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Network Congestion Diffusion Model Considering Congestion Distribution Information

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ABSTRACT Network congestion diffusion has become the most stubborn disease and scourge of networks. With the help of widely used congestion distribution information, making full use of network capacity dynamically is a feasible and hopeful way to alleviate network congestion diffusion. Existing studies on network congestion diffusion considering congestion distribution information mainly focus on road networks and describe the distribution information of congestion areas with statistical parameters but not take dynamical congestion distribution into account. However, it is difficult to quantify dynamical congestion distribution as it has multiple influencing factors and complex dynamical coupling relationships, and thus there is still a lack of common network congestion diffusion model considering dynamical congestion distribution information. Inspired by the Langevin diffusion model in signal transduction networks, we propose a novel model for common network congestion diffusion considering the influence of dynamical congestion distribution information based on a set of differential equations. In these equations, we quantify the crosstalk influence of dynamical distribution information by a parameter with reference to the routing optimization method in the ant colony algorithm. And, then firstly the complex dynamical coupling network congestion diffusion under the influence of congestion distribution information is analyzed and simulated in a measurable way. The simulation results prove that there are obvious alleviated effects on network congestion diffusion with proper information influence weights, which is shown to be a bathtub curve relationship. Our model provides a simple mathematical approach to discover the relationship between network congestion diffusion and the influence of dynamical congestion distribution information. Based on this relationship, we can relieve network congestion by dynamically adjusting congestion distribution information influence.

INDEX TERMS Network congestion diffusion, information influence, congestion distribution, Langevin diffusion model, ant colony algorithm, routing optimization method, signal transduction network.

I. INTRODUCTION

Network congestion diffusion, which means an excessive or non-equal load distribution and diffusion process, is becoming a common problem and always causing great economic and social damages in many fields. For example, because of road network congestion diffusion, more than one hour a day is spent on commuting to and from work in American metropolitan areas [1], and the figures are similar or even worse in many developing countries [2], [3]. In addition to the overall loss of time, congestion underlies many major economic and urban issues, such as increased gas consumption, infrastructure deterioration, and CO_2 emissions [4]. It is reported that the economic loss of road congestion is about 2% of GDP, and the road congestion is also a primary air pollution source [5], [6]. Meanwhile, the network congestion diffusion in Internet and mobile telecommunication network is becoming one of the top network failures [7]–[10], and the famous disasters of electrical blackouts in Italy, US and Canada are also due to network congestion diffusion [11], and the blackout in USA and Canada resulted in \$4 billion loss [12].

As the ongoing rapid expansion of Internet of Things (IoT), cyber-physical systems (CPS), etc., it is a feasible

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and hopeful way to alleviate network congestion diffusion with the help of congestion distribution information, since it has been proved that many other network congestion diffusions are obviously influenced by information [13]–[16]. And here this congestion distribution information means the distribution information with regard to the ratio of load to capacity on different parts of a congestion network. Though the interplay of capacity and load determines the level of congestion [4], it is difficult either to enlarge capacity or to decrease load in reality. And the red or yellow congested road sections on Google maps are always helpful to relieve network congestion diffusion by reminding drivers to choose a better route, and then a worse traffic congestion diffusion could be avoided [17]. With the help of the congestion distribution information, the network capacity can be fully utilized in spatio-temporal patterns. Drivers with a Google map will avoid the congestion road, which means that congestion distribution information could influence routing paths and change the load distribution and then possibly alleviate the network congestion diffusion. Many studies have shown that different congestion distribution information has different influence on routing methods, and different routing methods also have different influence on the network congestion diffusion in road networks and other networks [4], [7], [18]–[23]. Tesla even declared that there would be no road congestion if all cars were self-driving because of the perfect use of information [24].

However, some researchers believe that perhaps network congestion diffusion would be worse when users with the congestion distribution information selfishly and unwisely choose another longer way, which will cause more capacity occupancy and intensify congestion diffusion. This means that the congestion distribution information will not alleviate network congestion diffusion absolutely due to various influencing factors and complex relationships [25]. No conclusion can be made that congestion distribution information from Google or Baidu maps has a direct positive influence on network congestion diffusion because there are no reliable evidences [26].

Therefore, it is necessary to build a network congestion diffusion model considering the influence of congestion distribution information to analyze the network congestion diffusion under the condition of congestion distribution information influence.

Existing network congestion diffusion models considering the influence of congestion distribution information mainly focus on road networks. For example, based on cellular automaton models, network congestion diffusion considering city central business congestion district distribution has been simulated by giving an additional travel time weight to describe the congestion district [27]. However the congestion distribution influence expressed by a unified and fixed weight is not suitable for distribution of dynamical varying congestion. Besides, using advanced traveler information systems (ATIS) and Bureau of Public Roads (BPR) function to make travel routing decisions and calculate travel time, Zhong *et al*. [28] proposed a reliability-based congestion model, which can be used to analyze the network congestion diffusion. Similarly, Wang *et al*. [29] analyzed the network congestion diffusion by modified BPR function. Jia *et al*. [30] used available traffic big data and an autoregressive integrated moving average model to predict a reliable congestion time of urban transportation. But these models are unsuitable for common networks because of their special characters as they pay too much attention to the travel time on road, restricting to road edges and unsuitable for nodes. But in the common network, such as communication network, the congestion happens always on nodes in stead of on edges.

In common networks, network congestion diffusion models considering congestion related information can be divided into two main types according to whether overload nodes or edges will be removed from networks. The first type focuses mainly on unrecoverable physical node or edge failures and neglects the situations of recoverable performance degradation, such as the widely known cascading models, including capacity-load models [31], [32], the binary influence models [11], [33], and stochastic flow network models [34]. In power grid networks and some other networks, the nodes or edges are indeed removed because the damaged nodes or edges cannot be recovered and used again. In these networks, the information influence is always considered as a control signal and taken as a node and then interdependent networks appear [11], [32]–[36]. However, in most networks, such as, road networks or Internet, congested nodes or edges should not be removed because they will soon recover their performance with less congestion, and then performance degradation models appear. Zheng *et al*. [37] proposed a congestion diffusion model, which is also a set of differential equations to describe the flow interactions between a node and its neighbors, but the node load distribution is considered completely equally, and so the routing choice influenced by congestion distribution information was not taken into consideration. Serdar *et al*. [4] proposed that routing choices also had much influence on congestion diffusion, so they examined congestion relief contrasting with a centralized routing scheme with varying levels of awareness of social good, based on the assumption that users are partially altruistic or spiteful [38]. The awareness of social good could be considered as information, but is different from our congestion distribution information. Crucitti *et al*. [39] presented a cascading congestion diffusion model based on the dynamical redistribution of the flow on the network and found that there is a certain node breakdown influence on the efficiency of entire system. These models have given some close methods to describe network congestion diffusion influenced by information, but the congestion distribution information and its influence on routing paths and then on the relief of network congestion is out of consideration. There is still a lack of a common network congestion diffusion model to simultaneously describe dynamic recoverable performance degradation congestion diffusion under the influence of congestion distribution information.

The main contributions of this work include: (1) A novel common network congestion diffusion model considering the influence of dynamical congestion distribution information is proposed, which is inspired by the Langevin diffusion model applied for biomolecule concentration diffusion under information influence in signal transduction networks; (2) The influence of complex dynamical congestion distribution information on congestion diffusion is described by analyzing the routing optimization method in the ant colony algorithm.

This paper is mainly organized as follows: In Section II, the related work of considering biomolecule concentration diffusion under the influence of crosstalk information is firstly discussed. In Section III, we innovate and transform the related model by employing the basic idea of the routing optimization method in the ant colony algorithm to fit a common network diffusion and then propose our novel congestion diffusion model. In Section IV, the simulation and discussion are carried out. The simulation results show that there are different alleviation effects on network congestion diffusion under different information influence factors, which are consistent with actual situations.

II. RELATED WORK

The mechanism of network congestion diffusion under the influence of congestion distribution information, is similar to the mechanism of proteins concentration diffusion under signal crosstalk regulations in signal transduction networks. Information transmission in communication network is realized by changing the stage of carriers at different nodes, and the stage is expressed by an analog or digital value. Correspondingly, signal transmission in signal transduction networks is also realized by changing the concentration of biomolecules, e.g., Ryan *et al.* provided a direct math function to express the concentration of Ca^{2+} varying with the light signal in biological systems [40], and the signal transduction is always realized by the concentration variation of biomolecules in signal transduction networks [41], [42]. If we take the concentration of a biomolecule as congestion of a node, then network congestion diffusion under the influence of congestion distribution among nodes can be taken as concentration variation under crosstalk influence among biomolecules. Both of them are dynamically varying under crosstalk coupling influence between a physical network layer and a logical network layer. After carefully studying the diffusion model considering crosstalk pathways in signal transduction networks which has been proposed by Ammar *et al.* [43], we propose a novel network congestion diffusion model considering the influence of congestion distribution information.

The concentration variation under the crosstalk influence among biomolecules in signal transduction networks was expressed with the Langevin diffusion model [44]. There are crosstalk pathways among different nodes in signal transduction networks. As illustrated in Fig.1, Tareen *et al.* [43] proved that the concentration of proteins was changed by the direct input-output and crosstalk channels in signal transduction networks. In each channel, the input represents the concentration of inactivated proteins, and the output represents the concentration of proteins activated by its input or other inputs.

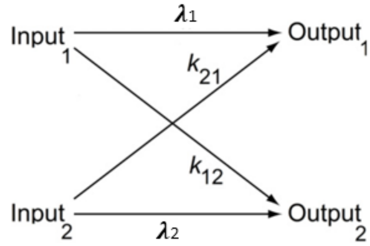

FIGURE 1. Direct input-output and crosstalk channels in signal transduction networks.

TABLE 1. Parameter denotations in the Langevin diffusion model.

Parameter	Denotation
$J_i^*(t)$	The concentration of activated protein i at time t
$J_i(t)$	The concentration of inactive protein i at time t
$k_{(i,j)}(t)$	The reaction rate of node j activated by node i at time t
$V(t)$	The system volume at time t, which controls the noise level
λ_i	The activation rate of node i, which can be a stable value
$\xi_i(t)$	The stochastic Gaussian white noise with zero mean at time t

In order to model the dynamic behavior of a well-stirred mixture of molecular species under the influence of concentration information, Tareen *et al.* [43] employed the Langevin diffusion model, which was expressed in (1) as follows:

$$\frac{\mathrm{d}J_i^*(t)}{\mathrm{d}t} = A_i(t) + B_i(t)\xi_i(t) \tag{1}$$

The $J_i^*(t)$ describes the concentration of activated biomolecule i at time t; $A_i(t)$ and $B_i(t)$ are the deterministic and stochastic part of the Langevin diffusion model at time t respectively, which are defined as:

$$A_i(t) = \sum_j k_{(j,i)}(t)J_j^*(t)J_i(t) - \lambda_i J_i^*(t)$$
$$B_i(t) = [(\sum_j k_{(j,i)}(t)J_j^*(t)J_i(t) + \lambda_i J_i^*(t))/V(t)]^{\frac{1}{2}} \tag{2}$$

and the denotations of parameters in (2) are explained in Table 1.

This classical model provides the dynamically varying concentration influenced by other concentration information, which also is the similar problem we are trying to solve.

III. INFORMATION INFLUENCING NETWORK CONGESTION DIFFUSION MODEL AFTER ADAPTIVE INNOVATIONS

Though the Langevin diffusion model discussed in Section II can provide a frame structure for network congestion diffusion model considering the influence of dynamical congestion distribution information, there are still many differences between signal transduction networks and common networks.

TABLE 2. Denotation transformations of corresponding parameters.

Parameter	Denotation in the Langevin diffusion model	Transformed denotation in common network
$J_i^*(t)$	The concentration of activated protein i at time t	The proportion of load to capacity on node i at time t
$J_i(t)$	The concentration of inactive protein i at time t	The proportion of empty capacity to capacity on node i at time t
$k_{(i,j)}(t)$	The reaction rate of node j activated by node i at time t	The crosstalk influence on node j from node i at time t
$V(t)$	The volume of the system at time t, which controls the level of noise	The volume of whole network at time t
λ_i	The activation rate of node i	The processing ability of node i
$\xi_i(t)$	The stochastic Gaussian white noise with zero mean at time t	The stochastic Gaussian white noise with zero mean at time t

Therefore, it is necessary to innovate and transform, and even redefine the parameter denotations in the Langevin diffusion model to fit a common network congestion diffusion and some parameters need to be completely redefined. And these works are also our main innovations.

A. TRANSFORMATION OF PARAMETER DENOTATION IN LANGEVIN DIFFUSION MODEL

According to the parameter denotations in Langevin diffusion model and similar meanings in a common network congestion diffusion, the transformed denotations are listed in Table 2.

Here, congestion distribution information is the different proportion of load to capacity on every node, which is expressed by $J_i^*(t)$ in Table 2. The sum of the $J_i^*(t)$ and $J_i(t)$ equals 1.

B. DENOTATION INNOVATION FOR CROSSTALK INFLUENCE PARAMETER

After the above transformations in Table 2, every parameter has a clear corresponding meaning except the crosstalk parameter $k_{(i,j)}(t)$. Thus it is necessary to redefine a proper denotation of the crosstalk influencing parameter between origin node and destination node under dynamical congestion distribution information influence. This parameter represents the flow on the edges between connected nodes influenced by node congestion information. The routing optimization selection probability considering the mutual information in the hybrid ant colony algorithm provided a referential reasonable equation to deal with the similar problem [45]. The routing optimization selection probability is expressed in (3) as follows:

$$p_{(i,j)}(t) = \frac{[\tau_{(i,j)}(t)]^{\alpha}[\frac{1}{d_{(i,j)}}]^{\beta}[MI_{(i,j)}]^{\gamma}}{\sum\limits_{s \in allowedSET}[\tau_{(i,s)}(t)]^{\alpha}[\frac{1}{d_{(i,s)}}]^{\beta}[MI_{(i,s)}]^{\gamma}} \tag{3}$$

where $\tau_{(i,j)}(t)$ is the pheromone, a kind of chemical factor excreted by ants for others to follow the same way; $d_{(i,j)}$ is the distance of the path; $MI_{(i,j)}$ is the mutual information which also helps to choose a better way. And this equation is telling us a common path selection probability rule, in which the relationship between path selection probability and the positive or negative influencing factors is described clearly.

Inspired by routing optimization selection probability considering the mutual information in the hybrid ant colony algorithm, we propose a crosstalk parameter $k_{(i,j)}(t)$, which can be expressed in (4).

$$k_{(i,j)}(t) = p_{(i,j)}(t) = \frac{(k_j)^{\alpha}(\frac{1}{J_j^*(t)})^{\beta}(J_i^*(t))^{\gamma}}{\sum\limits_{i \in DC}(k_j)^{\alpha}(\frac{1}{J_j^*(t)})^{\beta}(J_i^*(t))^{\gamma}} \tag{4}$$

where $k_{(i,j)}(t)$ is given by $p_{(i,j)}(t)$, which means the probability of load transforming from node i to node j at time t, k_j is the degree of node j. $J_i^*(t)$ and $J_j^*(t)$ represent the congestion information of origin node i and destination node j at time t respectively because the proportion of load to capacity on nodes can be taken as its quantitative congestion information; α, β and γ are the influencing factors of degree, destination node and origin node, respectively.

Equation (4) provides a clear description of load transforming probability, which has a positive correlation with the degree of destination node j and current load proportion on origin node i, and has a negative correlation with current load proportion on destination node j. The reason why we give such an equation is that the degree of a node is always used to express the importance of this node in various fields [46]–[48], and it is obvious that if the more load of destination node, and the less empty capacity of the node to accept the new incoming load so the probability is lower; If the origin node has more load proportion, the transforming probability will be increased because more load are badly needed to be transformed. The whole equation is proposed according to the hybrid ant colony algorithm, and the simulation results prove that it is proper and reasonable in real situations.

C. MODEL FOR NETWORK CONGESTION DIFFUSION INFLUENCED BY CONGESTION DISTRIBUTION INFORMATION

After the above adaptive innovations in subsection III-A and subsection III-B, the meanings of relative parameters have been given. Then a novel model for network congestion diffusion influenced by dynamical congestion distribution information is obtained according to (1) and (4) and Table 2. And the model can be expressed in (5) as follows:

$$\begin{aligned}\frac{dJ_i^*(t)}{dt} &= [\sum_{j \in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) - \lambda_i J_i^*(t)] \\ &\quad + [\sum_{j \in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) + \lambda_i J_i^*(t)]^{\frac{1}{2}}\xi_i(t)\end{aligned} \tag{5}$$

Since this differential Equation (5) provides the load proportion variation rate on nodes, the computer simulation formula can be obtained according to the following

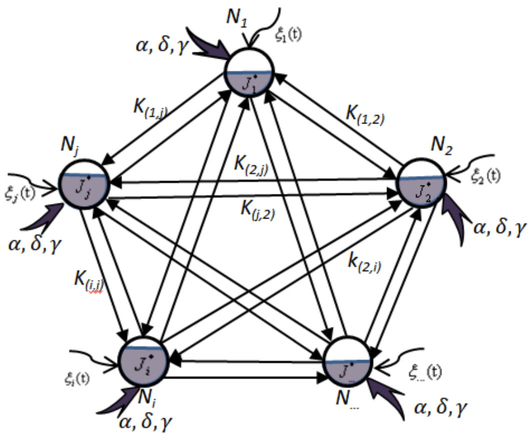

FIGURE 2. Network congestion diffusion process among nodes.

Equation (6).

$$\begin{aligned} J_i^*(t+1) &= J_i^*(t) + [\sum_{j\in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) - \lambda_i J_i^*(t)] \\ &\quad + [\sum_{j\in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) + \lambda_i J_i^*(t)]^{\frac{1}{2}}\xi_i(t) \\ &= (1-\lambda_i)J_i^*(t) + \sum_{j\in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) \\ &\quad + (\sum_{j\in DC} k_{(j,i)}(t)J_j^*(t)J_i(t) + \lambda_i J_i^*(t))^{\frac{1}{2}}\xi_i(t) \end{aligned} \quad (6)$$

where $J_i^*(t)$ denotes the load proportion of node i at time t; $J_i(t)$ denotes the empty capacity proportion of node i at time t; λ_i is the processing ability of node i, which means the percent of the current load can be transformed away. DC means the set of direct connected nodes in the network. According to (4), $k_{(i,j)}(t)$ denotes the crosstalk strength at which the load is transmitted from node i to node j, and this crosstalk parameter $k_{(i,j)}(t)$ can be expressed in (7).

$$k_{(i,j)}(t) = \frac{(k_j)^\alpha(\frac{1}{J_j^*(t)})^\beta(J_i^*(t))^\gamma}{\sum_{i\in DC}(k_j)^\alpha(\frac{1}{J_j^*(t)})^\beta(J_i^*(t))^\gamma} \quad (7)$$

and the meanings of these parameters are the same as before.

Congestion distribution information is the load proportion on different nodes. Load proportions on nodes are dynamically varying and coupling with the node processing ability, congestion distribution of nodes, network topology and etc. A dynamical coupling process of network congestion diffusion among nodes is illustrated in the following Fig.2.

Equations (6) and (7) give description of network congestion diffusion among nodes on the micro level, and congestion diffusion of the whole network is generally described by Equation (8) as follows, which is the variance of the load on all nodes and a popular congestion parameter definition [37], [49].

$$D(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(J_i^*(t) - \overline{J^*(t)})^2} \quad (8)$$

where the N represents the number of all nodes; And $\overline{J^*(t)}$ is the mean load proportion of all nodes at time t. Then $D(t)$ can represent the network congestion at time t.

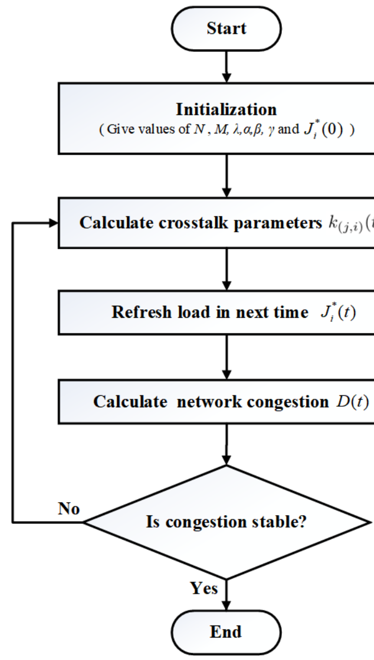

FIGURE 3. Flow chart of simulations.

IV. SIMULATIONS AND DISCUSSIONS

The proposed model in subsection III-C should be tested to prove its reasonableness and validity. In this section, network congestion diffusion under the influence of congestion information is simulated in a certain network. Here are the simulation steps. As shown in Fig.3, the simulation flow is provided as follows:

Step 1:Initialization

First, a network should be provided. Here a BA (Barabasi-Albert) network and an ER (Erdos-Renyi) network with 200 nodes and 5800 edges are produced randomly, and thus $N = 200$ and $M = 5800$. The load congestion proportions of nodes are also given randomly with the normal distribution ranged from 0 to 1, and a node with load congestion proportion 1 means a congested node with no capacity to accept any extra load from others and vice versa. In the simulation, the relative parameters λ, α, β and γ respect the processing ability, node degree influencing factor, destination node congestion influencing factor, origin node congestion influencing factor respectively, and they should be settled at the beginning according to the purpose of a certain simulation. The node processing ability λ is assumed to be the same in our simulation.

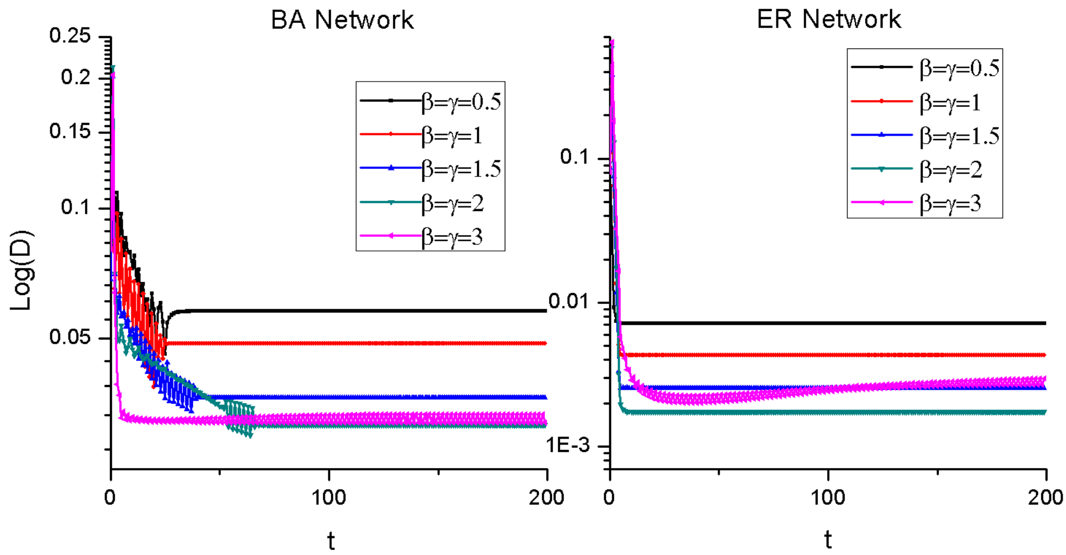

FIGURE 4. Congestion diffusion with different information influence factors in BA network and ER network.

Step 2: To calculate crosstalk parameter $k_{(j,i)}(t)$

With the given parameters in Step1 and Equation (7), the crosstalk parameter $k_{(j,i)}(t)$ is calculated for Equation (6). The parameter $k_{(j,i)}(t)$ needs to be calculated circularly and dynamically because the load congestion is varying with time. The $k_{(j,i)}(t)$ should be set to be 0 if the load of destination node exceeds its full capacity.

Step 3: To refresh the load in the next time

The load of every node is dynamically varying because part of the load flows out due to the processing ability, and there are new load incomes from the directly connected nodes. Equation (6) can be used to calculate the load in the next time.

Step 4: To calculate network congestion

The aim of the model is to consider the congestion distribution information influence on the network congestion diffusion. The congestion information influence can be adjusted by β and γ, and the congestion diffusion of the whole network can be described by $D(t)$ in Equation (8).

Step 5: To judge whether the congestion stabilization

Since the aim of this paper is to model network congestion diffusion under the influence of congestion distribution information, it is necessary to get the stable value of $D(t)$ under certain information influencing factors β and γ. Therefore, we give a value e, which is the upper error limit of $D(t)$ between two following steps. According to Equation (9), the simulation will stop if the $D(t)$ is stable and within the given upper error limit e. In our simulations, the value of e is set to 0.0001.

$$|D(t+1) - D(t)| \leq e \tag{9}$$

From the above simulation, we obtain some interesting relationships between the network congestion diffusion and the influence of congestion distribution information. Because the congestion distribution information is the load congestion situation on different nodes, which are expressed by a plenty of $J_i^*(t)$, and the γ and β are the influencing factors of the congestion distribution information. Thus, it is meaningful to discuss the overall congestion $D(t)$ varying with the β or γ since the γ equals β. Results in Fig.4 and Fig.5 are obtained with $\lambda = 0.5$, $\alpha = 0.5$, and $\gamma = \beta$. The reason why we let $\gamma = \beta$ is that both γ and β belong to congestion information influence, and the situation is similar when the parameters vary.

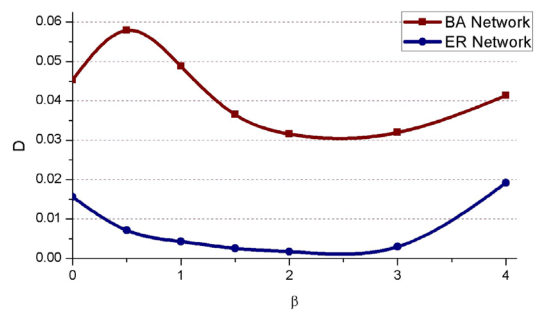

FIGURE 5. Relationship between information influence factors and the congestion diffusion.

As shown in the Fig.4, the network congestion diffusion value $D(t)$ can be stable as time goes on. Besides, the larger the information influence factor is, the better the congestion diffusion is, but this effect will change when the influence factor is too large.

In the Fig.5, the information influence on the congestion diffusion is obvious and the relationship between information influence factor β and the congestion diffusion $D(t)$ is clear. A proper β will result in less congestion diffusion $D(t)$ and here the congestion diffusion $D(t)$ becomes the least when the β approaches the value of 2.5. This means that if the influence of information is properly adjusted and then the

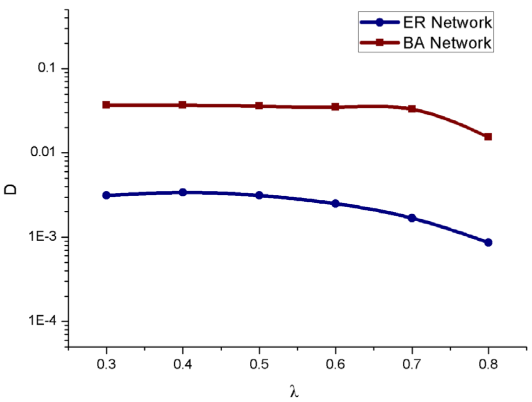

FIGURE 6. Relationship between the processing ability and the congestion diffusion.

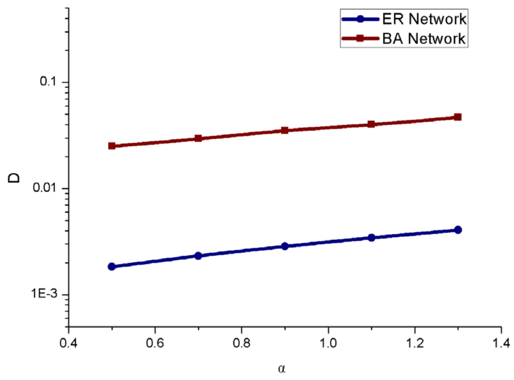

FIGURE 7. Relationship between degree influencing factors and the congestion diffusion.

whole network system will achieve a least congested state, which will bring great contributions for large-scale network systems. A reasonable phenomenon is found that the ER network is less congested than the BA network because the node degree distribution in the ER network is more regular than in the BA network. And the trends of two networks grow to be increasingly similar as the information influencing factor β grows greater and the relative influence of degree grows smaller. The different congestion diffusion trends at the beginning are caused by different distributions of degrees and their relative influencing values of information.

According to the curves in Fig.5, the influence of information on the congestion diffusion unstrictly follows a bathtub curve, which means that too large or small information influence will lead to serious congestion diffusion, and there is a relatively broad range in which the information influence makes little difference. A best value of information influence still exists because the bathtub curve is not so strict. And this law will helps to reach the optimal state of network congestion by dynamically adjusting the influence of congestion distribution information. For example, we can adjust the color depth of congested roads on navigation maps, which will change the congestion information influence and then adjust the network congestion.

Fig.6 shows the relationship between congestion $D(t)$ and processing ability λ. It is reasonable that BA networks are more congested than ER networks because the node degree distribution in BA networks is more irregular than that in ER networks. Besides, when the processing ability λ is larger, the average load will be less, and then the congestion $D(t)$ will be relieved and less. The results in Fig.6 are obtained with varying λ under the condition of $\alpha = 1, \gamma = \beta = 1$ and many other simulation results have been carried out and the conclusion is similar.

In the Fig.7, the relationship between congestion $D(t)$ and degree influencing factor α is shown. It is reasonable that BA networks are more congested than ER networks because the node degree distribution in BA networks is more irregular than that in ER networks. Besides, the degree influencing factor α is larger, the irregularity of node degree will be greater, and then the congestion $D(t)$ will be increased. The data in Fig.7 are obtained with varying α under the condition of $\lambda = 0.5, \gamma = \beta = 1$. Many other simulation results have been carried out and the conclusion is similar.

As mentioned above, the phenomena shown in these figures are suitable to the actuality, and the simulation results are reasonable. Hence, our model is a feasible mathematical method to describe network congestion diffusion under the influence of congestion distribution information.

V. CONCLUSION

In this paper, by analyzing the Langevin diffusion model of biomolecule concentration in signal transduction networks and the routing optimization method in the ant colony algorithm, a novel model is proposed to describe network congestion diffusion under the influence of congestion distribution information after adapting innovation. Then the dynamic process of common network congestion diffusion under the influence of congestion distribution information is firstly described by a set of differential equations. Simulation results show that network congestion diffusion under information influence can be reasonably interpreted by our model, and the bathtub curve law reflecting network congestion diffusion under information influence appears. This model provides a novel method to study network congestion diffusion under information influence and more valuable rules can be obtained in future works. Besides, network congestion diffusion under multiple influencing factors can be further studied based on the similar method.

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