Game-Theoretic Analysis of Cooperation Incentive Strategies in Mobile Ad Hoc Networks

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Abstract—In mobile ad hoc networks (MANETs), tasks are conducted based on the cooperation of nodes in the networks. However, since the nodes are usually constrained by limited computation resources, selfish nodes may refuse to be cooperative. Reputation systems and price-based systems are two main solutions to the node non-cooperation problem. A reputation system evaluates node behaviors by reputation values and uses a reputation threshold to distinguish trustworthy nodes and untrustworthy nodes. A price-based system uses virtual cash to control the transactions of a packet forwarding service. Although these two kinds of systems have been widely used, very little research has been devoted to investigating the effectiveness of the node cooperation incentives provided by the systems. In this paper, we use game theory to analyze the cooperation incentives provided by these two systems and by a system with no cooperation incentive strategy. We find that the strategies of using a threshold to determine the trustworthiness of a node in the reputation system and of rewarding cooperative nodes in the price-based system may be manipulated by clever or wealthy but selfish nodes. Illumined by the investigation results, we propose and study an integrated system. Theoretical and simulation results show the superiority of the integrated system over an individual reputation system and a price-based system in terms of the effectiveness of cooperation incentives and selfish node detection.

Index Terms—MANET, Distributed network, Reputation system, Price-based system, Game theory.

1 Introduction

A distributed network is a self-organizing network without centralized management, in which each node functions autonomously. A mobile ad hoc network (MANET) is a distributed network. In a MANET, because of the short transmission range, a packet is forwarded in a multi-hop fashion to its destination relying on the nodes in the routing path. Thus, MANETs require the cooperation of every node in the path for successful packet transmission. In military and disaster discovery MANET applications, nodes cooperate with each other since they are under the control of the same authority. However, many other MANET applications, such as data sharing [1], traffic monitoring [2], emergency assistance services [3] and multimedia data transmission [4], are not controlled by an authority. Since nodes in MANETs are usually constrained by limited power and computational resources such as CPUs or batteries, the nodes (and the device holders) may not be willing to be cooperative so as to save their limited resources. It has been proved that the presence of only a few selfish nodes can dramatically degrade the performance of an entire system [5]. Additionally, identifying and punishing selfish nodes will decrease the throughput of cooperative nodes and lead to complete network disconnection [6]. Therefore, encouraging nodes to be cooperative and detecting selfish nodes in packet transmission is critical to ensuring the proper functionalities of MANETs.

Recently, numerous approaches have been proposed to deal with the node non-cooperation problem in wireless networks. They generally can be classified into two main categories: reputation systems and price-based systems. The basic goal of reputation systems [7–18] is to evaluate each node's trustworthiness based on its behaviors and detect misbehaving nodes according to reputation values. Reputation systems enable each node to maintain a reputation table recording the reputation values of other nodes. Most reputation systems set up a reputation threshold to distinguish between misbehaving nodes and cooperative nodes. Nodes whose reputation values are higher than the threshold are regarded as cooperative nodes; Otherwise the nodes are regarded as selfish nodes. During packet routings, a node selects cooperative nodes as relay nodes and avoids selfish nodes. Price-based systems [19–25] treat packet forwarding services as transactions that can be priced and introduce virtual credits to manage the transactions between nodes. A service receiver pays virtual credits to a service provider that offers packet forwarding. In spite of the efforts to develop reputation systems and price-based systems, there has been very little research devoted to investigating how much incentive these systems can provide for node cooperation encouragement.

Game theory [26] is a branch of applied mathematics that models and analyzes interactive decision situations called games. Based on whether the players make binding agreements in a game, game theory models can be classified into cooperative game models and non-cooperative game models. In the former, the players act based on their binding agreements. In the latter, the players are self-enforcing entities (i.e., nodes can change their strategies at any time to maximize their benefits). In this paper, we use game theory to study reputation systems and price-based systems, and analyze their underlying incentives and deficiencies.

Firstly, we use a cooperative game to explore ways to form a rational coalition that can optimize the benefit of each node. We find that in the cooperative game, each node earns its maximum benefit only when the nodes form a grand coalition, in which all nodes in the system are cooperative. Later, we use a non-cooperative game to investigate the best strategy for each node to maximize its benefit and find that the cooperation incentives provided by both reputation systems and price-based systems are limited. The strategies of using a threshold to determine the trustworthiness of

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a node in the reputation system and the strategies of rewarding cooperative nodes in the price-based system may be manipulated by clever but selfish nodes. Specifically, the reputation systems treat nodes whose reputation values are higher than the threshold equally. Thus, a node can keep its reputation value just above the threshold to receive the same benefit as the nodes with much higher reputations. Though many reputation systems have been proposed with various reputation calculation mechanisms, this behavior is not affected by the reputation calculation mechanisms and can exist in all reputation systems with the threshold strategy. The price-based system lacks an effective method to detect a selfish and wealthy node that earns many credits by cooperating initially but becomes non-cooperative (selfish and non-cooperative are interchangeable in this paper) later without penalty. The price-based system is also unfair to nodes in low-traffic regions that have few chances to earn credit.

We observe that a promising method to provide strong incentives is to combine a reputation system and a price-based system. Illumined by the investigation results, we propose an integrated system to leverage the advantages of both systems and overcome their individual disadvantages, making reciprocity the focal point. We also build a game theory model for analyzing the integrated system. We find that the integrated system can provide higher cooperation incentives than either the reputation system or the price-based system and is more effective in selfish node detection.

This paper is intended to answer the following questions.

(1) Is it possible to encourage the nodes in a system to be cooperative without any cooperation incentive strategy?
(2) How effective are the cooperation incentives provided by the individual reputation system and the price-based system?
(3) What are the deficiencies of individual reputation systems and price-based systems?
(4) Can the proposed integrated system overcome the deficiencies of individual reputation or price-based systems, and provide higher cooperation incentives?
(5) Why can the integrated system provide higher incentives than the reputation system and the price-based system?

Although a number of works [27–39] have already been proposed using game theory for packet forwarding in MANETs, they focus on studying individual nodes adjust interaction strategies based on the behaviors of others in order to maximize their benefits. However, the works do not consider how to encourage nodes to choose a cooperative strategy, which is the only way to maximize the overall system benefit. As far as we know, this is the first work that uses game theory to investigate the incentives provided by the existing reputation systems and price-based systems, identify their individual weaknesses for cooperation encouragement, and provide a generic solution to effectively encourage nodes to be cooperative. Note that in addition to MANETs, this work is also applicable to all distributed networks, including peer-to-peer networks and wireless sensor networks. It provides an exciting research direction towards the strategic design of strong cooperation incentive in distributed networks.

The remainder of this paper is organized as follows. Section 2 provides related works. Section 3 introduces the basic game theory models. Section 4 presents the game theory based analysis for the individual defenseless system, the reputation system and the price-based system. This section also describes and analyzes the proposed integrated system with game theory model. Section 5 presents the simulation results of the integrated system in comparison with other systems. Section 6 concludes the paper.

2 RELATED WORKS

Reputation Systems. Reputation systems and price-based systems are two main approaches proposed to encourage cooperation between mobile nodes in MANETs. A reputation system gathers observations of node behaviors and calculates node reputation values [7–18]. The system detects and punishes low-reputed nodes by isolating them from the MANETs. There are two types of reputation systems: first-hand based and second-hand based.

In the first-hand based reputation systems [7–10], a node only believes its own observations about other nodes' behaviors, and the exchanges of reputation information between nodes are disallowed. Conti *et al.* [7] and Dewan *et al.* [8] let the source node choose the next hop node with sufficiently high reputation during the packet routing in order to achieve routing reliability. OCEAN [9] avoids indirect (second hand) reputation information and uses only direct (first-hand) observations in order to see the performance of this method. Liu *et al.* [10] proposed to expand the scope of the behavior observation from one hop to two hops.

In the second-hand reputation systems [11–18], nodes share observations of node behaviors by periodically exchanging observed information. In Core [11], CONFIDANT [12] and the work in [13], a node promiscuously listens to the transmission of the next node in the path to detect misbehavior, and aggressively informs other nodes of the misbehaviors by reporting around the network to isolate the misbehaving nodes. Some works [14–18] use different machine learning techniques to increase the misbehavior detection accuracy. Although observation sharing has some potential drawbacks such as increased transmission overhead, misreporting and collusion, it can detect node misbehavior faster than the first-hand based reputation systems.

Although these reputation systems use linear [7–15] or non-linear reputation adjustment mechanisms [16–18] for reputation calculation, they still use a threshold to distinguish selfish nodes from cooperative nodes. Thus, clever selfish nodes can wisely maintain their reputation value just above the threshold by selectively forwarding others' packets regardless of the reputation calculation mechanism. Such nodes can take advantage of other cooperative nodes without being detected. Also, these methods cannot reward high-reputed nodes differently or punish low-reputed nodes in different reputation levels.

Price-based Systems. In the price-based systems, nodes are paid for offering packet forwarding service and pay for receiving forwarding service. The payments can be in money, stamps, points or similar objects of value [19–25]. Buttyan and Hubaux [19–21] introduced nuglets as credits for managing forwarding transactions. Crocraft *et al.* [23] and Anderegg *et al.* [24] consider how to determine the prices for the forwarding services to discourage the selfish behaviors in MANETs. Zhong [22] and Janzadeh *et al.* [25] consider how to defend against cheating behavior such as requiring credits for fake service requests and denying service after receiving credits in the price system.

Although the price-based systems can stimulate nodes to be cooperative, most systems fail to provide a way to know the service quality of a node. Moreover, they fail to punish a selfish and wealthy node that earns many credits by being cooperative but drops others' packets later on. Also, a cooperative node in a low-traffic region may not be treated fairly. The node receives few data forwarding requests, and may not have chances to earn

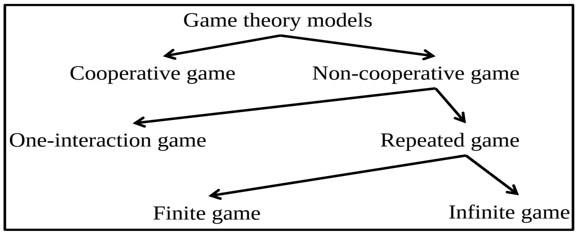

Fig. 1: Classification of game theory models.

enough credits to pay for its required services. Furthermore, the nodes that do not need forwarding services can always refuse to help others to forward packets.

Game Theory Works. Numerous works use game theory to optimize the packet routing in MANETs and the allocation of resources including channel and power resources in wireless networks. These works use either non-cooperative game theory [6, 27–34] or cooperative game theory [35–38, 40]. Among these works, the most relevant works to this work are in [6] and [28] that studied the punishing mechanisms in order to encourage nodes to be cooperative in the non-cooperative game. We consider both cooperative game and non-cooperative game in node interaction modeling in studying incentive systems.

3 Overview of Game Theory Models

Game theory is a theory of applied mathematics that models and analyzes systems in which every individual tries to find the best strategy dependent on the choices of others in order to gain success. As shown in Figure 1, game theory models can be generally categorized as cooperative games or non-cooperative games. In cooperative games, the nodes agree on their strategies and cannot change their strategies later on. In contrast, nodes in non-cooperative games can change their strategies at any time in order to maximize their benefits. Non-cooperative games can be further classified into one-interaction games and repeated games. In the former, individuals only interact with each other once. In the latter, individuals interact with each other multiple times. Repeated games can be further classified into finite repeated games or infinite repeated games. In finite repeated games, a pair of players have a finite number of interactions, while in infinite repeated games they interact with each other infinitely many times. Game theory provides analytical tools to predict the outcome of complex interactions among rational and self-interested entities, who will always try to reach the best outcome [41].

Regarding nodes in MANETs as rational and self-interested entities, a game theory model can be built. We use $\mathcal{N} = \{1, 2, ..., n\}$ to denote the set of all mobile nodes (i.e., game players) in a routing path. In an interaction between a pair of nodes in routing, each node requests the other node to forward a packet, and the other node either forwards the packet or drops the packet. We use A_i to denote the action set for node i, and $A_i = \{I, C\}$; the C (i.e., cooperative) action means the node is willing to help the other node to forward a packet, while the I (i.e., incooperative, non-cooperative) action means it drops the packet. Action and strategy are interchangeable terms in this paper. The action chosen by node i is denoted by a_i, and the actions chosen by other nodes are denoted by an action set $\mathbf{a_{-i}} = \{a_1, a_2, a_3, ...a_{i-1}, null, a_{i+1}, ..., a_n\}$. $\mathbf{a} = (a_i, \mathbf{a_{-i}}) = \{a_1, a_2, a_3, ...a_{i-1}, a_i, a_{i+1}, ..., a_n\}$ denotes the action set of all the nodes on a path for the routing of one packet. If any node is uncooperative, the packet will be dropped. We use D to denote the Cartesian product of the action set of a node, $U_i(a_i, \mathbf{a_{-i}})$ to denote the utility (i.e., payoff, benefit) function of a node i given the strategies used by other nodes and U($\mathbf{a}$) to denote the sum of the utilities of all nodes. The game theory model for MANETs is denoted as follows: Given a normal form of game G,

$$G =< \mathcal{N}, D, U_i(a_i, \mathbf{a_{-i}}) > .$$

TABLE 1: Parameters used in the analysis.

c	packet forwarding cost	m_r	packet forwarding reward
m_p	packet forwarding price	n_d	the number of dropped packets
n_g	the number of generated packets	n_r	the number of received packets
p	packet forwarding benefit	v	characteristic function
x	allocated payoff	A	action set
$\mathcal{N}$	the set of total mobile nodes	$\mathcal{S}$	a subset of mobile nodes
U	payoff	P_d	average packet drop probability
P_s	the probability of an account state	R	current reputation value
T_R	reputation threshold	V	current account value

TABLE 2: An example for cooperative and non-cooperative games.

		Node j	
		Cooperative	Non-cooperative
Node i	Cooperative	(4,4)	(0, 6)
	Non-cooperative	(6, 0)	$(1, 1)^*$

Every rational node in the system intends to choose an action that maximizes its utility for a given action tuple of the other nodes. That is, the best action $a_i^* \in A_i$ is the *best response* of node i to $\mathbf{a_{-i}}$ iff for all other $a_i \in A_i$, $U_i(a_i^*, \mathbf{a_{-i}}) \geq U_i(a_i, \mathbf{a_{-i}})$.

Definition 1. A Nash Equilibrium (NE) is an action tuple that corresponds to the mutual best response. Formally, the action tuple $\mathbf{a}^* = (a_1^*, a_2^*, a_3^*, ..., a_n^*)$ is a NE if $U_i(a_i^*, \mathbf{a^*_{-i}}) \geq U_i(a_i, \mathbf{a^*_{-i}})$ for $\forall a_i \in A_i$ and $\forall i \in \mathcal{N}$ [41], where A_i denotes the action set (cooperative, non-cooperative) for node i. Therefore, a NE is an action set where no individual rational node can benefit from unilateral deviation.

Definition 2. An outcome of a game is non-Pareto-optimal if there is another outcome which would give all players higher payoffs, or would give partial players the same payoff but the other players a higher payoff. An outcome is Pareto-optimal if there are no other such outcomes [26].

Proposition 3.1: Suppose $\mathcal{N} = 1, 2, ..., n$ is a set of nodes in the routing path of a packet from source node 1 to destination node n. In order to ensure that $(C_1, C_2, ...C_n)$ is NE and Pareto-optimal, we need to ensure the interaction strategy between two neighboring nodes in the routing path is NE and Pareto-optimal.

Proof: For the nodes in the routing path from source node 1 to destination node n, since the packet forwarding interaction only occurs between two neighboring nodes,

$$\mathbf{a} = (a_1, a_2, ..., a_n) = \cup_{i=1}^{n-1}(a_i, a_{i+1}). \quad (1)$$

In order to ensure that $(C_1, C_2, ...C_n)$ is NE, according to Definition 1, we should guarantee that for any node i ($i \in [1, n-1]$), $U_i(a_1^*, a_2^*, ..., C_i, ..., a_n^*) \geq U_i(a_1^*, a_2^*, ..., a_i, ..., a_n^*)$. Based on Equation (1), the problem is reduced to ensure $U_i(C_i, a_{i+1}^*) \geq U_i(a_i, a_{i+1}^*)$. That is, for the interaction between two neighboring nodes i and $i+1$, we need to ensure that node i cannot gain more benefits if it deviates the cooperation strategy. Also, in order to ensure that $(C_1, C_2, ...C_n)$ is Pareto-optimal, according to Definition 2, we should guarantee that $U_i(C_1, C_2, ..., C_i, ...C_n) \geq U_i(a_1, a_2, ..., a_i, a_n)$. Based on Equation (1), the problem is reduced to ensuring $U_i(C_i, C_{i+1}) \geq U_i(a_i, a_{i+1})$. That is, for the interaction between two neighboring nodes i and $i+1$, we need to ensure that the cooperation strategy (C_i, C_{i+1}) is Pareto-optimal. $\square$

In this paper, we consider the collaboration of nodes along one routing path in forwarding one packet in order to guarantee its successful delivery from the source to the destination. For the case that multiple nodes transmit packets to the same next hop node, we can separately consider the interactions between the multiple nodes and the next hop node according to different packets. Before we build the game models, we first use an example to explain non-cooperative and cooperative games.

Non-cooperative game. Table 2 shows an example of a payoff matrix for a non-cooperative game of two-node interaction. If node i is cooperative, node j's payoff is 4 when being cooperative, and is 6 when being non-cooperative. Hence, node j chooses the I strategy. If node i is non-cooperative, node j's payoff is 0 when being cooperative, and 1 when being non-cooperative. Thus, node j still chooses the I strategy. As a result, no matter which strategy node i selects, being non-cooperative produces more utility than being cooperative for node j, i.e., $U_j(I, \mathbf{a_{-j}}) > U_j(C, \mathbf{a_{-j}})$. Similarly, no matter which strategy node j chooses, being non-cooperative generates more utility than being cooperative for node i, i.e., $U_i(I, \mathbf{a_{-i}}) > U_i(C, \mathbf{a_{-i}})$. We use I_i and C_i to represent the cases that node i takes the I and C actions, respectively. In this game, action set (I_i, I_j) dominates other action sets. We say that (I_i, I_j), marked with a star in the table, is the NE of this game. From the payoff matrix, we can see that no individual node can get more benefit by unilaterally deviate from action set (I_i, I_j). However, the payoff of the action set (I_i, I_j) is not the best outcome of the payoff matrix; the optimal payoff $(4, 4)$ is brought by the action set (C_i, C_j). (C_i, C_j) is the Pareto-optimal of this game. An effective cooperation incentive system should aim to achieve outcomes that are both NE and Pareto-optima, rather than just NE.

Cooperative game. We use the same example in Table 2 to explain the cooperative game by analyzing the interactions between the players in the game. We show whether nodes sometimes have an incentive to form a coalition to optimize their utilities, how the nodes form a coalition, and whether the utility allocation to each node in the coalition is reasonable.

Definition 3. In cooperative games, the *characteristic function* describes how much collective payoff a set of players can gain by forming a coalition. The collective Pareto-optimal payoff is denoted by $v(\mathcal{S})$, where $\mathcal{S} \subseteq \mathcal{N}$ is a subset of total players. $v(i)$ is the characteristic function of player i in no coalition with other nodes (i.e., single member coalition) [42].

The single member coalition in the cooperative game is equivalent to the non-cooperative strategy in the non-cooperative game. $v(i)$ equals to the NE payoff of player i in the uncooperative game.

Definition 4. Let x_i be the payoff received by player i $(i \in \mathcal{S})$. A vector $\overrightarrow{x} = (x_1, ...x_n)$ is a rational utility allocation if (1) $x_i \geq v(i)$ and (2) $\sum_{i=1}^{n} x_i = v(\mathcal{N})$ [42]. Definition 4 implies that a rational utility allocation should guarantee that a node earns more payoff by forming a coalition with other nodes (Condition (1)). Also, the total allocated payoff of all players in a coalition should equal the collective Pareto-optimal payoff of all players (Condition (2)). Therefore, a node prefers to join a coalition that will bring it more payoff than the single member coalition. Also, a node prefers to choose an optimal coalition from a number of coalition options. In non-rational utility allocation, a node may choose not to join a coalition or to leave its current coalition in order to gain higher payoff from another coalition.

Definition 5. A coalition is called a stable coalition when no other coalitions can yield a higher payoff for each individual player in the stable coalition.

According to the payoffs shown in Table 2, in a single member coalition, $v(i)$=1 and $v(j)$=1. However, if player i and player j decide to form a coalition and ask a third party to enforce their strategies (i.e., the (C_i, C_j) strategy set is formed), the maximum payoff of the coalition is $v(i, j) = 8 > v(i) + v(j) = 2$. Also, for the payoff allocation in the coalition, $x_i > v(i)$ and $x_j > v(j)$. That is, forming a cooperative coalition can bring more benefits to the nodes than forming a single member coalition. The (C_i, C_j) coalition is stable since no other coalitions can bring more benefits.

In the following, we build the game theory models for a defenseless MANET, a MANET with a reputation system, and a MANET with a price-based system, respectively. We rely on the models to analyze the effectiveness of cooperation incentives in each of the systems.

4 Analysis of Cooperation Incentive Strategies

4.1 Game Theory Model for the Defenseless System

In an interaction between node i and node j, node i sends a packet to node j and node j sends a packet to node i. The packet receiver can then choose to forward or drop the packet. If it chooses to forward the packet, it consumes resources for receiving, processing and transmitting the packet. The resource consumption cost of forwarding a packet depends on a number of factors such as channel condition, file size, modulation scheme, and transmission inference. As a generic model, we use c to denote the resource consumption cost for a node to forward a packet, and use p to denote the benefit gained by a node after its packet is forwarded by another node. We assume that c and p can be generalized to the same measurement units. The benefit p includes the units of benefit gained by a node when its packet is successfully forwarded and corresponding units of resources used for forwarding the packet. Thus, $p > c$, which is reasonable since it is not rational for a user to use a device with $p \leq c$. We use p and c to represent the utility values in the game theory models for the cooperation incentive analysis. Then, the payoff for each node when both nodes are cooperative in an interaction is $(p-c)$. If one node is non-cooperative in transmitting a packet and the other is cooperative in transmitting a packet, the selfish node earns a profit of p while the cooperative node earns a profit of $-c$. This is because the selfish node's packet has been forwarded by the cooperative node, but the selfish node has not forwarded the cooperative node's packet. If both nodes are non-cooperative in forwarding packets, the payoff of this action set is $(0, 0)$ because both nodes gain no benefits and cost no resources.

4.1.1 *Non-cooperative Game for the Defenseless System*

One-interaction game. Based on the cost and benefit of forwarding a packet between a pair of nodes in an interaction, we build a one-interaction game model as shown in Table 3. The table shows the payoff matrix for each combination of different actions taken by node i and node j. From the figure, we can see that since $p > p - c$ and $-c < 0$, no matter which strategy node j chooses, I is the best strategy for node i. Since $p > c$, no matter what strategy node i takes, I is also the best strategy for node j. Therefore, action set (I_i, I_j) is the NE in this interaction.

TABLE 3: Payoff matrix for defenseless systems.

		Node j	
		Cooperative	Non-cooperative
Node i	Cooperative	(p-c, p-c)	(-c, p)
	Non-cooperative	(p, -c)	$(0,0)^*$

However, (C_i, C_j) is the optimal outcome since it leads to payoff $(p-c, p-c)$ that is much higher than $(0,0)$. In this payoff matrix, the NE is not Pareto-optimal. The nodes do not choose the Pareto-optimal action set because every node in the system is independent and self-interested and each node in a pair does not know which action the opponent will take. If one node chooses C but the other chooses I, the payoff for the cooperative node will be the lowest. Therefore, the self-interested nodes will normally choose the safest strategy over the strategy which may lead to the best outcome [26] in a one-interaction game, at risk of a high cost.

Repeated games. Since in a real system the interactions between nodes are repeated, we also analyze the cooperation incentives in repeated games. Different from the one-interaction game, a player in repeated games learns the action history of other nodes, which helps it to make subsequent choices accordingly.

TIT-For-TAT has been recognized as the most effective interaction strategy so far for repeated interaction games [26]. In TIT-For-TAT, given a pair of nodes i and j, node i is initially cooperative with node j. If node j is also cooperative, node i will continuously use strategy C. Whenever node j is non-cooperative, node i will immediately become non-cooperative. Since (C_i, C_j) is Pareto-optimal, node i will forgive node j's non-cooperative behavior and periodically check whether node j wants to be cooperative again. An iterative (i.e., repeated) defenseless system (IDS) with TIT-For-TAT can effectively encourage node cooperation in an infinite game. The fundamental reason is that the repeated games can change the Pareto-optimal strategy in payoff matrix to NE when nodes interact with each other for infinitely many times; based on the interaction history of the opponents, the players can adjust their action strategy to be the Pareto-optimal in order to maximum their benefits. For a pair of nodes i and j in an infinite game, even though node i may lose some benefit by being cooperative firstly when node j is uncooperative, its cooperation will stimulate node j to be cooperative, leading to a much higher payoff for itself. Thus, by punishment (being non-cooperative) and forgiveness (being cooperative), a node can earn a high payoff in the long term.

However, IDS with TIT-For-TAT cannot encourage node cooperation in a finite game when the number of interactions is unknown to both nodes. The basic reason is that (C_i, C_j) is Pareto-optimal but not NE in IDS. That is, the strategy I always dominates the strategy C. In a finite game, the best strategy for a node is to keep being cooperative and deviate in the last round from (C_i, C_j) if it knows when the interaction ends. For a node that wants to use the best strategy but does not know when the opponent will leave, it may suspects that the opponent will leave in the next round. Thus, the trust relationship between the interacting nodes will break down. The only resolution to this problem is to make the (C_i, C_j) action set both NE and Pareto-optimal. In this situation, each node can gain the same payoff or even higher payoff when its opponent deviates its current action. Thus, each node has no incentive to deviate from the current cooperation strategy and is not afraid of the other's deviation at any time during the interaction. One feature of repeated games is that they can change the Pareto-optimal strategy in a payoff matrix to be NE when nodes interact with each other for infinitely many times. However, since the nodes in a MANET may randomly leave or join the network, the interaction between two nodes is actually an finite game with unknown number of interactions. In this situation, TIT-For-TAT cannot provide incentives for node cooperation. Therefore, the only method to encourage node cooperation in a MANET is to make (C_i, C_j) both NE and Pareto-optimal. In this case, regardless of whether node j deviates from (C_i, C_j) or not, the payoff received by node i will not be reduced, rather it will always be increased by choosing the cooperate strategy. Therefore, in MANETs, how to provide incentives for node cooperation is essentially how to make (C_i, C_j) to be both NE and Pareto-optimal in the payoff matrix.

Also, IDS with TIT-For-TAT can only provide the best action strategy to a node to get the best benefit based on other nodes' actions, but cannot monitor, detect and punish the misbehaving nodes in an efficient way. If node j is always uncooperative, node i can only be non-cooperative to j or sometimes change to be cooperative. Node j will not be punished.

4.1.2 Cooperative Game for the Defenseless System

Suppose the players can enforce contracts on each other through a third party then form a coalition to maximize their individual utilities. Take a three-node based coalition as an example. The coalitions that node i can choose include $\{i\}, \{i,j\}, \{i,k\}$ and $\{i,j,k\}$. Since all nodes in the system are identical, they have the same strategy options as node i. From the two-node interaction matrix shown in Table 3, we get $v(i) = 0$, since $v(i)$ equals the NE payoff of player i in the non-cooperative game (Definition 3). Below, we analyze the $\{i,j\}$ coalition. When player i and player j form a coalition, they would choose the Pareto-optimal strategy (C_i, C_j) to interact with each other. Thus, the collective payoff of the $\{i,j\}$ coalition from their interaction is $(2p-2c)$. Since player k chooses NE strategy to interact with each of them, the collective payoff of the $\{i,j\}$ coalition from the interaction with k is $(-2c)$. Therefore, the collective payoff of the $\{i,j\}$ coalition is $v(i,j) = max\{2p-4c, 0\}$. Similarly, $v(i,k) = max\{2p-4c, 0\}$ and $v(i,j,k) = 6(p-c)$. Therefore, $v(i,j,k) = 6(p-c)$ is the highest utility the players can get when they form a grand coalition, in which all nodes in the system are cooperative. Since $x_i = x_j = x_k = 2(p-c) > v(i) = v(j) = v(k) = 0$ and $\sum_{i=1}^{n} x_i = v(\mathcal{N})$, according to Definition (3), the payoff allocation resulted from the grand coalition is rational.

Proposition 4.1: In the n-node cooperative game, the grand coalition with the $(C_1, C_2, ...C_n)$ action set is the only stable coalition.

Proof: Table 3 shows that the (C_i, C_j) action set leads to the Pareto-optimal payoff and (I_i, I_j) leads to the NE payoff. Therefore, in the n-node cooperative game, the action set $(C_1, C_2, ..., C_n)$ leads to a Pareto-optimal payoff. According to Definition 2, the Pareto-optimal action set $(C_1, C_2, ..., C_n)$ has the highest collective payoff. Since no other coalition can generate higher payoff, according to Definition 4, $(C_1, C_2, ...C_n)$ action set is a stable coalition. Because $v(\mathcal{S}) < \sum_{i\in\mathcal{S}} x_{i_N}$ for all $\mathcal{S} \subset \mathcal{N}$, where x_{i_N} is x_i for node i in grand coalition. Therefore, the grand coalition is the only stable coalition. □

In conclusion, in a defenseless system, if the strategies of the nodes can be enforced by a third party, being cooperative in packet forwarding is the best choice for all rational nodes.

TABLE 4: Payoff matrix for reputation systems.

		Node j	
		Cooperative	Non-cooperative
Node i	Cooperative	(p-c, p-c)	$U(C_i, I_j)$
	Non-cooperative	$U(I_i, C_j)$	(0, 0)

$$U(C_i, I_j) = \begin{cases} (-c, p) & \text{if } R_{I(j)} > T_R \\ (0,0) & \text{if } R_{I(j)} \leq T_R \end{cases} \quad (2)$$

$$U(I_i, C_j) = \begin{cases} (p, -c) & \text{if } R_{I(i)} > T_R \\ (0,0) & \text{if } R_{I(i)} \leq T_R. \end{cases} \quad (3)$$

4.2 Game Theory Model for the Reputation System

One-interaction game. Most reputation systems, regardless of whether the reputation value changes linearly or non-linearly, use a reputation threshold to distinguish selfish nodes from cooperative nodes. If some nodes are cooperative in packet forwarding, the reputation values of these nodes are increased. If some nodes are found to be uncooperative, their reputation values will be reduced. When the reputation value of a node is below threshold T_R, it will be detected as a selfish node, and its generated packets will be refused to be forwarded by other nodes [43].

We build a one-interaction game theory model for reputation systems as shown in Table 4 along with Equation (2) and (3). The model illustrates the payoff matrix for reputation systems. We can see that when the reputation value of the node is above T_R, the non-cooperative action set (I_i, I_j) with payoff $(0, 0)$ is NE, but (C_i, C_j) is Pareto-optimal. Only when reputation value of the node is below T_R does the (C_i, C_j) become both NE and Pareto-optimal. It is because when the R of a node is below the T_R all other action sets except the (C_i, C_j) action set produce $(0, 0)$ payoff. In this situation, as no individual rational node can benefit from unilateral deviation of (C_i, C_j), (C_i, C_j) becomes NE. As it can yield the maximum benefit for each node, (C_i, C_j) is also Pareto-optimal. Based on the above analysis, we can retrieve the following proposition.

Proposition 4.2: Given a pair of nodes i and j in a reputation system, if their reputation values are larger than the reputation threshold T_R, the (I_i, I_j) strategy is NE and the (C_i, C_j) strategy is Pareto-optimal. If the reputation value of either node in the pair is less than T_R, the (C_i, C_j) strategy is both NE and Pareto-optimal.

Proposition 4.3: The cooperation incentive strategy provided by reputation systems will result in a situation where node reputation values are around the reputation threshold.

Proof: As the payoff matrix in Table 4 shows, when the reputation value of a node is above T_R, (I_i, I_j) is the NE. Therefore, the node has a high incentive to be non-cooperative. Then, its reputation value continues to decrease as

$$\lim_{R \to T_R} R = T_R + \sigma,$$

where σ ($\sigma \to 0$) is a variable. When a node's reputation value is below T_R, (C_i, C_j) is the NE. Hence, the node will cooperate to increase its reputation value. The value continues to increase as

$$\lim_{R \to T_R} R = T_R - \sigma.$$

Consequently, the reputation values of nodes converge to T_R and may fluctuate around it. □

Proposition 4.3 implies that reputation systems cannot provide incentives to encourage nodes to be more cooperative when their reputations are close to and above T_R. It can only encourage nodes not to misbehave. Therefore, nodes keep their reputation values close to and above the reputation threshold. If a node cleverly manipulates this policy by accepting some transmission requests to keep its reputation just above the threshold, the performance of the system is impeded due to packet drops.

We use R to denote the current reputation value of a node. We assume that of the first n_r packets that a node has received, it drops n_d packets and forwards n_r-n_d packets. We use ΔR^+ to denote the *r*eputation increase rate that is the increased reputation value for a cooperation action, and use ΔR^- to denote the *r*eputation decrease rate that is the decreased reputation value for a non-cooperation action.

Proposition 4.4: If a selfish node manages to keep its reputation value closely above the threshold, the upper bound of the packet drop rate P_d is

$$P_d \geq \frac{\Delta R^+}{\Delta R^+ + \Delta R^-}.$$

Proof: Suppose that in the first n_r interactions, a selfish node can choose the I strategy for n_d interactions before its reputation value falls below T_R. Therefore,

$$n_d \cdot \Delta R^- - (n_r - n_d) \cdot \Delta R^+ \geq R - T_R,$$

$$\Rightarrow P_d = \frac{n_d}{n_r} \geq \frac{\frac{R - T_R}{n_r} + \Delta R^+}{\Delta R^+ + \Delta R^-},$$

$$\Rightarrow \lim_{n_r \to \infty} P_d \geq \lim_{n_r \to \infty} \frac{\frac{R - T_R}{n_r} + \Delta R^+}{\Delta R^+ + \Delta R^-} = \frac{\Delta R^+}{\Delta R^+ + \Delta R^-}. \quad (4)$$

□

Proposition 4.4 implies two points. First, in a MANET with a reputation system, the packet drop rate of rational nodes is determined by the reputation increase rate for a cooperative behavior and the decrease rate for a non-cooperative behavior. Second, the packet drop rate is irrelevant to the threshold value. Therefore, in order to reduce the packet drop rate, a reputation system should have a low reputation increase rate and a high reputation decrease rate.

Propositions 4.3 and 4.4 show that the reputation system can only provide incentives to encourage nodes to keep their reputation values just above the reputation threshold rather than encouraging them to be more cooperative in packet forwarding. Since as long as a node has a R just higher than the threshold it can always be served in the packet transmission, the reputation system treats all the nodes whose Rs are above reputation threshold the same regardless of their different cooperative levels. Therefore, a reputation system needs to have a complementary method to encourage all nodes to be highly cooperative to each other and to differentially reward nodes in different altruistic levels.

Repeated games. In the repeated games of reputation systems, for a pair of nodes i and j the Pareto-optimal action set alternates between (C_i, C_j) and (I_i, I_j) because the reputation values of the nodes fluctuate near T_R. Since (C_i, C_j) cannot always be the NE, the nodes will not always choose (C_i, C_j). Therefore, the reputation systems cannot always encourage nodes to be cooperative in repeated games.

4.3 Game Theory Model for the Price-based System

One-interaction game. A price-based system uses virtual credits to encourage node cooperation in the system. If a node does not have enough credits for packet forwarding, all of its transmission requests will be rejected. In addition to the transmission cost c and transmission benefit p, we introduce the additional reward m_r and price m_p for service transactions set in the price-based system. m_r denotes the packet forwarding reward in credits for one cooperative forwarding behavior, and m_p denotes the packet forwarding price in credits for one forwarding service. A node can use earned reward credits to buy resources for packet forwarding service. We assume that m_r and m_p use the same measurement units as c and p. We do not specifically incorporate m_r and m_p into p and c in the utility function in order to study how m_r and m_p in the price-based system affect node cooperation incentives. In an interaction between a pair of nodes i and j with the strategy set (C_i, I_j), node j drops node i's packet and node i forwards node j's packet. Although the selfish node j can save the transmission cost c by refusing to forward node i's packet, it must still pay m_p for node i's forwarding service. On the other hand, although the cooperative node i loses packet transmission payoff p as its packet has been dropped by node j, it can still earn payoff m_r due to its cooperative behavior in forwarding node j's packet. Based on the packet forwarding benefit, cost, price and reward, we build the one-interaction payoff matrix for a pair of interacting nodes in a price-based system, as shown in Table 5, where $\triangle m$ = m_p-m_r. In one interaction, both nodes are cooperative in forwarding each other's packet. For the (C_i, C_j) strategy set, since both nodes are cooperative in the packet routing, they both earn payoff p and spend cost c for packet transmission. Also, since each node should pay m_p for the packet forwarding by the other and earn m_r for its own cooperative behavior, the payoff for (C_i, C_j) is (p-c-m_p-m_r, p-c-m_p-m_r). Similarly, the payoff for (C_i, I_j) and (I_i, C_j) can be calculated as shown in Equations (5) and (6). For example, in the (C_i, I_j) action set, since node i forwards node j's packets but does not get its packet forwarded by node j, the payoff for node i is m_r-c. Meanwhile, since node j's packets are forwarded by node i, node j should pay credit for the forwarding. Therefore, the payoff for node j is p-m_p. V_i and V_j denote the account value (i.e., credit amount) of node i and j respectively. When $V_i < 0$ or $V_j < 0$, there is no interaction between the nodes. Therefore, the payoff is (0, 0).

Proposition 4.5: Price-based systems can make (C_i, C_j) NE iff the transmission cost c, transmission benefit p, packet forwarding price m_p and packet forwarding reward m_r satisfy $p > m_p$ & $m_r > c$.

Proof: In order to change the (C_i, C_j) action set to the NE, (C_i, I_j), (I_i, C_j) and (I_i, I_j) should not be the NE. That is ,

$$\begin{cases} p - c - m_p + m_r > p - m_p \\ p - c - m_p + m_r > -c + m_r \\ -c + m_r > 0 \end{cases}$$
$$\Rightarrow p > m_p \ \& \ m_r > c.$$

□

Proposition 4.6: In a price-based system, the (C_i, C_j) is Pareto Optimal iff $p > m_p$ & $m_r > c$.

Proof: Proposition 4.5 shows that iff $p > m_p$ & $m_r > c$, (C_i, C_j) is the NE. Also, (C_i, C_j) is the best outcome in the system. Therefore, (C_i, C_j) is Pareto Optimal. □

Proposition 4.6 indicates that the price-based systems can provide effective cooperation incentives to the nodes.

Proposition 4.7: Suppose a selfish node has dropped n_d packets and forwarded $n_r - n_d$ packets from its received n_r packets and that it has enough credits to pay the forwarding services for its generated n_g packets. If the selfish node manages to keep its credit amount above zero, the lower bound of its packet drop rate P_d is

TABLE 5: Payoff matrix for price-based systems.

		Node j	
		Cooperative	Non-cooperative
Node i	Cooperative	(p-c-$\triangle m$, p-c-$\triangle m$)	$U(C_i, I_j)$
	Non-cooperative	$U(I_i, C_j)$	(0, 0)

$$U(C_i, I_j) = \begin{cases} (-c + m_r, p - m_p) & \text{if } V_j > 0 \\ (0, 0) & \text{if } V_j < 0 \end{cases} \tag{5}$$

$$U(I_i, C_j) = \begin{cases} (p - m_p, -c + m_r) & \text{if } V_i > 0 \\ (0, 0) & \text{if } V_i < 0 \end{cases} \tag{6}$$

$$P_d \geq \begin{cases} 1 - \alpha \cdot \frac{m_p}{m_r}, & \text{if } \lim\limits_{n_r \to \infty} \dfrac{V}{n_r} = 0, \ < a > \\ 1 - \alpha \cdot \frac{m_p}{m_r} + \frac{\beta}{m_r}, & \text{if } \lim\limits_{n_r \to \infty, V \to \infty} \dfrac{V}{n_r} = \beta, \ < b > \end{cases} \tag{7}$$

where $\alpha = \frac{n_g}{n_r}$ and V is the account value of the node.

Proof: The selfish node has dropped n_d packets and forwarded $n_r - n_d$ packets from its received n_r packets, and it has enough credits to pay the forwarding services for its generated n_g packets. Therefore,

$$(n_r - n_d) \cdot m_r + V - n_g \cdot m_p \leq 0$$
$$\Rightarrow P_d = \frac{n_d}{n_r} \geq \frac{n_r \cdot m_r + V - n_g \cdot m_p}{n_r \cdot m_r}$$
$$\Rightarrow \lim_{n_r \to \infty} P_d \geq \lim_{n_r \to \infty} \frac{n_r \cdot m_r + V - n_g \cdot m_p}{n_r \cdot m_r}$$
$$= \begin{cases} 1 - \alpha \cdot \frac{m_p}{m_r}, & \text{if } \lim\limits_{n_r \to \infty} \dfrac{V}{n_r} = 0 \\ 1 - \alpha \cdot \frac{m_p}{m_r} + \frac{\beta}{m_r}, & \text{if } \lim\limits_{n_r \to \infty, V \to \infty} \dfrac{V}{n_r} = \beta. \end{cases}$$

□

Price-based systems detect selfish nodes by checking node account value. Nodes with account values no more than zero are regarded as selfish nodes. Proposition 4.7 implies that the price-based systems cannot detect some selfish nodes since they can drop packets while still keeping their account value above zero. Specifically, the systems cannot detect selfish nodes in three cases. First, the price-based system cannot detect selfish and wealthy nodes. Such a node has a considerable amount of credits (i.e., $V \rightarrow \infty$), which may lead to a large β and subsequently a large drop rate P_d according to Equation (7)<b>. Due to its extremely large V, the selfish node is not easily to be detected. Second, the price-based system cannot punish the selfish nodes in a high-traffic region where a node receives more packets than it generates (i.e., $n_g < n_r$). This situation leads to small α, which subsequently produces a large packet drop rate P_d according to Equation (7). Since the node consumes much fewer credits, it cannot be easily detected. On the other hand, the price-based system is unfair for nodes in low-traffic regions. Such a node may not be able to accumulate enough credits to buy forwarding services for its own packets despite it is a cooperative node. Third, when the packet forwarding price is much smaller than forwarding reward (i.e., $m_p \ll m_r$), P_d becomes very large according to Equation (7). Since a node's single cooperative behavior enables it to buy several forwarding services, it can easily keep its account value above zero.

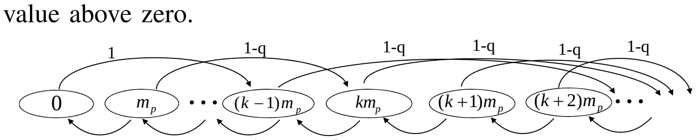

Fig. 2: The Markov chain of the account states of a node when $k \geq \alpha$.

Proposition 4.8: Given a price-based system with node packet drop probability q when its $V > 0$, its average packet drop probability is:

$$P_d = \begin{cases} q, & \text{if } k \geq \alpha \\ \frac{k \cdot q}{k \cdot q + 1}, & \text{if } k < \alpha, \end{cases}$$

where $k = \frac{m_r}{m_p}$.

Proof: The process of account value change can be modeled as a Markov chain as shown in Figure 2 and Figure 3. Each cycle denotes the account state of a node with its account value. An arrow with a label between two states denotes the state transferring probability from one state to the other. We use s to denote a node's account state, and $P_s(s)$ to denote the probability that the node in state s.

Case 1 ($k \geq \alpha$): Figure 2 shows the Markov chain of the account states of a node when $k \geq \alpha$ (i.e., $m_r \cdot n_r \geq m_p \cdot n_g$). As shown by the right arrows, when the node forwards a packet, it gains m_r-m_p=$(k-1)m_p$ credits given $n_g = n_r$. As shown by the left arrows, when the node drops a packet, it pays m_p credits for the forwarding service. When $s = 0$, the node has only one action choice – to be cooperative in order to buy service for its own packets. Therefore, the node jumps from state 0 to state $(k-1)m_p$ with probability 1. For other states, since $m_r \cdot n_r \geq m_p \cdot n_g$, i.e., the node has enough credits to pay its packet forwarding service, it can choose to drop or forward its received packets with probabilities q and $1-q$, respectively. Since the states in the Markov chain are infinite, i.e., $n_s \to \infty$ where n_s is the number of all states in the Markov chain, the probability that a node stays in state 0 is $\lim_{n_s \to \infty} P_s(0) = 0$. Because a node drops a packet with probability q only when $s \neq 0$, its average packet drop probability is

$$P_d = (1 - \lim_{n_s \to \infty} P_s(0)) \cdot q = q. \quad (8)$$

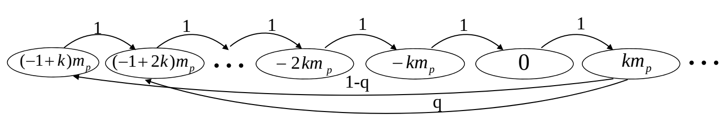

Fig. 3: The Markov chain of the account states of a node when $k < \alpha$.

Case 2 ($k<\alpha$): Figure 3 shows the Markov chain of the account states of a node when $k<\alpha$ (i.e., $m_r \cdot n_r < m_p \cdot n_g$). It shows that states $\{(-1+k)m_p, (-1+2k)m_p, ..., -2km_p, -km_p, 0, km_p\}$ form a closed cycle. Thus, these states are called absorbing states [44] and the whole Markov chain can be reduced to the absorbing states because a node cannot leave the closed cycle once it stays in one of the absorbing states. As the left arrows show, when a node stays in the state km_p and moves to state $(-1+k)m_p$ when it loses m_p credits by dropping a packet with probability q, it moves to state $(-1+2k)m_p$ when it earns $(-1+k)m_p$ credits by forwarding a packet with probability $(1-q)$. In other absorbing states, since its account value is not positive, the node has only one action choice – to be cooperative to increase its account value. Thus, as the right arrows show, a node forwards the packets with probability 1 in these states. Based on the global balance equations [44], we can get

$$\begin{cases} P_s((-1+k)m_p) = q \cdot P_s(km_p) \\ P_s((-1+2k)m_p) = (1-q) \cdot P_s(km_p) + P_s((-1+k)m_p) \\ P_s((-1+3k)m_p) = P_s((-1+2k)m_p) = ... = P_s(0) = P_s(km_p) \\ P_s(km_p) + P_s(0) + ... + P_s((-1+2k)m_p) + P_s((-1+k)m_p) = 1 \end{cases}$$

$$\Rightarrow P_s(km_p) = \frac{1}{q + \frac{1}{k}} = \frac{k}{k \cdot q + 1}.$$

Since the node will drop packets only in state km_p as shown in the Markov chain, its packet drop rate is $P_d = \frac{k \cdot q}{k \cdot q + 1}$. □

Repeated games. In the price-based system, according to Proposition 4.5, when $p>m_p$ & $m_r>c$, the (C_i, C_j) strategy is both NE and Pareto-optimal. Therefore, in the repeated cooperation game with finitely many interactions, all nodes will choose (C_i, C_j) stably and continuously. Therefore, in repeated games with a price-based system, (C_i, C_j) is still the NE and Pareto-optimal.

4.4 The Design and Game Theory Model for the Integrated System

One-interaction game. A system that can effectively encourage the cooperation of nodes should have two features: (1) strong incentives to encourage nodes to be cooperative and (2) quick, effective detection of selfish nodes for punishment. The reputation system uses a reputation threshold to distinguish between selfish and cooperative nodes. However, it cannot provide strong incentives for cooperation. The price-based systems can provide strong incentives for node cooperation, but fail to provide an effective mechanism for misbehaving node detection. We propose an integrated system combining the reputation system and the price-based system. By integrating the misbehavior detection mechanism of the reputation system and the cooperation incentive mechanism of the price-based system, the integrated system can overcome the drawbacks of either individual system.

In addition to the strategies of the individual reputation system and the price-based system, the integrated system has additional strategies. Node i's packet forwarding price is determined from its reputation value by $m_p = \frac{a}{(R_i)^b}$, where a and b are constant parameters and b is used to control the increase/decrease speed of m_p based on R_i. Thus, a node with a higher reputation value needs to pay less for the packet forwarding service compared to a low reputation node. The reputation value R and account value V of each node are still used to distinguish selfish nodes and cooperative nodes. Nodes $V < 0$ or $R < T_R$ are regarded as a selfish node and their transmission requests will be rejected by other nodes.

Compared to the reputation system, the integrated system can effectively prevent some selfish nodes from keeping their reputation values just above the threshold value because the selfish nodes need to pay more credits for packet forwarding, which will deplete their credit account shortly. Also, the system avoids discouraging the cooperation of high-reputed nodes, since a higher reputed node can pay less for packet forwarding. Compared to the price-based system, the integrated system encourages wealthy nodes to always be cooperative in packet forwarding because these nodes try to gain a higher reputation for a lower service price. The integrated system can also detect selfish and wealthy nodes in a high traffic region by reputation values and encourage these nodes to be cooperative. If a node's reputation value is below the threshold ($R < T_R$) its transmission requests will be rejected by other nodes, regardless of its wealth. Therefore, the nodes stay cooperative for packet forwarding. Moreover, even in a low traffic region where a node has few chances to earn credits, a high-reputed node can still have its packets forwarded because it pays a low price.

A system design of such an integrated system is introduced in [45]. It selects trustable nodes in a MANET to form a distributed hash table (DHT) for efficient reputation and price management for all nodes. For the details of the system design,

TABLE 6: Payoff matrix for the integrated system.

		Node j	
		Cooperative	Non-cooperative
Node i	Cooperative	$U(C_i, C_j)$	$U(C_i, I_j)$
	Non-cooperative	$U(I_i, C_j)$	(0, 0)

$$U(C_i, C_j) = (p - c + (m_r - \frac{m_p}{R_i}), p - c + (m_r - \frac{m_p}{R_j})). \tag{9}$$

$$U(C_i, I_j) = \begin{cases} (-c + m_r, p - \frac{m_p}{R_j}) & \text{if } V_j > 0 \ \& \ R_{I(j)} > T_R \\ (0, 0) & \text{if } V_j \leq 0 \ \| \ R_{I(i)} \leq T_R. \end{cases} \tag{10}$$

$$U(I_i, C_j) = \begin{cases} (p - \frac{m_p}{R_i}, -c + m_r) & \text{if } V_i > 0 \ \& \ R_{I(i)} > T_R \\ (0, 0) & \text{if } V_i \leq 0 \ \| \ R_{I(i)} \leq T_R. \end{cases} \tag{11}$$

please refer to [45]. In this paper, we analyze the cooperation incentives of the integrated system. We build a game theory model for the integrated system as shown in Table 6. The table shows a one-interaction payoff matrix for a pair of nodes in the integrated system.

Proposition 4.9: In the integrated system, (C_i, C_j) is both NE and Pareto-optimal if transmission cost c, current reputation value R_j and R_i, and packet forwarding reward m_r satisfy $m_r > c$ & $p > \frac{m_p}{R_i}$ & $p > \frac{m_p}{R_j}$.

Proof: In order to make the (C_i, C_j) strategy to the NE and Pareto-optimal, the payoff values of the integrated system should satisfy

$$\begin{cases} p - c + m_r - \frac{m_p}{R_i} > p - \frac{m_p}{R_i} \\ p - c + m_r - \frac{m_p}{R_j} > p - \frac{m_p}{R_j} \\ p - \frac{m_p}{R_i} > 0 \\ p - \frac{m_p}{R_j} > 0 \end{cases}$$

$$\Rightarrow m_r > c \ \& \ p > \frac{m_p}{R_i} \ \& \ p > \frac{m_p}{R_j}.$$

□

Equations (9), (10) and (11) represent the payoffs of $U(C_i, C_j)$, $U(C_i, I_j)$, and $U(I_i, C_j)$. When the reputation value of a node is lower than threshold T_R, the node is regarded as a selfish node and punished. Therefore, node i needs to ensure $R_i > T_R$. That is, $p > \frac{m_p}{R_T} \rightarrow p > \frac{m_p}{R_i}$. As a result, the (C_i, C_j) strategy is always the NE and Pareto-optimal iff $m_r > c$ & $p > \frac{m_p}{R_T}$. Equations (9), (10) and (11) show that a high reputation value leads to a high payoff for cooperative behavior. Therefore, the integrated system can provide higher incentives than the price-based system for cooperative behavior, because the payoff earned by a cooperative behavior in the integrated system is higher than that in the price-based system.

In addition to providing higher node cooperation incentives, the integrated system can also effectively detect selfish nodes by monitoring node reputation and account value. A selfish node is detected when its $R < T_R$ or $V < 0$. We discuss the performance of the integrated system on detecting wealthy and silly selfish nodes, and wealthy and clever selfish nodes. A wealthy and silly selfish node initially has a large amount of credits and keeps dropping packets regardless of whether its reputation value is below the reputation threshold T_R or not. A wealthy and clever selfish node initially has a large amount of credits and drops packets, but it keeps its reputation value above T_R. The wealthy and silly selfish node cannot be detected by the price-based system in a short time, but can be detected by the reputation component in the integrated system quickly when its reputation falls below T_R. Similarly, the selfish behaviors of the nodes with small packet forwarding requests cannot be detected by the price-based system, but can be detected by the integrated systems when its reputation falls below T_R. A wealthy and clever selfish node can avoid being detected in the reputation system. In the integrated system, the node's reputation drops quickly, and then its credits are quickly used up as it always pays a very high price for packet forwarding services based on the price policy in the integrated system. Finally, it is detected upon account starvation.

Repeated games. In the one-interaction game of the integrated system, the (C_i, C_j) action set is both NE and Pareto-optimal iff $m_r > c$ & $p > c$. Thus, for a repeated cooperation game, each interacting node has no incentive to deviate from the (C_i, C_j) action set. Even if some nodes deviate from (C_i, C_j), the remaining nodes' payoffs will not be reduced because (C_i, C_j) is the NE. Unlike IDS, nodes in the integrated system can safely choose the cooperation strategy all the time. Hence a MANET with the integrated system can always provide incentives for the nodes' cooperation. We define the *relative success rate* of a strategy as the rate of the total payoffs of nodes employing the strategy to the total payoffs of all nodes in the system. We also define a *round* as a sequence of system interactions in which each pair of nodes have an interaction with each other. We use $f_{C/I}[t]$ to denote the percent of nodes using strategy C or I in round t over all nodes.

Proposition 4.10: The percent of the nodes adopting the cooperation strategy is

$$f_C[t] = \frac{f_C[0]}{f_C[0] + f_I[0](\frac{U_i(I_i,C_j)+U_i(I_i,I_j)}{U_i(C_i,C_j)+U_i(C_i,I_j)})^{(t-1)}}.$$

Proof: According to evolutionary game theory [26] and the linearity property of expectation [44], we can determine that the percent of nodes adopting the cooperation strategy scales with the relative success rate of the cooperation strategy. According to the definition of the relative success rate, we get

$$\frac{f_C[t]}{f_I[t]} = \frac{f_C[t-1]}{f_I[t-1]} \cdot \frac{U_i(C_i, C_j) + U_i(C_i, I_j)}{U_i(I_i, C_j) + U_i(I_i, I_j)}.$$

$$\Rightarrow \frac{f_C[t]}{f_I[t]} = (\frac{U_i(C_i, C_j) + U_i(C_i, I_j)}{U_i(I_i, C_j) + U_i(I_i, I_j)})^t \frac{f_C[0]}{f_I[0]}$$

Since $f_I[t] = 1 - f_C[t]$, we get

$$f_C[t] = \frac{f_C[0]}{f_C[0] + f_I[0](\frac{U_i(I_i,C_j)+U_i(I_i,I_j)}{U_i(C_i,C_j)+U_i(C_i,I_j)})^{(t)}} \tag{12}$$

□

Interestingly, in the repeated games, if a selfish node becomes cooperative in the next round $(t+1)$, the decrease of the packet forwarding price is

$$\frac{m_p}{R(t+1)} - \frac{m_p}{R(t)} = \frac{(R(t+1) - R(t)) \cdot m_p}{R(t) \cdot R(t+1)}, \tag{13}$$

where $R(t)$ denotes the node's reputation at time t. That is, whether a node is high-reputed or low-reputed, the price for its packet forwarding requests always decreases in the next round if it is cooperative, and the price always increases in the next round if it drops packets. Therefore, the price policy in the integrated system can encourage both high-reputed and low-reputed nodes to be cooperative. Also, as Formula (13) shows that lower reputed nodes have more price reduced if they are cooperative in the next round, the lower reputed nodes receive higher incentives to be cooperative.

5 Performance Evaluation

5.1 Comparison of Incentives of Different Systems

In this section, we evaluate the effectiveness of the incentives in the defenseless system, reputation system, price-based system, and integrated system in a repeated game, in which the nodes

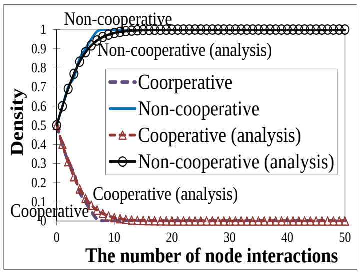

Fig. 4: The defenseless system.

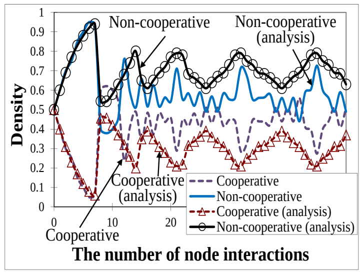

Fig. 5: The reputation system.

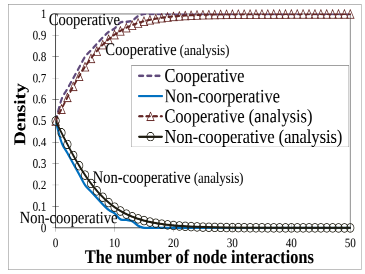

Fig. 6: The price-based system.

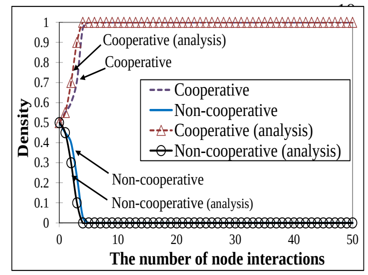

Fig. 7: The integrated system.

can change their interaction strategies adaptively. Nodes always choose the strategy that maximizes their benefit. The purpose of this experiment is to show whether the integrated system can improve the performance of cooperation of the existing incentive systems. We developed a simulator based on the Monte Carlo method [46] to randomly pair up two nodes for interaction in order to statistically test the evolution of the interaction strategies adopted by nodes over the rounds. At every game round, each randomly formed pair of nodes have an interaction. That is, the nodes send a packet to each other, and drop or forward their received packet from the other. In the simulation, 100 nodes are independently and identically distributed in the system. 50 nodes are cooperative and 50 nodes are non-cooperative at the start. The number of players using a strategy in the next round was set to the product of the *relative success rate* of this strategy in the previous game round and the node population.

In the test, the packet forwarding reward is $m_r = 2$ units, the packet forwarding price is $m_p = 1$ unit, the transmission benefit is $p = 4$ units, and the transmission cost is $c = 2$ units. The initial reputation value for each node is 1.0 and the reputation threshold is $T_R = 0.3$. The maximum reputation value is 1.0. Every time a node helps to forward a packet, its reputation value is increased by 0.1. Otherwise, its reputation value is reduced by 0.1. These setups do not affect the relative performance between different systems. Most existing reputation systems use a threshold to evaluate node trustworthiness, though they differ in reputation calculation. Our objective is to show the influence of the threshold strategy on the effectiveness of its cooperation incentive, which is not affected by reputation calculation mechanisms. Therefore, our experimental results on the reputation system can represent those of all the reputation systems with the threshold strategy. We define the density of the (non-)cooperative nodes as the percent of the nodes employing the (non-)cooperative strategy among all the nodes. In each figure, the analytical results calculated by Formula (12) are included based on the simulation parameters with individual payoff matrix.

Figure 4 shows the change of the density of cooperative and non-cooperative nodes in a defenseless MANET. The figure shows that after several interactions, the selfish nodes dominate the population of the system. It is because in the defenseless system, the non-cooperative strategy is the NE, although not Pareto-optimal. Therefore, the nodes using the non-cooperative strategy can receive much more payoff than the nodes using the cooperative strategy. Since the number of nodes using a strategy depends on the relative success rate of the nodes using this strategy in the last round, the number of players using cooperative strategy decreases sharply. Therefore, the defenseless MANET without any cooperation incentive or misbehavior detection mechanism will finally collapse. Also, from the figure we can see that the simulation results are consistent with the analytical results in Proposition 4.10.

Figure 5 shows the change of the density of cooperative and non-cooperative nodes in a MANET with the reputation system. The figure indicates that in the first 8-9 interactions, the density of non-cooperative nodes increases and the density of cooperative nodes decreases. It is because during these game rounds, (I_i, I_j) is the NE continually. The non-cooperative strategy can bring much more payoff than the cooperative behavior, which results in a dramatic decrease of the population of the cooperative nodes. However, when the reputation values of some nodes falls below the reputation threshold, the payoffs of (I_i, I_j) and (C_i, I_j) and (I_i, C_j) turn to (0, 0), according to Table 4. Therefore, the cooperative strategy is the NE and Pareto-optimal. At this time, since the cooperative action can generate much higher payoff than the non-cooperative action, the population of cooperative nodes increases. However, after the reputation values of the nodes increase above the threshold, they will choose (I_i, I_j) again. Then, the density of the selfish nodes increases. The figure also shows that the percentages of cooperative nodes and selfish nodes finally approach a constant value, which is the reputation threshold value. This result closely matches Proposition 4.3, which indicates that the strongest incentive provided by reputation systems will results in a situation where nodes keep their reputation close and above the reputation threshold. The simulation results are in line with our analytical result in Proposition 4.10.

Figure 6 shows the change of the density of cooperative and non-cooperative nodes in a MANET with the price-based system. The figure shows that cooperative nodes eventually dominate the population of the nodes in the system because nodes are rewarded for providing packet forwarding services to others and charged for receiving packet forwarding service from others. It increases the payoff of the cooperation strategy and decreases the payoff of the non-cooperation strategy. Therefore, (C_i, C_j) is the NE, so the density of the cooperative nodes increases sharply and that of the selfish nodes decreases rapidly. The results are in line with Proposition 4.5, Proposition 4.6 and Proposition 4.10. Figure 7 shows the change of the density of cooperative and non-cooperative nodes in a MANET with the integrated system. The integrated system can distinguish the service quality of nodes based on their reputation values which reflect their cooperation levels. In the integrated system, a lower-reputed node receives lower payoff, while a higher-reputed node receives higher payoff for providing service. Because the cooperation strategy becomes both NE and Pareto-optimal, a cooperative node earns a much higher payoff than a non-cooperative node. Therefore, the number of cooperative nodes is more than the number of selfish nodes. Meanwhile, as the number of game rounds grows, the reputations of the nodes increase. Consequently, the payoff for (C_i, C_j) also increases. That is why the number of selfish nodes in the integrated system drops much faster than in the price-based system. Therefore, the integrated system can provide higher incentives

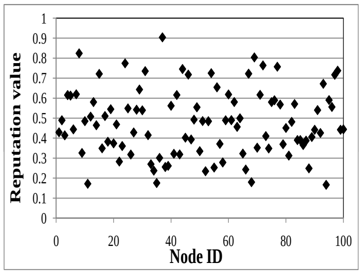

Fig. 8: Distribution of initial reputation values.

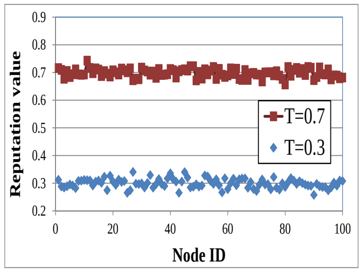

Fig. 9: Converged reputation values in the reputation system.

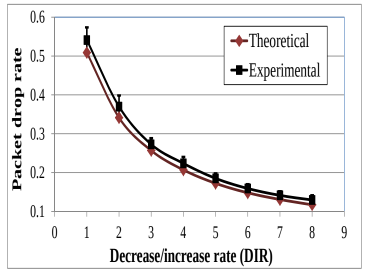

Fig. 10: Packet drop rate vs. DIR.

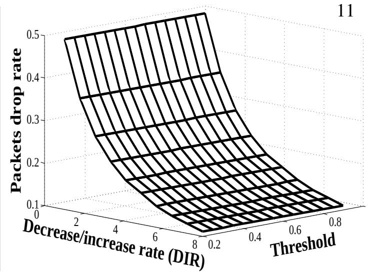

Fig. 11: Packet drop rate vs. DIR and reputation threshold.

to encourage the cooperation of the nodes than other systems. The simulation results are consistent with our analytical result in Proposition 4.10.

5.2 Evaluation of the Reputation System

The Monte Carlo method cannot simulate a network scenario. We further investigate the effectiveness of these systems on selfish node detection in a MANET scenario based on NS-2 [47]. In the simulated MANET, 100 nodes are independent and identically distributed (i.i.d) in a 500m$\times$ 500m square area. The transmission range of each node is 250m. Each node randomly selects a position in the area and moves to the position at a speed randomly selected within $[10-20]$m/s. In the test, we first assign each node a reputation value randomly chosen from $[0,1]$. We then randomly select 10 source nodes every second. Each of the 10 nodes sends a packet to a randomly chosen neighbor. If the neighbor's reputation value is lower than T_R, it drops the packet and its reputation value is decreased by 0.1. Otherwise, the neighbor forwards the packet, and subsequently its reputation value is increased by 0.1. The simulation time for each test is 10000s.

Figure 8 shows the initial reputation values of all nodes in the system. The reputation values are spread over the range $[0,1]$. Since the nodes are punished only when their reputation values fall below T_R, they can randomly drop packets in order to save energy when their reputation values are above the threshold. When their reputation values are below T_R, they are cooperative in packet forwarding to increase their reputation values above T_R to avoid being punished. We test how reputation value changes with different values of T_R as 0.3 and 0.7 respectively. Figure 9 shows the final reputation values of all nodes in the system after 10000s. We can see that the reputation values of all nodes converge to the reputation threshold in each case. The result is consistent with Figure 5 and Proposition 4.3. By keeping its reputation value just above the threshold, a node can be uncooperative while still avoiding being punished. Therefore, the reputation system cannot provide highly effective incentives to encourage the nodes to be cooperative.

We use the *decrease/increase rate* (DIR) to denote the ratio of the reputation decrease rate to the reputation increase rate. The packet drop rate is the total number of dropped packets divided by the total number of received packets. In this experiment, we vary DIR from 1 to 8 with 1 increase in each step, and test the packet drop rate for each DIR in a 10000s simulation. Specifically, the reputation increase rate is 0.1, and the reputation decrease rate is ranged from 0.1 to 0.8 with 0.1 increase in each step. Figure 10 shows the experimental and theoretical results of packet drop rate versus DIR. The theoretical results are calculated according to Formula 4 in Proposition 4.4. The figure shows that as DIR increases, the packet drop rate decreases. A higher DIR means a node's reputation value decrease for its uncooperative behavior is greater than a node's reputation increase for its cooperative behavior. Thus, with a higher DIR, a node needs to be cooperative for DIR times in order to make up its reputation value decrease due to one uncooperative action. Since a higher DIR stimulates nodes to be cooperative, the packet drop rate decreases as DIR increases. The measurement results are approximately in line with the theoretical results, with error bar within only 0.05.

Figure 11 further shows the packet drop rate versus DIR and reputation threshold. The figure exhibits the same phenomenon as Figure 10 in the relationship between the packet drop rate and DIR. It is very intriguing to see that the reputation threshold does not affect the packet drop rate and that the rate is only affected by DIR. As shown in Figure 9, the nodes' reputation values finally converge to the threshold regardless of the threshold value. Some nodes keep their reputations just above the threshold. If a node drops a packet, its reputation value falls below the threshold, and it needs to be cooperative for DIR interactions to raise its reputation value above the reputation threshold. That is why the packet drop rate is only determined by DIR. Higher DIR leads to lower drop rate and vice versa. This result is very intriguing and consistent with Proposition 4.4.

In a nutshell, reputation systems cannot effectively encourage the nodes to be cooperative in the system, but only to keep their reputation values around the reputation threshold. In order to reduce the packet drop rate, the reputation decrease rate should be higher than the reputation increase rate.

5.3 Evaluation of the Price-based System

In this section, we evaluate how a price-based system encourages the cooperation of the nodes in the system. The simulation setup and scenario are the same as in Section 5.2, but instead of rating node reputation values, a node pays credits to the forwarding nodes for their services. Since this is a generic price-based system, we do not consider the details of how nodes pay for the price of packet forwarding. We assign 1000 credits to each node initially. A packet receiver drops the packet if its account value is above zero. The forwarding price is 50 credits. We use RRP to denote the Ratio of packet forwarding Reward to forwarding Price and test the packet drop rate with different RRPs. Specifically, we initially set the forwarding reward to 25 credits, and then increase it from 50 credits to 350 credits with a 50 credit increase in each step. The entire simulation time for each RRP value is 10000s.

Figure 12 shows the experimental and theoretical results of packet drop rate versus RRP. The theoretical results are calculated based on Equation (7)<a> in Proposition 4.7. The figure demonstrates that the packet drop rate grows as RRP increases. This is because when the reward is larger than the price, a selfish node can drop more packets and forward fewer packets while still keeping its account value above zero. Thus, a higher RRP leads to more dropped packets by selfish nodes. The measured results

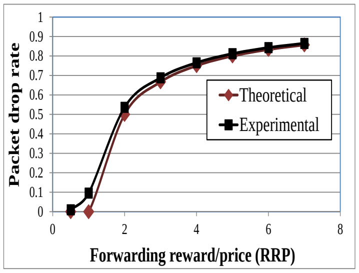

Fig. 12: Packet drop rate vs. RRP.

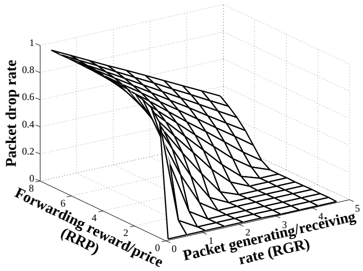

Fig. 13: Packet drop rate vs. RRP and RGR.

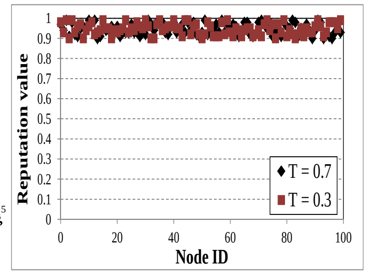

Fig. 14: Converged reputation value in the integrated system.

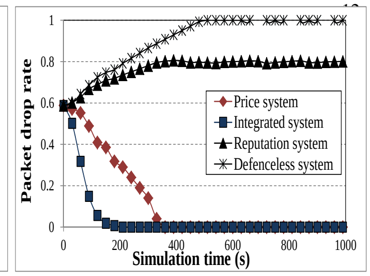

Fig. 15: Packet drop rate over time.

are closely consistent to the theoretical results in Proposition 4.7. In order to restrict the packet drop rate of selfish nodes, the forwarding reward should be less than the forwarding price in a price-based system.

Packet generating and receiving rates are the number of bits per second a node has generated to send out and received to forward, respectively. We use RGR to denote the Ratio of packet Generating rate to the packet Receiving rate of a node. In this experiment, a randomly chosen node i generates and sends packets to m ($m \in [1,5]$) randomly chosen neighbors at the speed of $2k/s$ for each packet stream. We also randomly choose a node i's neighbor j and let it generate and send packets to node i at the speed of $2k/s$. The size of one packet is $2k$. Thus, node i's RGR is changed from 1 to 5 with 1 in each step.

Figure 13 plots node i's packet drop rate versus its RGR and RRP. The figure shows that as RGR increases, the packet drop rate decreases sharply. Higher RGR means that a node's packet generating rate is faster than its packet receiving rate. That is, the credits needed to pay for the forwarding services are more than the credits that can be earned. Insufficient credits stimulate the node to be cooperative. The figure also shows that a larger RGR and smaller RRP make the packet drop rate decrease faster. Recall that a small RRP and a large RGR respectively impose significant effort on reducing the packet drop rate. Under the impact of both factors, the packet drop rate is reduced sharply. Therefore, a node with a high packet generating rate is unlikely to be uncooperative in a MANET using a price-based system. However, the nodes with a low packet generating rate are likely to drop packets since they do not need to earn credits for their packet forwarding requests.

5.4 Evaluation of the Integrated System

In this section, we demonstrate how the integrated system can improve the effectiveness of both reputation systems and price-based systems in cooperation encouragement and selfish node detection. In this experiment, both the reputation increase rate and decrease rate were set to 0.1. The initial reputation value of each node was set to 1. Each node was initially assigned 1000 credits, unless otherwise specified. At every second, ten source nodes are randomly selected, each of which sends a packet to a randomly chosen neighbor. The source node i pays the forwarder $m_p = 50$ credits in the price-based system and $50/R_i$ credits in the integrated system, where R_i is the source node's current reputation. The entire simulation time is 1000s. In the integrated system, we assume nodes choose the strategy that maximizes their benefit (i.e., the cooperative strategy) with probability $\min(0.8 + \frac{\Delta m_p}{m_p}, 1)$, where $\Delta m_p = m_p(t) - m_p(t+1)$. 0.8 and $\frac{\Delta m_p}{m_p}$ are the probabilities that a node is cooperative because of the reputation system and price-based system, respectively.

Figure 14 shows the converged reputation values of nodes in the integrated system after 10000s. As the experiment of Figure 9 for a reputation system, we set the reputation threshold of the nodes in the system to $T_R = 0.3$ and $T_R = 0.7$, respectively, and the initial node reputation distribution is shown in Figure 8. Comparing Figure 14 with Figure 9, we see that rather than converging to the reputation thresholds respectively as in the reputation system, the node reputation values in the integrated system are converged to 1. Nodes always choose the action strategy that maximizes their utilities. In the integrated system, the forwarding strategy can provide a node with the best utility. Therefore, nodes always forward packets for others and their reputation values increase to the maximum. In the reputation system, when a node's reputation value is just above the threshold, it does not have incentives to forward others' packets because the forwarding cannot bring about more utility. These results prove the higher effectiveness of the integrated system in cooperation encouragement than the reputation system.

Figure 15 shows the packet drop rates in different systems over the simulation time when the reputation threshold equals 0.2. We see that as time goes on, the packet drop rates of the price-based and integrate systems decrease and those of the reputation and defenseless systems increase. This is because the forwarding strategy can always ensure that the nodes in both the price-based and integrated systems gain higher utility, but cannot ensure this in the reputation and defenseless systems. We also find that the rate drops much faster in the integrated system than in the price-based system. This is because the low-reputed nodes in the integrate system have higher incentives to be cooperative than in the price-based system because of the differentiated reputation-based prices. As the defenceless system has no mechanism to encourage cooperative behaviors or punish selfish behaviors, all nodes in the system are uncooperative. In the reputation system, since maintaining the reputation value only above the reputation threshold can maximize a node's utility, the packet drop rate increases and then stays at around 0.8 because the reputation threshold was set to 0.2. These results are in line with the density result in Figure 4, Figure 5, Figure 6 and Figure 7 and verify that the integrated system provides the strongest cooperation incentives.

In order to show the effectiveness of the integrated system in selfish node detection, we let a packet receiver drop the packet if its account value is greater than zero and its reputation value is above the threshold, and then its reputation is decreased by 0.1. Otherwise, the receiver forwards the packet and its reputation is increased by 0.1. We randomly choose a node to function as a selfish node, count the number of interactions between the selfish node and other nodes during the simulation time, and measure the account value of the node corresponding to different numbers of

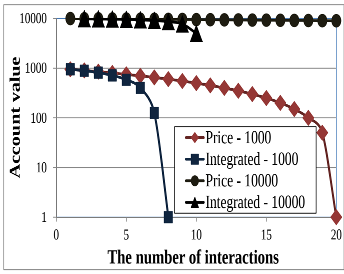

Fig. 16: Detection of silly selfish nodes.

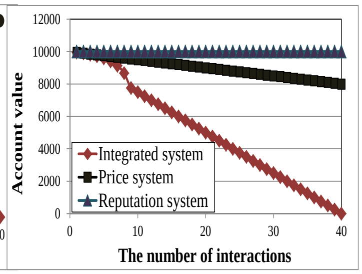

Fig. 17: Detection of clever selfish nodes.

interactions. When the selfish node's reputation falls below the threshold or its account value falls below zero, it is put into a blacklist. All other nodes refuse to interact with the node in the blacklist. We consider two kinds of selfish nodes: wealthy and silly selfish nodes and wealthy and clever selfish nodes.

Figure 16 shows the account value of the selfish node in the price-based system and integrated system. We initially assign 10000 and 1000 credits to the selfish node to see the systems' effectiveness in detecting the selfish node when it is wealthy and not wealthy. In the figure, "Integrated-1000" represents the scenario of the integrated system and 1000 initial credits. The notation applies to others. When the initial credits are 1000, the selfish node's account value becomes 0 after 20 interactions in the price-based system and after 8 interactions in the integrated system; thus, the integrated system takes much less time to detect the selfish node. This is because the forwarding price in the integrated system is determined by the source node's reputation instead of staying constant as in the price-based system. As the reputation of the selfish node decreases, it needs to pay more for packet forwarding service. Therefore, the selfish node will run out of credit faster in the integrated system than in the price-based system.

The figure also shows that when the initial credits are 10000, i.e., when the selfish node is wealthy, its account value decreases very slightly in the first 20 interactions. According to this decrease rate, it will take a significantly long time for the price-based system to detect the selfish and wealthy node based on its account value. The integrated system detects the selfish node only after 9 interactions because as the selfish node keeps dropping packets, its reputation value drops quickly even though it still has a high account value. Subsequently, it is detected when its reputation value falls below the reputation threshold.

A clever, selfish and wealthy node tried to keep its reputation just above the reputation threshold to avoid being detected. Figure 17 shows the account value of such a node when it has 10000 credits in the integrated system, reputation system and price-based system. Its account value keeps 10000 in the reputation system since it does not need to pay a price for packet forwarding. Because it can keep its reputation value at the reputation threshold, the selfish node cannot be detected in the reputation system. The account value of the node drops slowly in the price-based system, while sharply in the integrated system. For the price-based system, since the selfish node has a large amount of initial credits, it takes a long time for it to be detected by account starvation. In contrast, the integrated system can detect the selfish node within only 40 interactions according to account starvation. This is because when the selfish node's reputation is at the threshold 1/5, it needs to pay a 5 times higher price than in the price-based system for each forwarding service. Therefore, its credits are used up quickly even though it is wealthy initially.

The experimental results verify that the integrated system is more effective in detecting selfish nodes even though they are wealthy and clever.

We further investigate the impact of reputation threshold, the number of interactions and the forwarding price on the account value of the selfish node with 1000 initial credits. In Figure 18, "Integrated-50" represents the integrated system with a packet forwarding price of 50 credits. This notation applies to the other notations. The figure shows that at a certain reputation threshold and same forwarding price, the account value decreases faster in the integrated system than in the price-based system. This is due to the adaptive forwarding price based on reputation in the integrated system and constant forwarding price in the price-based system. The result confirms that the integrated system can detect selfish nodes more quickly. Comparing the results of "Integrated-50" and "Integrated-100", we observe that "Integrated-100" decreases much more rapidly because a higher forwarding price leads to a faster account value decrease.

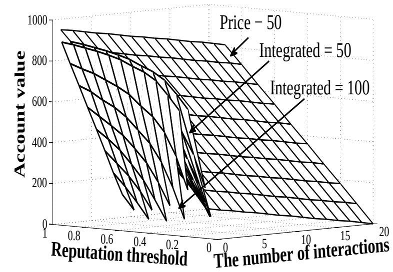

Fig. 18: Account value vs. reputation threshold and number of interactions.

The figure also shows that as the reputation threshold decreases, the account value drops faster for both "Integrated-50" and "Integrated-100". Since a clever selfish node has a high incentive to keep its reputation value around T_R, a low T_R will lead to a low stable reputation value for the selfish node. Then, the selfish node uses up its account value more quickly due to the reputation-adaptive forwarding price. In addition, we observe that the reputation threshold does not affect the account value in the price-based system because the system does not consider reputation. We also observe that if a low-reputed node forwards a packet, its packet forwarding price decreases much faster than a high-reputed node. Therefore, in the integrated system, low-reputed nodes are highly encouraged to be cooperative.

Based on the result, we can conclude that compared to the reputation system and price-based system, the integrated system can more effectively defect selfish nodes.

6 Conclusions

MANETs require all nodes in a network to cooperatively conduct a task. Encouraging this cooperation is a crucial issue for the proper functioning of the systems. Reputation systems and price-based systems are two main approaches to dealing with the cooperation problem in MANETs. In this paper, we analyze the underlying cooperation incentives of the two systems and a defenseless system through game theory. To overcome the observed drawbacks in each system, we propose and analyze an integrated system which leverages the advantages of reputation systems and price-based systems. Analytical and simulation results show the higher performance of the integrated system compared to the other two systems in terms of the effectiveness of cooperation incentives and selfish node detection.

The current integrated system aims to provide stronger cooperation incentives but does not focus on security issues such as compromised cooperative nodes or attacks on the system. Building a secure integrated system is left as our future work.

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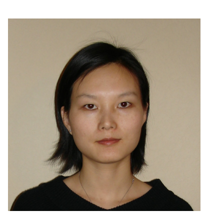

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