

MODEL AND SIMULATION OF INFORMATION DIFFUSION BASED ON NETWORK DIMENSION-FORCE

YIRUI DENG, XIAOFENG XU

School of Economics & Management, China University of Petroleum, Qingdao 266555, Shandong, China

ABSTRACT

The superiority dimension-forces which network has make information diffusion in realistic space change in the nature through information coupling. It means that information diffusion in realistic space is no longer affected by geography, volume and time constraints. Under the promoting of network dimension-force, the source information can reach any sink fast and synchronously in broad spatial scope and accumulate information instantaneously to surmount the threshold value of sink, and then realize the diffusion distance willfully far, the quantity of information destination willfully more, the diffusion effect obviously enhanced. In order to measure the diffusion effect under the promoting of network dimension-force, on the basis of the core idea of the network dimension-force theory, using for reference from the Markov drift chain theory, this paper carries on the model construction and simulation of information diffusion. This model attempts to describe systematically and semantically the motion state of information diffusion from the macro level, and the simulation results reveal the positive promoting role of network dimension-force on information diffusion.

Keywords: *Network Dimension-force, Information Diffusion, Space-time Model*

1. INTRODUCTION

The purpose of information diffusion is to share. Information is normally present on the material vector in realistic space, supplier and demander of information need to move geographically to achieve information diffusion, and the process of diffusion is limited and blockaded by these relevant elements, such as circulation channel, place and time, administrative restraint, and so on. All of these influences make information diffusion having various disadvantages. In a way, the appearance of network avoids these problems, because it provides a full-featured opening diffusion and resource sharing platform for information, and makes information diffusion really breakthrough in space-time and geographical constraints.

From the literatures which are already existed, the related research on the model and simulation of information diffusion is only limited to realistic space, and about network space hasn't set foot [1]. Therefore, from the view based on information theory, cybernetics and system theory, the paper has carried on exploratory research and exposition about the model and simulation of information diffusion based on network dimension-force.

2. NETWORK DIMENSION-FORCE THEORY

Network dimension-force theory refines three properties in which network space is stronger than realistic space, including intercommunication force, clustering force and synchronization force. These three properties are described in the Cartesian coordinates to format the effectiveness system of information amount & time value [2]. This theory's core ideas are as follows:

(1) The intercommunication force

Because that there're the net surface connection's diffusion and the infinity of the data transmission, the node P_i is in random in network space, its position can be the any position and does not affect the interconnection. P_i may intercommunicate with the far node P_j , namely network space supports the nodes' interconnection of the entire net. That is to say, it allows that the position of the nodes in network space can be random, the distance between the nodes is away from infinite, and each node may exchange the interconnection. We define this intercommunication characteristic power of the network as the intercommunication force, which is also called the entire net's intercommunication, with expression L_{∞} .



$$L_{\infty} : l_{ij} \rightarrow \infty$$

l_{ij} --the distance between the node P_i whose position is in random and the farthest node P_j , $i=1,2,\dots,n$; $j=1,2,\dots,n$

The action object of intercommunication force is node, the ability is information flowing, and the done degree is the intercommunication nodes full (qualitative measurement).

(2) The clustering force

Because of the existence of intercommunication force, the quantity of the nodes in network space may be infinity. Namely when and only when L_{∞} exists, network space can let the node P_i which is in network space in random get together with other relational node P_j ($j=1,2,3,\dots,n$), and the quantity of the gathering may be possible to realize the infinity. We define this characteristic power of the network which can contain all relational nodes and increase the quantity as the clustering force. The clustering force is also called the infinity of the intercommunication between the nodes. It comes from the infinity of network space, and supports the infinite distributed node quantity, and uses the expression as P_{∞} .

$$P_{\infty} : M_p \rightarrow \infty$$

M_p --the quantity of nodes that the subspace may accommodate.

The action object of clustering force is also node, the ability is the clustering of nodes, and the done degree is the group big (qualitative measurement).

(3) The synchronization force

As a result of the leap development of the transmission medium, the transmission mode and the transmission technology, the speed of the data transmission in network space is infinity. Then the time that the data transmission of the nodes consumes will be infinitely great. That is to say, the time when the node P_i which is in network space in random transmits information to P_j ($j=1,2,3,\dots,n$) is $T_{ij} \rightarrow 0$ ($j=1,2,3,\dots,n$), namely the information may reach the node P_i synchronously. We define this characteristic power of network space which can make the time and the time difference minimum when information flows among the nodes as the synchronization force. The synchronization force is also called the minimum of the time

difference when information flows among the nodes. It comes from the maximum of the flowing speed, and uses the expression as T_{δ} , which explains that the time difference when information flows between the nodes is minimum.

The action object of synchronization force is node, the ability is the flowing time difference, and the done degree is the synchronization good (qualitative measurement).

(4) Network dimension-force

From the above analysis, the action objects of the clustering force P_{∞} and the synchronization force T_{δ} are both the node P . From the trend, the node amount Q_p is equivalent to the amount of information Q_i . That is to say, Q_p and Q_i have the same change trend. If Q_p increases, then Q_i also increases. Similarly, T_{δ} is equivalent to the time value of information N_i . The reduction of T_{δ} means N_i increases. Accordingly, the purpose of P_{∞} is to access information through the node clustering, and the purpose of T_{δ} is to increase the time value of information through the node synchronization. That is to say, the network characteristic force is ultimately oriented information.

In the Cartesian coordinates system, the information function $Q_i(t)$ with the time T as the independent variable and the time value function of information $N_i(t)$ intersect at one point. The information value and the time value of information which this point corresponds are the effectiveness of information amount & time value, and it's denoted by F_1 : $F_1 = f(Q_i, N_i)$. The pursuit of F_1 is the balance between $Q_i(t)$ and $N_i(t)$ at a certain moment in information interaction, specifically as shown in Figure 1.

Where:

Q_i --information (the effectiveness of amount);

N_i --the time value of information (the effectiveness of time);

T --time;

F_1 --the effectiveness of information amount & time value of network space Ω_1 ;

F_2 --the effectiveness of information amount & time value of realistic space Ω_2 .

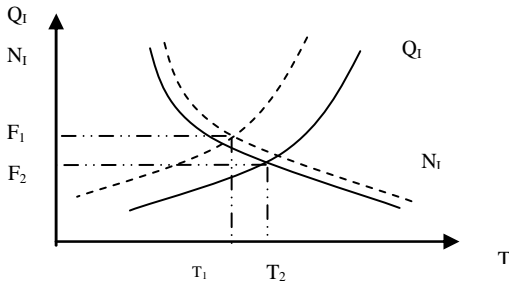


Figure 1: The Relation Between Information Amount & Time Value And Time

In Figure 1, the solid line represents the relation between information amount & time value and time of realistic space Ω_2 , and the dotted line represents the relation between information amount & time value and time of network space Ω_1 . From Figure 1, we can see that: (1) with the increasing of T , Q_i increases and N_i decreases. (2) at the time T_2 , the point group obtains the balance of information amount & time value in Ω_2 , and the effectiveness of information amount & time value is F_2 . However, under the effect of P_∞ in Ω_1 at the time T_2 , the increasing of Q_p leads to Q_i increase, so that the dotted line of Q_i will move up, and at the moment T_2 , the dotted line of N_i in Ω_1 is not lower than in Ω_2 at least. The effectiveness of information amount & time value in Ω_1 is F_1 . (3) F represents the time point at which it realizes the balance between the effectiveness of amount and the effectiveness of time. In Figure 1, the increasing of the effectiveness of information amount & time value in Ω_1 is bigger than in Ω_2 , increment is $\Delta F = F_1 - F_2$. Specific performances are: the contradiction balance (solve) time advances $\Delta T = T_2 - T_1$, the time effectiveness of information increases $\Delta N_i = N_{i1} - N_{i2}$, and the amount effectiveness of information increases $\Delta Q_i = Q_{i1} - Q_{i2}$.

Thus, it completes the transformation and the proof from the network elements characteristic forces to the information characteristic forces, and realizes that this information characteristic force is described in Cartesian coordinates. Therefore, network dimension-force is found. So network dimension-force is information characteristic force of network, and has the time-effect and amount-effect two dimensions. Its object is information.

Therefore, the effectiveness of information amount & time value is the advantage characteristic force of network information, which the strength of network dimension-force lies in.

3. INFORMATION DIFFUSION SYSTEM

Information diffusion from the perspective of network is based on network platform, it is the process that network dimension-force makes the information of a node fast synchronization up to any node in a broad range, and the node information is decided to adopt and apply in accordance with other nodes according to reality environment. It expresses specially a space phenomenon that the adoption of diffusion of information is increased by time, the scale and scope of adoption are ever-expanding. Information diffusion from the perspective of network is a complex process between lapse of time and space sprawls, its “expand” is to the number of nodes P , and “break up” is to the distance L , the pursuit of diffusion are the effective P and L [3].

Here, the node is the network node in particular, namely the man-machine interface spot in network. It’s the intelligent agent, and is the smallest function unit in network space. In order to study conveniently, the node which outputs information is defined the source, and the node which inputs information is defined the sink in this paper.

Information diffusion based on network dimension-force is the complex process involving numerous factors that it takes the diffusion behavior participant as the foundation, takes the network environment as the support, takes the information potential difference as the power, and takes the information circulation and the information transmission as the condition. Therefore, the paper takes the information diffusion question in network space as the complicated system which is composed of many incident cross-correlations, interaction’s essential factors and carries out the specific function to study, with the aim of grasping the law of motion and the effect change of information diffusion comprehensively. This system is the complex compound composed of source, sink, information, noise and network medium and so on, and is the multi-level and the complex organic function system that realizes the benign information diffusion between source and sink.



4. MODEL OF INFORMAITON DIFFUSION

Under the action of network dimension-force, the process of information diffusion forms a Markov process with drift. If using mathematical language to describe the diffusion process, it can be expressed this:

Suppose $S_t = \{x_t, e_t\}$ is the state parameter sets of information diffusion, the state space $I = \{0,1\}$ is two states of the sink in the diffusion space. Among them, $\{0\}$ is that the sink doesn't adopt the source information, which belongs to the not adopted state; $\{1\}$ is that the sink has adopted the source information, which belongs to the adopted state, besides the presence of other state. Suppose that the source information begins to diffusion at the time $t = 0$ and over at the time $t = T$ ($[0, T]$ is the information value interval), then for any time $t \in (0, T)$, the probability p that the not adopted sink whose node quality difference is z adopts the source information at the time $t + 1$ is:

$$p\{S_{t+1}|S_t, S_{t-1}, \dots, S_1, S_0\} = p\{S_{t+1}|S_t\} \quad (1)$$

The process that the formula (1) expresses is Markov process, and the state parameter set $\{S_t\}$ of the diffusion is called Markov chain.

Markov drift chain is one of Markov process, and is the vector Markov process with drift coefficient. If $\{S_t\}$ is Markov chain, then Markov drift chain can be expressed as $Y_t = \{S_t, \mu t\}$ [4]. Among them, constant μ is drift coefficient. The Markov drift process is equivalent to give the standard Markov process a driving force to accelerate the diffusion process and enhance the diffusion efficiency. This makes the diffusion process have the micro random motion and the macro rules drift, which reflects in the amplification effect that the drift coefficient exerts on the state transition probability. Now we should definite the state transition probability of the Markov drift process at first.

According to the Markov equation with drift, we can solve the state transition probability that the sink transfers from the not adopted state to the adopted state in the information diffusion system. Suppose that the adoption that the potential adoption sinks adopt the source information is all at once, and giving up is all at once. Therefore, the state transition probability is the one-step transition

probability, namely either the sink transfers from the not adopted state to the adopted state at one step, or from the adopted state to the not adopted state, and only the two transfer case.

It can be defined as follows: there's $i, j \in I$, for any sink z , let

$$P_{ij}(z, t) = P(z, Y_{t+1} = j | z, Y_t = i) \quad i, j \in \{0, 1\} \quad (2)$$

Where: $0 \leq P_{ij}(z, t) \leq 1$. $P_{ij}(z, t)$ is called the state transition probability that the sink z transfers from the not adopted state to the adopted state at the time t , and its function form is called the state transition probability function. Among them, $P_{i=0, j=1}(z, t)$ is the transition probability that the sink z makes decision and adopts the source information and transfers from the not adopted state to the adopted state at the time t , denoted by $P_{01}(z, t)$. $P_{i=1, j=0}(z, t)$ is the transition probability that the sink which has adopted the source information exits adoption and transfers to the not adopted state, denoted by $P_{10}(z, t)$.

The promoting effect that network dimension-force has on the diffusion process reflects in the amplification effect that the drift coefficient has on the state transition probability. But how the transition probability embodies the amplification effect of the drift coefficient? If let $p_{ij}(z, t)$ be the state transition probability of the standard Markov process under no action of the external force, then the transition probability $P_{ij}(z, t)$ of Markov drift chain can be expressed as:

$$P_{ij}(z, t) = p_{ij}(z, t) (1 + \mu\sqrt{\Delta t}), \Delta t \rightarrow 0 \quad (3)$$

Where: $P_{ij}(z, t)$ is the state transition probability of the Markov drift process of information diffusion. $p_{ij}(z, t)$ is the state transition probability of the simple Markov drift process. μ is the drift coefficient, and $0 \leq \mu \leq 1$.

The drift coefficient μ of the formula (3) isn't the simple Figures in $[0, 1]$, but is the function about ΔF . The value range of μ is $[0, 1]$, and it represents symbolically the promoting effect that network has on information diffusion. If $\mu = 0$, it indicates that the effectiveness of time-value & information amount in network hasn't exert effect on information diffusion, and the diffusion process



is the standard Markov process with no drift, namely the diffusion is in realistic space. If $0 < \mu \leq 1$, it indicates that the effectiveness of time-value & information amount in network promotes information diffusion, and the Markov process is the positive drift, this information diffusion is this paper's research contents. If $\mu = 1$, it indicates that the promoting effect that the effectiveness of time-value & information amount in network has on information diffusion plays to the limit. As for the value of μ , it should be considered according to the specific circumstances of network.

From the formula (3), we can see that when network dimension-force plays the promoting role to information diffusion, the drift coefficient μ has the amplification (or reduce) effect on the state transition probability. The drift coefficient is called the accelerator to information diffusion in the time and space. At the same time, the formula (3) shows that as long as obtaining the transition probability of the standard Markov process, then giving the drift coefficient a proper value, we can solve the state transition probability of the Markov drift chain.

The solving process of the state transition probability of the standard Markov process is as follows: the probability of the sink in the state j at the time t can be estimated by the transfer probability.

$$\forall t_1, t_2 \in T \text{ and } i, j \in I$$

$$p(z, S_{t_2} = j) = \sum_j p(z, S_{t_2} = j | z, S_{t_1} = i) p(z, S_{t_1} = i) \quad (4)$$

The formula (4) is Chapman-Kolmogorov equation, which is the basic equation of Markov process [5].

There're only two states of the sink in the state space of information diffusion, and there isn't the intermediate state. That is to say, the state transition is completed in one step. Therefore, the formula (4) can be simplified to:

$$p(z, S_{t_2} = j) = p(z, S_{t_2} = j | z, S_{t_1} = i) p(z, S_{t_1} = i) \quad (5)$$

Where: $p(z, S_{t_2} = j)$ is the probability that the sink is in the state $j \in I$ at the time t_2 , denoted by $p_j(z, t_2)$. $p(z, S_{t_1} = i)$ is the probability that the

sink is in the state $i \in I$ at the time t_1 , denoted by $p_i(z, t_1)$.

Let $t_1 = t, t_2 = t + \Delta t$, then

$$p_j(z, t + \Delta t) = p_{ij}(z, t) p_i(z, t) \quad (6)$$

The formula (6) is the probability that the state of the sink z at the time t transfers to the state j at the time $t + \Delta t$.

Despite the transition probability p of the diffusion determines Markov process, but it's very difficult to obtain a specific transition probability function whether in theory or in practice. Therefore, we should consider the relevant content which can decide the transition probability function, and then the concept of the transition probability density function of the diffusion is introduced.

Let $i, j \in I, \delta \in T$, if the limit

$$\lim_{h+k \rightarrow 0} \frac{p_{ij}(z, t-h, t+k) - \delta_{ij}}{h+k} = q_{ij}(z, t) \quad (7)$$

exists (where: δ_{ij} is the probability that the sink transfers from the state i at the time t to the state j at the time $t + \Delta t$ when $\Delta t \rightarrow 0$), then the function $q_{ij}(z, t)$ is called the transition probability density function of information diffusion.

In fact, the transition probability density function $q_{ij}(z, t)$ is the function about the time variable t and the space variable z of information diffusion, and is the binary transition probability density function of information diffusion. With a clear sense probability, it has the following properties:

$$q_{ij}(z, t) \geq 0$$

$$\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} q_{ij}(z, t) dz dt = 1 \quad (8)$$

The transition probability density function of the diffusion is solved easily from the actual observation. Now, according to the path that the probability function is pushed to the probability density function, we can seek the method that the probability function is back deduced from the density function.

Let the transition probability $p(z, S_{t+\Delta t} = j | z, S_t = i)$ expand according to the secondary Taylor series:



$$p(z, S_{t+\Delta t} = j | z, S_t = i) = p(z, S_t = j | z, S_t = i) + \Delta t \frac{dp(z, S_{t+\Delta t} = j | z, S_t = i)}{dt} \quad (9)$$

$\frac{dp(z, S_{t+\Delta t} = j | z, S_t = i)}{dt}$ is the transition probability density function $q_{ij}(z, t)$ of the diffusion.

According to the definition of the transition probability, $p(z, S_t = j | z, S_t = i) = 0$, then

$$p_{ij}(z, t) = \Delta t q_{ij}(z, t) \quad (10)$$

$$p_j(z, t + \Delta t) = q_{ij}(z, t) p_i(z, t) \Delta t \quad (11)$$

The formula (10) indicates that the probability that the sink transfers from the state i at the time t to the state j at the time $t + \Delta t$ can be solved by the probability density function in the standard Markov process.

Using the formula (10) and (11), we can obtain the state transition probability p_{ij} of the standard Markov process that doesn't consider the promoting effect of network dimension-force on the diffusion. According to the formula (3), through the state transition probability of the standard Markov chain, we can get the state transition probability $P_{01}(z, t)$ of the Markov drift chain under the promoting effect of network dimension-force:

$$P_{01}(z, t) = p_{01}(z, t) (1 + \mu \Delta t) = q_{01}(z, t) (1 + \mu \Delta t) \Delta t \quad (12)$$

and the probability $P_1(z, t)$ that the sink z adopts the source information and then is at the adopted state at the time $t + \Delta t$.

$$P_1(z, t) = q_{01}(z, t) (1 + \mu \Delta t) P_0(z, t) \Delta t \quad (13)$$

In the Markov drift process formed by information diffusion, the sink is possible to adopt the source information at any time, which makes the state of the sink transfer from the not adopted state $i=0$ to the adopted state $j=1$. Suppose that the sink z adopts the source information at the time s ($s \in [0, T]$), and its state transfers, then the probability $P_1(z, t)$ that the sink z is at the adopted state $\{1\}$ at the time t is:

$$P_1(z, t) = \sum_{s=0}^T q_{01}(z, s) (1 + \mu \Delta t) P_0(z, s) \Delta s \quad (14)$$

If the density function is continuous at the time, then the probability $P_1(z, t)$ that the sink z is at the adopted state at the time t can be denoted by:

$$P_1(z, t) = \int_0^T q_{01}(z, s) (1 + \mu \sqrt{\Delta t}) P_0(z, s) ds \quad (15)$$

In contrast, the probability $P_0(z, t)$ that the sink z is at the not adopted state $\{0\}$ at the time t is:

$$P_0(z, t) = 1 - P_1(z, t) \quad (16)$$

The formula (7) only describes the probability that the sink whose node quality difference is z is at the adopted state at the time t . Then to the whole diffusion system, how expresses the overall adoption probability of the sink?

The diffusion nodes comprise the diffusion space overall. The sum of the sinks at the adopted state whose node quality difference is z reflects the overall adoption probability of the sink. Due to the diffusion space is composed by the sinks that have the node quality difference, so the diffusion space is discrete and does not have continuity. Therefore, the overall adoption probability $P_1(t)$ of the sink at the time t is described by the ratio of the sum of the adopted sink with the each node quality difference level and the total quantity of the sink[6], denoted by:

$$P_1(t) = \frac{1}{N_0} \sum_{z=0}^{\infty} P_1(z, t) n_z$$

$$P_0(t) = 1 - P_1(t) \quad (17)$$

Where, n_z is the quantity of the sinks whose node quality difference is z in the diffusion space. N_0 is the quantity of all diffusion nodes in the diffusion space.

The formula (15) and (17) are the distribution functions of the general adoption probability as the time and the space in the information diffusion system. According to the formula (15) and (17), if the transition probability q_{ij} and the initial conditions of the diffusion $P_i(z=0, t=0)$ are known, then we can deduce the adoption probability of any sink at any time, which can help us to understand the space-time distribution model and characteristics of information diffusion. Therefore, we should analyze concretely the initial conditions



and the transition probability density function of information diffusion.

(1) The initial conditions

According to the hypothesis, there must be a certain amount of diffusion nodes in the space after the source information diffuses successfully. Suppose that the number of nodes is a certain value N_0 . When the diffusion is at the beginning, let $t = 0$, that means that the timing game enters the first stage. Due to the sink does not know the source information, and the source information meets their demand is uncertain, so most sinks support the wait-and-see attitude, and no sink makes the decision to adopt. At this time, only the source has diffusion information in the diffusion system, then the initial adoption probability of the diffusion is $P_1 = 1/N_0$, and $P_0 = 1 - P_1$. According to the definition of the node quality, the node quality difference of the source is 0 in the diffusion system, which can determine the initial state of the diffusion, i.e.:

$$t = 0, P_1(z = 0, t = 0) = \frac{1}{N_0} \quad (18)$$

The initial conditions of the diffusion are known, if we can determine the transition probability P , then we'll determine the Markov drift process of the diffusion and deduce the macro diffusion model of the information space-time diffusion.

(2) The transition probability density function

It should be emphasized that which quality level of the sink adopts the source information at first is random to the single sink in the diffusion space, but the macro distribution of the diffusion in the diffusion space shows the certain regularity. We study the correlation between the node quality difference and the adoption probability from the transition probability density of the single sink, and the macro model that the adoption probability in the diffusion space shows.

The transition probability density function of the information space-time diffusion can be derived by the expected adoption utility function:

$$q_{01}^*(z, n, I_{zt}) \equiv \frac{1}{n-1} \frac{\rho \Delta U(n, z, I_{zt})}{e^{-\rho \Delta} [\Delta U(n-1, z, I_{zt}) - \Delta U(n, z, I_{zt})]} \quad (19)$$

(3) Special case

We also should discuss about the probability that the sink at adopted state gives up the adoption and returns to the not adopted state.

In the derivation of the formula (10), it implies a putative that the state of the sink which has adopted the source information becomes the adopted state and until finally it no longer recovers the not adopted state. In fact, there's the individual sink which has adopted the source information. These sinks can't use the source information due to various restriction conditions, and then are forced to withdraw from the adopted state. But the probability of this case is very small. In the model, $P_{10}(z, t)$ indicates the state transition probability that the sink z gives up the source information after a period of adoption and recovers the not adopted state.

If we consider that the adopted sink gives up the source information and exits the adoption. Suppose that the sink adopts the source information at the time s , and gives up the source information and exits the adoption at the time u . Let $0 < s < t_1 < u < t$, then the probability $P_1(z, t)$ that the sink z which is at the adopted state $\{1\}$ at the time t is:

$$P_1(z, t) = \int_0^{t_1} P_{01}(z, s) P_0(z, s) ds - \int_{t_1}^t P_{10}(z, u) P_1(z, u) du \quad (20)$$

Although it also occurs that the adopted sink gives up the source information and exits the adoption in the information diffusion process, but the probability is very small. Therefore, this paper won't consider the exit probability, and thinks that the sink once adopts the source information, it will adopt for ever and not be back to the not adopted state.

5. SIMULATION OF INFORMATION DIFFUSION MODEL

Information diffusion process under the action of network dimension-force is a Markov process with drift. Solving this Markov process can obtain the probability distribution of the diffusion, and establish the probability model of the space-time diffusion. The application of the space-time model is mainly to predict the trend of information space-time diffusion. The method is to calculate the adoption probability according to the model, and then draw the diffusion rate curve which changes with the time and the poor quality, so as to predict

the approximate trend of the information space-time diffusion [7]. This section will carry on the simulation of the information diffusion probability distribution curve, which can illustrate the explanation and prediction function of this model.

(1) Function of the expected adoption utility

According to the formula $\Delta U = f(z, t)$, and ΔU is the increasing function of t and the decreasing function of z , now we suppose that ΔU changes according to the following function form:

$$\Delta U = q \exp(t^2/z) \quad (21)$$

Where:

q -- coefficient of the expected adoption utility function. In order to simulate simply, we makes $q = 1$;

z -- the poor node quality. In order to simulate simply, the source quality is set to 1, and the sink quality is standard according to the source quality. $z = (M_0 - M_i)/M_0$, $z \in (0, 1]$, z is the poor node quality after the standard.

(2) The simulation of the information diffusion probability distribution curve

This section uses Matlab7.0 mathematical software to simulate the time distribution of information diffusion, so as to obtain the information diffusion rate curve. In the simulation, some parameters of this model should be set.

For convenience in simulation, in the transition probability density function $q_{01}^*(z, n, I_{zt})$, when n changes from 2 to ∞ , the value of $1/n - 1$ changes between 0 and 1. Because its value has little effect on $q_{01}^*(z, n, I_{zt})$ and isn't the main variables that affects $q_{01}^*(z, n, I_{zt})$, so we let it a constant 0.5. At the same time, we set the parameters of the transition probability density function $q_{01}^*(z, n, I_{zt})$: $\rho = 0.1$ and $\Delta = 0.01$. Then the transition probability density function $q_{01}^*(z, n, I_{zt})$ at the time t is:

$$\begin{aligned} q_{01}^*(z, n, I_{zt}) &\equiv \frac{1}{n-1} \frac{\rho \Delta U(n, z, I_{zt})}{e^{-\rho \Delta} [\Delta U(n-1, z, I_{zt}) - \Delta U(n, z, I_{zt})]} \\ &= \frac{0.05 \times \exp(t^2/z)}{e^{-0.001} \{ \exp[(t+1)^2/z] - \exp(t^2/z) \}} \quad (22) \end{aligned}$$

Because diffusion of this paper is the active diffusion, network dimension-force plays a positive

promoting role on information diffusion, so the drift coefficient of diffusion is greater than zero, i.e. $\mu \in [0, 1]$ and $\Delta t = 0.01$. Then the probability $P_1(z, t)$ that the sink z is at the adopted state at the time t can be expressed as:

$$P_1(z, t) = \int_0^t \int_0^\infty \frac{0.05 \times \exp(t^2/z)}{e^{-0.001} \{ \exp[(t+1)^2/z] - \exp(t^2/z) \}} (1 + 0.1\mu)(1 - P_1(z, t)) dt dz \quad (23)$$

In the equation (23), the instantaneous transition probability function $P_1(z, t)$ that the sink z adopts diffusion information at the time t is the function about time variable t and spatial variables z , its value changes with t and z . If we set the time or the space is a certain value, then we can get the adoption probability curve on time or in space.

If the space is fixed and we set $z = z_1$, then the adoption probability $P_1(z_1, t)$ of the sink on time is:

$$P_1(z_1, t) = \int_0^t \frac{0.05 \times \exp(t^2/z_1)}{e^{-0.001} \{ \exp[(t+1)^2/z_1] - \exp(t^2/z_1) \}} (1 + 0.1\mu)(1 - P_1(z_1, t)) dt \quad (24)$$

Setting $\mu = 0.5$, we simulate the probability function on the time axis. When $z_1 = 0.1, 0.5, 0.8$, according to the formula (24), making the time change among $[0, 1]$ (the diffusion time is set 1, the units is set depending on the specific circumstances), we can get the adoption probability curve of sinks which are at the different quality level on time. These curves are simulated in the same graph, and the results are as shown in Figure 2.

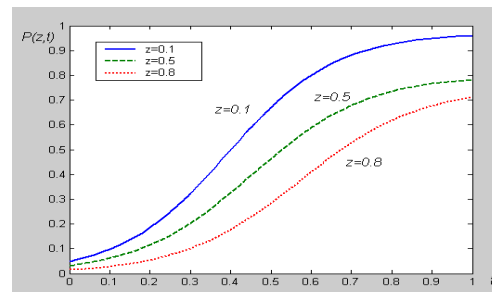


Figure 2: Adoption Probability Curve Of Information Diffusion On Time

The adoption probability curve of sinks which are at the different quality level on time is simulated in Figure 3. The results show that: although the slopes of difference curves are

different at the same time, and the time entering rapid growth period is different, but they are showed a typical S shape in general. That is to say, with the passage of time, the adoption probability significantly increases. Comparison of three curves, it can be found that: along with the node quality difference increasing, curves downward movement, which reflects the poor quality and the adoption probability have the strong correlation. In the period of diffusion, the adoption probability of the sink whose the poor quality is small is significantly higher than that of the larger poor quality at any moment, and its increasing rate of the adoption probability with time is significantly higher than that of the larger poor quality sink. In Figure, the slope of the adoption probability curve of the sink whose the poor quality is smaller is greater.

On the basis of the adoption probability changing on time, now we consider the influence which the drift coefficient μ has on this curve. Let $z_1 = 0.5$ and $\mu = 0, 0.5, 1$, according to the formula (24), we makes the time value is between $[0, 1]$, then we can get the adoption probability curves on time which have the same quality level and the different drift coefficient. These curves are simulated in the same graph, and the results are shown as in Figure 3.

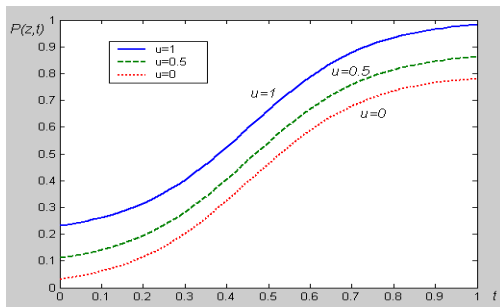


Figure 3: The Influence Of The Drift Coefficient On The Adoption Probability Curve On Time

From Figure 3, we can see that the value of μ tends to 1, and the adoption probability curves which are determined by the same z are more closely to $P(z,t) = 1$. Then the diffusion rates double, which reveals the positive promoting role of network dimension-force on information diffusion.

(3) The simulation of the information diffusion probability curve in space

If we set the time is a certain value and let $t = t_1$, then the probability $P_1(z, t_1)$ that the sink z is at the adopted state is:

$$P_1(z, t_1) = \int_0^1 \frac{0.05 \times \exp(t_1^2/z)}{e^{-0.1} \{ \exp[(t_1+1)^2/z] - \exp(t_1^2/z) \}} (1 + 0.1\mu)(1 - P_1(z, t_1)) dz \quad (25)$$

Setting $\mu = 0.5$, we simulate the probability function on the space axis. When $t_1 = 0.1, 0.4, 0.8$, according to the formula (25), making z change among $[0, 1]$, we can get the adoption probability curves which changes with the quality difference at the different time. These curves are simulated in the same graph, and the results are as shown in Figure 4.

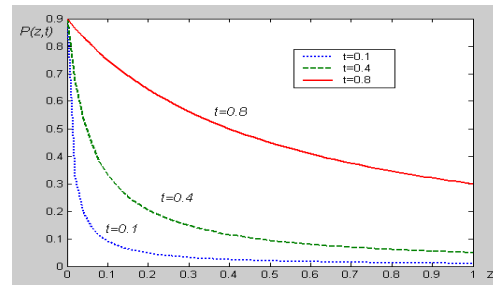


Figure 4: The Adoption Probability Curves Changing With The Quality Difference At The Different Time

When $t_1 = 0.1, 0.4, 0.8$, the adoption probability curves in space are simulated in Figure 4. In Figure 5, the axes of z is the poor node quality which has been standardized, and its value is $[0, 1]$. z only shows the order relations of the size between potential adoption sink quality and source quality, and is no unit. Figure 5 shows that: at any moment, the adoption probability curve in space presents the curve that convexes to the origin. Although the three curves' shape is slightly different, but the changing trends are obvious, all show the clear trend that the adoption probability decreases with the poor quality increasing. On the other hand, along with the diffusion time prolonging, these curves move to upper-right, which shows the trend that the adoption probability overall increases on time.

On the basis of the adoption probability changing with the poor quality, now we consider the influence which the drift coefficient μ has on this curve. Let $t = 0.4$ and $\mu = 0, 0.5, 1$, according to the formula (25), we makes the value of the poor quality z is between $[0, 1]$, then we can get the adoption probability curves which change with the poor quality at the same time and the different drift coefficient. These curves are simulated in the same graph, and the results are shown as in Figure 5.

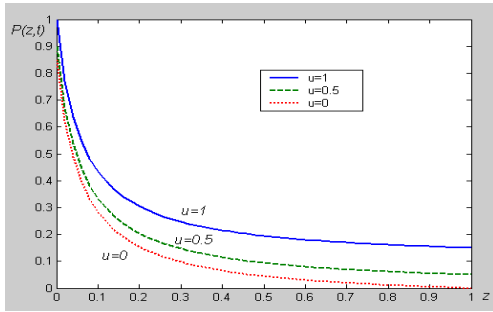


Figure 6: The Influence Of The Drift Coefficient On The Adoption Probability Curve In Space

From Figure 6, we can see that the value of μ tends to 1, and the adoption probability curves which are determined by the same t are more closely to $P(z,t)=1$. Then the diffusion rates double, which reveals the positive promoting role of network dimension-force on information diffusion.

(4) The probability curve of information space-time diffusion

The adoption probability curves in Figure 5 and Figure 6 are simulated when the time is a certain value ($t=t_1$). If the time is not constant, the adoption probability of the potential sinks changes not only with the space, but also with the time. According to formula (23), we set $t \in [0,1]$ and $z \in [0,1]$, and put the above two curves into the three-dimensional space, then we can get the diagram that the adoption probability changes with the time and the space at the same time, as shown in Figure 7[8].

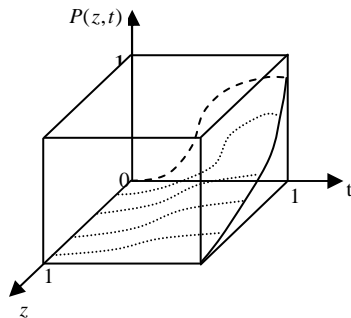


Figure 7: Probability Surface Of Information Time-Space Diffusion

In Figure 7, the axis t represents the time, its value range is $[0,1]$, and the unit is set depending on the specific circumstances. The axis z is the poor node quality after the standard, and its value range is $[0,1]$. z only shows the order relations of the size between potential adoption sink quality and source quality, and is no unit. The longitudinal axis $P(z,t)$

represents the probability that the sink z adopts diffusion information at the time t . From Figure 7, we can see that: diffusion of the source information includes both the adoption accumulation process on time and the distribution status of the adoption probability in space. They are two aspects of the same process.

6. CONCLUSION

Information diffusion process under the action of network dimension-force is a Markov process with drift. Using for reference from the Markov drift chain theory, this paper establishes the space-time diffusion model, which describes the space-time expansion model and the characteristic of diffusion. And the paper uses Matlab7.0 mathematical software to simulate the effectiveness of the space-time model. The simulation results show that the general trend of the information diffusion rate changing with time and space is: if we don't consider the space factors, the adoption probability (the diffusion rate) in time shows a typical S shape in general. When the time is fixed, the adoption probability on space decreases with the poor node quality increasing. And when the poor node quality increases to a certain extent, the value of the adoption probability is 0. If the time and the space factors are considered at the same time, then the adoption probability curves on time and in space forms a probability surface. In addition, the value of the drift coefficient μ tends closely to 1, and then the adoption probability that is determined by the same t and z is closely to 1, which reveals that network dimension-force plays a strong positive promoting role on information diffusion.

ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (70971028), the research grants from the Fundamental Research Funds for the Central Universities (27R110647B0).

REFERENCES:

- [1] Arash Massoudieh, Daeyoung Ju, Thomas M. Young, Timothy R.Ginn, "Approximation of a radial diffusion model with a multiple-rate



- model for hetero-disperse particle mixtures”, Journal of Contaminant Hydrology, Vol. 97, No. 4, 2008, pp. 55-66.
- [2] Jinlou Zhao, “Management innovation based on network original characters”, Ph.D. Thesis, Dept. Management, Harbin Engineering University, Harbin, China, 2006.
- [3] Yirui Deng, “Research on the Dynamic Mechanism of Information Diffusion in Network Environment”, Library and Information Service, Vol. 52, No. 9, 2008, pp. 94-96.
- [4] Gunter Franke, Dieter Hess, “Information diffusion in electronic and floor trading”, Journal of Empirical Finance, Vol. 7, No.5, 2000, pp. 455-478.
- [5] James Po-Hsun Hsiao, Chyi Jaw, Tzung-Cheng Huan, “Information diffusion and new product consumption: A bass model application to tourism facility management”, Journal of Business Research, Vol. 62, No. 7, 2009, pp. 690-697.
- [6] Zheng Liang, Bingying Xu, Yan Jia, Bin Zhou, “Mining evolutionary link strength for information diffusion modeling in online social networks”, Applied Mechanics and Materials, Vol. 157, No.2, 2012, pp.567-572.
- [7] Arash Massoudieh, Daeyoung Ju, Thomas M. Young and Timothy R.Ginn. “Approximation of a radial diffusion model with a multiple-rate model for hetero-disperse particle mixtures”, Journal of Contaminant Hydrology, Vol. 97, No.4, 2008, pp. 55-66.
- [8] Kai Kang and Huiyun Zhang, “Space-time diffusion model and simulation of technology innovation”, Journal of Hebei University of Technology, Vol. 31, No.6, 2002, pp.23-26.