Transmission Mechanism and Influencing Factors of Green Behavior in Dynamic Multiplex Networks

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ABSTRACT With the global warming, soil erosion and a series of environmental problems are worsening. Green sustainable development has increasingly become a major issue of human concern. This study established a dynamic interaction model to explore the influence of green information and the social relations. Due to the continuous evolution of the network and the heterogeneity of individuals, the transition probability of each node is combined with time-varying parameters that reflect its current state. Then, guided by hypernetwork theory and microscopic Markov chain approach, this model is analyzed. Furthermore, the effects of various adjustment parameters on the green behaviors are compared and tested. The results show that behavior diffusion is not only affected by the diffusion of green information, but also closely related to the change of social relations. Finally, combined with the diffusion of green information, a propagation mechanism that simulates damped harmonic motion is proposed to maximize the green behavior. The results show that the final practice fraction of green behavior has been significantly improved.

INDEX TERMS Analytical models, complex networks, diffusion processes, dynamics, multiplexing.

I. INTRODUCTION Green behavior refers to the activities of social organizations or natural persons following the green concepts of the world, such as choosing public transportation, recycling materials, effective using energy and protecting the living environment and species. Resources, environment and development are the core issues of concern to the inter-national community [1], [2]. Enterprises vigorously develop green economy and effectively implement industrial upgrading [3], [4]. Citizens actively practice green behaviors in daily life, such as the purchase of energy-saving products and the travel choice of sustainable transportation, which are important driving forces to realize comprehensive coordination of resources, environment, and economy [5]–[7]. Therefore, how to use scientific methods to encourage enterprises and individuals to actively practice green behavior has become an urgent issue of environmental protection and social economy.

Up to now, many researchers have tried to identify the factors that promote people to actively practice green behaviors. Considering the influence of group psychology and self income, Li et al. [8] established an individual green behavior game model from the perspective of complex networks and game theory. Research found that when people show higher connectivity or lower activity rates, they are more inclined to adopt green behaviors. The study of Paço et al. [9] confirmed that green values have a positive impact on the acceptance of green communication and purchase behavior. In the same year, Varela-Candamio et al. [10] proposed that environmental education is the main driving force to generate green behavior among citizens. Simultaneously, as a well-known attitude-behavior relationship theory in social psychology, planned behavior theory has also been introduced into the dynamic analysis of green behavior [11]. In addition, some researchers are concerned about green behaviors of individuals, including green consumption [12]–[14], green travel [15], and the choice of green furniture or decoration [16], [17]. Actually, various connections between real individuals occur at different levels and interact with each
other [18], [19]. Hence, only focusing on one layer inevitably ignores the interaction with other layers. In recent years, as an efficient way to describe the interaction between individuals at different levels, multiplex networks have been widely used to model this dynamic propagation process [20], [21]. Gao et al. [22] constructed a policy regulation model of city residents’ green awareness-behaviors communication, and found that the promotion of government policies plays a vital role in the dissemination of residents’ green behavior. Reference [23] proved that the coupling interaction weakens the diffusion of green behavior in the network. In addition, the effects of information [20] and negative information [24] on the spread of green behavior have also been discussed.

The previous research on green behavior diffusion provides great reference and theoretical support for our work. However, most of these set the information and behavior to propagate in closed static systems. Although in the work Deffuant model of opinion formation in one-dimensional multiplex networks, a dynamical multiplex network model is constructed with edges being created and removed following Poisson processes [25]. But unfortunately, many current multiplex network models used in risk assessment [26], disease transmission [27], [28], rumor transmission [29] and other fields are still based on the assumption that the scale and relationship of people are static.

In fact, the reality system is an open and dynamic platform, on which individuals constantly enter and leave [30]. Then, the link structure and node scale of the network also change accordingly. Hence, a dynamic evolution network model established in this paper aims to more truly reflect the dynamic interaction between green behavior and information. The dynamic evolution of network links and nodes will occur in a certain probability at each time step. Additionally, considering the individual heterogeneity and time factors, the damped harmonic motion is combined with the diffusion of green information in the network to explore the propagation mechanism of green behavior maximization.

The rest is organized as follows: SGR-NAN dynamic propagation model is introduced in Section 2. The corresponding theoretical analysis is shown in Section 3. Simulation results and the strategy of maximizing green behavior propagation are given in Section 4. Finally, conclusions and future directions are discussed in Section 5.

II. MODEL DESCRIPTION

A. DYNAMIC EVOLUTION OF NETWORK LINK AND SCALE

The rapid development of online social platforms has provided channels for people to obtain information and communicate online. In addition, the government can also rely on the Internet as a basis for behavior guidance. The experiments of Bond et al. [31] have confirmed that online messages directly affect users’ information seeking and behavior. Furthermore, this influence will also extend to the user’s friends and friends of friends. Therefore, with the increasing attention to environmental protection, green information may attract more people to participate in the practice of green behavior when it is spread through online social networks.

Therefore, we established an online social network and real-world interactive communication model. As shown in Fig. 1, the upper is an awareness layer, which depicts the dissemination of green information in online social network, while the lower is the green behavior layer based on the complex network, revealing the spreading of green behavior through face-to-face contact in reality. Since the complex network is an abstraction of the complex system, the nodes in the complex network correspond to individual entities in the complex system. Edges are the links between nodes in the network, corresponding to the connection between different entities in the complex system. It is generally believed that the transmission of human behavior is realized through contact in real life. Therefore, the spread of green behavior is carried out in a behavior network, in which nodes correspond to real individuals, and links represent the relationships of people who are contacted in daily life.

However, the diffusion of green information in social networks depends on various social platforms, such as communities, post bars and forums, involving a large number
of people. The underlying structure of complex network is generally regarded as a group of simple graphs, which cannot provide a complete description of dynamic reality system. In a simple graph, an edge can only link two nodes, while a hyperedge of a hypergraph can contain arbitrary number of nodes. The mathematical definition of a hypergraph is: \( V = \{v_1, v_2, \ldots, v_n\} \) is a finite set, \( E_c = \{E_1, E_2, \ldots, E_m\} \) is a subset family of \( V \), and it is described as \( E_i = \{v_{i_1}, v_{i_2}, \ldots, v_{i_k}\} \) \((v_{i_k} \in V, k = 1, 2, \ldots, j)\). The pair \( H = (V, E_c) \) is called a hypergraph. An element in \( V \) is a node, and \( E_i (i = 1, 2, \ldots, m) \) is a set of non-empty subsets of \( V \), referred to as a hyperedge.

Hence, the hypergraph is introduced to represents the social relations of the awareness layer. In the hypernetwork of awareness layer, nodes correspond to the social individuals existing in the social network, and hyperedges represent the connections between these individuals. The nodes in the model are one-to-one corresponding in the network, which represents the state of the same individual at different levels.

In addition, with the development of online social media, the social circle of the public has expanded from the original acquaintance society to the global scope, and the stranger social contact has become the focus. Compared with the real system, the connection between individuals in social network is no longer based on stable interpersonal relationship, but more on content. When individuals discuss the same post or the film, they may not know each other, but they are connected by these contents. Under the background of rapid updating of social products, social relations have become extremely unstable. According to the actual social system, we summarize the following possible changes:

1. Individuals browse information and express opinions on different online social media, thus forming new social relations with people who participate in the same message.
2. Social individuals may reorganize their relationships by leaving this forum or site and choosing to join another. This means that the old relationships have been replaced by new ones.
3. The online social system is an open and dynamic system, in which some existing individuals may choose to leave and new individuals will join in.

The scale and link of social network changes with the continuous addition and departure of individuals. Meanwhile, the hyperedges representing social relations in the awareness layer will also evolve. Besides, with the increase of network communication channels, a person may be active in many numerous social networks. Moreover, each social circle or platform will gather a large number of people. Therefore, in order to describe this complex and changeable system more realistically, evolutionary hypergraph is introduced in the modeling process of awareness layer. Poisson process is a classic stochastic process model with a wide range of applications. It is an important form of distribution in many fields such as natural sciences, economic sciences, and management sciences. Consider that the ratio of individuals participating in and leaving social platforms is not necessarily the same, we assume that the entry and exit of an individual follow a Poisson process with the rates of \( \xi_1 \) and \( \xi_2 \), respectively. In addition, to ensure the growth of the network, let \( \xi_1 > \xi_2 \). Then, the above process can be summarized as the following dynamic mechanism:

(1) Adding \( m \) new hyperedges among the existing \( n + 1 \) nodes in the network, where \( n \) is any random number greater than 0. Considering that some well-known individuals or organizations tend to be more attractive to others. Therefore, in the process of social network evolution, we introduce the mechanism of hyperdegree preferential attachment. This means that the probability of each node being selected to a new hyperedge is proportional to its own hyperdegree. For specific expression formulas, please refer to the above references.

(2) Rewiring the \( m \) hyperedges. Randomly break the \( m \) existing hyperedges in the network, and replace them with new ones that contain common nodes. The selection of nodes in each new edge also follows the mechanism described in (1).

(3) Update the nodes in the network. \( m_1 \) nodes are randomly selected from the existing nodes of the network to be removed, and \( m_2 \) new ones are introduced.

In each time step, the dynamic evolution process will take place with a certain probability in the awareness layer. Simultaneously, in order to ensure the occurrence of evolution process, we set the probability of these processes as \( p \), \( q \) and \( r \), where \( p + q + r \equiv 1 \). However, the links on the behavior network correspond to the relationships of family, colleagues or neighbors, it is much more stable than the relationships established by the community, post bar, forum and other social platforms at the awareness layer. In reality, the probability of disconnection and reconstruction of this relationship is relatively small. Therefore, only node scale evolution occurs on the behavior layer, and there is no link transfer.

**B. DISSEMINATION MECHANISM OF GREEN INFORMATION AND BEHAVIOR**

Since the system is dynamic and open, in each time step, the evolution of node scale and hyperedge may occur. However, the probability of the node receiving information and the transition of state are closely related to their hyperdegree and degree at that time. Therefore, considering the heterogeneity of the individual and the dynamic mechanism of the network, we propose to use the node’s current hyperdegree and degree as the node’s state transition reference instead of a fixed parameter.

The diffusion of green information in awareness layer can be represented by S-G-R model. As shown in Fig. 2 (a), the node may be in one of three states: sensitive (S), green (G), and resistant (R). The node in the sensitive (S) state does not receive green information, but when received, it may become the G state that adheres to the green concept, or the R state resisting the green concept. Considering that the larger the node’s hyperdegree, the more channels it has to receive green
information in the real social network. Moreover, the continuous evolution of connections and nodes in social networks will make the hyperdegree change accordingly. Therefore, we assume that the probability of sensitive node $n_{ij}$ receiving green information is $k_1 R(h_j(t, t_i))$, and when they become informed, they will be converted to state G with probability $\delta$ or state R with probability $1 - \delta$. Where $n_{ij}$ is a specific number set for each node according to the time it enters the system. Parameter $R(h_j(t, t_i))$ is a hyperdegree ratio of the node $n_{ij}$ to the largest one at time $t$, and $k_1$ is the regulating parameter.

$$ R(h_j(t, t_i)) = \frac{h_j(t, t_i)}{\text{Max}(h(t))} \quad (1) $$

Individuals with greater influence will actively respond to the government’s call. Hence, we assume that the probability of a node in R state transforming into G state is proportional to $\delta$ or state R with probability $1 - \delta$. Where $n_{ij}$ is a specific number set for each node according to the time it enters the system. Parameter $R(h_j(t, t_i))$ is a hyperdegree ratio of the node $n_{ij}$ to the largest one at time $t$, and $k_1$ is the regulating parameter.

$$ D(d_j(t, t_i)) = \frac{d_j(t, t_i)}{\text{Max}(d(t))} \quad (2) $$

According to the individual’s practice of green behavior in the real world, the nodes on the behavior layer are designated as one of two states: positive (A) and negative (N). Positive nodes can actively practice green actions such as low carbon or green travel in reality, while negative state are not interested in green actions. Due to the individual’s attitude towards green behavior in real life is changeable, and people living beside us usually have a certain impact on our behaviors and attitudes. Therefore, the states between nodes with links can be converted to each other. Here, two independent parameters $\alpha$ and $\beta$ are used to represent the probability of node state transition. In each time step, the node in N state will change to A according to probability $\alpha$. Meanwhile, A state nodes will be converted to state N with probability $\beta$.

### C. Interaction Between Layers

According to the SGR-NAN model, individuals can be in one of six states: sensitive-positive (SA), sensitive-negative (SN), green-positive (GA), green-negative (GN), resist-positive (RA), and resist-negative (RN).

The reception of green information by individuals in the awareness layer will have a certain impact on their actual practice of green actions. For example, individuals with green concept are more likely to take green actions in reality than those who resist them, and those who receive green information will perform better than those who do not. Hence, compared with the SN and RN state nodes, the GN state nodes will practice green actions with a higher probability.

In our model, compared with the probability $\beta^R$ of RN state and the probability $\beta^S$ of the node in SN state, GN state nodes will practice green action with a higher probability $\beta^G$. Since the node of RN state and SN state are not active enough to adopt green behavior, we do not make a more detailed division here, namely, $\beta^R = \beta^S$.

$$ \beta^G = \gamma \beta^R = \gamma \beta^S \quad (3) $$

Here, we regulate the effect of awareness layer on behavior layer through the parameter $\gamma$, where, $\gamma = [1, 1/\beta^R]$.

In addition, individuals who actively take green actions in reality are more likely to adhere to green ideas. Therefore, compared with the probability $k_1^N R(h_j(t, t_i))$ of SN state, the node of SA state will transition to the GA with a higher probability $k_1^A R(h_j(t, t_i))$.

$$ k_1^A = \theta k_1^N \quad (4) $$
Here, we regulate the effect of behavior layer on awareness layer through the parameter $\theta$, where, $\theta = [1, 1/k^N \xi]$. In conclusion, the modeling mechanism is summarized in two steps: First, we establish a two-layer network model as the initial network, in which the behavior layer is a complex network and the awareness layer is a hypernetwork [34] based on a hypergraph. Then, in each time step, the network links and nodes will evolve according to the dynamic process described in Section 2 Part A, and the state of nodes will be updated in the light of the propagation mechanism in Section 2 Part B. Meanwhile, the impact mechanism between different layers is shown in Section 2 Part C.

### III. THEORETICAL ANALYSIS

We associate an adjacency matrix $A = \{a^uv_{ij}\}$ to the awareness layer, where $a^uv_{ij} = 1$ if node $n_{ij}$ and node $n_{uv}$ are contained by the same hyperedge; else, $a^uv_{ij} = 0$. Meanwhile, another adjacency matrix $B = \{b^uv_{ij}\}$ is associated with the behavior layer, where $b^uv_{ij} = 1$ if node $n_{ij}$ is connected to node $n_{uv}$; else, $b^uv_{ij} = 0$.

In this model, the number of nodes is a variable due to the continuous entry and departure of individuals. Hence, we set the total number of nodes in the network is $N(t)$ at the time $t$. Since the hyperdegree $h_j(t, t)$ is a continuous variable affected by process (1)-(3). Thus, the hyperdegree of an arbitrary node $n_{ij}$ in the network satisfies the following three equations:

$$\frac{\partial h_j(t, t)}{\partial t} = pm(\xi_1 - \xi_2) \left[ \frac{h_j(t, t)}{N(t)} + \sum_{ij} h_j(t, t) + 1 \right] + \sum_{ij} h_j(t, t) + 1$$  \(5\)

$$\frac{\partial h_j(t, t)}{\partial t} = qm(\xi_1 - \xi_2) \left[ \frac{h_j(t, t)}{N(t)} + \sum_{ij} h_j(t, t) + 1 \right]$$  \(6\)

$$\frac{\partial h_j(t, t)}{\partial t} = -\xi_2 m_{ij} \frac{h_j(t, t)}{N(t)}.$$  \(7\)

Summing up the equations (5) - (7), we get:

$$\frac{\partial h_j(t, t)}{\partial t} = \frac{m(p - q) (\xi_1 - \xi_2) - r \xi_2 m_{ij}}{N(t)} \frac{h_j(t, t)}{N(t)} + \sum_{ij} h_j(t, t) + 1.$$  \(8\)

For large $t$, $N(t) \approx (\xi_1 - \xi_2) t$. Here, $N(t)$ is the total number of nodes in the network at time $t$. Since the entry and exit of the node follow the Poisson process, the average number of events occurring in a unit time and the increment of the hyperdegree in each time step are used to approximate the sum of the hyperdegree.

$$\sum_{ij} h_j(t, t) + 1 \approx E(N(t)) [mp(\eta + 1) - rm_1 + m_2]$$  \(9\)

Consequently,

$$\frac{\partial h_j(t, t)}{\partial t} = \left[ m(p - q) - r \xi_2 m_{ij} h_j(t, t) \right] \frac{1}{t} + \frac{m(p - q) \eta}{mp(\eta + 1) - rm_1 + m_2} (h_j(t, t) + 1) \right] \frac{1}{t}.$$  \(10\)

Solving Eq. (10), we obtain

$$\frac{h_j(t, t)}{h_j(t, t)} = \frac{r + N + M}{E} = \frac{\frac{m(p - q) n}{mp(\eta + 1) - rm_1 + m_2}}{E}.$$  \(11\)

where, $N = m(p - q), M = \frac{m(p - q) n}{mp(\eta + 1) - rm_1 + m_2}$, and $E = \frac{m(p - q) n}{mp(\eta + 1) - rm_1 + m_2} - \frac{r \xi_2 m_{ij}}{\xi_1 - \xi_2}.$

Then, the probability that any node $n_{ij}$ in the network receives green information can be summarized as the following expression:

$$R(h_j(t, t)) = \frac{r + N + M}{E}.$$  \(12\)

Further, combined with the status of the individual in the online social network and the real world, node $n_{ij}$ in the model may be in one of the six states, and the corresponding probability at any time $t$ are represented as: $p^{RN}_{ij}(t, t), p^{RK}_{ij}(t, t), p^{SN}_{ij}(t, t), p^{SA}_{ij}(t, t), p^{GN}_{ij}(t, t)$ and $p^{GA}_{ij}(t, t)$. The probability that a node is in one of these six states at any time $t$ is similar to the sampling event with replacement in Statistics. Here, we suppose these probabilities are independent of each other, and then get

$$Q^N_j(t, t) = \prod_{u} \left(1 - a^uv_{ij}(t, t)\right) k^N N(t) R(h_j(t, t))$$  \(13\)

$$Q^A_j(t, t) = \prod_{u} \left(1 - a^uv_{ij}(t, t)\right) k^A N(t) R(h_j(t, t))$$  \(14\)

$$Q^G_j(t, t) = \prod_{u} \left(1 - b^uv_{ij}(t, t)\right) k^G N(t) R(h_j(t, t))$$  \(15\)

$$Q^R_j(t, t) = \prod_{u} \left(1 - b^uv_{ij}(t, t)\right) k^R N(t) R(h_j(t, t))$$  \(16\)

$$Q^G_j(t, t) = \prod_{u} \left(1 - b^uv_{ij}(t, t)\right) k^G N(t) R(h_j(t, t))$$  \(17\)

where $p^G_{ij}(t, t)$ denotes the probability that node $n_{uv}$ is informed and adheres to the green concept. $Q^N_j(t, t)$ represents the probability that when $n_{ij}$ is in SN state, it is not guided to change attitude. If $n_{ij}$ is in SA state, the probability is expressed as $Q^A_j(t, t)$ represents the probability that node not inspired to practice green action by any person who is in daily contact with when $n_{ij}$ is in SI state. Similarly, if $n_{ij}$ is in GI or RI state, the probabilities correspond to $Q^G_j(t, t)$ and $Q^R_j(t, t)$, respectively. Then, we obtain the
transition probability trees for 6 potential states as shown in Fig. 3.

Then, the dynamic evolution equation for six possible states of node $n_{ij}$ are summarized as Eqs. (18)-(23). Where $t$ represents the current time step of the evolution, and $t + 1$ denotes the next time step. Equation (18)-(23) express the evolution probabilities that node $n_{ij}$ at time $t + 1$ being in SN, SA, GN, GA, RN and RA state, respectively. It is worth noting that the above evolution equation satisfies $P_j^{SN}(t, t_1) + P_j^{SA}(t, t_1) + P_j^{GN}(t, t_1) + P_j^{GA}(t, t_1) + P_j^{RN}(t, t_1) + P_j^{RA}(t, t_1) = 1$ at each time step.

\[
\begin{align*}
    p_j^{SN}(t + 1, t_1) &= p_j^{SN}(t, t_1) Q_j^N(t, t_1) q_j^s(t, t_i) \\
    &+ p_j^{SA}(t, t_1) Q_j^A(t, t_1) \beta, \\
    &\text{(18)} \\
    p_j^{SA}(t + 1, t_1) &= p_j^{SN}(t, t_1) Q_j^N(t, t_1) (1 - q_j^s(t, t_i)) \\
    &+ p_j^{SA}(t, t_1) Q_j^A(t, t_1) (1 - \beta), \\
    &\text{(19)} \\
    p_j^{GN}(t + 1, t_1) &= p_j^{SN}(t, t_1) \delta (1 - Q_j^N(t, t_i)) q_j^G(t, t_i) \\
    &+ p_j^{SA}(t, t_1) \delta (1 - Q_j^A(t, t_i)) q_j^G(t, t_i) \beta, \\
    &\text{(20)} \\
    p_j^{GA}(t + 1, t_1) &= p_j^{SN}(t, t_1) \delta (1 - Q_j^N(t, t_i)) (1 - q_j^G(t, t_i)) \\
    &+ p_j^{SA}(t, t_1) \delta (1 - Q_j^A(t, t_i)) (1 - \beta), \\
    &\text{(21)} \\
    p_j^{RN}(t + 1, t_1) &= p_j^{SN}(t, t_1) (1 - \delta) (1 - Q_j^N(t, t_i)) q_j^R(t, t_i) \\
    &+ p_j^{SA}(t, t_1) (1 - \delta) (1 - Q_j^A(t, t_i)) \beta, \\
    &\text{(22)} \\
    p_j^{RA}(t + 1, t_1) &= p_j^{SN}(t, t_1) (1 - \delta) (1 - Q_j^N(t, t_i)) q_j^R(t, t_i) \\
    &+ p_j^{SA}(t, t_1) (1 - \delta) (1 - Q_j^A(t, t_i)) \beta.
\end{align*}
\]
$p_j^{RA} (t+1,t_i)$

$$= p_j^{SN} (t, t_i) (1 - \delta) \left( 1 - Q_j^N (t, t_i) \right) \left( 1 - q_j^R (t, t_i) \right) + p_j^{SA} (t, t_i) (1 - \delta) \left( 1 - Q_j^A (t, t_i) \right) (1 - \beta) + p_j^{RN} (t, t_i) (1 - k_2 D (d_j (t, t_i))) \left( 1 - q_j^R (t, t_i) \right) + p_j^{RA} (t, t_i) (1 - k_2 D (d_j (t, t_i))) (1 - \beta).$$

(23)

When the time step is large enough, the proportion of nodes in each state reaches a stable state. Therefore, when $t \to \infty$, for any node $n_j$ in SN state, we have $P_j^{SN} (t+1, t_i) = P_j^{SN} (t, t_i) = P_j^{SN}$. The similar equations hold for nodes in SA, GN, GA, RN and RA states. According to Eqs. (19), (21) and (23), we can calculate the probability of $P_j^A$ in steady state as:

$$P_j^A = P_j^{SA} + P_j^{GA} + P_j^{RA}$$

$$= p_j^{SN} Q_j^N (1 - q_j^S) + \left[ p_j^{SN} \delta (1 - Q_j^N) + p_j^{RN} k_2 D (d_j) + p_j^{GN} \right] (1 - q_j^G) + \left[ p_j^{SN} (1 - \delta) (1 - Q_j^N) + p_j^{RN} (1 - k_2 D (d_j)) \right] (1 - q_j^R) + \left( p_j^{SA} + p_j^{GA} + p_j^{RA} \right) (1 - \beta).$$

(24)

It is worth noting that in this model, time-varying parameters such as hyperdegree and degree of node are used as the reference of its state transition probability. When the values of the parameters $R (h_j (t, t_i))$ and $D (d_j (t, t_i))$ are fixed constants, our model can be reduced to the propagation model introduced in [23].

IV. SIMULATION AND ANALYSIS

First, we construct a two-layer network model with 10000 nodes in each layer as the initial network. The upper layer is a scale-free hypernetwork, and the lower layer is generated by the configuration model with a degree distribution of $P(k) \sim k^{-2.5}$. In the upper-layer hypernetwork model describing the process of green information dissemination, the number of nodes $\eta$ contained in the hyperedge is a random number from 1 to 20, and keep $\eta (t) < N (t), t \in [1, +\infty)$. Then, in each time step, the structure of the network and the state of the nodes proceed according to the dynamic mechanism described in Section 2 Part B. The simulation runs until the green practice fraction $\rho^A (t)$ reaches a stable state. Here, $\rho^A (t)$ is given by

$$\rho^A = \frac{1}{N} \sum_{ij} p_{ij}^A. \quad (25)$$

The evolution model of green behavior propagation is tested by MATLAB. In order to eliminate the influence of randomness, all of the results are obtained through an average of more than 30 independent operations.

A. THE IMPACT OF INTER-LAYER ADJUSTMENT PARAMETERS

In order to better characterize the influence of inter-layer interaction on green practice fraction of dynamic model, the effect of green attraction rate $\alpha$ on practice fraction $\rho^A$ is tested under the condition of different inter-layer adjustment parameters. In Fig. 4, we take the practice fraction $\rho^A$ as a function of the $\alpha$ to perform a comparative test for different values of $\theta$. Then, we can find an interesting phenomenon that whether $\gamma = 1$ in Fig. 4(a) or $\gamma = 4$ in Fig. 4(b), when the value of $\theta$ increases from 1 to 6, the data points hardly change, and all the scatters almost coincide. This means that the impact of $\theta$ on the green practice fraction $\rho^A$ is almost
negligible. In addition, by comparing Figure 4(a) and (b), we can see that the practice fraction in the two graphs have similar values at steady state, but when $\alpha$ increases from 0 to 0.7, the practice fraction in Fig. 4(b) are significantly higher than in Fig. 4(a). For example, when $\alpha = 0.2$, the value of $\rho^A$ in Fig. (a) is about 0.25, while in Fig. (b) it is as high as 0.4.

To confirm this finding, we conducted a comparative test of the practice fraction $\rho^A$ under three different values of $\gamma$. As shown in Fig. 5, the practice fraction is significantly higher than $\gamma = 1$ when the value of $\gamma$ increases from 3 to 6. It is worth noting that the increment of practice fraction gradually decreases with the increase of $\gamma$. When the green attraction rate $\alpha$ is higher than 0.4, this effect disappears. In addition, by comparing Fig. 5 (a) and (b), it can be found that the practical fraction curves in the two figures are very similar, which confirms our previous conjecture that the parameter $\theta$ has a slight effect on green practice fraction.

**FIGURE 5.** The impact of inter-layer adjustment parameter $\gamma$. Green practice fraction $\rho^A$ as a function of attraction rate $\alpha$ and inter-layer parameter $\gamma$. The parameter settings for each panel are: (a) $\theta = 1, p = 0.2, q = 0.2, m = 2, m_1 = 1, m_2 = 2, \delta = 0.5, \beta = 0.3$. (b) $\theta = 4$, and other parameter settings are consistent with (a).

Further, we draw the practice fraction curve of the parameter $\gamma$ under two networks with different structures, aiming to visually compare the effects of the network structure on the practice fraction. As shown in Fig. 7, when $\gamma = 1$, the dynamic evolution process is actually carried out in an independent network, so it is consistent with the practice curve in the static network. However, when $\gamma > 1$, as shown in Fig. 7(b) and (c), the practice fraction of dynamic structure is always slightly lower than that of static structure in the stage of $\alpha < 0.9$. Interestingly, the practice fraction of static structure network tends to be stable after reaching the turning point, while the fraction under the dynamic structure network shows a continuous growth trend with the increase of $\alpha$.

**C. MAXIMUM DIFFUSION MECHANISM OF GREEN BEHAVIOR**

With the increasing concern about global warming, researchers are committed to determining the determinants of green behavior, ranging from green information [23], negative information [24] to awareness and policy [21]. However, most of these studies are based on static structure network. This study discusses methods to improve the fraction of green behavior from the following two aspects: information diffusion under the decline mechanism and network dynamic structure.

1) **INFORMATION DIFFUSION MECHANISM BASED ON DAMPED HARMONIC MOTION**

Individuals exist in multiple online social networks, and information is transmitted simultaneously, which creates a new dimension for the diffusion of green information. Through the test of the adjustment parameters in Section 4, Part A, we confirmed that the propaganda of green information on the awareness level has a certain impact on the
individual behavior. In a real system, the promotion of information diffusion on green behavior can be described as green attraction [23]. Actually, the attraction of green to individuals is not a fixed parameter, but varies with individual attitude, time step and the period of forgetting-remembering. Therefore, the damped harmonic motion is introduced in the process of green behavior transmission.

In mechanics and physics, damped harmonic motion is a periodic or oscillatory motion, usually described as a ball connected to a horizontal spring on a table. When the ball is moved, it stretches the spring. The damped harmonic motion experiences friction, in which the dissipative force finally restrains the motion until the small ball no longer oscillates [35].

On the basis of existing research, we analyzed the behavior of individuals to green information diffusion and get the following conclusions: At the initial stage of green information release, the effect of education is significant. Individuals, especially those with green concept, will actively practice green actions. However, with the passage of time, some green information will be covered by other information, which will reduce its attention and attractiveness. Hence, the increase of time decay intensity (TDI) will reduce the practice proportion of green behavior. Due to the factors of forgetting-remembering (FR), people will have the characteristics of forgetting the information. Additionally, some individuals will spontaneously spread green information and practice green actions through the re-memory mechanism. The spread of information is generally considered to be eye-catching. However, due to the hesitation mechanism (HM), a person can finally have an incubation period before taking green action [36].

While analyzing the effect of green information diffusion on individual green behavior, inspired by the physical model of behavior description, we find that the attraction of green to individuals is similar to an oscillating system. The amplitude of the motion is high at the beginning and then decreases according to the damping parameters. In this case, the damping parameter is expressed as TDI with respect to the time decay intensity. Due to the HM factor, an individual’s
incubation period before spreading green behavior is similar to the systematic phase. Finally, the FR factor indicates the periodicity of switching between forgetfulness and memory. Therefore, we define the attractiveness of green, low-carbon and other publicity information to personal green behavior as follows:

$$A(t) = A_{\text{int}} e^{-\psi t} \cos(\omega t + \sigma)$$  \hspace{1cm} (26)

where $A(t)$ is the attraction of green behavior to individuals at time $t$, $A_{\text{int}}$ is the initial attraction of green behavior. The time decay intensity is expressed by the parameter $\psi$, FR factor is the period of forgetting and remembering, which is represented by parameter $\omega$, and $\sigma$ is the degree of interest in the received green information. In order to make the proposed formula applicable to the actual situation, we set the non-negative value of individual attraction. As shown in Fig. 8, we consider $A(t) = |A(t)|$. Then, green attractiveness is defined as follows:

$$A(t) = A_{\text{int}} e^{-\psi t} |\cos(\omega t + \sigma)|.$$  \hspace{1cm} (27)

Considering the influence of information dissemination on individual’s daily behavior and the mechanism of information decline, we innovatively propose that the probability of nodes in state N to A in each time step is $k_3 A(t)$, in which $A(t)$ is the green attraction parameter as described as above, and $k_3$ is the adjustment parameter. In Fig. 9(a), the green attraction increases rapidly to the maximum, and then shows a downward trend with the increase of the time step, until it finally approaches 0. This is consistent with the actual system. At the beginning of the information release, people’s attention to it gradually increased. However, due to the forgetting mechanism or being covered by other information, people’s attention to it will gradually decrease. Fig. 9(b) shows the change of individual green practice fraction over time steps. Obviously, with the decline of green attraction, although the fraction has rebounded, it still shows a downward trend overall.

On this basis, a green information promotion mechanism at the awareness level is proposed. We assume that the promotion of green information is introduced at every time step.
Then, based on the damped harmonic motion, we established the following information accumulation formula:

\[
A(t) = 0.3A(t-1) + 0.25A(t-2) + 0.2A(t-3) + 0.15A(t-4) + 0.1A(t-5) + e^{-\psi t} |\cos (\omega t + \sigma) | \nu.
\]  

(28)

Curve IMPROVED in Fig. 9(a) is the individual’s green attraction after improving the dissemination method. We can see that the continuous output of green information on social networks is conducive to enhancing the attractiveness to individuals. As expected, the green practice fraction in Fig. 9(c) gradually increases with the increase of time step until it stabilizes. In addition, compared with the original simulation results, we also found that the green practice fraction has been improved by nearly 20%.

2) NETWORK STRUCTURE

To figure out which specific evolution process in the awareness layer affects the green practice fraction, it’s necessary to test each dynamic process in turn. Fig. 10 shows the green practice fraction for different structural evolution processes with increasing values of time step from 0 to 100.

The information diffusion mechanism adopted in Fig. 10 is the improved mechanism described in Section 4, Part C. We can find that the green practice fractions in the steady state are all around 0.7, which is an increase of nearly 20% compared to Fig. 6. This further validates the effectiveness of our strategy.

In addition, the practice fraction of individuals is gradually increased with the evolution of the time step until it approaches a steady state. As the parameters \( p \) and \( q \) increase from 0 to 1, Fig. 10(a) and (b) show a transition from a low score to a high one. This is because in real social networks, the formation and reorganization of social relations will broaden the communication channels for the widespread of information among individuals. It is worth noting that the reorganization of social relationships does not add new communication channels, so the practice fraction between \( p = 0 \) and \( p = 1 \) has only slightly increased. However, in Fig. 10(c), we can clearly observe that the fraction distribution in the middle part is slightly higher than that on both sides. One plausible explanation is that as the probability of individual evolution increasing, some newly entered negative individuals replace the original positive ones, which leads to the decrease of practice score. The establishment and
replacement of social relationships provide convenience and support for the widespread diffusion of green information in social channels. Meanwhile, it is also very necessary to effectively control the replacement of new and old individuals on social networks.

V. CONCLUSION AND FUTURE DIRECTION

In this study, a dynamic evolution model is established to describe the interaction between green information and behavior. In addition, the transition probability of individual state is not a fixed constant, but is closely related to the dynamic parameters of the node’s degree, hyperdegree, and state in another level. Then, based on the hypergraph theory and micro Markov chain, the corresponding theoretical analysis and simulation tests are carried out. The results show that the information propaganda of awareness layer and the dynamic evolution of network structure have certain impact on the model. Further, based on the test results and information decline mechanism, a green behavior individual accumulation formula that simulates damped harmonic motion is proposed to maximize the green behavior. Based on this mechanism, the green practice score is improved by nearly 20%. Therefore, we recommend combining network structure management with information dissemination. While promoting the promotion of green information on social networks, it is also necessary to strengthen the control of the relationships between individuals.

However, our research is only a starting point, there are still some limitations. First, the degree of communication between individuals is different. Therefore, the hyperedges representing information channels need to be classified by weight. It is similar to giving each information channel a weight, which is used to represent the degree of communication between the social individuals on the channel. The greater the weight, the higher the interaction frequency. In addition, although the theoretical results of the model are reported in this paper, corresponding examples are still needed to verify the current research. Future work will focus on estimating human factors from real user configuration information, so as to obtain accurate results for the information promotion mechanism based on damped harmonic motion.

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