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Mining and Construction of Information Opportunity Cooperation Mode Based on Big Data Fusion Internet of Things

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ABSTRACT This paper introduces evolutionary game theory as an analysis tool to study the evolution of the cooperative behavior of nodes in the opportunistic network. At the same time, considering the spatial distribution of nodes in the opportunistic network and the corresponding cooperative interaction relationship, the evolutionary graph theory is further applied to study the cooperative behavior in the context of considering the network space. In the collaboration model of this article, the vertices in the evolutionary graph theory are used to represent the nodes in the network, and the edges in the graph represent that the node pairs are within the communication range of each other. The node will play a game with neighboring nodes according to the payout matrix. Through repeated games between nodes, the network reaches a relatively stable final state, and the distribution of nodes with different behaviors in the final state of the network is checked. By adjusting the network parameters, we can analyze the distribution and evolution of cooperation in the network, and study the stability of the network. We realize the credible collaborative evolutionary game model by building a comprehensive simulation platform and verify its effectiveness and scalability. We design and implement an evolutionary game model independent of routing protocols, so that the model can be quickly deployed in traditional routing protocols. Subsequently, simulations verified that the reputation model played a role in guiding nodes to actively participate in network collaboration during the collaborative evolution process. And the greater the strength of the reputation incentive mechanism, the better the effect of the evolutionary model. The evolution model is deployed in multiple routing protocols, verifying that the model can play a role in different routing protocols. In addition, the evolution model can also play a role in different network environments and has good scalability.

INDEX TERMS Opportunity network, collaboration mechanism, evolutionary game, big data, Internet of Things.

I. INTRODUCTION

At present, most sensor nodes in the Internet of Things have limited computing and storage resources. However, with the development of technology and the widespread popularity of Internet of Things applications in next-generation embedded computing devices, the physical resources of each node will be further expanded [1], [2]. This will alleviate the current dependence on resource constraints of a single sensor node. Most IoT applications such as smart logistics, smart transportation, smart grid, smart environmental protection, smart home, etc. form the basic form of smart infrastructure [3]. However, different applications in the Internet of Things have different requirements. The service-oriented Internet of Things abstracts and combines data and finally encapsulates them into various types of services, thereby providing different data requirements for different applications and meeting the needs of smart infrastructure [4], [5].

The Internet of Things expands the previous access terminals from independent computing devices to ordinary life items, so that people can more conveniently obtain the status information of their environment and related equipment

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through network connections. The Internet of Things connects the information world and the physical world through the information network. In order to better utilize and process the large amount of information obtained in these physical environments, this article refers to the proposed architecture of the related Internet of Things, and designs an SOA-based Internet of Things Data processing middleware architecture, through the application of data processing middleware, it is possible to better integrate Internet of Things data with existing Internet data, and realize the reuse of Internet of Things data. The policy update rule of the node adopts the imitation update process. Every time a node meets a new node, a policy update will occur. It will continue to adhere to its own policy or imitate a neighbor's policy according to a certain fitness ratio. The payment matrix of the game aims at the two behaviors of cooperation and selfishness. Through the unified quantification of energy expenditure and information income, the final matrix obtained has the characteristics of prisoner's dilemma. Specifically, the technical contributions of this article can be summarized as follows:

First: In the process of establishing the model structure, the concept of permutation diagram is emphasized and a clear distinction is made between it and the interaction diagram. The two diagrams in the model in this article are equal. On this basis, a time-sensitive historical record setting is used to target the dynamic characteristics of the network. Historical record statistics can be performed based on time period or number of times. The history of the node always saves the latest k times of connection history, which makes the relationship graph a random k-regular graph. The degree of each node in the regular graph is k, but the connected nodes are not fixed. Random k-regular graphs have both randomness and stability, and can be well used in the derivation of evolutionary graph theory to complete the prediction of system evolution.

Second: In the derivation process, we first establish paired events and corresponding paired dynamics according to two behaviors of cooperation and selfishness, and obtain the relationship between local density and global density in the case of weak selection. It is found that among neighbor nodes, the types using the same strategy have a local density higher than the global density, while the types using different strategies have a local density lower than the global density. Further using this local density to complete the derivation of local competition, the payout matrix of local competition can be obtained. The payout matrix of local competition is a partial modification of the initial payout matrix. The conclusion is that to apply the classic evolutionary game theory to a network with a specific spatial structure is to add a partial payment correction term to the initial payment matrix. This correction term is not only related to the initial payment matrix, but also to the nodes in the network. Since the relationship graph used in this model is a random k-regular graph, the degrees of nodes in the network are all k. We further considered a more general prisoner's dilemma payment matrix and found that under certain conditions, the prisoner's dilemma payment matrix can be changed to an eagle-pigeon game matrix, so that the cooperation and selfish behaviors in the system can coexist in a certain proportion.

Third: This article introduces the experimental platform of this article—the open source opportunity network simulation tool (The ONE), and introduces the architecture and main functions of the tool. Subsequently, the simulation environment settings are given, and the specific parameters of the simulation experiment and the values of the parameters of the trusted collaborative evolution model are listed in detail. It was verified through experiments that the reputation model played a key role in the evolution of node collaboration, which could promote the positive development of evolution and quickly converge to the state of universal collaboration. Then through a large number of comparative experiments, it is verified that the trusted cooperative evolutionary game model has good performance in the message delivery success rate, network responsibility, average relative delay, etc., and it has better restrained the influence of abnormal nodes on the performance of the opportunistic network. By comparing the experimental results under different network scales, node moving speeds and message generation speeds, it proves that the trusted evolutionary game model has good scalability and strong practicability.

The rest of this article is organized as follows. Section 2 discusses related work. Section 3 designs a SOA-based IoT data processing middleware framework. Section 4 constructs an opportunity network collaboration model based on evolutionary graph theory. Section 5 carries on the simulation and experimental analysis of the evolutionary game algorithm. Section 6 summarizes the full text.

II. RELATED WORK

Different sensors generally have different data formats and data models, leading to certain defects in the integration and utilization of heterogeneous data in the Internet of Things [6]–[8]. In addition to information fusion technology, abstraction and virtualization in the cloud-centric Internet of Things can be used to discover diverse combinations of heterogeneous information, thereby enhancing data flexibility and better solving application heterogeneous data scenarios [9], [10].

The classic routing algorithms in opportunistic networks all imply an important precondition, that is, there is no selfish behavior in the network. In the actual network, because the data collection and transmission process needs to consume the node's own resources (such as energy, cache, computing power, etc.) to provide services for other nodes, and also need to bear the risk of personal privacy leakage, collaborative transmission will be difficult to be guaranteed. Therefore, it is more necessary to analyze and study the cooperation mechanism in the opportunistic network to more effectively guarantee the quality of network transmission services. At the same time, in the opportunistic network environment, the user's willingness to cooperate shows dynamic changes with the change of time and space situations, which makes the one-size-fits-all incentive mechanism in traditional self-organizing networks unsuitable.

The research focus of domestic and foreign researchers on opportunistic networks mainly focuses on the distributed structure of the network, user contact behavior analysis, message forwarding mechanism, user collaboration and incentives in opportunistic networks, and privacy protection in opportunistic networks [11]–[13]. Although the academic community has been working on these key technologies of opportunity networks for a short period of time, progress has been rapid and some research results have been formed [14]. The information perception of opportunity network is the foundation of opportunity network research, and it is also one of the key points of opportunity network research [15]–[17]. Studies have shown that the probability of a node meeting other nodes is positively related to the activity ability of the node [18], [19]. The stronger the activity ability, the more chances of meeting and forwarding messages. Discovering such network nodes and reasonably driving their willingness to forward messages can significantly increase the successful delivery of messages [19]–[21]. The node activity degree reflects the status of the node in the network to some extent. The node activity degree can be used to select the central node of the network, and then the network is divided into different communities according to the relationship between the node and the central node. Node activity can also be applied in other areas, such as designing new caching schemes and routing algorithms [22], [23]. Since there is no end-to-end complete path between nodes in the opportunistic network, the message starts from the source node and requires multiple intermediate nodes to be transmitted to the destination node by hop-by-hop opportunity forwarding, and the intermediate nodes are reasonably selected for single copy or multiple copies [24]–[26]. The message forwarding will be able to effectively reduce transmission redundancy. The real-world social network shows a strong clustering phenomenon, and there are certain laws in the state of nodes and the interaction between nodes [27]. Relevant scholars use the "small world" principle in sociological theory to detect bridge nodes in the opportunistic network community that can be used to carry and forward messages between communities by constructing node centrality [28]. Related scholars use a community detection algorithm to clearly distinguish different communities instead of fuzzy detection methods based on similarity between nodes, and then detect bridge nodes between communities [29]. Related scholars proposed the People Rank social relationship sorting algorithm, which uses the relevance of the more stable social information of the node to measure the position of a node in the social graph [30]. The core idea is that the node has a higher status value, which means that the entire social graph is higher.

Relevant scholars use the node's motion model to estimate the probability of encountering, use the similarity and encounter frequency of the node set to estimate the actual spatial distance between nodes, and then forward the message to a relay node closer to the destination node in order to deliver the message to the destination node [31]. Researchers believe that message forwarders and recipients in opportunistic networks are similar to the customer and service models in social networks [32]. Combined with the network application of the publish/subscribe model in opportunistic networks, they propose the use of metric-based predictive social activities to determine the routing method of the message carrier, which lacks the predictive measurement of the resources of the newly added node, has the problem of cold start [33]. Researchers believe that the connection state between nodes is time-varying, and the model is established by analyzing the time series of stored node encounter information, so as to dynamically perceive network resources and node connection relationships. Related scholars put forward the concept of time distance, which defines the global time parameter including the dynamic connection information of the entire network and the local time parameter of the connection information between a node and its neighboring nodes in a period of time, which dynamically reflects the time sequence and message of the encounter. The researchers abstracted the communication paths that appeared into time-tagged edges, but did not consider the encounter frequency of nodes or node groups, nor did they consider temporarily disconnected nodes. Scholars point out that research on influential members of human networks is an important research topic in community network analysis, and the dynamic evolution of network topology is an inherent attribute of many systems [34]. They proposed a metric that considers the time centripetality of the interaction between members over time. This method is similar to the analysis of node connection status in the opportunity network, and is more accurate than the traditional static method.

III. DESIGN OF MIDDLEWARE FRAMEWORK FOR DATA PROCESSING OF INTERNET OF THINGS BASED ON SOA

A. IoT ARCHITECTURE AND DATA CHARACTERISTICS

1) IoT ARCHITECTURE

Multi-source heterogeneous information processing is a key problem that needs to be solved first in the data processing middleware of the Internet of Things. In order to achieve interoperability between interconnection, internal communication and heterogeneous information, the system structure of the future Internet of Things should be open, layered and scalable. The architecture of the Internet of Things is shown in Figure 1.

Specific hardware resource devices in the perception layer can use IPv6 to address them uniformly. IPv6 addresses mainly solve the limitation of the number of terminal device addresses when accessing the Internet. The main idea of the network layer is to use the existing Internet as the main dissemination and shared bearer exchange platform for various wireless access network access information. Each wireless access method has its own characteristics and application scenarios. Compared with other wireless broadband technologies, Wi-Fi has the advantages of wider coverage, faster

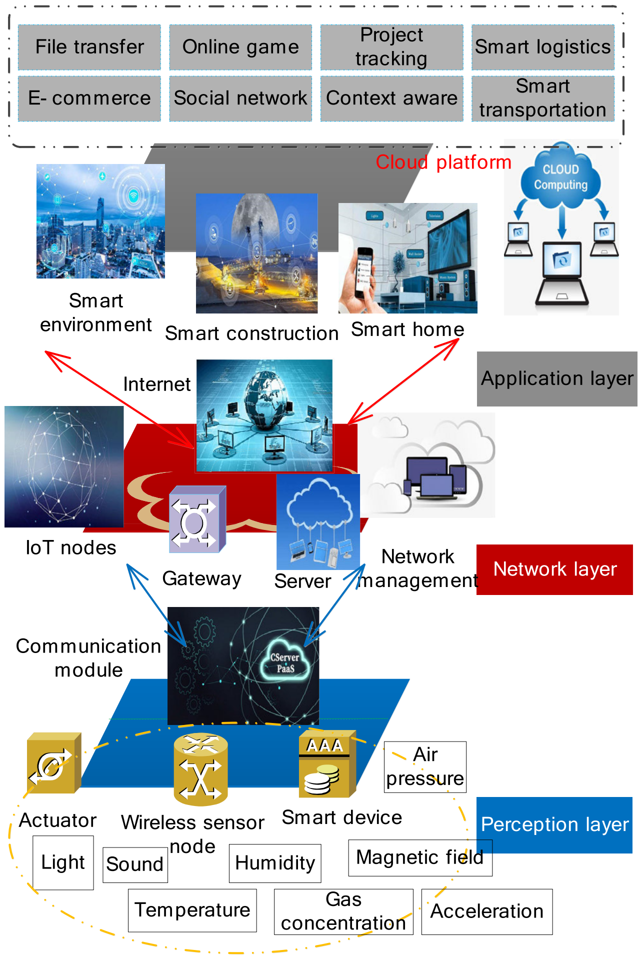

FIGURE 1. The hierarchical structure of the Internet of things.

transmission, high speed, reliability, low cost, and ability to bypass obstacles in transmission. Low-speed wireless networks, such as Zigbee wireless personal area network, Bluetooth, and infrared low-speed network protocols, have the characteristics of low communication radius of nodes that adapt to resource constraints, low computing power, and low energy consumption. The mobile communication network with extensive coverage has the ability to fully and effectively access the platform at any time and any place.

The main component of the perception layer is the wireless sensor node. Through various types of sensors, a variety of physical properties can be measured, such as light, temperature, humidity, air pressure, acceleration, sound, magnetic field and carbon dioxide concentration. Sensor nodes usually sense physical quantities of the surrounding environment. In addition to sensors, the perception layer also contains a large number of information generating devices, including RFID positioning systems, and various smart devices, such as smart phones, PDAs, multimedia players, laptops, and so on. It can be seen that the diversity of generated information is one of the important characteristics of the Internet of Things.

The middleware layer can solve heterogeneity problems through flexible interface design. The functions of the middleware layer mainly include data storage (database and large-scale storage technology), heterogeneous data retrieval (search engine), data mining, data security and privacy protection, etc.

2) INTERNET OF THINGS DATA CHARACTERISTICS

The most important difference between the current Internet and the Internet of Things data is the difference in data sources. User input in traditional Internet applications is the most important source of network storage information, including human language and multimedia data that can be directly understood by humans. However, the main source of data in the Internet of Things has changed.

The types of messages on the Internet can be divided into two categories: control information transmitted by network protocols and specific types of load data that need to be transmitted carried in network data packets. These two types of main information are produced by manual editing and produced by communication protocols between different software systems. It can be seen that most of the data transmitted on the Internet has semantic nature. The nature of this semantic originates from the user's editing or the communication protocol requirements of the upper-level software system (including semantics, syntax and timing). The semantics implied in the transmission of data on the Internet is completely transparent, and the semantics of the data will only be parsed after it reaches a specific terminal or destination node. The network layer of the Internet only completes data storage and forwarding functions.

The main data processed by the Internet of Things comes from the real physical world. The status information of various terminal devices is collected by various types of sensors and then transmitted through the Internet. Through pre-designed applications, these data are used in specific applications in the physical world, such as fire alarms, intelligent agricultural crop pest monitoring, food safety monitoring, etc., but these data can only be applied to specific pre-designed application scenarios, data Reuse is low, so in this case, users cannot fully utilize the value of the data.

B. SOA-BASED IoT DATA PROCESSING MIDDLEWARE

Service Oriented Architecture (SOA) is a component model that uses different functional units (called services) of related applications and uses the defined interfaces and contracts between these services to build applications. The interface is defined in a neutral way, and it should be independent of the hardware platform, operating system, and programming language that implement the service. This allows services to interact in a uniform manner across a variety of systems. Services are the foundation of SOA, so that components can directly and effectively rely on the interaction of application systems and software agents.

By comparing the characteristics of data in the traditional Internet and the Internet of Things, this article adopts the

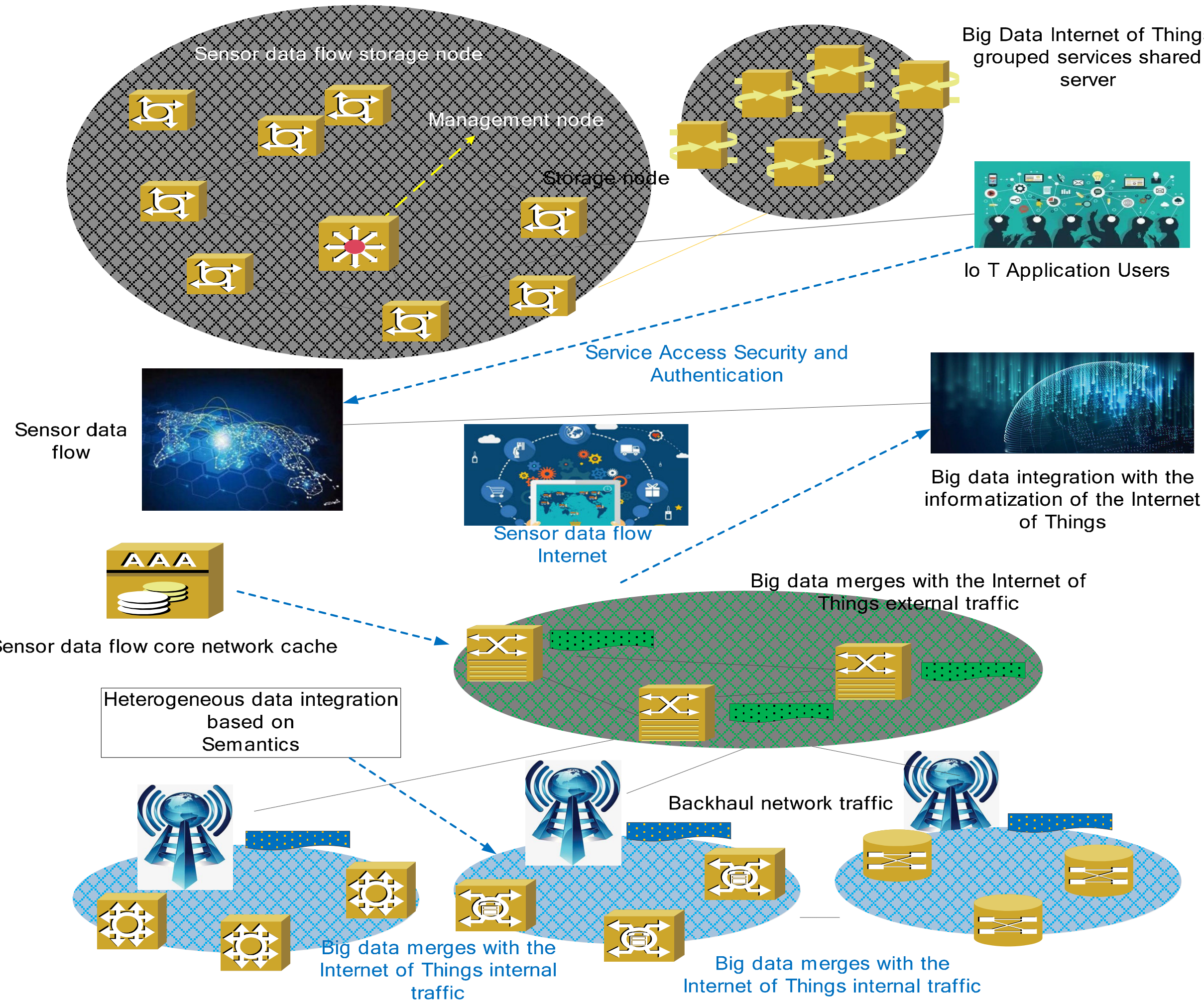

FIGURE 2. The hierarchical model of big data IoT middleware.

design summary of the middleware of the service-oriented architecture and integrated services to be compatible with various types of data and protocols. Therefore, this paper proposes an SOA-based big data IoT application model, as shown in Figure 2. Service providers use different types of sensing technologies. The data processing platform is responsible for data processing, data filtering and data integrity. It provides a unified description of heterogeneous data based on XML solutions to ensure the consistency and standardized processing of metadata. The basic framework of the IoT application is to generate real-time data streams based on sensor data streams in the physical world. In this architecture, these large amounts of real environmental sensing data are the basis of the entire application.

The data integration service layer is the core of the architecture and the key to heterogeneous data integration. In order to increase the scalability of the system, the structure designed in this paper includes two-tier services. A big reason for the difference in metadata models is based on heterogeneous sensor data resources. In order to better solve this problem, this article converts various types of data into XML format for expression, and sets unified operating rules for these metadata. On this basis, we create an integrated service layer for the underlying data. The second sub-layer service is a service based on the underlying heterogeneous data source XML document development. The application layer calls the corresponding upper-layer service according to the operational requirements, and then the upper-layer service calls the corresponding specific data from the client to manipulate the lower-layer service based on the parameter data. In this way, when the underlying heterogeneous data source changes, only the mapping between the basic service and the upper-layer application is more than changing the upper-layer. The realization process of data integration is completely transparent to users and can be compatible and interoperable in different systems.

In the design of semantic annotation service for heterogeneous data, the management of each information flow is regarded as the basic service unit. The semantic annotation service for heterogeneous data has four levels of services, as shown in Figure 3.

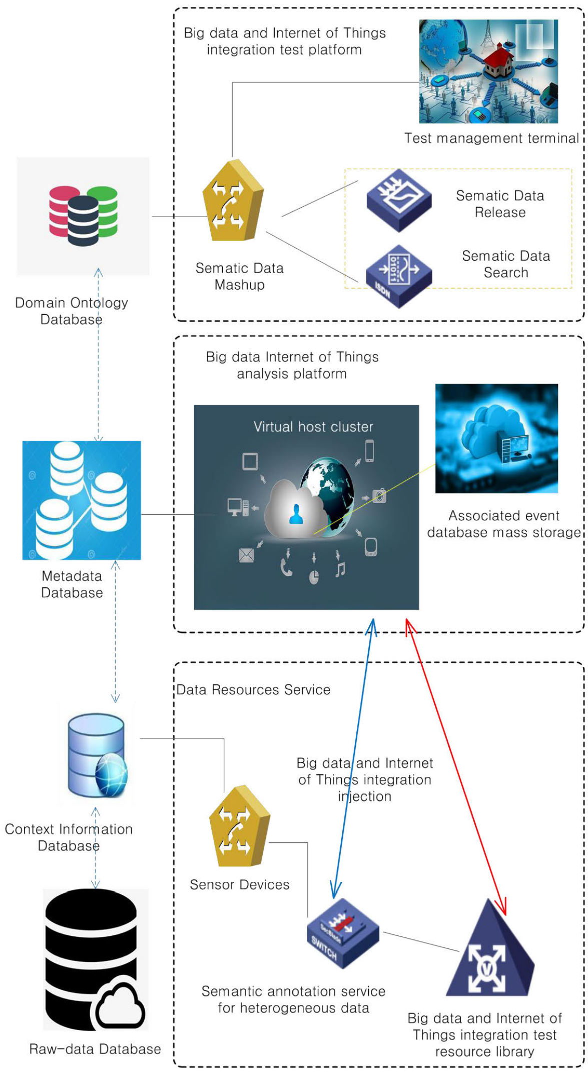

FIGURE 3. **Schematic diagram of data flow based on SOA IoT middleware.**

The data flow management service receives structured and unstructured data from the data resource service, and provides basic functional services for the upper layer. These basic functions include time synchronization, data collection, node location, data processing, data aggregation, energy management, service quality, node fault diagnosis and network diagnosis. The environment-aware information is stored in a context information database. With this data, the data stream generated by the underlying service can be marked and the RDF triples can be generated.

The semantic markup service has two main functions: generating RDF triples and collecting metadata for markup. This service obtains data streams from the data stream management service; but these obtained data streams contain raw data to be marked. The original sensor type and other information obtained from these data streams are used to mark semantic label metadata for upper-layer services. In addition, the metadata used for semantic labeling also comes from Web resources and contextual information obtained according to their environment.

IV. INFORMATIONIZATION OPPORTUNITY NETWORK COLLABORATION MODEL BASED ON EVOLUTIONARY GRAPH THEORY

A. ANALYSIS OF MODEL COMPOSITION

1) BASIC DESCRIPTION DIAGRAM

Similar to the description of complex networks, we use graphs to describe the basic structure of opportunistic networks. Each vertex in the graph represents a node in the opportunity network. This node has independent behavior ability, can observe the behavior of surrounding nodes, and change its own strategy through imitation or learning, thereby increasing its own income. There are only two strategies involved in the opportunistic network collaboration model, collaboration and selfishness (betrayal). For nodes in opportunistic networks to achieve effective communication, they must ensure that two nodes are within the communication range of each other, and two nodes that can communicate with each other will use an edge to connect on the graph. There are no edges between nodes that cannot communicate. Since the nodes in the opportunistic network are mobile, the communication links between the nodes are also dynamically changed, so the relationship between the edges in the graph is also relatively changed.

The graph describing the connection and encounter relationships between nodes in an opportunistic network can be called an interaction graph. And there is another kind of graph, called the permutation graph, which, as the name suggests, is the graph to be used when performing actions such as replacement and imitation between nodes. The nodes of these two graphs are the same, and each node can represent an individual in the opportunistic network. However, the edge connection relationship of the two graphs can be different. The different relationship between any two graphs will affect the analysis results. Here we adopt the simplest form for the simplicity of analysis, that is, the two graphs are completely equal. The discussion in the following part of this article is also based on the situation that the two graphs are the same.

In a normal static network, there is no historical relationship because it does not involve dynamic changes. But in opportunistic networks, the dynamic characteristics of nodes will cause the structure of the graph to change. Moreover, the number of connected nodes of each node and the duration of each connection also vary randomly. Therefore, in order to facilitate the analysis, we need to reduce the disturbance of these randomness to the system to a certain extent. A design based on history records can be adopted. Even if the real-time connection between a certain node m and the current node has been disconnected, the connection is still considered to exist for a period of time. During this period, m is still considered to be a neighbor of the current node. Taking a closer look, such a design is also reasonable. Because in a real opportunity network, when nodes make behavior decisions, on the one hand, they must use their current environment as a reference, and on the other hand, they must use their previous experience as a reference, and historical experience has its timeliness and other characteristics. Therefore, it is reasonable to use historical records based on a certain time delay, and it is also in line with the characteristics of opportunistic networks. The random distribution of relay nodes is shown in Figure 4.

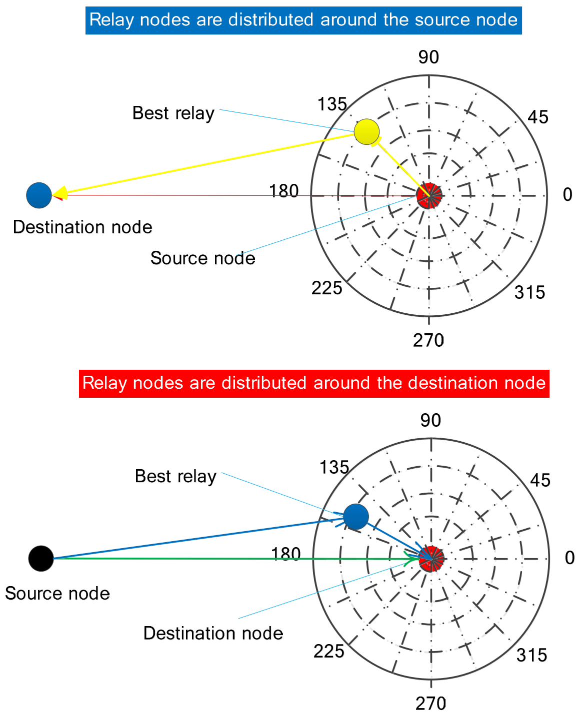

FIGURE 4. **Random distribution of relay nodes.**

2) COLLABORATIVE UPDATE RULES

The node strategy update mode is the core of the collaboration mechanism design. In opportunistic networks, nodes have highly dynamic characteristics, so global information is difficult to effectively spread in the network, and nodes rely more on local information. It is generally considered that the nodes in the opportunistic network will only exchange information with neighboring nodes in the surrounding communication range. Taking into account the delay inertia of the replacement relationship graph, the node will only refer to the behavior of the current neighboring node and the neighbor behavior in the historical record in the process of imitation and learning, which also conforms to the relevant assumptions in the evolutionary graph theory.

After having a specific relationship diagram, the imitation process will be adopted as the specific collaborative update rule. Every time a node meets a new node, it will update its strategy. It will either continue to stick to its own strategy or imitate a neighbor's strategy according to a certain fitness ratio. At the same time, it should be noted that the fitness here usually refers to the case of weak selection. The imitating update process conforms to the evolution of the cooperative behavior of nodes in the opportunistic network. In the game with neighboring nodes, nodes can change their strategies according to their own fitness (payout matrix of node revenue) to maximize their own interests.

3) COOPERATIVE UPDATE FREQUENCY AND TOPOLOGY CHANGE RATE

The opportunistic network is a dynamic network, and the movement of nodes will lead to changes in the topology. Evolutionary graph theory is based on static graphs. Therefore, in the process of applying evolutionary graph theory to opportunistic networks, it is necessary to consider the influence of graph topology changes.

The frequency of cooperative update is determined by the frequency of information generated by the node, and the topology change rate of the network structure is determined by the mobility model of the node. In order to make the design of the model closer to the static network, the frequency of cooperative updates is required to be much higher than the topology change rate. There is sufficient information exchange frequency in the gap time between each topology change, and each node can be fully evolved and updated to achieve local stability. The slight changes in the topology can be approximately ignored.

4) BASIC PAYMENT MATRIX

This involves another core issue in game theory-payout matrix. Only two kinds of behaviors, collaboration and selfishness, are considered in the opportunity network. An important assumption here is that nodes can fully observe the behavior of neighbor nodes, that is, they can know whether neighbors adopt cooperative or selfish behavior. Usually when two nodes meet, they need to complete data interaction with each other to ensure that the network realizes the relevant information routing function. Another important assumption is that the data interaction process is two-way, that is, two nodes in each communication have information interaction tasks that require the assistance of the other party to complete.

For a node that adopts a cooperative behavior, the node needs to pay a part of the cost to complete the information interaction between the nodes. This cost can be a part of the energy consumed to transmit and share information to other nodes. A node that takes selfish behavior will not lose energy because it will not actively share information, but simply receive information and can choose whether to discard the information. In the process of information exchange, the information obtained by one node from another node can be regarded as a kind of income. When two cooperative nodes meet, they will share information for each other, so as to realize two-way information interaction. Therefore, each node consumes part of the energy as a cost, and at the same time can obtain interactive information as a benefit.

B. MODEL ESTABLISHMENT

Aiming at the description of the opportunity network model and the design of related mechanisms, this section will complete the related mathematical derivation. Due to the use of evolutionary graph theory for quantitative analysis, both the interaction graph and the permutation graph in the opportunity network are a kind of random graph, and the random graph is usually processed in an approximate way. Evolutionary graph theory can usually handle complete graphs and K-regular graphs well (the degree of each node in the graph is K), while for scale-free graphs and random graphs, evolutionary graph theory can also have a good approximation.

According to the history record design based on times, the permutation graph can be transformed into a random k-regular graph. In a random k-regular graph, each node is connected to k nodes, but these k nodes are not fixed. Since the degree of each node in the random k-regular graph is a fixed value k, it can be processed similarly to the k-regular graph, which is also an approximate processing method.

The first thing to deal with is the distribution relationship of the neighbor nodes of a node in the network, that is, the local density, which is a different concept from the global density of the node. There are only two strategies involved here, collaboration and selfishness. It is also necessary to assume that it is a weak selection process. If the payout of a node in a certain game is P, then the fitness of this node can be expressed as 1-w+w P, where w represents the strength of the selectivity. When w is close to 0, it is a weak selection process, and when w is close to 1, it is a strong selection process. In the process of strong selection, the fitness of a node is directly proportional to its payment income, which is a relatively special situation. Because in the real environment, there are many factors that affect the adaptability of nodes, the use of weak selection process is more in line with objective reality. The parameter w introduced here will also play a key role. This parameter is usually ignored in traditional replication dynamic equations.

It is precisely because the introduction of w represents a process of weak selection, the fitness of each node is roughly similar, but it will fluctuate slightly according to the size of the payment, and it can be approximated as the same value.

The policy update rule uses the imitation rule. Let's study the local density under this rule, and we need to adopt the method of pair-pair approximation. Note that since there are only two strategies, they can be set to C (collaboration) and D (selfish or betrayal).

Since the probability of a node strategy being replaced is proportional to the fitness of its surrounding nodes, according to the definition of the weak selection process, the fitness of each node is the same and set to 1. Therefore, the probability of node strategy i being replaced by strategy j is proportional to the number of strategy j adopted in neighboring nodes around the node. In the case of uniform random selection, the probability that a node strategy of degree k is replaced by a certain node strategy around it should be 1/k.

Taking the calculation of the density of strategy D around strategy C as an example, it is expressed as qD/C, using conditional density, here:

$$q_{D/C} = \frac{|p_{CD}|}{p_C} \tag{1}$$

The probability of each event can be listed as an expression:

$$\bar{q}_{D/C} = \bar{P}_{CD} / P_C \tag{2}$$

$$\bar{P}_{CD} = -\frac{p_{CD}\left[1+(k-1)q_{D/C}\right]}{k} + \frac{2(k-1)q_{C/D}p_{DD}}{k} + \frac{2}{k}(k-1) \tag{3}$$

In the same way, the remaining local density probability expressions can be listed as follows:

$$\bar{q}_{C/D} = \bar{p}_{CD}/p_D \tag{4}$$

$$\bar{q}_{C/C} = \bar{p}_{CC}/p_C \tag{5}$$

$$\bar{p}_{CC} = -\frac{1}{k}p_{CD}\left[1+(k-1)q_{C/D}\right] + \frac{2}{k}(k-1)q_{D/C}p_{CC} \tag{6}$$

$$\bar{q}_{D/D} = \bar{p}_{DD} / P_D \tag{7}$$

$$\bar{P}_{DD} = \frac{p_{CD}}{k}\left[1+(k-1)q_{D/C}\right] + \frac{2}{k}(k-1)q_{C/D}p_{DD} \tag{8}$$

According to the above expressions, it can be found that when the local density of various strategies is stable, that is, when each derivative expression is 0, the local density at steady state can be calculated from this, and the following results are obtained:

$$q_{C/C} = {}^{1+(k-1)p_C}/_{k-1} \tag{9}$$

$$q_{C/D} = {}^{1+(k-2)p_C}/_{k-1} \tag{10}$$

$$q_{D/C} = {}^{(k-3)p_D}/_{k-2} \tag{11}$$

$$q_{D/D} = {}^{(k-4)p_D+1}/_{k-3} \tag{12}$$

From the calculation results, it can be found that among the neighbors of the nodes that adopt strategy C, the local density of strategy C is higher than the global density of strategy C, and the corresponding local density is lower than the global density of strategy D. To sum it up, among neighbor nodes, the types using the same strategy have a local density higher than the global density, while the types using different strategies have a local density lower than the global density.

After completing the calculation of the local density, we continue to study the specific process of strategy update. Assuming that the initial payment matrix is A, aij represents the specific payment of strategy i to strategy j. Here, the expression term (i;k1,k2,...,kn) is designed to represent the node. This formula indicates that the node adopts strategy i, and among the surrounding neighbors, k1 adopt strategy 1, and kn adopt strategy n. According to the weak selection process, fitness can be expressed as:

$$W_{(k_n;i)} = w + 2 - w\sum\nolimits_1 a_{i1}k_1 \tag{13}$$

After the local competition is added, a new term gi is added to the traditional dynamic replication equation. Since gi is also represented by a payout matrix, gi and fi can be combined as follows:

$$\bar{p}_1 = p_i\phi + p_j \sum_{j=0}^{n-1} \left|a_{ij} + b_{ij}\right| \tag{14}$$

If you design a new variable cij such that:

$$c_{ij} = \left|a_{ij} - b_{ij}\right| \tag{15}$$

The expression can be transformed into a standard dynamic copy equation:

$$\bar{p}_1 = p_i\phi + p_j \sum_{j=0}^{n-1} c_{ij}p_j \tag{16}$$

So far, it can be found that the spatial structure needs to be considered in the evolutionary game, that is, the evolutionary game needs to be applied to the k-regular graph. In fact, the initial payout matrix is appropriately changed and the correction parameters for local competition are added. Moreover, relevant simulation data show that this change in payment matrix can also be effectively applied to irregular graphs (such as random graphs and unscaled graphs). When applied to a random graph, the k value will be the average degree of all nodes in the network.

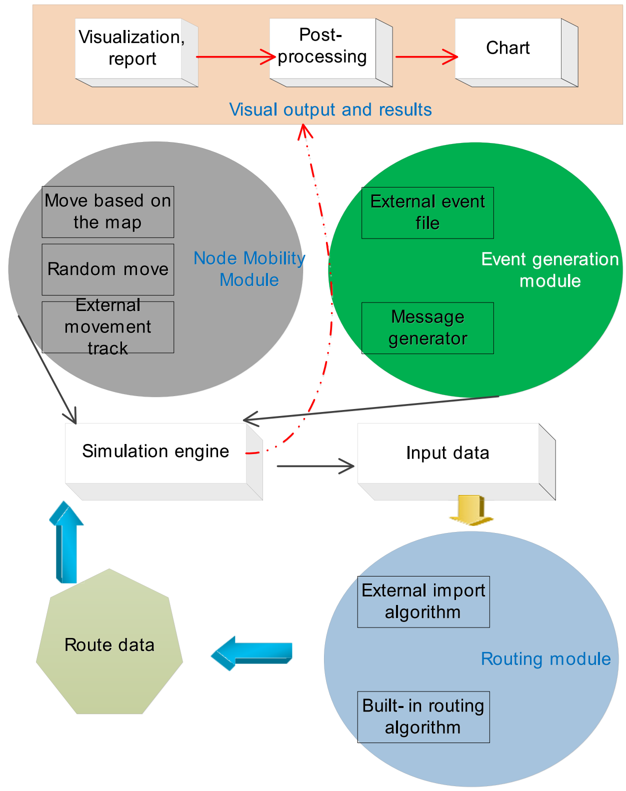

FIGURE 5. The one architecture design.

V. EVOLUTIONARY GAME ALGORITHM SIMULATION AND EXPERIMENTAL ANALYSIS

A. SIMULATION ENVIRONMENT

We build the experimental environment on The ONE (opportunistic networking environment) open source simulation tool. The ONE simulation tool was developed by researchers at the Helsinki University of Technology in Finland. The tool is specially designed for the simulation of opportunistic network routing and application protocols. The tool has built-in rich and realistic simulation scenes, such as streetcars, pedestrian streets and highway driving, and real scenes such as communities and workplaces.

The ONE simulation tool is mainly composed of the following modules: node movement, event and message generation, routing settings and other modules. The node movement module includes random walk, shortest path, etc., and can also customize the movement mode by importing external files. The event and message generation module can set the type of event occurrence, the rate of message generation, etc. The routing setting module contains classic routing implementations, and our algorithm models are generally implemented based on these routings. The tool also contains a graphical visual interface for easy debugging. The ONE simulation tool architecture design is shown in Figure 5.

There are mainly two types of abnormal nodes in the network, namely, selfish nodes and malicious nodes. Selfish nodes refuse to forward messages from other nodes, but hope to enjoy the network to provide forwarding services for them. Malicious nodes include Black Hole Attack, Grey Hole Attack and flooding attacks. The first two kinds of malicious nodes will randomly discard the data packets that need to be forwarded, while the latter malicious nodes will send a large number of junk data packets to the network. The sending speed is 5~8 times faster. In the simulation experiment environment of this paper, the above-mentioned abnormal nodes exist at the same time, and one of the attack methods is randomly assigned to the abnormal nodes when the network nodes are initialized. The network environment where different abnormal nodes are mixed can better reflect the real opportunity network environment. The experimental network environment parameter visualization is shown in Figure 6.

B. EVALUATION OF THE EFFECTIVENESS OF THE REPUTATION MODEL

1) PERFORMANCE COMPARISON BETWEEN ORDINARY EVOLUTIONARY GAME MODEL AND TRUSTED COOPERATIVE EVOLUTIONARY GAME MODEL

Compared with the trusted cooperative evolutionary game model, the ordinary evolutionary game model in the experiment refers to the fact that the reputation penalty factor is not added to the game profit function, and the selection process of learning objects adopts a random method. The experimental results are shown in Figure 7.

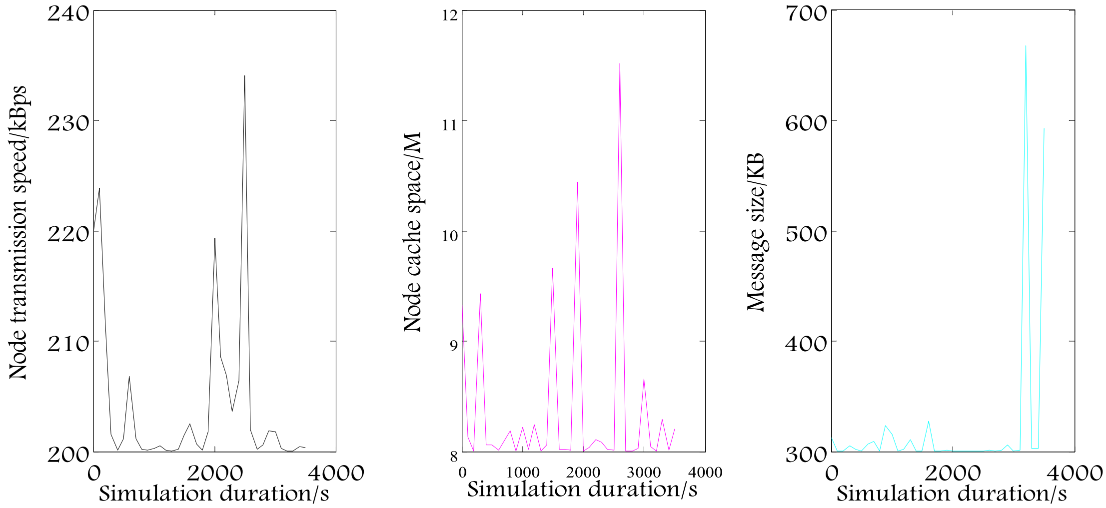

FIGURE 6. Visualization of simulation parameter settings.

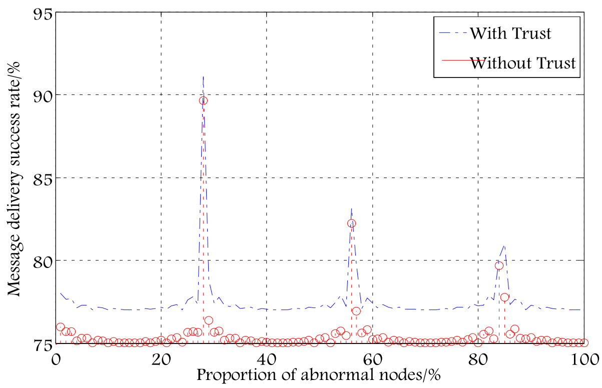

FIGURE 7. Performance comparison between ordinary evolutionary game model and trusted cooperative evolutionary game model.

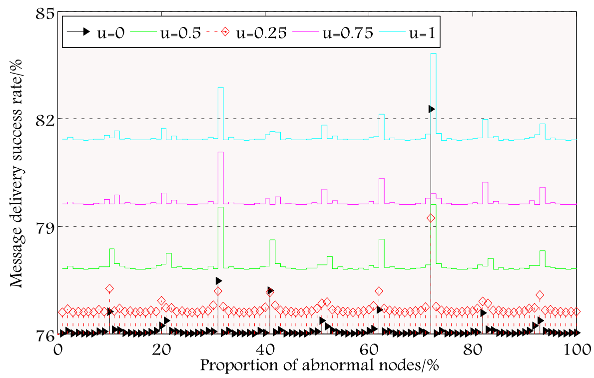

FIGURE 8. The influence of reputation confidence index u on the success rate of message delivery.

As the number of abnormal nodes increases, the success rate of opportunistic network delivery under the ordinary evolution model fluctuates. When the proportion of abnormal nodes increases from 0% to 100%, the message delivery success rate is above 75%. However, after adding the trusted cooperative evolution model of the reputation incentive mechanism, the increase in the proportion of abnormal nodes has a significant impact on the success rate of message delivery. It should be noted that when the proportion of abnormal nodes reaches 100%, the delivery success rate of the two models differs by about 2%. This is because there is no collaboration strategy for learning in the network, and both models degenerate to direct delivery routing algorithms, so the delivery success rate is basically the same.

Experimental results show that the reputation incentive mechanism has played an important role in the evolution of node collaboration. Because after adding the reputation penalty factor, the node's non-cooperative strategy leads to a serious decrease in its revenue, which improves the node's motivation to update the strategy. In addition, by screening learning objects by reputation, nodes have a greater chance of learning from high-reputation nodes, and high-reputation nodes often adopt collaboration strategies.

2) THE INFLUENCE OF REPUTATION CONFIDENCE INDEX ON THE SUCCESS RATE OF MESSAGE DELIVERY

The reputation confidence index u is proposed in the learning object screening method, and represents the confidence value of whether the reputation evaluation of the game opponent is correct. When u is larger, it means that there is a higher confidence in the evaluation of reputation; when u is close to 0, it means that the imitation object is randomly selected. In the experiment, we control the reputation confidence value u to be 0, 0.25, 0.50, 0.75 and 1, respectively. The simulation results are shown in Figure 8.

It can be seen from the experimental results that as the reputation confidence index u increases, the success rate of message delivery is less and less affected by abnormal nodes. When the confidence index value is 0, that is, the learning object is randomly selected, the trusted collaborative

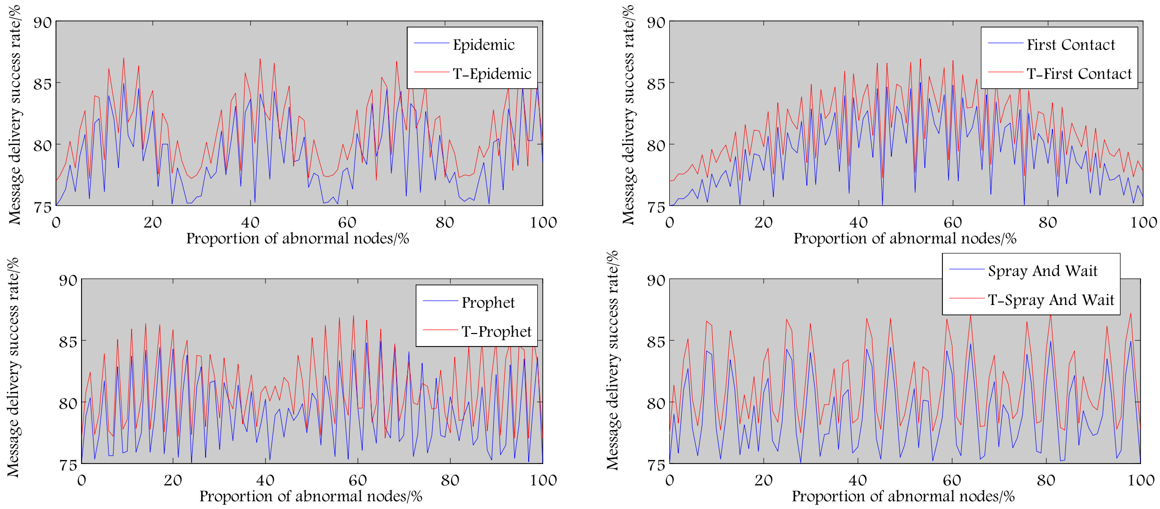

FIGURE 9. Message delivery success rate under the four kinds of information opportunity collaboration mode algorithms.

evolutionary game model degenerates to the ordinary evolutionary game model, and the message delivery success rate decreases linearly. When u increases to 1, the message delivery success rate of the network is basically stable at about 0.81, indicating that the level of network cooperation is in a stable state. It can be seen that the stronger the node's confidence in the reputation model, the stronger the ability of the trusted cooperative evolutionary game model to resist the impact of abnormal nodes on network performance.

This is because with the increase of u, the greater the role of the reputation value in the process of node selection of learning objects, the greater the probability that the node will select a node with high reputation as the learning object. According to the reputation evaluation model, nodes with high reputation values are often nodes that actively participate in network collaboration. Therefore, as time goes by, the collaborative strategy will eventually occupy the entire network and become an evolutionary stable strategy.

Through the above analysis, it can be seen that the reputation model plays a positive guiding role in the evolution of node collaboration. The credit penalty factor is added to the game revenue function, which greatly reduces the game revenue of abnormal nodes, and forces abnormal nodes to update their strategies. The reputation confidence value makes the node have a greater chance of learning the collaboration strategy, and promotes the rapid evolution of the network to the direction of collaboration.

C. PERFORMANCE EVALUATION OF TRUSTED COOPERATIVE EVOLUTIONARY GAME MODEL

1) THE IMPACT OF DIFFERENT ABNORMAL NODE RATIOS ON THE SUCCESS RATE OF MESSAGE DELIVERY

Abnormal nodes refer to selfish nodes and malicious nodes. In different scenarios of abnormal node ratios, the message delivery success rates of the four opportunistic network routes are shown in Figure 9.

The simulation results of the Epidemic routing algorithm show that abnormal nodes have little impact on the network, and even the existence of abnormal nodes can improve the success rate of message transmission. Because the routing algorithm uses the flooding transmission strategy of multiple message copies, there are excessive message copies in the network, which can be regarded as a spam message attack. The existence of abnormal nodes reduces excessive message copies in the network, and improves message transmission. But after the abnormal nodes reached 70%, the message delivery success rate deteriorated sharply. This is because there are too few nodes in the network that assist in the transmission of messages, and messages cannot be effectively delivered. After adding the game incentive mechanism (T-Epidemic), the message delivery success rate has been relatively high with the increase of abnormal nodes. It shows that the evolutionary game model has played a role, making the level of network cooperation in a relatively stable state. In addition, due to the particularity of the Epidemic routing algorithm, a small amount of misjudgment has increased the success rate of network message delivery.

Because First Contact routing is a single message copy routing, it is very sensitive to abnormal nodes, and a small number of abnormal nodes can seriously affect the message transmission of the network. The simulation results of the message delivery success rate of the First Contact routing algorithm show that when the number of abnormal nodes is about 60%, the network message delivery success rate begins to decrease. After adding the game incentive mechanism (T-First Contact), the network successfully resisted the influence of abnormal nodes. When all nodes in the network are abnormal nodes, the evolutionary game model is useless because there are no nodes in the network that adopt the cooperation strategy.

Prophet routing is a multi-copy routing algorithm based on probability. Its message delivery success rate varies with

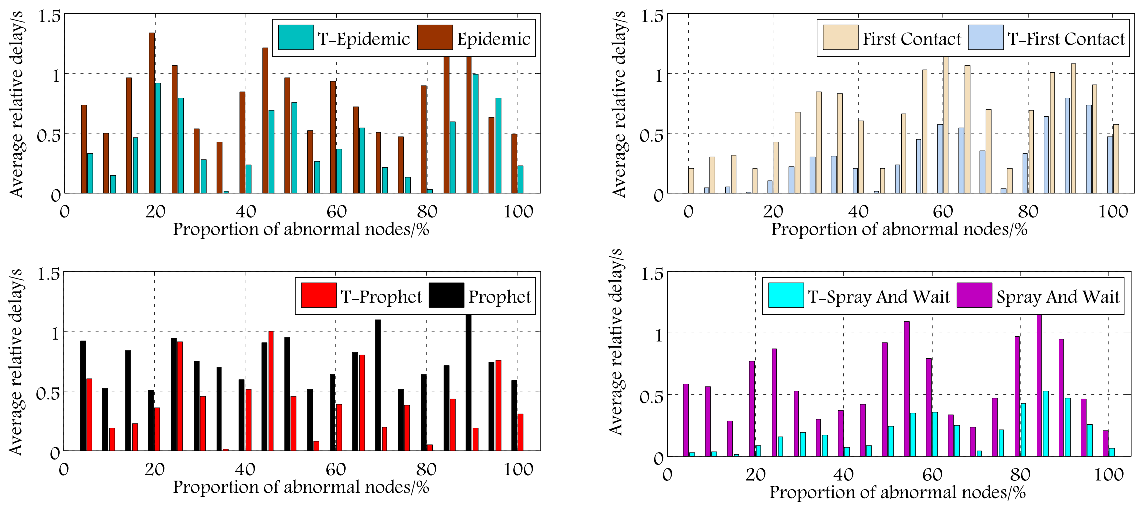

FIGURE 10. The average relative delay under the four kinds of information opportunity collaboration mode algorithms.

the proportion of abnormal nodes similar to Epidemic. The reason is that too many message copies hinder message transmission, and a small number of abnormal nodes play a positive role in network message delivery. After joining the game incentive mechanism (T-Prophet), the message delivery success rate is basically not affected by abnormal nodes, and is basically stable at around 0.80. However, we have observed that the delivery success rate curve has obvious bumps. The reason is probably that the evolutionary game model has affected the calculation of the transmission probability by the original routing algorithm. However, the negative impact of bumps did not affect the evolutionary game model to resist the impact of abnormal nodes on the network.

2) THE IMPACT OF DIFFERENT ABNORMAL NODE RATIOS ON THE AVERAGE RELATIVE DELAY

The average relative delay refers to the average time required for message delivery when delivering the same number of messages. In the experiment, we need to set the total delivery quantity. From the previous experiment results, each routing algorithm has a minimum message delivery rate. Here we set the experimental parameter to the lowest message delivery rate of each routing algorithm. It should be noted that because the lowest message delivery rate of each route is different, the horizontal comparison of the average relative delay between different routes has no practical significance.

The experimental results of the average relative delay of the Epidemic routing algorithm are shown in Figure 10(a). The experimental results show that with the increase of abnormal nodes, the average relative delay of Epidemic routing fluctuates. After adding the game incentive mechanism (T-Epidemic), when the proportion of abnormal nodes is small, the average relative delay decreases slightly as the proportion of abnormal nodes increases. That is to say, after joining the evolutionary game model, the damage of abnormal nodes to the network is restrained.

The average relative delay of the First Contact routing algorithm is shown in Figure 10(b). Different from the other three routing algorithms, the average relative delay of this routing algorithm decreases as the proportion of malicious nodes increases. This is caused by the characteristics of the First Contact routing algorithm. The routing algorithm is a single message copy routing. In a network environment with abnormal nodes, it is difficult for messages to be transmitted through intermediate nodes. The source node and destination node that can successfully deliver the message must be very close and can be delivered directly. Therefore, the more abnormal nodes, the greater the proportion of directly delivered messages, and the lower the average relative delay. However, this does not affect our judgment whether the game incentive mechanism is effective. From the experimental results, it can be seen that after adding the trusted cooperative evolutionary game model, it is similar to the network without abnormal nodes, indicating that the reputation incentive mechanism improves the level of network cooperation.

The experimental results of the average relative delay of the Prophet and Spray and Wait routing algorithms are shown in Figure 10(c) and Figure 10(d), respectively. Similar to the Epidemic routing algorithm, the number of abnormal nodes affects the two routing algorithms, causing their delays to increase. After adding the game incentive mechanism to these routing algorithms, the average relative delay of the network is basically in a stable state, and the reputation mechanism effectively offsets the negative impact of abnormal nodes. For Epidemic, Prophet, and Spray and Wait routing algorithms, when the proportion of abnormal nodes in the network is small, the average delay of routes added to the reputation incentive mechanism is longer than that of the original route. The reason is that the reputation incentive mechanism misjudges some normal nodes, which brings some negatives. influences.

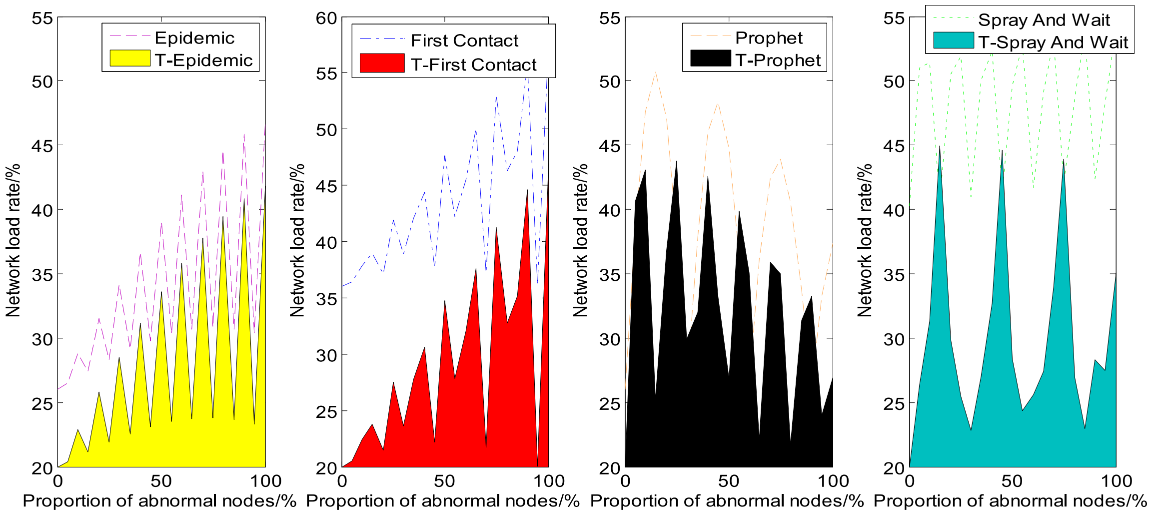

FIGURE 11. Network overhead under the four kinds of information opportunity collaboration mode algorithms.

3) THE IMPACT OF DIFFERENT ABNORMAL NODE RATIOS ON NETWORK OVERHEAD

The experimental results of the network overhead of Epidemic and Prophet routing algorithms are shown in Figure 11(a) and Figure 11(c). These two routing algorithms are multi-message copy routing algorithms, and their experimental images also show similarities. With the increase of abnormal nodes, the network overhead first decreases and then increases. The reason is that when the network collaboration rate is high, too many message copies will affect network transmission. After joining the evolutionary game model, the routing overhead has been maintained at a relatively low level. On the one hand, the reason is that the reputation mechanism inhibits a large number of invalid network transmissions. The evolutionary game model improves the level of network cooperation, making most of the network transmissions effective.

The experimental results of the network overhead of the First Contact routing algorithm are shown in Figure 11(b). With the increase of abnormal nodes in the network, different from the average network transmission delay, the network overhead is positively correlated with the proportion of abnormal nodes. The reason is that a large number of transmissions are interrupted by abnormal nodes, and the number of invalid transmissions naturally increases. After joining the game incentive mechanism, the network overhead is basically stable at about 45%, indicating that the network's collaboration level is equivalent to that without abnormal nodes.

The experimental results of the spray and wait routing algorithm network overhead are shown in Figure 11(d). It is worth noting that the network overhead under this route is negatively related to the proportion of abnormal nodes. The Spray and Wait route is a limited message copy route. In the experiment, we set 6 copies. Due to the increase of abnormal nodes, the transmission of some copies is interrupted, but because other copies are likely to reach the destination node, the interrupted copy transmission reduces unnecessary forwarding, that is, reduces network overhead and provides forwarding effectiveness. After joining the game incentive mechanism, the network cost stabilized at around 5.3, indicating that the reputation incentive mechanism can also play a role in the spray and wait routing algorithm. Although after joining the incentive mechanism, the network overhead is greater than without joining. However, the network overhead rate indicates that Spray and Wait is still an efficient routing algorithm after adding the incentive mechanism.

4) THE INFLUENCE OF REPUTATION INCENTIVE MECHANISM ON THE NUMBER OF NETWORK LOST PACKETS

The number of lost packets refers to the sum of the number of abnormal nodes maliciously discarding message packets and the number of normal nodes discarding message packets due to insufficient buffer space in the opportunistic network. This indicator intuitively reflects the harm of abnormal nodes to the network. The experimental environment and parameter settings used in this experiment are consistent with the message delivery success rate. At the end of the simulation experiment, the total number of message packets discarded during the simulation experiment is calculated.

Figure 12 shows the experimental results of the number of node packet loss for the four informatization opportunity cooperation mode algorithms. The results show that after adding the game incentive mechanism, compared with the original routing algorithm, the number of network packet loss is greatly suppressed and does not rise sharply with the increase of abnormal nodes in the network, but basically stabilizes in a lower range. Since the Epidemic and Prophet routing algorithms are multi-message copy algorithms and use flooding strategies to forward messages, the number of packet losses for these two routing algorithms is slightly greater than that of the First Contact and Spray and Wait routing algorithms.

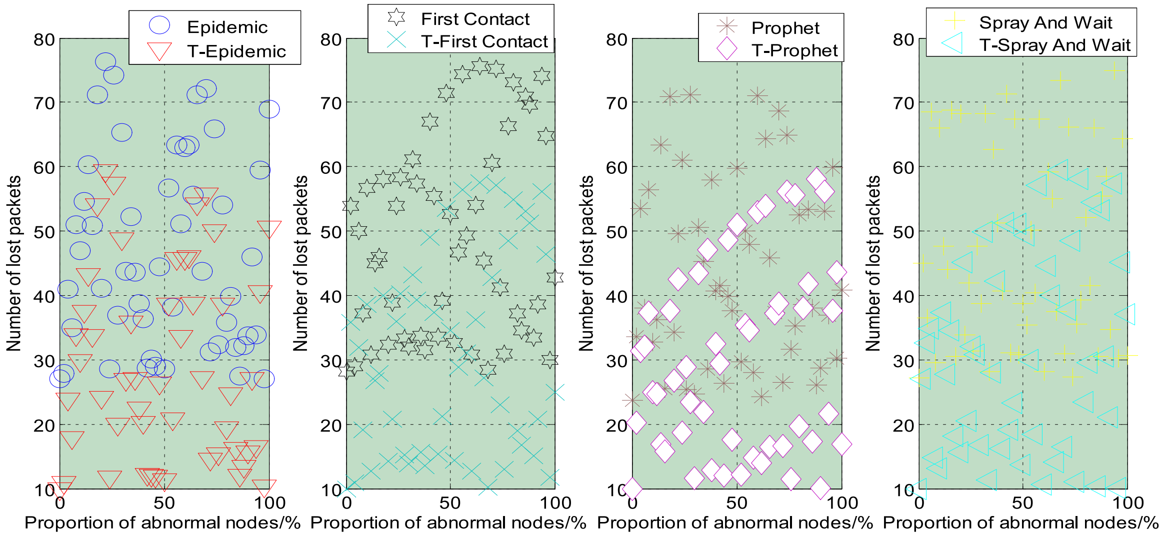

FIGURE 12. The number of lost packets under the four informatization opportunity collaboration mode algorithms.

VI. CONCLUSION

Using the method of pair-pair approximation, the changes in the payment matrix of the network under the condition of imitating the rules are analyzed. In order to enable evolutionary graph theory to be applied topological structure as a dynamic opportunistic network, it is necessary to ensure that the node strategy update frequency is much greater than the topological change rate. Under these conditions, modeling and theoretical derivation were completed, and a simple cooperative dominance law was obtained. This can also ensure that the cooperative strategy is the only evolutionary stable strategy in the game. By constructing an evolutionary game model, nodes are encouraged to actively participate in network collaboration in a self-evolving manner, so that the network maintains a cooperative state for a long time. Single-stage game analysis shows that the node message forwarding process is a typical prisoner's dilemma game. In order to guide the positive development of the game evolution, we have incorporated reputation incentives into the game revenue matrix and the node update mechanism. Specifically, a reward and punishment factor is introduced into the game revenue payment function to reward cooperative behavior and punish non-cooperative behavior at the same time. In the strategy update mechanism, the node chooses whether to modify the next round of game strategy according to the profit situation, and if it is modified, it will learn the strategy. The selection process of learning objects combines the comprehensive reputation of the node, with the purpose of increasing the probability of trusted nodes being learned. This article uses the open source opportunistic network simulation platform The ONE to verify the effectiveness of the proposed model, deploys the proposed model in multiple classic routing protocols, and designs different simulation environments for comparison experiments. Experimental results show that the reputation evaluation model can accurately detect abnormal nodes and provide positive incentives for the evolutionary game model. The trusted cooperative evolution model can play a role in different network environments and routing algorithms, and has good scalability.

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