Modeling the Dynamics of Fault Propagation in Complex Dynamical Network by Considering the Heterogeneity of Nodes

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***Abstract*—the process of fault propagation and study the dynamic behavior in complex dynamical network is modelled in this paper. A fault resistance factor and a weight factor of repair probability are defined to denote the heterogeneity of nodes. The effects of the key model parameters on the fault propagation dynamics are studied by numerical simulations with reference to the number of failed nodes, the fraction of nodes in the largest network component and the fault propagation cycle. Moreover, the node vulnerability is explored for different communication radiuses. The results obtained in the study show that the fault propagation dynamics will be affected by some parameters, such as communication radius, node density and moving speed. Hence, we should limit these parameters within a certain ranges so as to limit the fault propagation and reduce the loss caused by it.**

Keywords—dynamics; fault propagation; modeling; complex dynamical network; heterogeneity

I. INTRODUCTION

Fault propagation dynamics in complex networks is a hot issue that has attracted the attention of researchers [1-4]. Actually complex networks are prominent in describing a variety of dynamics in diverse sciences [5-6]. As a special complex network, the complex dynamical network (CDN) can be used to describe many real systems, such as Energy Internet and Energy system, mobile ad hoc networks, vehicle ad hoc networks, smartphone networks and disease propagation networks [7]. Because of the complexity of the structure and the dynamic coupling between network nodes, there are many challenges in CDN modelling and analysis, such as propagation dynamics, synchronization, network performance and reliability assessment [8-10]. Propagation dynamics has been one of the main topics of interest due to its various applications [11-12]. The existing research about propagation dynamics mainly focuses on two aspects. One is disaster propagation dynamics in abstract complex networks. However, the node dynamics and its influence on fault propagation dynamics are not considered. For these reasons, a fault propagation model that considers node dynamics was proposed in [13]. The research results show that the node dynamics can speed up the propagation velocity and increase the influence scope. However, the state of the node in the node dynamics description is considered only binary: functioning and failed, which is not enough to represent the change process from function to failure.

The other aspect is the epidemic propagation dynamics in social networks or the virus propagation dynamics in computer networks. SIS (susceptible-infected-susceptible), SIR (susceptible-infected-recovered), SEIR (susceptible-exposed-infected-removed) and other modified models [14-17] have been proposed to make the model closer to the actual situations. However, all models assume that the network is static, which cannot reflect the dynamical properties of CDNs. Moreover, they ignore the influence of the distance between nodes. To overcome these limitations, Bayesian networks have been introduced in [18] to build a fault propagation model for mobile ad hoc networks, in which the out-of-date situation and dynamic characteristics of topology are taken into consideration.

In CDN, with complex structures and functions, different nodes play different roles. To account for the heterogeneity of

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nodes, researchers have done some studies in recent years. In [19-22] the social relationship graph is constructed based on messaging records collected from real cellular networks to reflect the heterogeneity of nodes behavior of infection and resistance. The model is then used to study the dynamics of the worm propagation process by simulations. Besides, most existing researches focus on epidemic or virus propagation, whereas fault propagation of network is obtained only in very few papers. And there is a significant difference between epidemic propagation and fault propagation, whereby the result is achieved by contact with a certain probability, whereas fault propagation often comes from a cumulative effect.

In this paper, we introduce a new standard –exception –failure –recovery (SEFR) fault propagation model for complex dynamical networks with heterogeneous nodes. This is described in Section 2 with some necessary assumptions, definitions and lemmas. Numerical simulation results and the detailed analysis are described in Section 3. Finally, conclusions are given in Section 4.

II. MODEL FORMULATION

2.1. Network model

Consider an undirected connected network G=(A, E) of size N, where A is the set of vertices (nodes) that denote the components and E is the set of edges that denotes the connecting relations between the different components in CDN. In the model, the N nodes move on a continuous, square-shaped cell of size L with periodic boundary conditions [23-26]. Initially, nodes are randomly distributed on the cell. The widely used random waypoint mobility model is used in [27-28], including pause times between changes in direction and/or speed.

2.2. Fault propagation model

In our SEFR model, we make the following assumptions according to the characteristics of the CDN model introduced.

(1)The number of nodes N (the network size) is considered constant.

(2)At any time, each node is in one of four possible states corresponding to standard (S), exception (E), failure (F), and recovery (R), respectively.

(3)There are two processes can occur for each node in one time interval: movement process and relatively stationary process.

(4)The communication radiuses of all nodes are the same and all the nodes within the communication radius can contact each other.

(5)The failure nodes at the initial time are selected randomly.

(6)The more or longer two nodes stay in contact, the more influence they have on each other.

(7)The repair probability is larger for nodes with larger betweenness centrality.

A standard state means that the load processed by the node is within the normal range, but it can be influenced by the internal data flow from the nodes in state F around it. Exception state denotes that the load has exceeded the node processing capacity, but the node still functions although in a degenerate state, and will fail with a certain probability. A node in failure state cannot process the data flow and meanwhile it affects the nodes within its communication radius. The recovery state denotes that the node has been repaired from the failure state and it can be brought back to standard after a certain time.

The fault propagation process of the model is shown in figure 1.

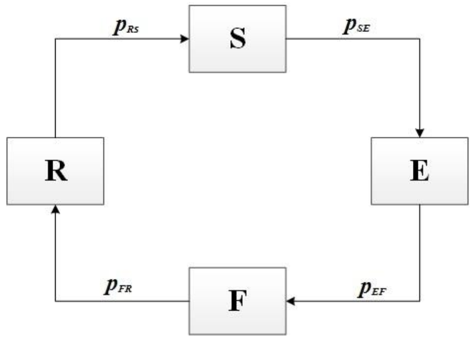

Figure 1. Fault propagation process of the novel SEFR model. p_{SE} denotes the probability of a node to make a transition from state S to E. p_{EF} denotes the probability of a node to make a transition from state E to F. p_{FR} denotes the probability of a node to make a transition from state F to R.

Also we define a weighed factor for the recovery probability of each node so as to reflect the heterogeneity of recovery capability of nodes. Given the length of simulation area, the average moving speed, the influence weight factor and the maximum recovery probability, we can get the average and maximum values of node betweenness for different nodes numbers N and communication radiuses r by simulations of MATAB code. Further, we can obtain the ratio of the average to the maximum values of node betweenness. These data are presented in figure 2 and figure 3.

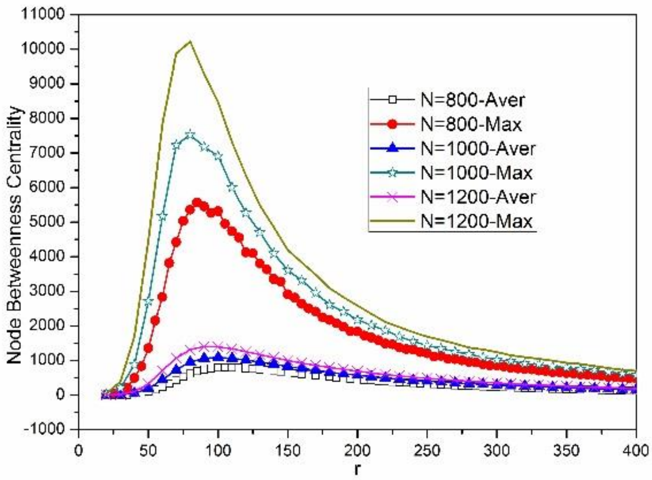

Figure 2. Average and maximum value of node betweenness centrality with respect to node number and communication radius.

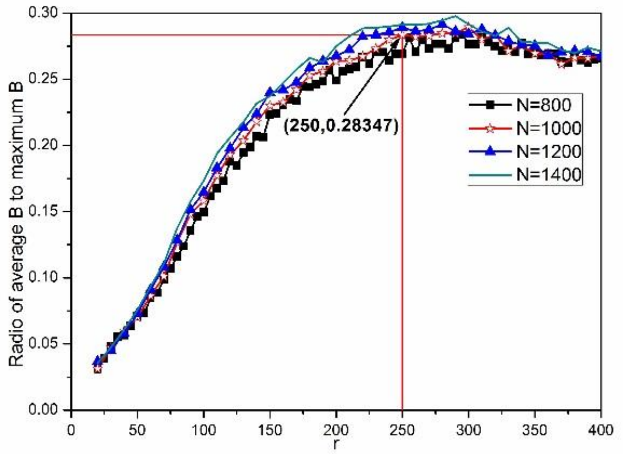

Figure 3. Ratio of average value to maximum value of node betweenness centrality for different node number value.

It can be seen that both the average and maximum values of node betweenness centrality increase with the increase of the value of *N*, and that the increased velocity of the maximum value of node betweenness centrality is greater than that of the average value of node betweenness centrality. When *N* is fixed, the value of node betweenness centrality increases to be maximum and then decreases with the increase of *r*. Moreover, the peak value of both the average and maximum node betweenness centrality shifts with the increase of *N*. On the other hand, the value of the ratio of the average betweenness to the maximum betweenness is monotonely increasing with *r* when the value of r is smaller than 250.

Assuming that the maximum recovery probability is θ, then the recovery probability of node *i* denoted by p_{FR}^{i} can be expressed as:

$$p_{FR}^{i} = \vartheta_i \times \theta = \left(B_i / B_{\max}\right) \times \theta \quad (1)$$

2.3. Terms definition

In order to study the propagation dynamics in CDN, we introduce the following definitions.

Definition 1: Fault propagation cycle T is defined as the time from the occurrence of a failure to the moment the network reaches the steady state.

Definition 2: The node vulnerability   is the ratio of the time that node i stays in abnormal state to the fault propagation cycle. It can be expressed as follows:

$$NV_i = T\left(s_i \neq 0\right) / T = \Psi_i / T \quad (2)$$

where $T\left(s_i \neq 0\right)$ stands for the time that node i stays in abnormal state denoted by Ψ_i. As a result, NV has a value between 0 and 1 for each node, where the higher the value, the most vulnerable the node is under the specified fault propagation scenario.

III. Simulation Results and Discussions

The scenario is generated by using the random waypoint mobility model with N nodes moving in an area of 800m×800m. A MATLAB simulator has been implemented for this study. Following the research results in [29], the simulation parameters are set and summarized in table 1. In order to eliminate the influence of randomness resulted from the initial position of the nodes and the probabilities used in the model, all the results presented in the following are average values over 100 simulations.

TABLE 1. Simulation Parameters Setting

Parameter	Value	Parameter	Value
N	800	L	800
r	70	I_0 [a]	200
$\overline{V}$ [b]	10	T [c]	1000
$\overline{T}$ [d]	5	w_1	0.4
w_2	0.6	λ	1
β	0.2	η_1	0.1
η_2	0.2	ξ	0.8
θ	0.6	μ	0.1

I_0^a is the number of failure nodes at the initial time, which can be caused by software failure or attack.

$\overline{V}^b$ is the average moving speed.

Tc is the total simulation time.

$\overline{T}^d$ is the average time a node will pause when it reach the destination position.

The evolution of the number of nodes in different states using the parameters listed in table 1 and the transient increment of nodes in state R and state F for different communication radius values are presented in figure 4, figure 5 , respectively.

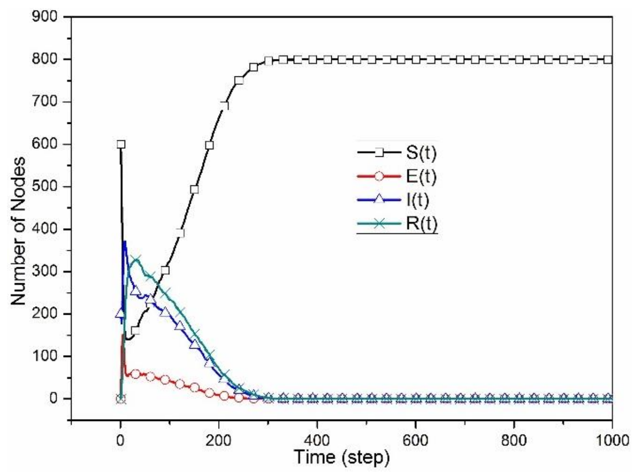

Figure 4. Evolution of the number of nodes in different states.

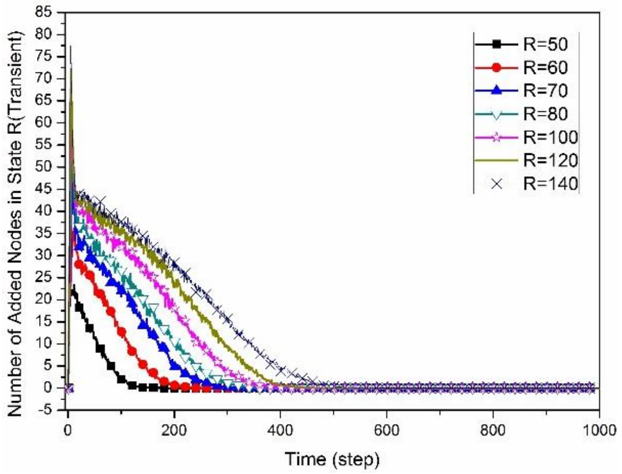

Figure 5. Transient increment of the number of nodes in recovery state in network with different communication radiuses.

It can be seen that the system will reach a steady state after 300 simulation steps, in which all the nodes in state E, F and R transfer into state S from figure 4. The numbers of nodes in state S, E and F will reach maximum values rapidly, then, reduce to zero slowly, we can see that the fraction of nodes in state R and F will first increase and then decrease with simulation time and increase with increasing r.

In order to study the evolution of the whole network features with time under different values of the key parameters, we select the largest network component as an indicator and study the change of the fraction of nodes in the largest network component for different values of communication radius and average moving speed of nodes, respectively. The results are presented in figure 6 and figure 7 in the following.

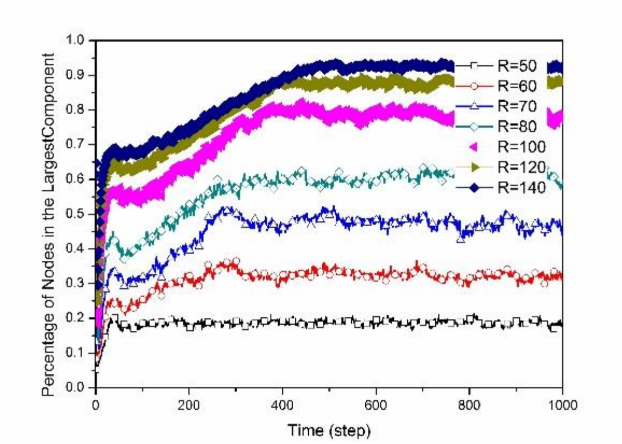

Figure 6. Evolution of the fraction of nodes in the largest network component made of nodes in state S, E and R for different communication radius, whereas the average moving speed of nodes is 10.

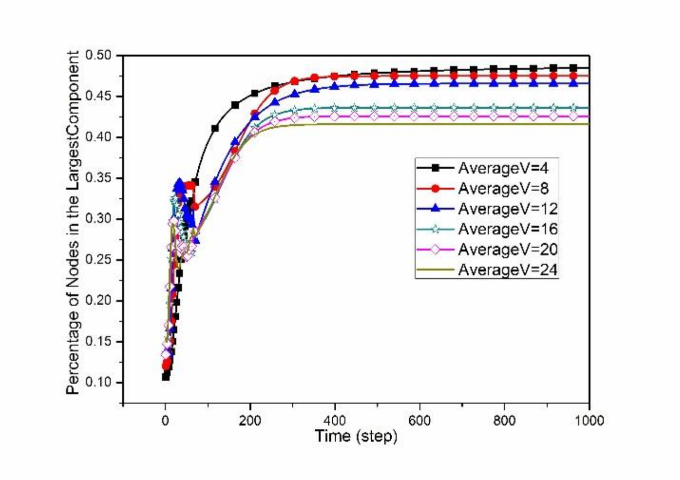

Figure 7. Evolution of the fraction of nodes in the largest network component which is consisted of nodes in state S, E and R. During the simulation, the average values of moving speed are different and the communication radius of node is 70.

We can see that the network will reach a steady state after a certain number of simulation steps when the communication radius and average moving speed take values in (50,140) and (4,24), respectively. The fraction of nodes in the largest network component increases with increasing r, while it decreases with increasing value of average moving speed. For each value of r and average moving speed, the fraction of nodes in the largest network component reaches a maximum value rapidly and, then, reaches steady state slowly. The fraction of nodes in the largest network component for different values of r at steady state can change from 0.2 to 0.9, while it is always less than 0.5 when the value of the average moving speed of nodes is larger than 4.

According to the definition of fault propagation cycle and the simulation results in figure 6, we get the result marked by filled rectangle in figure 8. It can be seen that the fault propagation cycle is a monotone increasing function of r if there is no other constraint condition, which is in coherent with the increasing rates of nodes in figure 5. Considering practical situations, we assume that r can only take values from 50 to 140. The analytical expression of the relationship between the fault propagation cycle and the communication radius can be obtained by curve fitting the data. The fitted curve is presented in figure 8 and the expression is presented as follows:

$$T = \frac{a-b}{1+e^{(r-r0)/c}} + b \tag{3}$$

$a = -1.117\times10^{6}$, b=448.24, c=25.23, r0=-152.34.

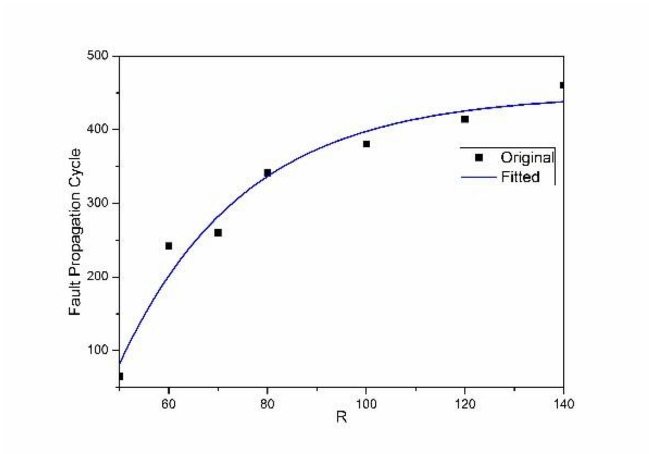

Figure 8. Fault propagation cycle as a function of communication radius and the fitted curve.

By Eq. (3), the fault propagation cycle for different values of communication radius can be obtained. Then, we can get the vulnerability of each node with different r. The node vulnerability distribution is presented in figure 9.

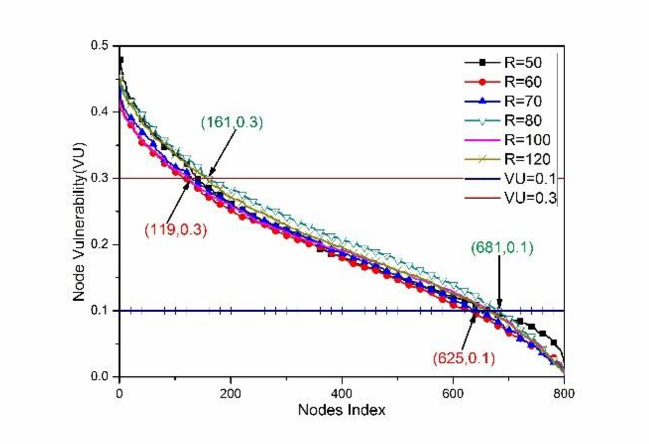

Figure 9. Node vulnerability value being sorted from the maximum to the minimum values for different R(r). The parameters have been set to N=800, L=800, Average V=10.

It is easy to see that the distribution of the node vulnerability shows the same trend with different communication radius values and that the value of node vulnerability mainly concentrates in the interval [0.1, 0.3]. For example, the fraction of nodes whose vulnerabilities are 0.66, 0.6325, 0.66, 0.65, 0.65, 0.68, 0.63 for r=50, 60, 70, 80, 100, 120, respectively. But there also exists some nodes whose vulnerability is larger than 0.3 or smaller than 0.1, which can also reflect the heterogeneity of nodes considering the differences of nodes of the network when studying the fault propagation dynamics.

IV. CONCLUSIONS

We have presented a model for studying fault propagation dynamics in complex dynamical networks and investigated its behavior with different network parameters. Compared to the existing models, we have made the following improvements in order to make the model more practical.

(1)The node dynamics is considered by modelling the mobility of nodes.

(2)The different effects of failure nodes are considered on standard nodes.

(3)Considering the heterogeneity of nodes in the ability of resistance to failure and the recovery from failure based on the contact between nodes and the betweenness centrality of nodes, respectively.

It turns out that key parameters of the complex dynamical network have a huge impact on: (a) the fault propagation cycle, the ability of network in stable state to keep connectivity and the vulnerability of nodes to fault propagation.

In conclusion, our research provides a model which consider the heterogeneity of nodes in resistance capacity and repair capacity. And they also facilitate a qualitative evolutions and quantitative assessments of the vulnerability, resilience and stability of a complex dynamical network with respect to the fault propagation dynamics. It gives the chance to understand the time dependence of fault propagation and identify points in challenged networks, where countermeasures in case of fault propagation must be taken within a certain time frame. Thereby, our research offers promising perspectives for failure preparedness and helps to improve the fault of Energy Internet and Energy system response management.

ACKNOWLEDGMENT

The authors are highly thankful for National Program on Key Basic Research Project (2014CB744900), National Natural Science Foundation of China (61773001), Beijing Natural Science Foundation-Rail Traffic Control Science and Technology Joint Fund (16L10010), Beijing Natural Science Foundation(172023), Beijing financial project, (PXM2017_178215_000001 No.17906) and Fundamental Research Funds for the Central Universities with No.YWF-17-BJ-Y-83.

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