced to the network topology and has proposed the topology potential index of power. It has studied the basic rules that the nodes effect in the network model with hops nonlinear attenuation, found the influence the rapid attenuation with the network node distance growth and meet with the short-range force field. The formula of the network topology potential is as follows:

$$\phi(v_i) = \sum_{i=1}^{n} m_j \times e^{-(\frac{d_{ij}}{\sigma})^2} \tag{16}$$

Among them, n is the number of nodes, m represents a quality function of node v_i .For the network topology and network G=(V,E) given, if the potential value of the nodes are $v_1, v_2, \ldots v_i$,the potential entropy is defined as:

$$H = -\sum_{i=1}^{n} \frac{\phi(v_i)}{Z} \log(\frac{\phi(v_i)}{Z})$$
$$Z = \sum_{i=1}^{n} \phi(v_i) \tag{17}$$

Z is a normalization factor. It can get Fig.3 curve of the relation.

When $\sigma \to 0$,he topology potential will approach to maximum entropy $\log(10) \approx 2.3025$. With σ value increases, entropy decreases and reaches a minimum value $H_{\min} = 2.267$ at a certain optimization σ. Then it increased gradually, when the σ is greater than the diameter 5 of network, once again it approaches the maximum value. Through the influence factor is optimized, the shannon entropy of the topology potential approaches minimum. If further adjusting factor σ and making the potential entropy of all node topology is minimum, by getting optimal values of the factor, so as to obtain the most reasonable topology distribution.

IV. THE MODEL DESIGN OF GRANULAR EVOLUTIONARY NEURAL NETWORK ALGORITHMS

A. The Theory of Quotient Space

Quotient space theory expresses the properties of the domain, properties structure in different granularity, and shows the nature of interdependence, mutual conversion relationship. The theory of quotient space uses three elements (X, F, T) to describe the problem, where X represents the universe of the problem; f indicates the attributes of the universe; T said that the structure of the universe. The structure is one of the main attributes of the object.

B. Genetic Algorithm (GA)

GA is presented with some main factors and considered as an optimizer.

1)Evolutionary Coding

Using evolutionary algorithm to resolve the evolutionary issues of the complex network, we must first solve the problem of attribute coding. After considering the actual features of the complex network, we adopt the binary bit matrix code forms based on [0, 1] symbol set in according to Definitions 1, 3.

2) The Fitness Function

The evolutionary algorithm is a method about searching minimum *of the fitness function. The fitness function is the only* certainty criterion to evaluate the fitness of the individual bit strings. Its form directly decides colony evolutionary action. For the complex network the paper adopts the potential entropy as fitness function（Formula 17）

$$F(x) = -\sum_{i=1}^{n} \frac{\varphi(x_i)}{Z} \log(\frac{\varphi(x_i)}{Z})$$

3) Reproduction:

This refers to two individuals being selected as parents, based on the fitness function in the current population, for the next generation. It plays a very important role in the GA. A roulette wheel selection scheme is used in this paper. The probability of selection P_i is calculated as $P_i = \frac{F_i}{\sum_{k=1}^{M} F_k}$, where, F_i is the fitness function and N_p is the population size.

4) Crossover and Mutation Are Genetic Operators

Crossover is the process of combining or mixing two different individuals in the population. The crossover operator includes the heuristic crossover, scattered crossover and the arithmetic crossover. The heuristic crossover is used in this paper. The mutation operator selects a few members of the population, determining a location on each string randomly, and switching 0 to 1.

This paper adopts uniform crossover. Two partnership individual processes crossover at the same crossover probability Pc, thus forms two new individuals. For example:

A:xxxxxxxxxx uniform crossover A':xyxyxyxyxy

B:yyyyyyyyyy W=0101010101 B':yxyxyxyxyx

5) Stopping Criteria:

This involves setting up the fitness function tolerance ε. If there is no improvement in the fitness function, the GA procedure will terminate.

C. The Evolutionary Follow Chart of the Complex Network About the GNN Algorithms

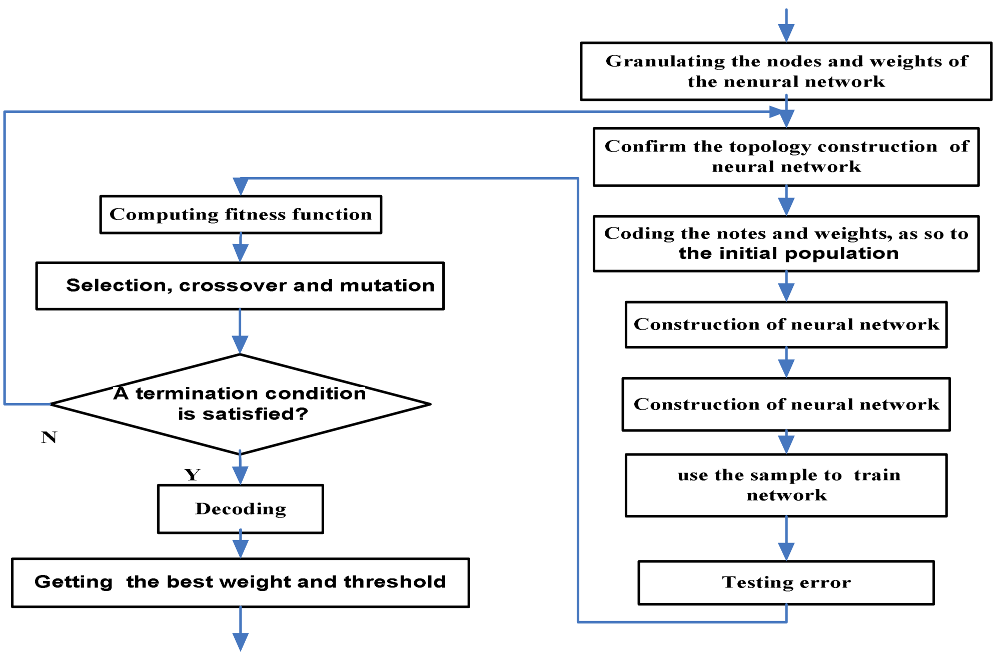

Fig. 5 The evolutionary follow chart of the complex network about GNN algorithms

Genetic algorithm for optimization of neural network is mainly divided into: determining the structure of the neural network, optimizing the right value and the node with genetic algorithm, training and testing the neural network, in which the topological structure of neural network can determine the number of input parameters according to the grain of equivalence class, so that you can determine the number of parameter optimization by genetic algorithm, thus determining population individuals code length. Because genetic algorithm optimization parameters are the initial weights and thresholds of the neural network, as long as the network structure is known. It can introduce genetic algorithm to obtain the optimal initial weights and thresholds. The evolutionary follow chart of the complex network about GNN algorithms is shown in Fig5.

V. SIMULATIONS AND DISCUSSION

In order to evaluate the performance of GN- alogrithms about complex network, a simulator has been developed on windows 7 matlab2009a. As graph instances, two types of random graphs are generated, where each weight E_{ij} is uniformly randomized between 1 and 100 for randomly weighted complete graphs, and each edge is randomly generated at the 50% probability with $E_{ij}=1$ for unweighted random graphs. The sample has 15 input parameters and 3 output parameters, the network structure is 15-31-3, the weight of the connection is 465 in the input layer and hidden layer, the threshold is 31 in the hidden layer, the connecting weight is 93 in hidden and output layer, the output threshold is 3, population size is 40, maxgen is 50, Px=0.7, Pm=0.01, ggap=0.95.The curve of revolutionary and rad. The curve of revolutionary procedure and random weight and threshold train is shown in Figs 6 and 7,respsectively

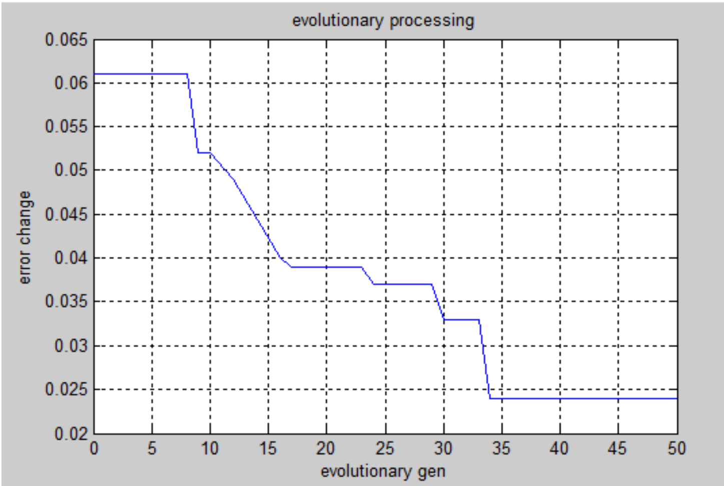

Fig. 6 The curve of revolutionary procedure

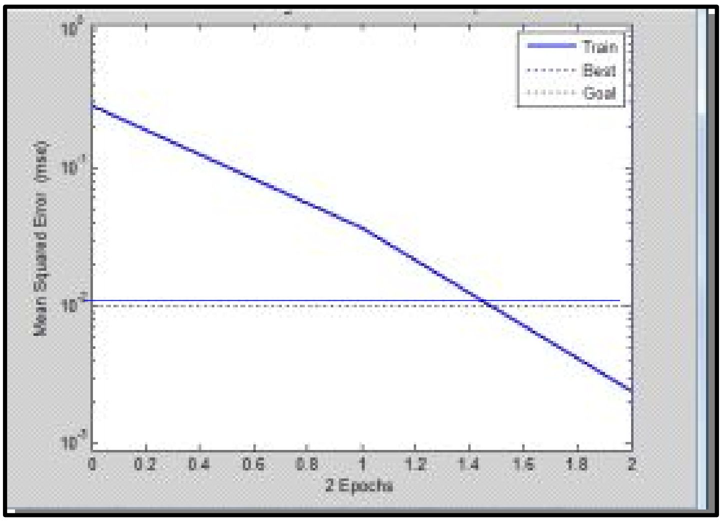

Fig. 7 The curve of random weight and threshold train

VI. CONCLUSION

This paper presents the Granular Neural Network Algorithms (GNN) for the evolutionary of the complex network problem. The evolutionary initialization scheme of the neural state can drastically improve the solution quality of the binary neural network with the shaking term in the motion equation. The simulation results in randomly weighted complete graphs and unweighted random graphs show that GNN finds better solutions than other approximation algorithms within the shortest time.

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