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Research on the Characteristic of Automotive Failure Diagnosis Based on Complex Networks

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Abstract: In order to research the mechanism of automotive failure diagnose and to improve, as well as to explore a new perspective to a find automotive failure diagnose quickly. This paper is based on the empirical data to analyze Xian's some 4S shop and its self-organized criticality proposed a new suggestion. In this paper, we analyze in depth the data of automotive failure running status and diagnose index of different period between 2014, based on the theory of automotive failure diagnosed complexity and self-organized criticality, and thus proves the characteristics of power-law under which lies the related scale. The result shows us that, automotive failure diagnose system is a dynamical system that's both extensive and dissipative. In addition, when STATUS is under 20 or less and TPI is above 6, the scale of influenced districts caused by index in automotive diagnose system and the related frequency fits the law-power distribution, and the rising of automotive will reach the state of self-organized criticality, and meets the characteristic of self-organized criticality.

Keywords: Automotive, failure diagnosis, characteristic, complex network.

1. INTRODUCTION

With the rapid development of economic and modernization of society, the scale of automobile's production are increased widely, and the use of automobile are also frequent. Use fault diagnosis system can help automotive repair business to diagnose the cause of the malfunction quickly and efficiently when the car has faults, and repair the faults in time, so as to ensure the safety and reliability of the car [1]. Traditionally, a single model of fault diagnosis cannot meet the needs of made diagnosis clipping and accurate, because of the complexity structure of the car and many kinds of faults [2]. Therefore, this paper gives an automotive fault diagnosis system based on complex network.

The extensive study on complex networks are pervading sciences and engineering today, from physical, technological, biological, to social sciences [3-5]. Their impacts on engineering and technology, in particular, are prominent and their influence is deemed to be far-facing. Familiar complex networks include the traffic network, wireless communication networks, biological neural networks, power grids, social relation and scientific cooperation networks and so on. Research on fundamental properties and dynamical behaviors of various complex networks have become overwhelming recently.

The field of complex networks is indeed developing so fast and so wide that most new comers typically feel difficult to start their leaning and research on the subject. Although there are some well written textbooks and research monographs that can be adopted for studies by the new comers. These references are generally too advanced or too board for them to comprehend especially in a relatively short period of time [6].

The development of the mathematical graph theory has a very slow start after Euler solved the Konigsburg seven-bridge problem. The first monograph on graph theory was published exactly two-hundred years later, in 1936. Nevertheless, the theory was developed rather rapidly thereafter, and the foundation of the now famous "random graph theory" was laid by two Hungarian mathematicians, Paul Erdos (1913-1970), As a historical remark, Pual Erdos is one of the most distinguished leading mathematician of the twentieth century, in the late 1950s, which is considered the first rigorous and complete modern graph theory.

Erdos and Renyi defined a random graph as N labelled nodes connected by n edges, which are randomly chosen from the $N(N-1)/2$ possible edges. A common way to generate an ER random graph is to start with N nodes, from which every possible pair of nodes are being connected with probability $p(0<p<1)$. More specifically, to generate an ER random network, one may start with N isolated nodes. Pick up every possible pair of nodes, once and once only from a total of $N(N-1)/2$ pairs of nodes, and then with probability p connect the pair with an edge. Here, with probability p can be performed as follows: run a pseudorandom number generator to generate a "1" with probability p; at any step if the generator yields a "1" then connect the pair of nodes by an edge, otherwise if the generator yields a "0" then do not connect them.

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Since every possible pair of nodes is picked up once, there will not be multiple edges between any pair of nodes and, moreover, no node has a self-connected edge.

It can be easily seen that in such an ER random graph of N nodes, the expectation value of the total number of edges will be $N(N-1)p/2$, which is a random variable because p is so. Consequently, the probability of obtaining a graph with N nodes and M edges is equal to $p^M(1-p)^{N(N-1)/2-M}$. Erdos and Renyi systematically studied many asymptotic properties, as $N\to\infty$, of such graphs and their relations with the edge-connectivity probability p. If a graph has a property P with probability 1 as $N\to\infty$, then they consider almost every ER random graph has property P. One theory is most important and also quite surprising discoveries are that many properties of ER random graphs emerge suddenly but not gradually, in the sense that for a given edge-connectivity probability p, either almost every ER random graph has a certain property P or almost every such graph does not have property P.

2. SMALL WORLD EXPERIMENT MODEL

2.1. Model Assumptions and Procedures

From a statistical point of view, although the network of automotive failure diagnose can be computed. They are nevertheless too small to be conclusive. Knowing this,, trying to carry out a large-scale international experiment to verify the hypothesis of small world. We selected some targeted automotive, with different brands, 4S shops. Notice that in this small world algorithm may destroy the network connectivity during the rewiring process, yielding possible some unconnected clusters. As a remedy, the small world algorithm is as follows:

(1) Start from a ring shaped network with N nodes, in which each node is connected to its $2K$ neighbors, where $K>0$ is an integer (usually small).

(2) For every pair of originally unconnected nodes, with probability p, add an edge to connect them.

In this process, between any pair of nodes there will not be multiple edges and node will have self-loops [7].

In the small world network, the case of $p=0$ corresponds to the original ring shaped network while $p=1$ eventually yields a fully connected network. By tuning the value of $p(0<p\prec 1)$, one can obtain a transition from a regular sparse network to a regular dense network. From small enough values of p, though, the small world models are about the same.

For the small world network model, the clustering coefficient is re-defined to be the ratio of the mean number of edges among the neighbors of a node and the number of all possible edges among the neighbors of the node [8]:

$$C_{Sw}=\frac{average\quad number\quad of\quad neighboring\quad edges}{total\quad possible\quad number\quad of\quad neighboring\quad edges}$$

Note that this definition differs from the original one only by a small amount of order $O(1/N)$, as further explained in the proof given below.

2.2. Theoretical Model

Theorem 1. For large enough size N, the clustering coefficient of the small world network model is given by

$$C(p)=\frac{3(K-1)}{2(2K-1)}(1-p)^3$$

For $p=0$, each node has $2K$ neighbours, so the number of edges among these neighbours is $N_0=3K(K-1)/2$, while the number of all possible edges among these nodes is $2K(k-1)/2)$. Therefore, $C(0)=3(K-1)/(2(2K-1))$. For $p>0$, two neighbours of node i, which were connected at $p=0$ are still neighbours of i and remain being connected with probability $(1-p)^3$, up to some terms of order $O(1/N)$. Thus, the mean number of edges among the neighbours of a node is $N_0=(1-p)^3+O(1/N)$. Consequently, the clustering coefficient is given by $N_0(1-p)^3/K(2K-1)$.

Theorem 2. The average path length of the small world network model is given by [9]

$$L(p)=\frac{2N}{K}f(2Np/K)$$

With

$$f(x)=\begin{cases} c & x<1 \\ \ln x/x & x>1 \end{cases}$$

The average path length of the small world network model is also given by [10]

$$f(x)\approx\frac{1}{2\sqrt{x^2+2x}}ar\tanh\sqrt{\frac{x}{x^2+2x}}$$

For the network model, with p fixed, first perform the renormalization process and let the number of sites of the resultant renormalized network be S. The average path length $L(p)$ is less than 1 and is increasing linearly as S gradually increases. But at some threshold value of S*, $L(p)$ will become bigger than 1. This leads to a phase transition, after which $L(p)$ will increase only logarithmically. To be more precise, consider only the case of K=1, namely, a perfect ring, and assume that $0<p<1$ and $S^*=1/p$, thus S*>1. In this case, $L(p)$ should obey a finite-size scaling law of the form $L(p) = Sf\left(S/S^*\right) = Sf\left(pS\right)$. From the renormalized network, it can be seen that $S = 2N/K$.

Theorem 3. The node degree distribution of the small world network model is given by [11]

$$P_p(k) = \sum_{i=0}^{\min(k-K,K)} \binom{K}{i} (1-p)^i p^{K-i} \frac{(Kp)^{k-K-i}}{(k-K-i)!} \exp(-Kp)$$

For the small world network model, with $p = 0$, each node has the same connectivity 2K. For the nodes being rewired with probability $p > 0$, they introduce non-uniformity to the network while maintaining a fixed average path length <k>=2K. Let this non-uniform probability distribution of network connectivity be denoted by $P_p(k)$. Since K of the initial 2K connections of each node are left unchanged by the construction, the degree of node i is $k_i = K + n_i$ with $n_i \geq 0$, where $n_i = n_i^1 + n_i^2$ in which $n_i^1 \leq K$ is the number of edges left unchanged and n_i^2 is the number of edges that have been reconnected to another node from node i. Thus, one has [7]

$$P_1\left(n_i^1\right) = \binom{K}{n_i^1} (1-p)^{n_i^1} p^{K-n_i^1}$$

$$P_2\left(n_i^2\right) = \frac{(Kp)^{n_i^2}}{n_i^2!} \exp(-Kp)$$

And generally,

$$P_p(k) = \sum_{i=0}^{\min(k-K,K)} \binom{K}{i} (1-p)^i p^{K-i} \frac{(Kp)^{k-K-i}}{(k-K-i)!} \exp(-Kp)$$

2.3. Empirical Research

In the future, vehicles communicate with vehicles though wireless communication technology. V2V is a big network based on large data. In recent years, along with the rapid development of the Internet and the Internet of Things, vehicle networking has become a major signal, announcing that years have entered into an intelligent era. The rapid development and popularization of vehicle networking technologies all over the world, has provided the conditions and foundations for remote fault diagnosis technology.

The engine is the power source of the vehicle with poor operating conditions, which results in relatively high failure rate. The structure of electronic control engine is more complex with more complicated failures and more difficulties of fault diagnosis. However, so far, knowledge for automotive electronic control engine fault diagnosis is often heterogeneous and lacking semantic associations between each other. Therefore, there is no universal conceptual model that can be commonly understood, which results in difficulty to knowledge acquisition, expression, sharing and reuse. Experimental procedure and data obtained are shown in Tables **1** and **2**.

Table 1. Examples of road running status at the moment.

	DAYTAG	MINTAG	COUNT
1	2014-10-01	0	2
2	2014-10-01	1	1
3	2014-10-01	2	1
4	2014-10-01	3	1
5	2014-10-01	4	1
6	2014-10-01	5	1
7	2014-10-01	6	4
8	2014-10-01	7	4
9	2014-10-01	8	7
10	2014-10-01	9	1

Table 2. Examples of failure diagnose status at the moment.

	DAYTAG	MINTAG	COUNT
1	2014-10-01	0	14
2	2014-10-01	1	1
3	2014-10-01	2	10
4	2014-10-01	3	2
5	2014-10-01	4	12
6	2014-10-01	5	1
7	2014-10-01	6	15
8	2014-10-01	7	5
9	2014-10-01	8	18
10	2014-10-01	9	3

With MATLAB7.0.1 data-calculation software as the assistance, this paper mainly studies the failure diagnosis emulation of auto engines, which includes the access to the sample set. The design of the network, the pre-treatment of information. It also makes a study on the trouble shooting of the misfire of an engine with the technology of complex network and ELMAN network. A comparison between complex network and ELMAN network is made and studied, which reaches a conclusion that the error amount of complex network is smaller than that of ELMAN network. But due to the feedback effect of ELMAN network, its error curve is smooth and tends to be a straight line, complex network can respond automotive fault diagnostic work fully. This article also uses the powerful data calculation functions of MATLAB and the powerful interactive features of VB, using Active}C technology between VB and MATLAB to achieve the seamless integration, completing the development of fault diagnosis system, with the help of VB and SQL's integration to achieve the fault system database modifications and updates. Comparison table of color-failure level index range and test group is shown in Tables **3** and **4**, respectively.

Table 3. Comparison table of color-failure level index range.

Color						
Level	No Data	Trouble Free	Minor Fault	Moderate Faults	Serious Faults	Unable to Travel
Index	—	[0, 2]	[2, 4]	[4, 6]	[6, 8]	[8, 10]

We have tested our strategy with different influencing factors concerning randomness of automotive failure diagnose network, the network model (Fig. **1**) and clustering coefficient with failure rate (Figs. **2**, **3**).

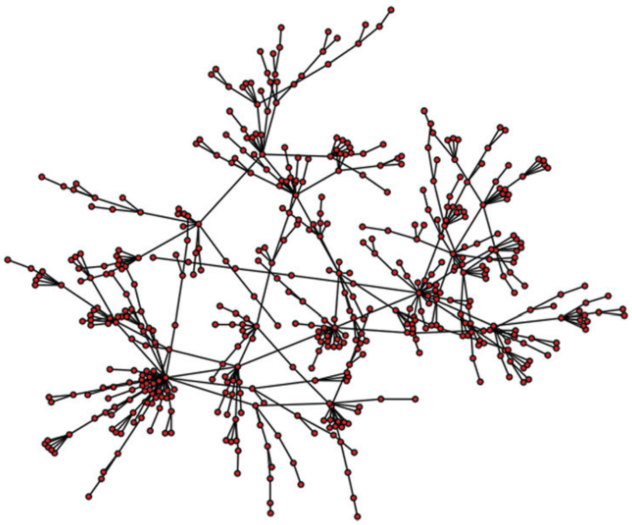

Fig. (1). The process of our strategy of the network *N*.

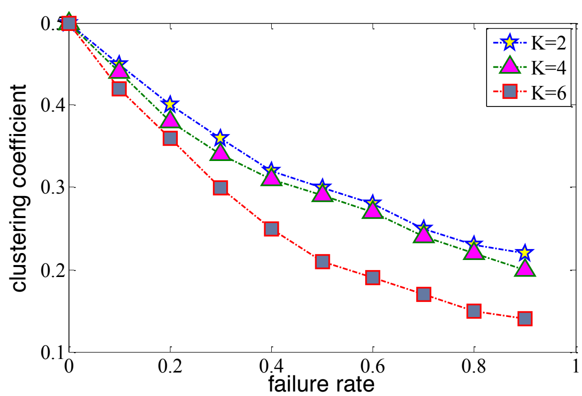

Fig. (2). The cluttering coefficient reduction results using our strategy, in basic network with node number K=2, 4, 6 respectively, when generating the small world network. (S=18, N=1000).

To represent and model automotive failure diagnose dynamic, a natural way is to put the framework into a complex network setting, in which a node represents vehicles and an edge represents the interaction between two of them. In the comparison of strategy performance between different sizes, we conduct some groups (Table **4**) of test. But in the first group and the fourth group, we set K=2 in all round of the test, and in the second and the fifth we set K=4 which is varied with N =500, 1000 and 1500, respectively. It is interesting that randomly connecting method gives better results than the low degree meth of in Fig. (**3**).

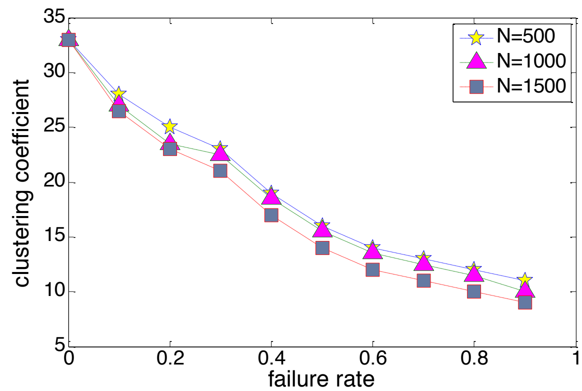

Fig. (3). The cluttering coefficient reduction results using our strategy, with N=500, 1000, 1500 respectively, when generating the small world network, connecting node pairs randomly with one node added and our strategy making random connections instead. (S=18, K=2).

Table 4. Test group.

Number	Group Name	STATUS	K	TPI
1	S60-TPI4	60(S60)	2	4(TPI4)
2	S60-TPI6	60(S60)	4	6(TPI6)
3	S60-TPI8	60(S60)	6	8(TPI8)
4	S20-TPI4	20(S20)	2	4(TPI4)
5	S20-TPI6	20(S20)	4	6(TPI6)
6	S20-TPI8	20(S20)	6	8(TPI8)

So a question is raised that whether the connecting preferences are helpful to the performance of our strategy. To explain this, we conduct another series of tests, as shown in Fig. (**3**), moreover, comparisons are made in three small world networks generated with node number N =500, 1000 and 1500, respectively. We line the results in Fig. (**4**).

3. SIMULATION AND RESULTS

3.1. Simulation

To resolve the uncertainty and modelling issues in fault diagnosis for vehicles, a fault diagnosis fusion system architecture is based on Bayesian network model construction is proposed. A fault diagnosis algorithm based on Bayesian network constructing is also advanced. This fault diagnosis approach handles with the uncertain representation and reasoning by exploiting the learning and probabilistic; inference abilities of Bayesian network. Moreover the provided system can realize the self-adaptation

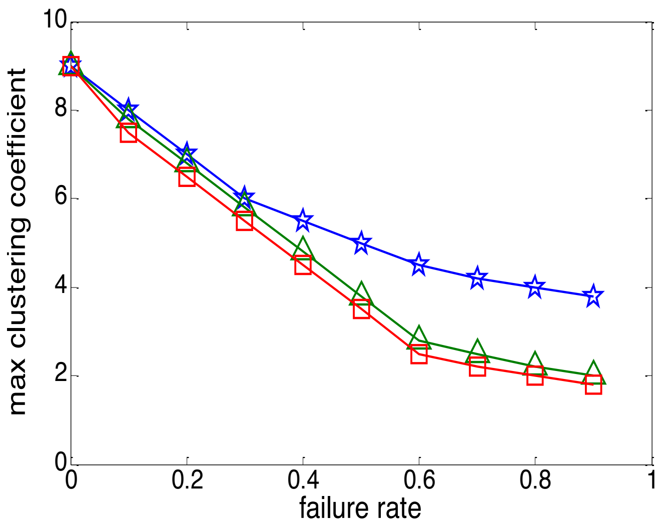

Fig. (4). The repeated tests results using maximum clustering coefficient.

via the fusion of domain prior knowledge and the distribution of real time data from the sensor system which is successfully applied in vehicle fault diagnosis. Experimental results demonstrate that the proposed approach can supply the accurate and reliable decision-making support in the fault diagnose. We can see the network structure as shown in Fig. (**5**).

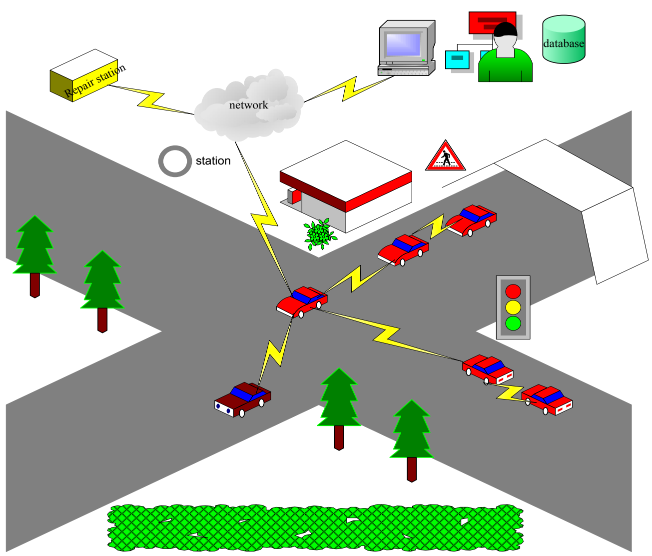

Fig. (5). Network structure.

3.2. Results

Recalling that in the small world network model, each node on the given ring shaped small world network has long range edges connecting to the other nodes with a certain probability in such a uniform random manner that every other node has an equal probability to receive the new edge, excluding self-loops and multiple connections. Now, instead of assuming that new long range connections are uniformly distributed over the whole network, we argue that intuitively it would be easier for a new edge to connect to a near neighbour than to the remote ones. Therefore assume that the connecting probability is reversely proportional to the distance between the two nodes. More specifically, we obtain the relationship between N and average path as shown in Fig. (**6**).

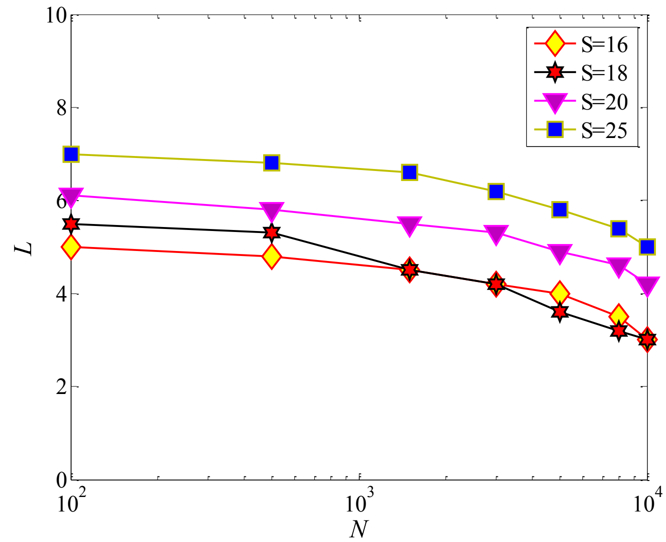

Fig. (6). The relationship of N and average path.

Next, we notice that during the growth of the small world model, the degree k of a node is also changing according to the following law [12]:

$$k = \sqrt{\frac{t}{t_i}}$$

where k is the degree of node i at time t and t_i is the instant at which node i is being added into the network. This growth rate of the node degrees in the small world model implies that the order of a node is bigger than its degree. In real life, however, this is not always true.

(1) Growth: start from a small world network of size $m_0 \geq 1$ and introduce one new node to the existing network each time, and with probability p this node given a fitness value.

(2) Preferential Attachment: the new node is connected to m existing nodes, each is according to the probability of connecting to node i of degree k with fitness value.

We calculate the relationship between k and $p(k)$ as shown in Fig. (**7**), in which we can see the linear relationship between them.

The model proposed above is simulated in the section. In light of the complexity of computing the k and $p(k)$ of a network, we first use just one basic network to evaluate the availability of our model (see Tables **5** and **6**), as well as some discussion factors of model.

A small world random network with 500 nodes is generated as the initial network for the first step in the tests. We report the distribution function between k and $p(k)$ in Table **5**. Similarly, more rounding tests are conducted on the basis network using different K and S, results for these three groups of test are shown in Table **6**.

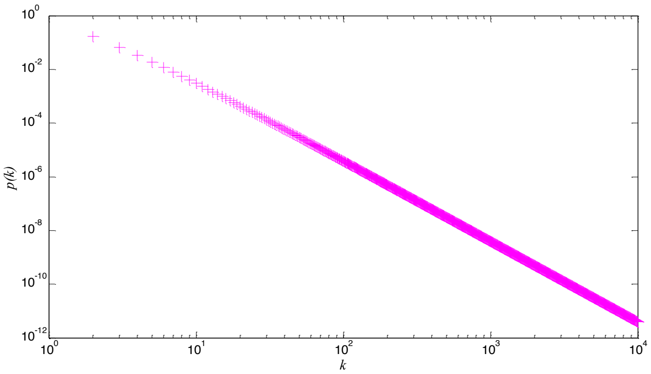

Fig. (7). The relationship of k and p(k).

Table 5. Three Sets of Statistical Results about S60-TPI6, S60-TPI4 and S20-TPI4.

	Correlation Coefficient	Variance	Distribution Function
S60-TPI6	0.6496	68.99	$y=-1.458x+13.66$
S60-TPI6	0.6438	32.7	$y=-1.056x+10.36$
S60-TPI4	0.7599	61.13	$y=-1.877x+15.81$
S60-TPI4	0.6488	69.45	$y=-1.046x+13.68$
S60-TPI4	0.5857	25.92	$y=-0.8078x+10.66$
S20-TPI4	0.753	36.84	$y=-1.857x+13.41$
S20-TPI4	0.7541	36.31	$y=-1.868x+13.39$
S20-TPI4	0.8051	24.95	$y=-1.802x+11.07$

Table 6. Statistical Results about S20-TPI6.

	Correlation Coefficient	Variance	Distribution Function
2014.10.01	0.7651	36.08	$y=-1.867x+13.37$
2014.10.07	0.8081	14.71	$y=-1.552x+9.953$
2014.10.14	0.7689	33.6	$y=-1.824x+13.38$
2014.10.21	0.8595	15.34	$y=-1.75x+10.9$
2014.10.28	0.7781	28.5	$y=-1.73x+13.28$
2014.11.01	0.8239	20.22	$y=-1.737x+11.4$
2014.11.08	0.8203	22.68	$y=-1.603x+12.51$
2014.11.15	0.8863	15.37	$y=-1.606x+12.33$

CONCLUSION

First, this paper analyzes the research status of vehicle networking, engineering applications, electronic control engine fault diagnosis and develops research content and design route for this paper. From view of application, this paper analyzes the complex network model, complex network rules, complex network structure designs, and the selection rules for initial value as well as the diagnostic process. The paper also presents the disadvantages of applying complex networks to failure diagnosis and its corrective methods.

CONFLICT OF INTEREST

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