

A Credit-based Incentive Mechanism for Recommendation Acquisition in Multihop Mobile Ad hoc Networks

Wei Zhou, Zhiqiang Wei, Mijun Kang
College of Information Science and Engineering
Ocean University of China
Qingdao, Shandong, China

Email: weizhiqiang@ouc.edu.cn, {weizhou.ouc, kangmijun}@gmail.com

Paddy Nixon, Lang Jia
Department of Computer Science
University College Dublin
UCD Belfield, Dublin 4, Ireland
Email: {paddy.nixon, lang.jia}@ucd.com

Abstract—Trust and reputation systems play an important role in collaborative operations in mobile ad hoc networks. However, the security of trust and reputation system itself is threatened by the existence of selfish nodes. Selfish nodes can make passive attacks on the foundational process of trust and reputation system, the recommendation acquisition, through non cooperation of packet forwarding and recommendation rendering. Existing trust and reputation systems commonly suffer from vulnerability caused by the failure of recommendation acquisition which refers to the unsuccessful recommendation information obtaining from one node to another node. A credit-based mechanism is proposed to address this problem by offering credits as incentives to both intermediate nodes and recommendation render nodes. Furthermore, competition between selfish nodes is explored to prevent selfish nodes being paid excessive credits. Simulation results show that the proposed mechanism can effectively improve the success rate of recommendation acquisition and lower the total paid payoffs.

Keywords—incentive mechanism; trust and reputation system; selfish attack; game theory

I. INTRODUCTION

In mobile ad hoc networks (MANETs), there is no priori common knowledge and relationships between nodes. Trust and reputation systems play a vital role in establishing the relationship between nodes which is the foundation of various operations such as service provision, access control and other collaboration in an open environment [1].

The proper function of trust and reputation systems heavily depends on the success of recommendation acquisition which represents the procedure for one node getting recommendation information from another node. The success rate of recommendation acquisition will determine the quantity of available information which influences the accuracy of the calculated trust value. A recommendation acquisition process includes three sub-processes: the delivery of the recommendation request packet from the requestor to the responder, the rendering of the recommendation information by the recommender and the reversed delivery of the recommendation packet. The recommendation acquisition can only be achieved when all the sub-processes are successfully completed. In many existing

trust and reputation systems in MANETs, it is assumed that the recommendation acquisition will be successfully achieved. However, this success is threatened by the existence of selfish nodes in two ways. First, since forwarding packets will consume already limited resources, selfish intermediate nodes are reluctant to relay others' packets. The non cooperative operation of any of the forwarders will lead to the complete failure. Besides, it may not be in a node's best interest to reply the recommendation acquisition request because of the resource consumption caused by cooperation. In other words, recommendation is a special kind of information and not free from the view of selfish nodes [2]. The 'selfish attack' caused by these two problems affect the likelihood of recommendation acquisition being achieved. Hence it is critical to design a mechanism to incentivize the cooperation of selfish nodes and enforce the successful recommendation acquisition to guarantee the functionality of trust and reputation systems in MANETs.

MANETs generally adopt a peer-to-peer architecture in which the nodes themselves provide routing and services to the networks [3]. Each node in a MANET has different roles and carries out different functions. From the view of the routing and network layer one node can forward traffic and from the view of application layer, one node can provide service such as rendering recommendation information. Hence multiple incentives on both routing layer and application layer for one node are necessary for recommendation acquisition.

Based on the consideration above, in this paper we propose a credit-based incentive mechanism for recommendation acquisition in MANETs. The scheme incentivizes both intermediate nodes to forward packets and server node to render recommendation. Our incentive mechanism can be incorporated into the existing trust and reputation systems in MANETs and stimulates nodes to provide reliable and as much reputation information as they can.

In our incentive mechanism, both asking prices requested by cooperators (i.e., the intermediate nodes and recommendation rendering nodes) and buying prices given by recommendation requestor are considered. We first study the situation where the

payoff paid to the selfish nodes equals to its operation cost. That is, only buying prices (i.e., payoffs as incentives) exists. A non cooperative game, the Recommendation Acquisition Game, is used to study the condition of buying prices for cooperation. Based on the conclusion drawn from the former game, we further exam the situation where there are ‘greedy’ selfish nodes which will earn as many credits as they can. That is, the asking prices should be considered besides the buying prices. To prevent such excessive payoffs, the Competition and Selection Game which is a cooperative game is utilized to study how the the requestor takes advantage of the competition between selfish nodes to minimize the total paid credits.

The rest of the paper is structured in the following way: Section 2 describes the selfish node model. Section 3 and 4 discuss the buying prices and the asking prices using two game theory models. The credit-based incentive mechanism and simulation results are given in Section 5. Related work is discussed in Section 6 and Section 7 draws conclusions from this work.

II. THE SELFISH NODE MODEL

Selfish nodes will drop a packet rather than take the cooperative action mainly due to the resource consumption caused by the cooperation. In this paper, selfish nodes are modeled as those who decide whether to cooperate or not according to their remaining energy, denoted by x . When selfish nodes do not receive any credits as incentives, they are said to be in *selfish mode*. If the remaining energy x is more than the upper bound η , no packets will be dropped. Packets will be dropped with probability $p(x)$ when x is between the upper bound η and lower bound μ . When x is less than the lower bound, all packets will be dropped.

$$p(x) = \begin{cases} 0 & \eta < x \leq 1 \\ 2 - e^{\ln 2 \frac{x-\mu}{\eta-\mu}} & \mu \leq x \leq \eta \\ 1 & 0 \leq x < \mu \end{cases} \quad (1)$$

Selfish nodes can be incentivized by giving them credits when their remaining energy is between the upper bound and lower bound. When the credits one selfish node received are enough for them, the selfish node is made in cooperation with the others nodes, that is, $p(x) = 0, \mu \leq x \leq \eta$. In this situation nodes are said to be in *incentive mode*. A selfish node requires an *asking price* to collaborate with others. A recommendation requestor pays a *buying price* for others’ cooperation to achieve recommendation acquisition. Moreover, the only purpose of each node is to earn credits by conditional cooperation and then obtain recommendations from other nodes by paying cooperative nodes enough credits.

Since in this paper we only focus on the passive attacks caused by selfish nodes. We assume the selfish nodes will follow the proposed scheme and provide truthful feedbacks. In other words, we only consider the selfish nodes rather than malicious nodes.

In next section, we will discuss the buying price conditions under which selfish nodes will cooperate with each other and complete the whole acquisition process.

III. THE RECOMMENDATION ACQUISITION GAME

We model the whole process of recommendation acquisition as a Recommendation Acquisition Game (RAG) which is a non cooperative game. There are three kinds of nodes: client nodes (*C node*), intermediate nodes (*I node*) and server nodes (*S node*). C node is the recommendation requestor and S node is the recommendation rendering node. There is only one C node and one S node in one acquisition game but several I nodes. The process of RAG is shown in Fig. 1 in which there are n I nodes and I_i represents the i^{th} intermediate node.

The credits are stored in the request and response packets. If a selfish cooperative node finds there are more credits left in the packet than the cooperation cost, it will take the credits and perform the corresponding action. We assume that the route from the C node to the S node and the reverse are the same and remain unchanged during the acquisition process.

In RAG, a C node can decide to submit a request (*R*) or to quit (*Q*). For an I node, it can choose to forward the packet (*F*) or to drop that packet (*D*). An S node may give feedback (*R*) or duck down (*D*, which means not to render feedback). The cost of making request, forwarding packet and rendering recommendation are positive numbers and denoted as C_{req} , C_{fw} and C_{rcd} respectively. I node and S node receive the credits R_I and R_{rcd} respectively which are the buying prices given by the C node. B_{rcd} is used to denote the benefit of obtaining a recommendation for the C node.

In this section, we consider the situation where there are no asking prices requested by the cooperative nodes. In other words, selfish nodes will cooperate if the received credits are more than the cooperation cost. For any intermediate node $I_i, i = 1, \dots, n$, its strategies are *F* and *D*. *F* is the dominant strategy (i.e., the best strategy among a multitude of options) if

$$R_{I_i} > C_{fw}, i = 1, 2, \dots, n. \quad (2)$$

And *R* is the dominant strategy for the S node if $R_{rcd} > C_{rcd}$. For C node, *R* is its dominant strategy only when $B_{rcd} - C_{req} - R > 0$ in which $R = \sum_{i=1}^n R_{I_i} + R_{rcd}$. In reputation

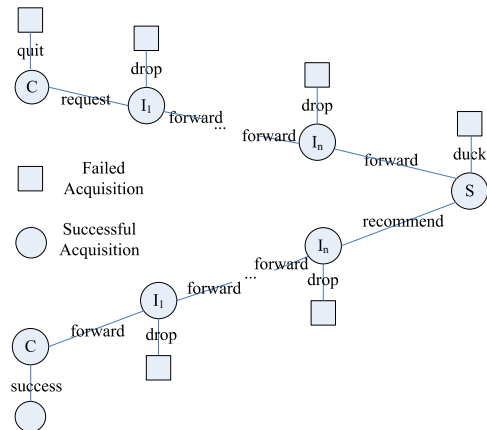


Fig. 1. The process of the Recommendation Acquisition Game

systems, we assume that the value of B_{rcd} is always more than $C_{req} + R$, i.e., the value of the available recommendation service is more than the paid credits.

So cooperation is Nash equilibrium(i.e., no node can gain more credits by changing only his own strategy unilaterally) in the RAG if

$$R_{I_i} > 2C_{fw} \text{ and } R_{rcd} > C_{rcd}, i = 1, \dots, n. \quad (3)$$

Therefore if the credits paid to cooperators satisfies the condition (3), a successful recommendation acquisition will be achieved.

IV. THE COMPETITION AND SELECTION GAME

In this section, we study how a C node determines the buying prices when there exist asking prices requested by the cooperative nodes. That is, cooperators become greedy and are willing to earn as many credits as they can rather than only more than the cooperation cost. To prevent the excessive payoffs, we consider the situation where there are several routes between the C node and the S node. The C node will select the appropriate I nodes and S node to form a route and use the competition between different coalitions to minimize the total credits paid to the cooperative nodes. This process is modeled as a cooperative game, named Competition and Selection Game (CSG).

In the following we first introduce some basic concepts about the cooperative game. [4][5]

Definition 1. Let $N = \{C, S, I_1, I_2, \dots, I_n\}$ be the set of all players. Any non-empty subset of N (including N itself and one-element subsets) is called a **coalition**. A characteristic function is a function v from coalition S to \mathbb{R} . The **gain surplus** is the difference between the coalition gain $v(S)$ and the sum of the gain of each node in S acting alone. A **cooperative game** is given by pair (N, v) , where v means the gain surplus gained by the coalition and satisfies the following conditions:

- (1) $v(\emptyset) = 0$.
- (2) **Super-additivity:** if coalitions S and T , $S \cap T = \emptyset$, then $v(S + T) \geq v(S) + v(T)$.

In the CSG, there is no surplus for each single coalition. Only the coalition whose members can achieve a recommendation acquisition will generate surplus. In the example showed in Fig. 2, $v(\{S\}) = 0$, $v(\{C, S, I_1\}) = 0$ and $v(\{C, I_1, I_3, I_4, S\}) = B_{rcd} - C_{req} - C_{rcd} - 3 \times 2C_{fw}$.

Definition 2. An **imputation** for a cooperative game (N, v) is a payoff vector $U = (U_c, U_s, U_{I_1}, \dots, U_{I_n})$ satisfying (i) $\sum_{i \in N} U_i = v(N)$, (ii) $U_i \geq v(\{i\})$. Condition (i) states group efficiency, i.e., the payoff vector exactly splits the total value and condition (ii) states individual rationality, i.e., the node can obtain the benefit no less than acting alone.

In the CSG, we name the coalition whose members can form a relay route from the C node to the S node a **relay coalition**. The relay coalition includes the C node, S node, the common path I nodes such as I_1 and non common path I nodes such

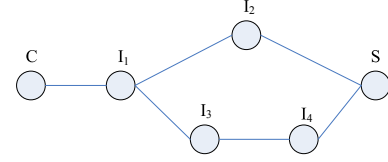


Fig. 2. The competition example in the Competition and Selection Game

as I_2, I_3 . The imputations under which relay coalition exists are named **relay imputations**. In one relay imputation,

$$\begin{aligned} U_C &= B_{rcd} - C_{req} - R_{rcd} - \sum_{i=1}^n R_{I_i} \\ &= B_{rcd} - C_{req} - \beta C_{rcd} - 2C_{fw} \sum_{i=1}^n \alpha_i. \end{aligned} \quad (4)$$

$$U_S = R_{rcd} - C_{rcd} = (\beta - 1)C_{rcd}. \quad (5)$$

$$U_{I_i} = R_{I_i} - 2C_{fw} = (\alpha_i - 1)2C_{fw}. \quad (6)$$

where $\alpha_i = R_{I_i}/2C_{fw}$ is the credit-cost ratio of the credits received from the C node, that is, buying price, to the cost of forwarding packet, and $\beta = R_{rcd}/C_{rcd}$ is the credit-cost ratio of the credits received from the C node, i.e., buying price, to the recommendation rendering cost.

α_i and β are named Buying Price Ratio (BPR) given by the node C. $\tilde{\alpha}_i$ and $\tilde{\beta}$ are used to denote Asking Price Ratio (APR) requested by nodes I and S. The purpose of I and S nodes is to obtain the maximum $\tilde{\alpha}_i$ and $\tilde{\beta}$ to maximize their own credits. When there is only one relay route from node C to node S, the node C has no choice and has to pay the credits the other nodes request, so $\alpha_i = \tilde{\alpha}_i$ and $\beta = \tilde{\beta}$. We can then get the below corollary.

Corollary 1. The necessary condition of a relay coalition exists is $\alpha_i \geq 1$ for all I nodes and $\beta \geq 1$ for the S node in this coalition.

Corollary 1 corresponds to the condition (3) and guarantees the enforcement of the cooperation.

When at least two relay routes exist, there is the competition between these coalitions and one of them will be selected. Note that when there is enough energy left, each node would like to be the number of the selected coalition and earn credits. Due to the competition, selfish nodes have to reduce their APRs and paid less credits to get the change to be selected. To make it easy to understand, consider a similar situation where there are more employees than needed in the job fare. The employer will only choose those who ask for the lowest salaries. But how low will the credits go regarding to the cooperation condition (3) and how that coalition will be selected? We use the concept **core** to address this problem.

Definition 3. Let x and y be two imputations, and let S be a coalition. We say x **dominates** y through S if (i) $x_i > y_i$ for

all $i \in S$, (ii) $\sum_{i \in S} x_i \leq v(S)$. Condition (i) states that the members S of all prefer x to y ; condition (ii) states that they are capable of obtaining what x gives them.

Definition 4. The set C of all undominated imputations for a game (N, v) is called the **core**, i.e.,

$$C = \{U : \sum_{i \in N} U_i = v(N), \sum_{i \in S} U_i \geq v(S), \forall S \in N\} \quad (7)$$

The core is the set of imputation under which no coalition has a greater value than the sum of its members' payoffs. The core contains all stable imputations and the imputations not in the core are unstable. For a unstable imputation y , some members will have incentive to leave the grand coalition (the whole group), form a coalition S and receive a larger payoff under another imputation x which dominates y through S .

Assume there exists m relay imputations in the CSG. We denote the payoff of the C node, S node and I_i node in the imputation vector by $U_C^k, U_S^k, U_{I_i}^k, k = 1, \dots, m$ respectively. Let I^k and $I^{k'}$ represent the common path I nodes and the non common path I nodes in the corresponding coalition. Let α_i^k and $\alpha_i^{k'}$ represent the corresponding BPR respectively. Then

$$U_C^k = B_{rcd} - C_{req} - \beta C_{rcd} - 2C_{fw} \sum_{i=1}^p \alpha_i^k - 2C_{fw} \sum_{j=1}^q \alpha_j^{k'} \quad (8)$$

where p, q is the number of I^k and $I^{k'}$ nodes.

Note that CSG is not a constant-sum game [4]. According to (4)(5)(6), the total surplus gained by the relay coalition is

$$v^k(N) = B_{rcd} - C_{req} - C_{rcd} - n \times 2C_{fw} \quad (9)$$

The total surplus gained by the coalition will be obtained by the C node in the form of obtaining the recommendation. The C node distributes the total surplus to other nodes in the coalition in the form of paying them buying prices.

Theorem 1. The core of CSG is not empty if there exists at least one relay coalition. The imputations in the core are those under which the coalition will form the shortest relay route.

Proof: Since only the relay coalition yields surplus we only consider the relay imputations which are possible to be undominated. If there is only one relay coalition, then the corresponding relay imputation is in the core. Consider there are m relay coalitions. Note that the C node, the S node and common path I nodes are in every relay coalition and a non common path I node can earn credits only when it is in the selected relay coalition. Hence the non common path I nodes will have to give up some credits to the other nodes in the coalition to make sure it can be chosen as a member of the selected relay coalition. Furthermore, according to (8) the payoff of C node is influenced by the ratios of non-common path I nodes. Hence the relay imputation is stable and undominated if the C node has no incentive to leave the coalition. Assume the k_i^{th} route is the shortest relay route

which contains the minimum number of $I^{k'}$ nodes and the minimum number of I nodes. Then the coalition will get the maximum total surplus v_N^k according to (9). Given that $\alpha_i^{k'} \geq 1$ for a relay coalition, all the nodes on the shortest relay route can achieve minimum $\sum_{i=1}^q \alpha_i^{k'}$. Therefore, according to (8), the C node will get more payoff comparing to forming a coalition with other $I^l (l \neq k)$ nodes. Therefore the C node has no incentive to leave the shortest relay coalition corresponding to the shortest relay route. Then the imputations reflecting the payoff distribution under this condition consist of the core. ■

If there exist two shortest relay routes k_1, k_2 , considering the BPRs for any $I_i^{k_1'}$ node in the k_1 route and any $I_j^{k_2'}$ in the k_2 route, we have

$$\alpha_i^{k_1'} = \alpha_j^{k_2'} = 1 \quad (10)$$

The C node will choose one of these two routes randomly and pay the corresponding credits.

If there exists only one shortest relay route k and let s be the second shortest relay route, for any $I_j^{s'}$ in the s route, $\alpha_j^{s'} = 1$. For any $I_i^{k'}$ in the k route, we have

$$\alpha_i^{k'} = v/u \quad (11)$$

where u is the number of $I_i^{k'}$ nodes and v is the number of $I_j^{s'}$ nodes. The C node gives the equal buying prices to the $I_i^{k'}$ nodes because of the equality of each node's marginal contribution.

Conditions (10) and (11) are the maximum APR the I' nodes can request considering the competition with other coalitions. The BPR given to the common path I nodes and S node are the APR they asked. In this situation, C node spends the least credits to succeed in finishing a recommendation acquisition.

The C node can only reduce the credits paid to the nodes which are non common path I nodes. However, these nodes may become common path I nodes or S nodes in other recommendation acquisitions and the C node will have to bear the high credits paid to them then. To avoid this, C node will pay some extra credits to incentivize the I' nodes to decrease their APRs so that it will face lower APRs later. Here we simply assume the I' nodes will decrease their own APRs by θ ($0 < \theta < 1$) when receive θ extra credits.

V. SIMULATION

In this section, we first describe the whole process of the credit-based incentive mechanism for recommendation acquisition. The pseudo-code of the incentive mechanism is given in Fig. 3. Note that our incentive mechanism needs the support from multipath routing protocols.

We evaluate the performance of credit-based incentive mechanism for the recommendation acquisition. The MANETs are simulated in JIST/SWANS [6]. The field is an area of $3000m \times 3000m$ and contains 40 nodes. We choose this setting to generate the competition between different relay coalitions. Only multihop recommendation requests are allowed to made

```

C node:
generate-recommendation-query:
Get routes to the S node by the multipath routing
protocol
If there are at least two routes
    Find out the common and non common path I nodes
Set BPRs for non common path I nodes according to
(10) (11)
Set BPRs for common path I nodes and S node to their
APRs
If there are local APR records
    Use local APR records as BPRs
Else
    Use default BPR
Calculate the total credits need to pay for this request
If the C node has enough credits to pay this packet {
    Add BPR info and credits into the request packet
    Add extra credits to incentivize the I' to decrease
their APR
    Send the request packet via the shortest route
}
not-receive-the-recommendation-response-in-the-given-time:
If there are any other routes{
    Select the second shortest route
    Recalculate and determine the BPR sets
    Send the request packet via this route
}
receive-recommendation-response:
Get the recommendation information
Update local BPR records of other nodes according to the
info contained in the response packet
Update C's current APR to the average of the used BPR of
I and S nodes in this recommendation acquisition

I node:
receive-recommendation-query/response:
Get the BPR given by the C node in the packet
If there are enough credits in the packet{
    Get the credits according to the BPR
    Update local APR records of other nodes' ratio in this
packet
    If there are extra incentive credits in the packet{
        Get the extra credits
        Decrease I's current own APR by  $\theta$ 
    }
    Add I's current own APR information into the packet
    Forward the packet
} Else Drop the packet

S node:
receive-recommendation-query:
Get the BPR given by the C node in the packet
If there are enough credits in the packet{
    Get the credits according to the BPR
    Initialize a recommendation response packet
    Add all APR information from the request packet into
the response packet
    Add S's current own APR information into the packet
    Update local records of other nodes' APRs
    Send the packet back to the C node via the same route
} Else Drop the packet

```

Fig. 3. Pseudo-code for Credit based Incentive mechanism

in the simulation. The random waypoint model with a minimum speed of 2m/s and maximum of 10m/s is used for mobility. The DSR is used as the routing protocol and is modified to find more than two routes when a request packet is generated so that the C node can set the appropriate BPR for I and S nodes. Energy model is implemented according to the model proposed in [7].

First, we evaluate the effectiveness of the incentive mechanism by comparing the success rate of recommendation acquisition between the selfish mode and the incentive mode. Fig. 4 plots the average success rate of recommendation acquisition. In this simulation, $\mu = 0.1$ and $\eta = 0.8$. At the end of the

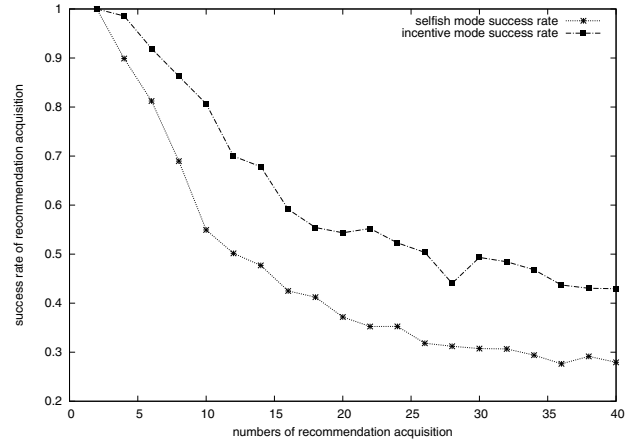


Fig. 4. Average success rate of recommendation acquisition

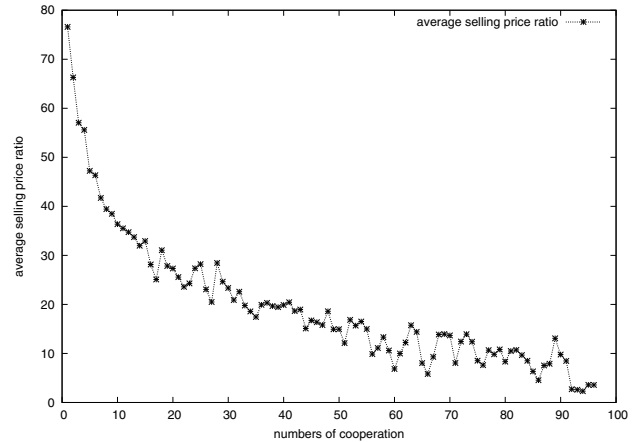


Fig. 5. Evolution of average asking price ratio

simulation, at least 80% of the nodes have used more than 90% of their energy. As depicted in Fig. 4, at the beginning recommendation acquisitions are 100% successfully achieved. Then the success rate drops dramatically in the selfish mode due to the non cooperation of I nodes and S nodes. In the incentive mode, the rate declines because the energy levels of some I nodes and S nodes reach the lower bound so that they choose not to cooperate. Experiment shows that the success rate is improved by approximately 15%-30% as a consequence of the use of the incentive mechanism.

We next evaluate how the APR evolves as more cooperation occurs. In the simulation, the initial APR and default BPR are set to 90 and 2.0 respectively for each node. The non common path I nodes will decrease the APR by $\theta = 0.1$ if they receive extra credits. From the results shown in the Fig. 5 we can see that the average APR drops dramatically at the beginning and gradually approaches the number 1.0 which means the asking price is equal to the real cost of the cooperation.

VI. RELATED WORK

There are mainly three basic classes incentive mechanisms existing in MANETs: credit-based [8][9], reputation-based and game theoretic mechanisms [10][11]. For credit-based incentive mechanism, a stimulation approach based on a virtual currency is proposed in [8]. However, this approach does not address the full cooperation of both intermediate nodes and service provider nodes. In [9], a utility-based incentive scheme for P2P file sharing is proposed to provide incentives to intermediate peers as well as the service provider. But the asking price query process will lead to considerable overhead energy consumption. For game-theoretic incentive mechanism, in [10], it is proved that the cooperation condition, without the incentive mechanism, is virtually never satisfied from the perspective of non cooperative game theory. So credits are employed as incentives in our approach. Besides, our work is inspired by [11], which shows that cooperative game theory can be used to analyze the stability and competition of collaborative application such as cooperative transmission.

VII. CONCLUSION AND FUTURE WORK

Recommendation acquisition which is the foundational process of trust and reputation system in MANETs is threatened by the passive attacks carried out by the selfish nodes. To address this problem, we have proposed a credit-based incentive mechanism to stimulate the cooperation of both intermediate nodes and the recommendation rendering nodes so that the recommendation acquisition can be successfully accomplished. A non cooperative game called Recommendation Acquisition Game is used to analyze the condition in which selfish nodes will cooperate with each other. An cooperative game called Competition and Selection Game studies how the C node chooses the cooperators and lower the total paid credits. Simulation results show that our incentive mechanism can effectively increase the success rate of recommendation acquisition by about 15%-30% and decrease the asking prices of the cooperators.

In future, we are going to incorporate our incentive mechanism into a real reputation system in MANETs and study how this mechanism can actually affect the precise of trust value. Besides, the relationship between the APR decreasing rate θ and the amount of received extra credits needs further investigation.

ACKNOWLEDGMENT

This work is sponsored by China Scholarship Fund and partially supported by Science Foundation Ireland under grant number 04/RPI/1544, "Secure and predictable Pervasive Computing", and partially by the Grant 863 Program of China (No.2008AA10080501), Program for New Century Excellent Talents in University (No.2006NCET-06-0600) and Science and Technology Development Plan of Shandong Province (No.2008GG30001010). We thank Lorcan Coyle, Juan Ye, Graeme Stevenson and Abdur Razzaque for many valuable suggestions.

REFERENCES

- [1] S. Ahamed, M. Haque, and N. Talukder, "Service sharing with trust in pervasive environment: now it's time to break the jinx," in *Proceedings of the 2008 ACM symposium on Applied computing*. ACM New York, NY, USA, 2008, pp. 1622–1628.
- [2] Y. Wang, Y. Hori, and K. Sakurai, "Characterizing Economic and Social Properties of Trust and Reputation Systems in P2P Environment," *Journal of Computer Science and Technology*, vol. 23, no. 1, pp. 129–140, 2008.
- [3] M. Razzaque, S. Dobson, and P. Nixon, "Cross-Layer Self Routing: A Self-Managed Routing Approach for MANETs," in *Networking and Communications, 2008. WIMOB'08. IEEE International Conference on Wireless and Mobile Computing*, 2008, pp. 284–290.
- [4] G. Owen, *Game Theory*. Academic Press, 1982.
- [5] R. Myerson, "Game Theory: Analysis of Conflict," *Boston, USA*, 1991.
- [6] R. Barr, "Swans-scalable wireless ad hoc network simulator," 2004.
- [7] L. Feeney, "An Energy Consumption Model for Performance Analysis of Routing Protocols for Mobile Ad Hoc Networks," *Mobile Networks and Applications*, vol. 6, no. 3, pp. 239–249, 2001.
- [8] L. Buttyan and J. Hubaux, "Enforcing service availability in mobile ad-hoc WANS," in *Mobile and Ad Hoc Networking and Computing, 2000. MobiHOC. 2000 First Annual Workshop on*, 2000, pp. 87–96.
- [9] A. Mawji and H. Hassanein, "A Utility-Based Incentive Scheme for P2P File Sharing in Mobile Ad Hoc Networks," in *Communications, 2008. ICC'08. IEEE International Conference on*, 2008, pp. 2248–2252.
- [10] M. Félegyházi, J. Hubaux, and L. Buttyán, "Nash Equilibria of Packet Forwarding Strategies in Wireless Ad Hoc Networks," *IEEE TRANSACTIONS ON MOBILE COMPUTING*, pp. 463–476, 2006.
- [11] Z. Han and H. Poor, "Coalition Games with Cooperative Transmission: A Cure for the Curse of Boundary Nodes in Selfish Packet-Forwarding Wireless Networks," in *Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks and Workshops, 2007. WiOpt 2007. 5th International Symposium on*, 2007, pp. 1–8.