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Wright–Fisher multi-strategy trust evolution model with white noise for Internetware

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ABSTRACT

A trust evolution model plays an important role in ensuring and predicting the behaviors of entities in Internetware system. Most of the current trust evolution models almost adopt expertise or average weight method to calculate entities' trust incomes, and focus on two strategies ('full trust', 'full distrust') to analyze trust behaviors. In addition, the researches on dynamics evolution models fail to consider the factor of noise, and cannot effectively prevent free-riding phenomenon. In this paper, a trust measurement based on Quality of Service (QoS) and fuzzy theory by considering timeliness of history data is proposed to improve the accuracy of trust measurement results. Furthermore, a trust evolution model based on Wright–Fisher and the evolutionary game theory is proposed. This model considers multi-strategy and noise problems to improve the accuracy of prediction and adaptability of model in complex networks. Meanwhile, in order to solve the free-riding problem, and improve the trust degree of a system, an incentive mechanism is established based on evolutionary game theory to inspire entities to select trust strategies. The simulation results show that this model has good adaptability and accuracy. In addition, this model can effectively improve network efficiency, and make trust income reach an optimal value, so as to improve trust degree of a system.

1. Introduction

A traditional software form is developed by a top-down analysis method. Entities cannot adapt to dynamic, versatile, complex and open network environment because of closure of traditional software. Therefore, Internetware, a new software form, is proposed. Internetware is an abstract of software systems that exists in open, dynamic and versatile environment. It is a natural continuation of traditional software structure. Independence, synergy, reactivity, evolution and polymorphism are characteristics of Internetware. Thus Internetware can sense the changing of outside environment, and dynamically adjust interactive mode between entities to complete complicated online tasks (Yang, 2005). In an evolution process of an Internetware system, people hope to control entities' behaviors and interactive strategies through effective means for making system converge to target state fast. Internetware's trust evolution presents the self-organizing process from 'disorder' to 'order'. Therefore, how to make Internetware approach good performance and stable state faster is one of the most important research focuses.

Network trust technology is a new security method based on network security technology. It strengthens a dynamic process of network state. In addition, trust technology provides the basis of strategies for implementing self-adapting network security and controlling service quality (Wang et al, 2006). However, trust is one of the most complex social relationships. Trust is an abstract psychological cognitive process with uncertainty, asymmetry, part transitivity, asynchronism, context independence, attenuation of space and time etc. Trust involves many factors, such as hypothesis, expectation, behaviors and environment. Thus it is hard to express and predict trust. In an Internetware system, because of the lack of corresponding incentive mechanism, 25% entities are free-rider, which leads to the free-riding phenomenon. That is to say, entities only download files from other nodes, but do not provide upload service (Guangxue et al., 2011; Jun and Ahamad, 2005). In the recent years, scholars have gained a series of research achievements on entities' evolution, complexity and fuzziness. They have promoted the development of dynamic evolution prediction effectively. However, there are still some problems as follows:

1. Most of the present trust evolution models adopt expertise or average weight method to calculate entities' trust incomes. Jingtao et al. (2007), Kamvar and Schlosser (2003) and Xiong and Liu (2004) adopted the averaging method to calculate recommendation trust value, and cannot reflect real situations of trust relationship. They fail to consider the timeliness of history behavior data and entities' aggregation degrees in complex

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network environment. As a result, the trust measurement results deviate from actual utility values of entities.
2. The present trust evolution prediction methods almost focus on two strategies, i.e., 'full trust' and 'full distrust', to analyze trust behaviors. Junhai and Mingyu (2008) proposed a trust model based on the game theory. It divided entities' behaviors into 'trust' and 'selfish'. However, in open and complex networks, entities' behaviors are multiple and fuzzy. Therefore, the traditional two-strategy game cannot reflect the real situation of complex networks.
3. The present researches about dynamics evolution model fail to consider the network noise. In addition, scholars establish models with deterministic dynamics mechanism. Li et al. (2010) proposed a clustering algorithm based upon games on evolving networks. It analyzed clusters of evolving networks based on the deterministic evolutionary game theory. However, the network environment is full of uncertainty, and the evolution process presents uncertainty. Therefore, the present researches on dynamics evolution models lack analysis concerning random perturbation.
4. The inherent feature of entity is to maximize its utility, while minimizing the utilities of other entities. This feature makes selfish behavior dominate trust evolution direction of the whole system, which introduces the free-riding (Karakaya et al., 2008) problem. It seriously influences the overall balance, and reduces system efficiency. Therefore, people want to control the game process by effective means to make 'trust' strategy be the preferred strategy of entities. In addition, people can ensure a system's overall income is optimal. According to this phenomenon, scholars proposed corresponding methods to prevent the free-riding problem (Tseng and Chen, 2010; Guangxue et al., 2011). However, it is also one of the most important problems to be solved urgently.

Considering the above shortages and complexity of open networks, this paper proposes the Wright–Fisher multi-strategy trust evolution model with white noise for Internetware. Firstly, considering timeliness of history behavior data and aggregation degree of entity in complex networks, a trust measurement method based on QoS and fuzzy theory is proposed to calculate entities' utility values in order to solve the problems of uncertainty and fuzziness about entities' behaviors. Secondly, according to utility values of entities with different trust levels, a multi-strategy trust evolution model with white noise for Internetware based on Wright–Fisher and evolutionary game theories is established. Because of the multiple and fuzzy behaviors, this model adopts the multi-strategy method to analyze the game between entities in order to reflect the real situation of complex networks. In addition, considering the uncertainty of evolution process, this paper extends deterministic dynamical equation, and puts white noise into evolution process of an Internetware system to take care of the uncertainty of evolution. Finally, an incentive mechanism based on the evolutionary game theory is proposed to inspire entities to select strategies that have high trustworthy. In order to solve the free-riding problem, this mechanism considers the selfish feature of entities, and establishes corresponding rules to control the trust evolution direction of Internetware. Therefore, this model can improve whole trust degree of an Internetware system through an incentive mechanism.

The rest of the paper is organized as follows: Section 2 reviews the related works and presents the motivation for our work. Section 3 introduces the proposed Wright–Fisher multi-strategy trust evolution model with white noise for Internetware. Section 4 presents our simulation results and analysis of the results. Conclusions and future work are discussed at the end.

2. Related work

Trust measurement is a kind of trust mechanisms that describes trust from many aspects. According to the present researches, the most important three trust measurement methods are: trust measurement under open network environment; trust measurement based on Agent software synergy service; trust measurement based on rough set theory.

(1) Trust measurement under open network environment In 1994, Thomas Beth proposed a trust measurement under open network environment. He divided trust into direct trust and recommendation trust, and adopted a probability method to signify trust. Yuan et al. (2006) proposed a trust model based on Bayesian networks. According to different environments, this model promoted entities to select different properties by describing different aspects of trust. Wang and Vassileva (2003) solved the problem of recommendation trust based on a Bayesian method. This method computes recommendation trust based on expert experience. Wen et al. (2010) proposed an evaluation method of software reliability under open network environment. It is believed that trust degree calculation was a bottom-up calculation process. This process can decompose and compute parallel structure, and calculate trust degree efficiently. But there are still some shortages about this model. It only adopts a probability method to establish the subjective trust model. In other words, subjectivity and uncertainty of trust are equivalent to randomness. And it adopts an averaging method to calculate recommendation trust value. Therefore, this model cannot reflect real situations of trust relationship.

(2) Trust measurement based on Agent software synergy service In an Agent software synergy service system, trust means that a synergic Agent predicts subjective possibility of an entity's activities. Prediction evidence comes from target entity's previous behaviors. Prediction results are affected by important degree evaluation for this synergic activity, such as key cooperation activities, secondary cooperation activities and so on (Manling and Zhi, 2011; Zhiming et al., 2008). Trust between Agents associates with other entities' subjective understanding. While this subjective understanding is fuzzy, this trust relationship cannot be described and managed by accurate logic. Therefore, scholars introduced 'Fuzzy Set' to trust management of software synergy service based on Agent. It not only reflects fuzziness of Agent trust, but also describes trust mechanism between Agents with intuitive and concise semantics.

(3) Trust measurement based on rough set theory Dynamic trust relationship model, one of the most complex social relationships in large-scale distributed systems, involves many factors, such as assumption, expectation, behavior, and environment. Therefore, it is difficult to accurately express and predict this dynamic trust relationship. Wen and Zhong (2003) established trust measurement model by combining the rough set theory and information entropy theory. The authors applied it to the open network environment. According to trust measurement indexes, this method mines data, and discovers knowledge. Therefore, this method has changed the traditional modeling ideas of trust relationship, and got rid of the shackles of a variety of subjective assumptions. It can overcome the problem that traditional model processes multi-dimensional data inadequately.

In addition, Advogato (Al-Oufi et al., 2012) attempts to determine the set of trusted users as many as possible while reducing the influence of unreliable attackers. Advogato utilizes a social graph that represents Advogato's members and their relationships. Each node in the graph represents an account, and a directed edge indicates a certificate. However, the Advogato measurement was originally designed for global trust measurement. Advogato assigns a capacity to each node according to its distance from the seed and, thus, the same capacity to nodes having the same distance. Zhiguo et al. (2010) proposed a dynamic P2P trust model based on time-window feedback mechanism. It considers the inherent connection among trust, reputation and incentive and the effect of time factor on the trust computation. The above models greatly promoted the development of trust measurement. However, in real network, there are a lot of complex trust relationships. The present trust measurement models fail to consider the timeliness of history behavior data and entities' aggregation degrees in complex networks. As a result, the trust measurement results deviate from actual utility values of entities.

On the aspect of trust evolution model, the main research methods are concentrated on the evolutionary game (Yanfang and Xinsheng, 2009) and neural networks theory. The principle of these research methods is to make entities learn through certain learning criterion, i.e., if entities have wrong behaviors, through network learning, they can reduce the possibility of making the same mistake next time.

(1) In the evolutionary game theory, the replicate dynamic equation is the dynamic evolution equation with selection mechanism. It can present dynamic convergence process of events which have evolution feature. The establishment of replicate dynamic equation is the important symbol that evolutionary game theory formed formally. Many game theory experts researched adjusting process of group behaviors, and have proposed a variety of dynamic evolution model, such as Imitation Dynamics model proposed by Weibull, Reinforcement Dynamics model proposed by Bergers and Sarin (1997). So far, basic evolutionary game thoughts are almost derived from the research results of Taylor, Taylor and Jonker (1978) and Maynard Smith. In replicate dynamic equation, the growth rate of pure strategy is proportional to the fitness of individual. Replicate dynamic equation strengthens dynamic processing for network's complex states. Therefore, the replicate dynamic equation provides strategy foundation for entities' trust evolution. At present, the replicate dynamic equation is widely applied in dynamic models of system evolution, so that its deformations have also been the hot issue of dynamic models (Bo et al., 2011; Mejia et al., 2011; Yang et al., 2008; Jing et al., 2007; Pelillo and Torsello, 2006; Bhaskar and Song Yun, 2009; Zheng and Shiyong, 2008).

(2) Neural networks is widely applied in the engineering field and economic research. Horie combined neural network with Nash equilibrium of game theory. He applied it in associative memory. Utilizing neural network, Chong and Yao (2005), Chong and Yao (2007) researched iterated prisoner's dilemma. In addition, they described entities' trust strategies, and established an evolution model. The work in Matsumura de Araújo and Lamb Luís (2004) simulated market model under bounded rationality condition by neural networks. This method regards each agent of market environment as a neural network. These agents can learn strategy rules through an evolutionary algorithm. On the aspect of evolution, reference (Weibing and Xianjia, 2007) introduced neural networks into evolutionary game. It simulated learning and adjusting process of bounded rationality gamers, and adopted particle swarm optimization algorithm to train neural networks. This research makes neural networks a powerful analysis tool for system evolution. In addition, it also adds new research method for trust evolution model.

In addition, the work in Mejia et al. (2011) proposed a trust model based on the game theory. In this trust model, the interactions among nodes are based on the iterated prisoner's dilemma under the random pairing game. Wan et al. (2006) combined evolutionary game and Agent, and proposed a model of agent self-organizing dynamics based on evolutionary games. These methods have greatly promoted the research of trust evolution model. However, in the game stage, they almost focus on two strategies, and fail to consider the game between complex strategies. Meanwhile, they do not consider the network noise, which fails to present the network uncertainty.

In the recent years, scholars proposed different trust incentive mechanisms (Ma et al., 2006; Xiong and Ling, 2004). In general, the incentive mechanism based on virtual payment and the incentive mechanism based on reputation, are two most significant incentive mechanisms.

(1) Virtual currency (Yang and Molina, 2003) is similar to market regulation of economics. It transforms entity's income to virtual currency. Virtual payment can track various trades through a billing system because of the issuance of virtual currency. Therefore, the entities that have consumed service can pay the price in form of virtual payment. In this mechanism, each entity's download quantity and upload quantity are divided into different levels. In addition, entity's utility is decided by request resource quantity, download resource quantity and network bandwidth. The advantage of this model is that it has relatively strong reliability. Buttyan and Hubaux (2000) proposed a currency called nuglets. The exchange of nuglets relies on a tamper-resistant security subsystem being present in every node. However, it needs a central server to issue, distribute and circulate currency, and security subsystem to ensure the safety of transactions. Therefore, this model has the server bottleneck problem. Besides of the poor feasibility, this model cannot manage the hidden information and asymmetry information well.

(2) Reputation mechanism (Wang et al., 2006; Tuyls and Hoen, 2006) is a grade concept. A system obtains the entity's reputation value through the evaluation of adjacent entities based on entity's history behaviors. In addition, according to request service entity's reputation value, other entities can provide corresponding service response in the later trading service. In a reputation mechanism, an entity's contribution values for other entities are stored in these entities' historical records. An entity gains the resources that provided by other entities in the later resource request based on entity's previous contribution. Jing et al. (2010) proposed a recommendation discovery method based on reputation. This method introduced a correlation factor to quantify recommended trust relationship in different context. This method adopted trust transfer and iterative calculation to determine recommendation information source. It can improve the efficiency of trust service evaluation more effectively. Bansal and Baker (2003) used both reputation to detect and punish selfish behavior, and micro-payment component to inspire cooperation. However, a reputation mechanism needs to obtain entity's trust behavior information from the third-party. Therefore, this mechanism has information reliability problem. What's more, how to reduce the large spending (information storing and sharing) and how to realize information sharing are also open problems.

In addition, Liu et al. (2010) proposed an incentive mechanism based on QoS in order to solve the free-riding problem. He proposed a strategy, which can guarantee QoS while suppressing free riders. However, this mechanism fails to consider the complex game relationships between entities, which results in the emergence of hot spots. Meanwhile, some other incentive mechanisms are also typical, such as Resource Bidding Mechanism (RBM) (Bertsekas and Gallager, 1992), Resource Bidding Mechanism with Incentive (RBM-I), Resource Bidding Mechanism with Utility Feature (RBM-U) (Shenker, 1995) and Resource Bidding Mechanism with Incentive and Utility Feature (RBM-IU). These incentive mechanisms are often applied to P2P networks. They can avoid resource wasting and inspire entity's behaviors. However, these methods fail to consider the dynamic and evolutionary features of networks. Therefore, they cannot inspire and punish entities' behaviors dynamically.

3. Proposed trust evolution model

This section presents our proposed approach for improving evolution efficiency of Internetware called Wright–Fisher multi-strategy trust evolution model with white noise for Internetware. The organizational chart is shown in Fig. 1. Firstly, considering timeliness of history behavior data and aggregation degree of entity in complex network environment, a trust measurement method is proposed to calculate entities' utility values based on QoS and fuzzy theory. Secondly, according to utility values of entities with different trust levels, this work establishes a multi-strategy trust evolution model with white noise for Internetware based on Wright–Fisher and evolutionary game theories. Finally, an incentive mechanism based on evolutionary game is built for inspiring entities to select strategies that have high trustworthy. Therefore, this model can improve whole trust degree of an Internetware system through an incentive mechanism.

3.1. Calculation method of entity's utility function based on QoS

In this paper, entity's trust degree is computed based on QoS. A service provider provides corresponding service level for service requestor through analyzing service requestor's current and historic behaviors. A service request process is shown in Fig. 2. Firstly, a service requestor requests service from a service provider. Then, the service provider calculates the service requestor's current trust degree combined with others' experience based on the service requestor's current and history behaviors. Finally, the service provider provides corresponding service for the service requestor through the service registry center.

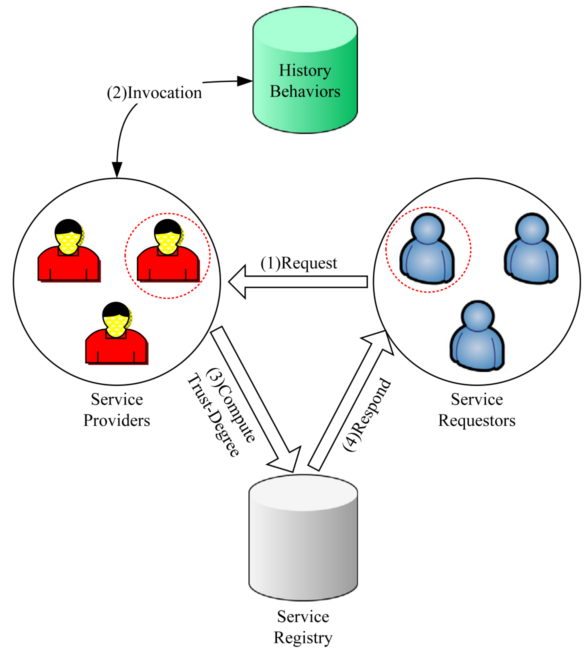

Fig. 2. Service request process.

In an Internetware system, entity's trust degree is not only related to the current transaction information, but also related to history mutual information. Therefore, in this paper, information's timeliness is added into the calculation on entity's trust degree. Fig. 3 shows the calculating process of entity's trust degree. In the current generation, if entity E_j request service from entity E_i, entity E_i not only considers its own experience that has interacted with entity E_j (current and historical interactions), but also considers other entities' history experience that have interacted with entity E_j, such as the 'blue entity' in the previous generation of Fig. 3.

Hermann Ebbinghaus, a German psychologist, researched forgetting phenomenon. He regarded meaningless syllables as memory material, and drew a curve based on experimental data. This curve is called the Ebbinghaus Forgetting Curve. This curve presents a rule of forgetting development: forgetting process is not balanced; in initial stage of memorization, forgetting speed is very fast; then the forgetting speed becomes slow gradually; to a certain stage, forgetting almost does not occur. Therefore, the forgetting

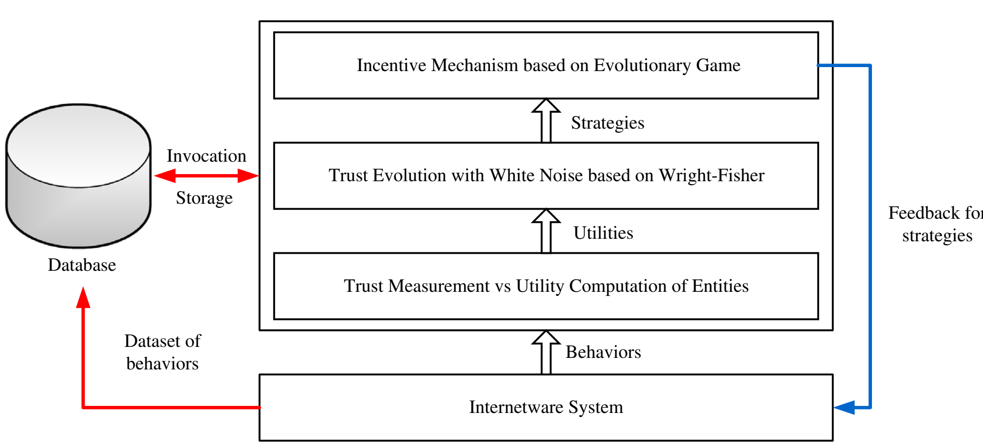

Fig. 1. Organizational chart.

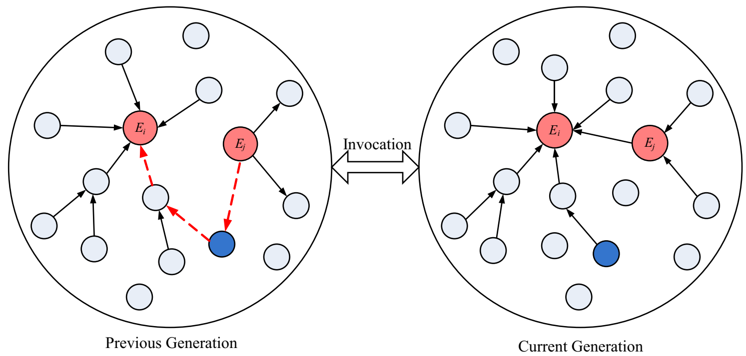

Fig. 3. Calculating process of trust degree.

speed is from fast to slow. Internetware is a system with ecological population characteristic, so memory between entities accords with the law of forgetting development. Therefore, entity's memory has timeliness characteristic, that is to say, forgetting of trust degree conforms the rule of Ebbinghaus Forgetting.

Because Internetware has reactivity and evolution, it can sense the changing of outside environment. According to characteristics of time decay factor, the calculation method of time decay factor $\lambda(k)$ is given based on Ebbinghaus Forgetting Curve. With the passage of time, the influence of history mutual information weakens gradually. It decays to a stable value that tends to '0', as shown in Eq. (1)

$$\lambda(k) = \begin{cases} 1 & k = m \\ e^{-\frac{1}{k}} & 1 \leqslant k < m \end{cases} \tag{1}$$

The changing rule of time decay factor is that if the time is closer to the current transaction, the influence is greater to the current transaction, the smaller the contrast. The changing rule of time decay factor is shown in Fig. 4. The calculation method of trust degree with time decay factor is shown in Eq. (2) based on entity's own experience

$$\tau_{\text{own}}(E_j) = \begin{cases} \frac{\sum_{k=1}^{m} T^k(E_j)\cdot\lambda(k)}{\sum_{k=1}^{m}\lambda(k)} & m \neq 0 \\ 0 & m = 0 \end{cases} \tag{2}$$

In Eq. (2), $\lambda(k)$ is the time decay factor. $T^k(E_j)$ indicates trust degree of service requestor E_j in the kth interaction between service provider E_i and service requestor E_j.

In an Internetware system, when an entity's own experience is little, the entity should consider others' experiences to calculate service requestor's trust degree. And 'others' means the entities that have ever interacted with both service provider and service requestor. The calculation method is shown in Eq. (3)

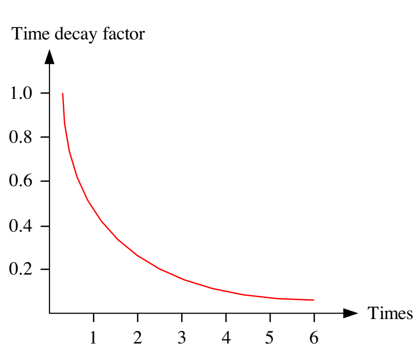

Fig. 4. Changing rule of time decay factor.

$$\tau_{\text{pub}}(E_j) = \begin{cases} \frac{\sum_{l=1}^{n} Inf_l(E_i)\cdot T_l(E_j)}{\sum_{l=1}^{n} Inf_l(E_i)} & n \geqslant 1 \\ 0 & n = 0 \end{cases} \tag{3}$$

In Eq. (3), $T_l(E_j)$ indicates the trust degree of service requestor E_j that to be calculated by the lth entity. The lth entity is a one that has ever interacted with both the service provider and service requestor. $Inf_l(E_i)$ expresses the lth entity's influence degree for service provider E_i.

Combining the entity's own experience and others' experience, the integrated trust degree of a service requestor is shown in Eq. (4)

$$T(E_j) = \omega\cdot\tau_{\text{own}}(E_j) + (1-\omega)\tau_{\text{pub}}(E_j) \tag{4}$$

In Eq. (4), ω indicates the influence degree of service provider's own experience for service requestor's trust degree.

This paper determines weight ω by calculating entity's clustering coefficient. An Internetware system has complex network feature, so the distance between arbitrary nodes is short, that is to say, entity has a high clustering degree. Therefore, if the entity's influence degree is higher, its clustering coefficient is bigger. Therefore, in this paper, the weight is calculated through the service provider's clustering coefficient, as shown in Eq. (5)

$$\omega = \frac{2C_i}{k_i(1-k_i)} \tag{5}$$

In Eq. (5), k_i indicates that service provider E_i has interacted with k_i entities. C_i represents the number of cooperation between k_i entities.

This paper divides entity's trust values into four levels. Different trust levels are provided with different service levels. So the corresponding relations are shown in Table 1.

In order to get utility function of entities with different trust levels, this paper solves uncertainty problem of trust level interval based on the fuzzy theory. Assume $[a,b]$ is an interval, R is inseparable relation in this interval, $[a,b] \subset [0,1]$. In this paper, parameter 'p' is used to divide interval. Let $x_1,x_2 \in [a,b]$, and $x_1Rx_2(|x_1 - x_2| \leqslant p)$, so $[a + j*p,\ a + (1 + j)*p] \subseteq [a,b]$, $j = 0,1,\ldots,n-2$. Interval $[a,b]$ is divided into n smaller intervals by p, and the top $n-1$ intervals are equal. Each small interval is called a division equivalence class, as a basic granulation. Therefore, an interval is divided

Table 1
Trust-service levels.

$T(E_j)$	Service
[0.75,1]	Service1
[0.5,0.75)	Service2
[0.25,0.5)	Service3
[0,0.25)	Service4

by relationship R, until $a+n*p>b$, and n is the total number of small intervals. Then, how to determine p? In this paper, the inseparable relation is defined based on the granular computing theory and golden section of mathematics. 0.618 is the optimal point in interval [0, 1], so this paper uses 0.618 to define this inseparable relation for involving fuzziness and uncertainty of things. According to the golden section principle, Eq. (6) shows the calculation method of p

$$p = \frac{0.618 \times (b-a)}{1+e^{-(b-a)}} \tag{6}$$

According to Eq. (6), trust level interval can be normalized to a certain value. Thus utility function with different trust levels is shown in Eq. (7). In Eq. (7), g is a trust level, and $g \in \{1,2,3,4\}$

$$U_g = \left(a + \sum_{j=1}^{n-1}(a+j\times p) + b\right)/(n+1), T(E_j) \in [a,b) \tag{7}$$

3.2. Wright–Fisher multi-strategy trust evolution model with white noise

3.2.1. Wright–Fisher model with two strategies

A Wright–Fisher process has a wide range of application. All of the individuals produce offspring in the same time based on the adaptability of individual. These offspring individuals generate an offspring set. The updated next generation generates randomly from this offspring set.

Let the two-strategy income matrix (trust, distrust) be the example to introduce the Wright–Fisher model. Table 2 shows the 2×2 symmetric game income matrix.

Assume the number of entities in an Internetware system is N, there are Q_i trust entities. Therefore, the trust and distrust entities' incomes are expressed respectively by Eq. (8). In Eq. (8), $i \in$ {trust, distrust}

$$\left.\begin{aligned} f_1 &= \tfrac{R(Q_i-1)+S(N-Q_i)}{N-1}, \\ f_2 &= \tfrac{T\cdot Q_i+P(N-Q_i-1)}{N-1}. \end{aligned}\right\} \tag{8}$$

Considering selection factor, based on genetic variation theory, the real trust and distrust entities' adaptabilities are shown in Eq. (9)

$$F_1 = 1-w+w\cdot f_1, \quad F_2 = 1-w+w\cdot f_2. \tag{9}$$

In Eq. (9), w is the selection factor that reflects the contributions of f_1 and f_2 for real adaptabilities. If $w = 1$, it is strong selection game which means this strategy is the optimal selection. It is also called a complete selection, that is to say, selection does not work.

The individuals obey a binomial distribution, because a Wright–Fisher process is *n-fold* Bernoulli trials in the offspring set. Assume $Y(n)$ is the number of trust individuals of the nth generation, and $Y(n) = Q_i$. Therefore, the probability, when $Y(n+1) = Q_i'$, is shown in Eq. (10). In Eq. (10), $i \in$ {trust, distrust}

$$P(Y(n+1)=Q_i'|Y(n)=Q_i) = \binom{N}{Q_i'}\left(\frac{Q_i\cdot F_1}{Q_i\cdot F_1+(N-Q_i)F_2}\right)^{Q_i'}\left(\frac{(N-Q_i)F_2}{Q_i\cdot F_1+(N-Q_i)F_2}\right)^{N-Q_i'}. \tag{10}$$

3.2.2. Trust multi-strategy game model

For classic two-strategy game, each entity has only two selections: 'trust' and 'distrust'. The two-strategy game matrix about entities' incomes is shown in Table 2. In this paper, the multi-strategy game for entities' behaviors is proposed based on two-strategy game. The global utility function can be obtained according to the above discussion. This paper games entities' multi-strategy behaviors to make the model more adapt to complex network environment. According to multi-strategy repeated game, the calculation function of entity's specific profit value is shown in Eq. (11)

$$pr_A = 2.5 - 0.5U_g^A + 2U_g^B \tag{11}$$

In Eq. (11), U_g^A and U_g^B are utility functions of participants A and B. This model reflects specific profits of entities with different trust levels after gaming each other. Taking four-strategy game for example, trust is divided into four levels: (1, 2, 3, 4). According to the above analysis, four-strategy game income matrix is shown in Table 3. By analyzing multi-strategy game of entity's behaviors, it is concluded that multi-strategy income matrix is also a symmetric game matrix. The game carries out repeatedly. In the end of every multi-strategy game, the strategy that has been adopted by any participant as history information can be known by other participants. Participants determine the strategy for the next game stage according to the history information.

In this paper, multi-strategy game based on two-strategy game is researched. The multi-strategy game rules are established to make this model conform to the complexity of open network environment. Therefore, multi-strategy game lays a foundation for the further research on trust evolution model.

3.2.3. Wright–Fisher multi-strategy game model

Section 3.2.1 has analyzed the Wright–Fisher two-strategy process model. In this section, the Wright–Fisher multi-strategy process model is investigated based on the Wright–Fisher two-strategy process model (taking four-strategy for example in Section 3.2.2).

Assume the total number of entities in an Internetware system is N. (1, 2, 3, 4) represents the different trust levels. Let the initial numbers of four trust levels be Q_1, Q_2, Q_3 and Q_4, respectively. Then, the calculation method of entities' incomes with different trust levels is shown in Eq. (12), where $i, j \in \{1, 2, 3, 4\}$

$$f_i = \frac{\left(\sum_{j=1}^{4} pr_{A_{ij}}\cdot Q_j\right) - pr_{A_{ii}}}{N-1} \tag{12}$$

Considering the selection factor, based on the genetic variation mechanism, the calculation method of entities' real adaptabilities with different trust levels is shown in Eq. (13), where $i \in \{1, 2, 3, 4\}$

$$F_i = 1-w+w\cdot f_i \tag{13}$$

In Eq. (13), w is also the selection factor which is the same as the selection factor in the Wright–Fisher two-strategy process model. It reflects the contributions of f_1, f_2, f_3 and f_4 for real adaptabilities. Similarly, a Wright–Fisher process is *n-fold* Bernoulli trials in the offspring set, so the individuals obey binomial distribution. Assume '$Y(n)$' is the number of individuals of the nth generation, and $Y(n) = Q_i$, (Q_1, Q_2, Q_3, Q_4). Then, the probability, when

Table 2
2×2 Symmetric game income matrix.

Strategy income	Trust	Distrust
Trust	*R, R*	*S, T*
Distrust	*T, S*	*P, P*

Table 3
Four-strategy game income matrix.

	Trust strategy	Entity *B*			
		1	2	3	4
Entity *A*	1	$pr_{A_{11}}, pr_{B_{11}}$	$pr_{A_{12}}, pr_{B_{12}}$	$pr_{A_{13}}, pr_{B_{13}}$	$pr_{A_{14}}, pr_{B_{14}}$
	2	$pr_{A_{21}}, pr_{B_{21}}$	$pr_{A_{22}}, pr_{B_{22}}$	$pr_{A_{23}}, pr_{B_{23}}$	$pr_{A_{24}}, pr_{B_{24}}$
	3	$pr_{A_{31}}, pr_{B_{31}}$	$pr_{A_{32}}, pr_{B_{32}}$	$pr_{A_{33}}, pr_{B_{33}}$	$pr_{A_{34}}, pr_{B_{34}}$
	4	$pr_{A_{41}}, pr_{B_{41}}$	$pr_{A_{42}}, pr_{B_{42}}$	$pr_{A_{43}}, pr_{B_{43}}$	$pr_{A_{44}}, pr_{B_{44}}$

$Y(n+1) = Q'_i, (Q'_1, Q'_2, Q'_3, Q'_4)$, is shown in Eq. (14), where $i, j \in \{1, 2, 3, 4\}$

$$P(Y(n+1) = Q'_i | Y(n) = Q_i) = \binom{N}{Q'_i} \prod_{i=1}^{4} \left(\frac{Q_i F_i}{\sum_{j=1}^{4} Q_j F_j} \right)^{Q'_i} \tag{14}$$

3.2.4. Trust evolution model

A Wright–Fisher process is a synchronous update process, so this paper utilizes $E(\Delta x)/\Delta t$ in the graphical game instead of replicated dynamic equation dx/dt in the evolutionary game. $E(\Delta x)$ indicates the individual frequency variation of some trust type; Δt indicates the update time step. According to the above analysis, the calculation equation of $E(\Delta x)$ is shown in Eq. (15), where Q_i indicates the number of individuals of nth generation, Q'_i indicates the number of individuals of $(n+1)$th generation, and $i, j \in \{1, 2, 3, 4\}$

$$\begin{aligned} E(\Delta x) &= \frac{\sum_{Q'_i=0}^{N} (Q'_i - Q_i) P(Y(n+1) = Q'_i | Y(n) = Q_i)}{N} \\ &= \frac{Q_i \cdot F_i}{\sum_{j=1}^{4} Q_j \cdot F_j} - x \end{aligned} \tag{15}$$

Let the proportions of entities with different trust levels be: $\frac{Q_1}{N} = v$, $\frac{Q_2}{N} = x$, $\frac{Q_3}{N} = y$, $\frac{Q_4}{N} = z$. Thus, based on Eqs. (14) and (15), the Wright–Fisher multi-strategy trust evolution model of Internetware is shown in Eq. (16), and the calculation method of I_1, I_2, I_3 and I_4 is shown in Eq. (17).

$$\left.\begin{aligned} dv = \left(\tfrac{v \cdot I_1}{I} - v\right)dt; \quad dx = \left(\tfrac{x \cdot I_2}{I} - x\right)dt; \\ dy = \left(\tfrac{y \cdot I_3}{I} - y\right)dt; \quad dz = \left(\tfrac{z \cdot I_4}{I} - z\right)dt. \end{aligned}\right\} \tag{16}$$

$$\left.\begin{aligned} I_1 &= v(1 - w + w \cdot pr_{A_{11}}) + x(1 - w + w \cdot pr_{A_{12}}) + y(1 - w + w \cdot pr_{A_{13}}) + z(1 - w + w \cdot pr_{A_{14}}); \\ I_2 &= v(1 - w + w \cdot pr_{A_{21}}) + x(1 - w + w \cdot pr_{A_{22}}) + y(1 - w + w \cdot pr_{A_{23}}) + z(1 - w + w \cdot pr_{A_{24}}); \\ I_3 &= v(1 - w + w \cdot pr_{A_{31}}) + x(1 - w + w \cdot pr_{A_{32}}) + y(1 - w + w \cdot pr_{A_{33}}) + z(1 - w + w \cdot pr_{A_{34}}); \\ I_4 &= v(1 - w + w \cdot pr_{A_{41}}) + x(1 - w + w \cdot pr_{A_{42}}) + y(1 - w + w \cdot pr_{A_{43}}) + z(1 - w + w \cdot pr_{A_{44}}); \\ I &= v \cdot I_1 + x \cdot I_2 + y \cdot I_3 + z \cdot I_4. \end{aligned}\right\} \tag{17}$$

(17), I_1, I_2, I_3 and I_4 respectively indicate the expected revenues of entities with different trust levels (1, 2, 3, 4). I is the average expected revenues of population.

3.2.5. Trust evolution model with white noise

Eq. (16) indicates the deterministic trust evolution model, so it is deterministic dynamics. However, it is obvious that a network is complex and full of uncertainties. One of the features is that the dynamic mechanism of system evolution is uncertain. Although system evolution mainly depends on entity's income pr_A, some unknown factors also take effect. The network environment is full of uncertainties, so an evolution process is uncertain. While deterministic dynamics does not consider the effect of random disturbance. Therefore, in this paper, Eq. (16) is extended into random dynamics equation by considering white noise in an evolution process of an Internetware system. Therefore, it can reflect the effect caused by random disturbance. The evolution model with white noise is shown in Eq. (18), where w indicates the one-dimension standard Brown movement. It means that w obeys normal distribution $N(0, t)$ for given time t. And dw obeys normal distribution $N(0, \Delta t)$. Therefore, it is Gaussian White Noise. That is to say, if the noise's amplitude obeys Gaussian distribution, and its power spectral density is evenly distributed, it is called Gaussian White Noise.

$$\left.\begin{aligned} dv &= \left(\tfrac{v \cdot I_1}{I} - v\right)dt + \sqrt{v \cdot (1 - v)}dw; \\ dx &= \left(\tfrac{x \cdot I_2}{I} - x\right)dt + \sqrt{x \cdot (1 - x)}dw; \\ dy &= \left(\tfrac{y \cdot I_3}{I} - y\right)dt + \sqrt{y \cdot (1 - y)}dw; \\ dz &= \left(\tfrac{z \cdot I_4}{I} - z\right)dt + \sqrt{z \cdot (1 - z)}dw. \end{aligned}\right\} \tag{18}$$

The entity proportions with different trust strategies also turn into random processes, so Eq. (18) is a random dynamics equation. In addition, the above differential is the famous *Itô* differential of stochastic analysis theory. The meanings of $\sqrt{v \cdot (1 - v)}dw$, $\sqrt{x \cdot (1 - x)}dw$, $\sqrt{y \cdot (1 - y)}dw$ and $\sqrt{z \cdot (1 - z)}dw$ are as follows.

(1) There are many factors that affect the stability of evolution, including internal and external factors. Each factor is not a decisive role. This shows the significance of normal distribution.
(2) $\sqrt{v \cdot (1 - v)}$, $\sqrt{x \cdot (1 - x)}$, $\sqrt{y \cdot (1 - y)}$ and $\sqrt{z \cdot (1 - z)}$ ensure the values of v, x, y and z be in interval $[0, 1]$.
(3) $\sqrt{v \cdot (1 - v)} \leqslant \frac{1}{2}$, $\sqrt{x \cdot (1 - x)} \leqslant \frac{1}{2}$, $\sqrt{y \cdot (1 - y)} \leqslant \frac{1}{2}$, and $\sqrt{z \cdot (1 - z)} \leqslant \frac{1}{2}$. If and only if $v = 1 - v$, $x = 1 - x$, $y = 1 - y$, $z = 1 - z$, they reach maximum, i.e., the disturbances reach the maximum. It reflects that the process of evolution is easy to be disturbed, if the entities' proportions are almost equal with different strategies. However, when proportions are quite different, the disturbance is small. This reflects the correction for disturbance that the entities' group-psychology brings.

3.3. Incentive mechanism based on evolutionary game

In order to determine four-strategy income matrix of Internetware, in this paper, an incentive mechanism based on evolutionary game is proposed. Evolutionary stable strategy is that, an individual obtains incomplete information about trust, and it can only adopt testing, learning, adapting and growing behavior logic. In a constant repeated process, to pursue their own interests, entities constantly adjust their strategies to achieve a credible dynamic balance. In this equilibrium state, the entities are no longer willing to unilaterally change their own strategies. Therefore, the strategy that leads to equilibrium state is called Evolutionary Stable Strategy-ESS.

In an Internetware system, when distrust individual games with trust individual, the distrust individual will gain profit through damaging the trust individual's profit. Its behavior violates fairness norm, which leads to the free-riding phenomenon. Therefore, if gamer is influenced by fairness norm, distrust individual's profit will be reduced because of 'compunction' that it has damaged fairness. And trust individual's profit will be increased because of

Table 4
Four-strategy income matrix with incentive mechanism.

$pr_{A_{11}}, pr_{B_{11}}$	$pr_{A_{12}} + \mu_1(pr_{A_{12}} + pr_{B_{12}})$, $pr_{B_{12}} - \mu_1(pr_{A_{12}} + pr_{B_{12}})$	$pr_{A_{13}} + \mu_2(pr_{A_{13}} + pr_{B_{13}})$, $pr_{B_{13}} - \mu_2(pr_{A_{13}} + pr_{B_{13}})$	$pr_{A_{14}} + \mu_3(pr_{A_{14}} + pr_{B_{14}})$, $pr_{B_{14}} - \mu_3(pr_{A_{14}} + pr_{B_{14}})$
$pr_{A_{21}} - \mu_1(pr_{A_{21}} + pr_{B_{21}})$, $pr_{B_{21}} + \mu_1(pr_{A_{21}} + pr_{B_{21}})$	$pr_{A_{22}}, pr_{B_{22}}$	$pr_{A_{23}} + \mu_1(pr_{A_{23}} + pr_{B_{23}})$, $pr_{B_{23}} - \mu_1(pr_{A_{23}} + pr_{B_{23}})$	$pr_{A_{24}} + \mu_2(pr_{A_{24}} + pr_{B_{24}})$, $pr_{B_{24}} - \mu_2(pr_{A_{24}} + pr_{B_{24}})$
$pr_{A_{31}} - \mu_2(pr_{A_{31}} + pr_{B_{31}})$, $pr_{B_{31}} + \mu_2(pr_{A_{31}} + pr_{B_{31}})$	$pr_{A_{32}} - \mu_1(pr_{A_{32}} + pr_{B_{32}})$, $pr_{B_{32}} + \mu_1(pr_{A_{32}} + pr_{B_{32}})$	$pr_{A_{33}}, pr_{B_{33}}$	$pr_{A_{34}} + \mu_1(pr_{A_{34}} + pr_{B_{34}})$, $pr_{B_{34}} - \mu_1(pr_{A_{34}} + pr_{B_{34}})$
$pr_{A_{41}} - \mu_3(pr_{A_{41}} + pr_{B_{41}})$, $pr_{B_{41}} + \mu_3(pr_{A_{41}} + pr_{B_{41}})$	$pr_{A_{42}} - \mu_2(pr_{A_{42}} + pr_{B_{42}})$, $pr_{B_{42}} + \mu_2(pr_{A_{42}} + pr_{B_{42}})$	$pr_{A_{43}} - \mu_1(pr_{A_{43}} + pr_{B_{43}})$, $pr_{B_{43}} + \mu_1(pr_{A_{43}} + pr_{B_{43}})$	$pr_{A_{44}}, pr_{B_{44}}$

Table 5
Four-strategy income values.

	Trust strategy	Entity *B*			
		1	2	3	4
Entity *A*	1	3.817,3.817	3.317,3.942	2.817,4.067	2.317,4.192
	2	3.942,3.317	3.442,3.442	2.942,3.567	2.442,3.692
	3	4.067,2.817	3.567,2.942	3.067,3.067	2.567,3.192
	4	4.192,2.317	3.692,2.442	3.192,2.567	2.692,2.692

'dissatisfaction' that distrust individual has violated fairness. Therefore, the four-strategy income matrix with incentive mechanism is shown in Table 4.

From Table 4, it can be seen that when two entities game, the system increases the profit of entity that has high trust level based on fairness norm. And let μ be the incentive-punishment parameter. From the income matrix, it can be seen that this matrix is a symmetric matrix, so the incentive-punishment parameter is also symmetrical.

Through the effect of incentive mechanism, system feedbacks the result to the calculation model of utility function. This result will promote entity to select the strategy with high trust level. Therefore, an entity with high trust level will get a better income. However, an entity with low trust level will receive corresponding punishment. So with incentive mechanism, the system will evolve towards a high trust level direction, so as to improve the whole trust degree of the system.

4. Simulations and performance analysis

To verify the validity of the model, we simulate an evolution process of Internetware under open network environment.

The hardware experiment environment is: Intel Core (TM) Duo 2.66 GHz CPU, 2 GB Memory, Windows XP operating system, Matlab 7.0 simulation platform. Firstly, for open network environment, entity's trust is divided into four levels. We set selection factor w to be 0.9, and initial proportions of the four trust levels are: $v(0) = 0.25$, $x(0) = 0.25$, $y(0) = 0.25$ and $z(0) = 0.25$. According to the utility functions with different trust levels, entities' utility values are shown as follows.

$$U_1 = 0.878; \quad U_2 = 0.628; \quad U_3 = 0.378; \quad U_4 = 0.128.$$

Through the utility values of entities with different trust levels, the game income matrix can be obtained, i.e., entities' incomes with different strategies after gaming with each other. The four-strategy income values are shown in Table 5.

Taking the income values of Table 5 into Eqs. (16) and (17), the trust evolution trend result of Internetware without white noise is shown in Fig. 5. From Fig. 5, it can be seen that when system evolves to about 120th generation, 'distrust' strategy becomes entity's first choice. And it occupies the leading position of the whole system in the end, causing the free-riding phenomenon. Based on this model, the trust evolution trend of Internetware with white noise is shown in Fig. 6. It can be seen that after considering the effect of white noise, the system's evolution process has slight fluctuations. This situation is more in line with the real evolution process of a network. It is because that the network environment has

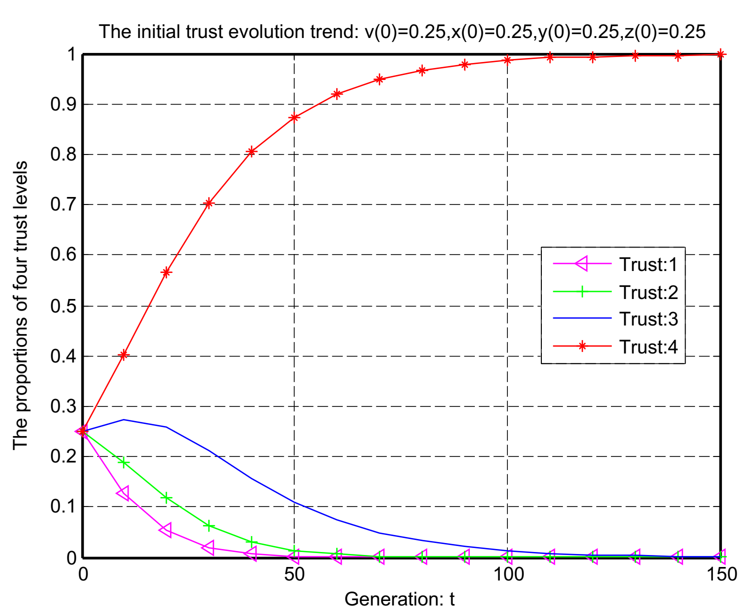

Fig. 5. Trust evolution trend of Internetware without white noise.

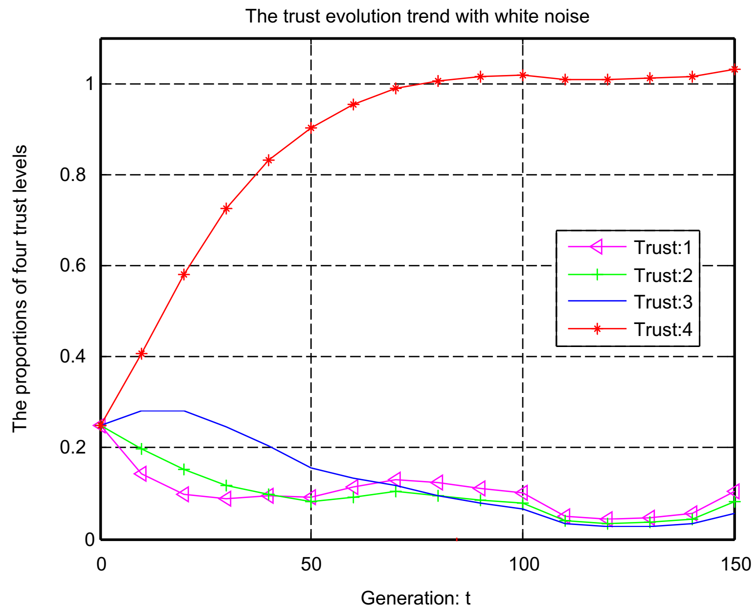

Fig. 6. Trust evolution trend of Internetware with white noise.

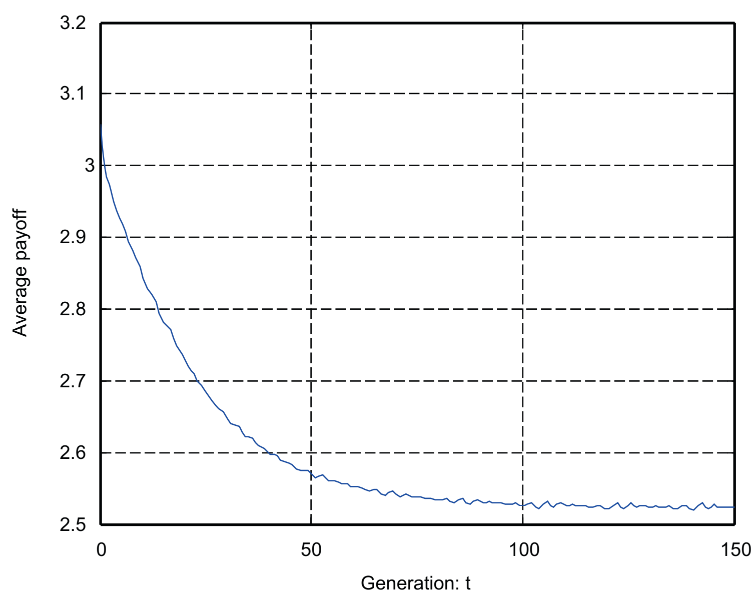

Fig. 7. Average income of Internetware system.

uncertainties, the evolution process of Internetware must perform in an uncertain manner. However, the whole evolution trend does not change from Figs. 5 and 6. Therefore, in this case, the evolution trend of average income of an Internetware system is shown in Fig. 7. It can be seen that the average income presents downtrend, i.e., the performance of the Internetware system declines gradually. The system evolves into distrust system in the end. This is because that the entity's selfish behaviors lead to the free-riding phenomenon. The simulation results accurately reflect the trust situation of software entities in open network environment.

From the above simulation results, it can be seen that in order to make trust strategy be the dominant strategy, entities need to be inspired to select the trust cooperation strategy. According to the proposed incentive mechanism, this model can adjust income matrix through incentive-punishment parameter μ. In this experimental section, let $\mu_1 = 0.05$, $\mu_2 = 0.06$, and $\mu_3 = 0.07$. The four-strategy income values with incentive mechanism are shown in Table 6.

Table 6
Four-strategy income values with incentive mechanism.

	Trust strategy	Entity *B*			
		1	2	3	4
Entity *A*	1	3.817,3.817	3.680,3.579	3.230,3.654	2.773,3.736
	2	3.579,3.680	3.442,3.442	3.267,3.242	2.810,3.324
	3	3.654,3.230	3.242,3.267	3.067,3.067	2.855,2.904
	4	3.736,2.773	3.324,2.810	2.904,2.855	2.692,2.692

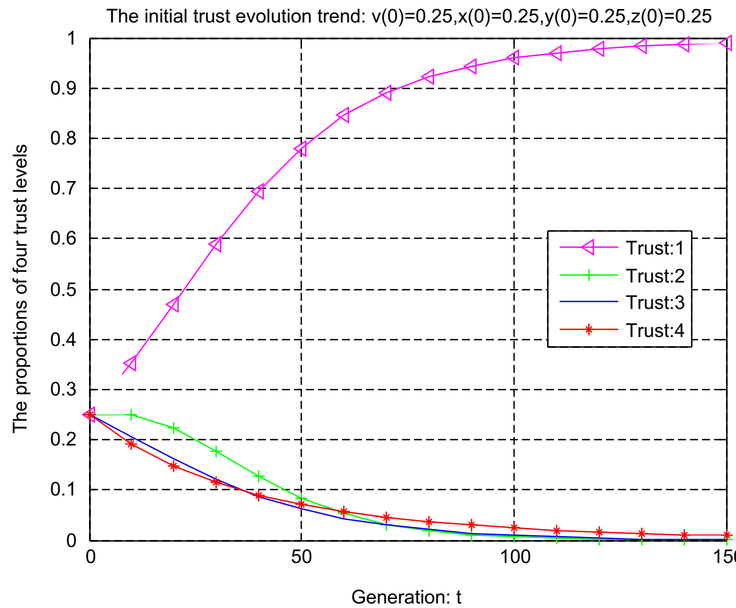

Fig. 8. Based on incentive mechanism trust evolution trend of Internetware without white noise.

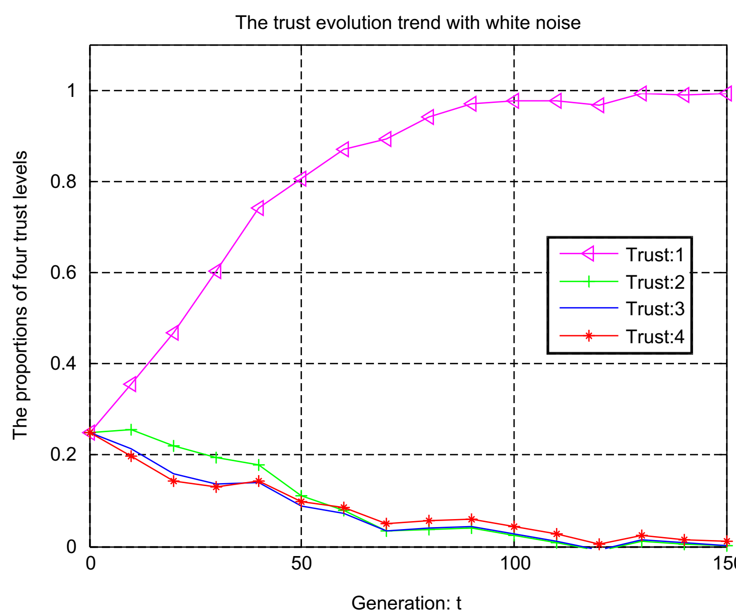

Fig. 9. Based on incentive mechanism trust evolution trend of Internetware with white noise.

Taking the income values of Table 6 into Eqs. (16) and (17), the trust evolution trend of Internetware without white noise based on the incentive mechanism, is shown in Fig. 8. It can be seen that when system evolves to about the 150th generation, 'trust' strategy becomes entity's first choice. It occupies the leading position of the whole system in the end, so as to make system to be in a stable and trust state. Based on this experiment, the trust evolution trend of Internetware with white noise is shown in Fig. 9. It shows that after adding the incentive mechanism, the trust evolution trend of Internetware with white noise is similar with the trust evolution trend of Internetware without white noise as shown in Fig. 8, and finally tends to be in the stable state. In this case, the evolution trend of average income of an Internetware system is shown in Fig. 10. It shows that the average income presents uptrend, i.e., the performance of an Internetware system improves gradually. Therefore, a system can avoid the free-riding phenomenon fundamentally with the incentive mechanism. To obtain higher profit, entities select a high trust strategy to be their first choice strategy. Therefore, this incentive mechanism can promote a system to evolve to a stable and trust state in the end.

In order to improve evolution speed of Internetware, this model can control evolution speed of system through adjusting incentive-punishment parameter μ. Based on the above experiment, let $\mu_1 = 0.06$, $\mu_2 = 0.07$, and $\mu_3 = 0.08$. The four-strategy income values after adjusting incentive-punishment parameter μ are shown in Table 7.

Taking the income values of Table 7 into Eqs. (16) and (17), the trust evolution trend of Internetware without white noise after

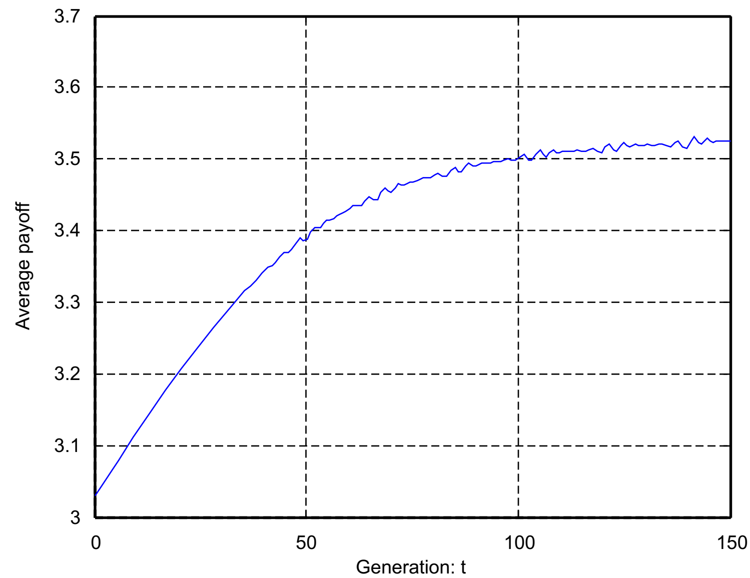

Fig. 10. Based on incentive mechanism average income of Internetware system.

Table 7
Four-strategy income values after adjusting incentive-punishment parameter.

	Trust strategy	Entity *B*			
		1	2	3	4
Entity *A*	1	3.817,3.817	3.753,3.506	3.299,3.585	2.878,3.671
	2	3.506,3.753	3.442,3.442	3.333,3.176	2.871,3.263
	3	3.585,3.299	3.176,3.333	3.067,3.067	2.913,2.846
	4	3.671,2.878	3.263,2.871	2.846,2.913	2.692,2.692

adjusting the incentive-punishment parameter is shown in Fig. 11. It shows that when the system evolves to about the 100th generation, it tends to be in stable and trust state. Thus it can be seen that along with the enhancement of incentive-punishment strength, the evolution speed of a system will be improved. Based on this experiment, the trust evolution trend of Internetware with white noise is shown in Fig. 12. The evolution trend of average income of an Internetware system is shown in Fig. 13. Similarly, from Fig. 13, it can be seen that there is a great improvement on the aspect of system's evolution speed. Therefore, enhancing the incentive-punishment strength can improve the whole evolution efficiency of Internetware.

In order to contrast evolution trend of average incomes of Internetware under the above three cases, this paper conducts contrast experiment of system's evolution trend. The evolution trends of average incomes for different cases are shown in Fig. 14. It can be seen that the system can avoid the free-riding phenomenon effectively by adjusting the incentive mechanism. Therefore, it can improve system's overall profit. In addition, the evolution speed of a system will be improved by enhancing the incentive-punishment strength. Therefore, this incentive mechanism can effectively improve evolution efficiency of an Internetware system.

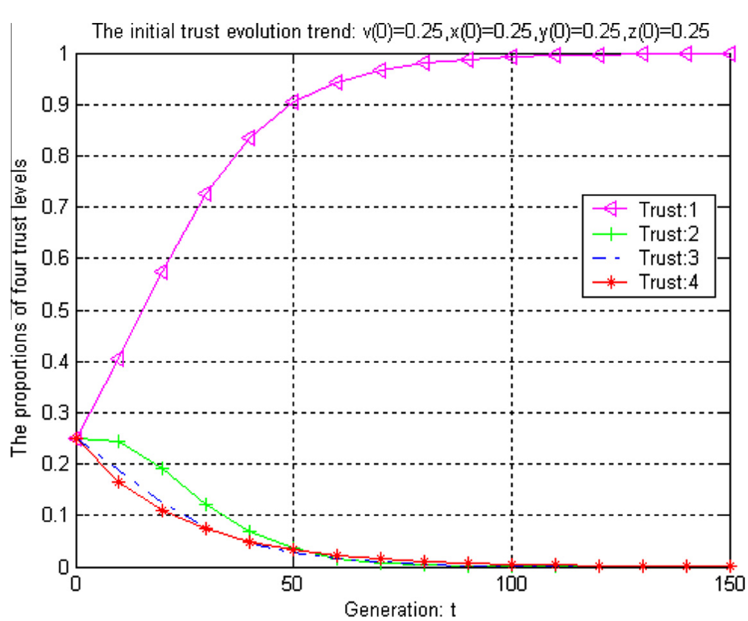

Fig. 11. Trust evolution trend of Internetware without white noise after adjusting incentive-punishment parameter.

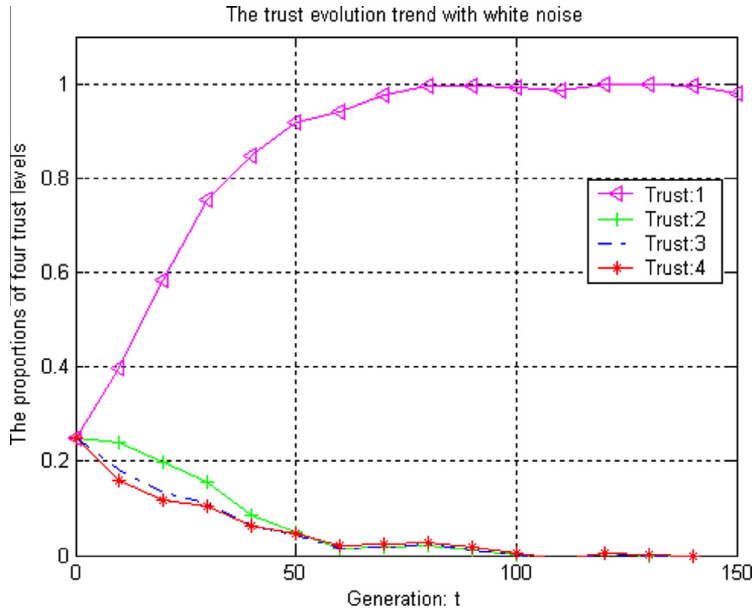

Fig. 12. Trust evolution trend of Internetware with white noise after adjusting incentive-punishment parameter.

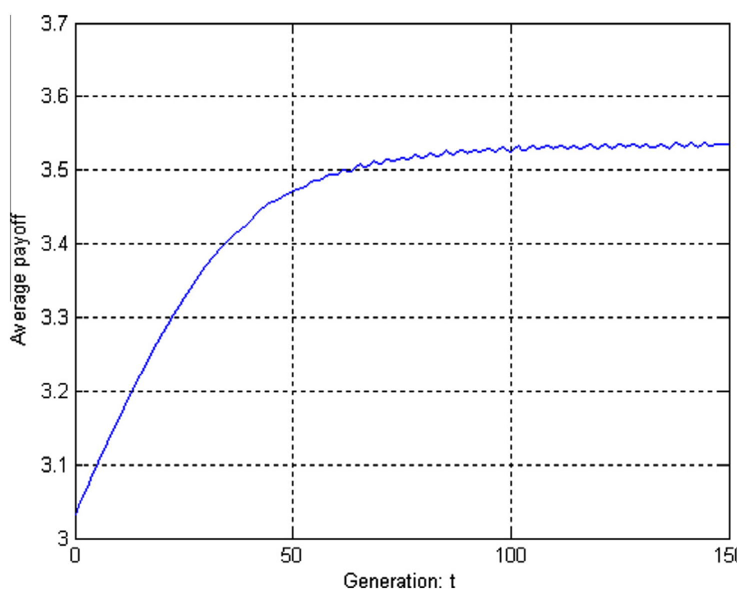

Fig. 13. Average income of Internetware system after adjusting incentive-punishment parameter.

5. Conclusions

Considering the typical shortages of previous trust evolution model and complexity of open networks, in this paper, a trust measurement model based on QoS is established. Through taking into account the timeliness of history behavior and aggregation degree of entity in complex network environment, entity's utility value based on fuzzy theory is calculated in order to take care of uncertainty of behaviors. Then according to utility values of entities that have different trust levels, a multi-strategy trust evolution model with white noise for Internetware is established based on the Wright–Fisher and evolutionary game theories. This model considers both complexity and uncertainty of an evolution process, so as to improve accuracy and adaptability. Finally, in order to solve the free-riding problem and improve trust degree of a system, an incentive mechanism is established to inspire entities to select trust strategies based on evolutionary game theory. From the simulation results, it can be seen that this model can more accurately reflect evolution dynamics characteristic of an Internetware system. It can also solve the free-riding problem. This model can effectively restrict the 'distrust-noncooperation' tendency of selfish entities, and inspire entities to select 'trust-cooperation' strategy, so that it can make an Internetware system converge to trust and stable state faster. This model has good adaptability and accuracy, and can effectively improve efficiency of a network to make the profit of Internetware reach optimum.

As future work, we will focus on the evolution characteristic of an Internetware system. On the aspect of trust measurement, we

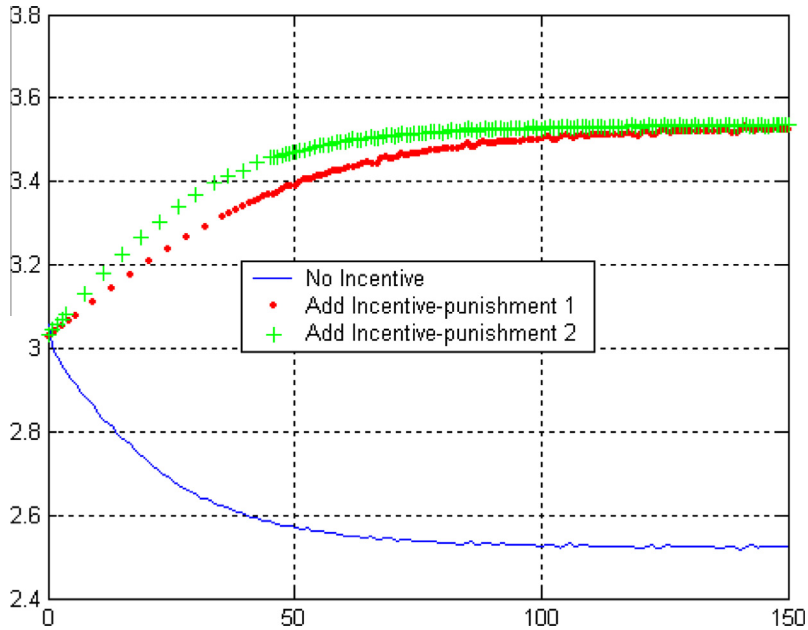

Fig. 14. Evolution trend of average incomes for different cases.

will further consider the specific trust relationships between entities (e.g., family, best friends, classmates, etc.), and investigate how to find ordered trust-entity set in an Internetware system. In addition, according to the multi-strategy game mechanism, we will design a more effective incentive mechanism to inspire a system to be optimal, so as to improve the whole trust degree of Internetware.

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