DARWIN: Distributed and Adaptive Reputation mechanism for WIreless ad-hoc Networks

Juan José Jaramillo
Coordinated Science Laboratory and
Dept. of Electrical and Computer Engineering
University of Illinois at Urbana-Champaign
jjjarami@uiuc.edu

R. Srikant
Coordinated Science Laboratory and
Dept. of Electrical and Computer Engineering
University of Illinois at Urbana-Champaign
rsrikant@uiuc.edu

ABSTRACT

Mobile ad-hoc networks are deployed under the assumption that participating nodes are willing to forward other nodes' packets. In reputation-based mechanisms cooperation is induced by means of a threat of partial or total disconnection from the network if a node is non-cooperative; however packet collisions and interference may make cooperative nodes appear selfish sometimes. In this paper we use a simple network model to first study the performance of some proposed reputation strategies and then present a new mechanism that we call DARWIN (Distributed and Adaptive Reputation mechanism for WIreless ad-hoc Networks). The idea is to avoid a retaliation situation after a node has been falsely perceived as selfish so cooperation can be restored quickly. We prove that our strategy is robust to imperfect measurements, is collusion-resistant and can achieve full cooperation among nodes.

Categories and Subject Descriptors

C.2.0 [**Computer - Communication Networks**]: General—*security and protection*; C.2.1 [**Computer - Communication Networks**]: Network Architecture and Design—*distributed networks, packet-switching networks, wireless communication*

General Terms

Algorithms, Design, Security, Theory

1. INTRODUCTION

Mobile ad-hoc networks have been a topic of intense research for the last several years. Such networks consist of a set of mobile nodes that are self-configuring and do not rely on an infrastructure to communicate. Typically, a source communicates with distant destinations using intermediate nodes as relays. The promise of quickly deployable networks has several uses ranging from military applications such as battlefield networks, to civilian applications like disaster recovery efforts and temporary networks for conferences or expeditions. In the case of civilian applications, where all the nodes are not under the control of a single authority, cooperation cannot be taken for granted. There can be selfish users that want to maximize their own welfare, defined as the benefit of their actions minus the cost of their actions. Thus, it is necessary to develop incentive mechanisms that allow cooperation to emerge among selfish users.

Mechanisms can be broadly divided in two types: credit-exchange systems and reputation-based systems. In credit-exchange schemes [6, 18, 19, 22, 7, 8, 1], nodes receive a payment every time they forward a packet, and this credit can later be used by these nodes to encourage others to cooperate. Some proposals rely on the use of tamper-proof hardware to store credit information which may hinder their ability to find wide-spread acceptance; others use an off-line central trusted authority, which requires an infrastructure to work. In reputation-based schemes [12, 13, 5, 3, 10, 11, 14, 17], a node's behavior is measured by its neighbors, and selfishness is deterred by the threat of partial or total disconnection from the network. However, due to packet collisions and interference it is not always possible to detect if a given node actually forwarded a packet as expected, so sometimes cooperative nodes will be perceived as being selfish, which will trigger a retaliation situation that can potentially decrease the throughput of cooperative nodes.

The contributions of this paper are twofold: we first use a simple network model to understand the impact of imperfect measurements on the robustness of some previously proposed reputation strategies. In the analysis it is shown that the schemes punish selfish behavior at the expense of decreasing the throughput of cooperative users, and in some cases this can lead to complete network disconnection. Second, we propose a new strategy that we call DARWIN (Distributed and Adaptive Reputation mechanism for WIreless ad-hoc Networks) that is able to effectively detect and punish selfish behavior. The conditions under which no node can gain from deviating from our strategy are presented. We also prove that our scheme is collusion resistant and can achieve full cooperation among nodes.

2. BASIC GAME THEORY CONCEPTS

Here we introduce the concepts from Game Theory [9] that are used in this paper. As an illustration, we use a well-known game between two players known as *The Prisoners'*

Research supported by Motorola through the Motorola Center for Communication.

MobiCom'07, September 9–14, 2007, Montréal, Québec, Canada.

Table 1: Payoff Matrix of the Prisoners' Dilemma Game

		Player 2			
		Cooperate		Defect	
Player 1	Cooperate	1	1	-1	2
	Defect	2	-1	0	0

Dilemma. Both players have two possible *pure strategies*, Cooperate (C) or Defect (D), and the payoffs they receive for their actions are given in Table 1. Then player i's *strategy space* S_i is defined to be the set of pure strategies available to it. In this case $S_i = \{C, D\}$ for $i = \{1, 2\}$. A *strategy profile* is defined to be an element of the product-space of strategy spaces of each player. An example is for player 1 to play D and player 2 to play C.

Definition 1. *A* Nash equilibrium *is a strategy profile having the property that no player can benefit by unilaterally deviating from its strategy.*

Such a strategy profile is considered to be *self enforcing*. In this example, the Nash equilibrium would be the strategy profile $s = (D, D)$. Assume now that this game is repeated infinitely many times, and for each k, the outcomes of the $k-1$ preceding plays are observed before the k-th stage begins. In this case, the total payoff of the game for player i is the discounted sum of the stage payoffs. Denoting the stage payoffs by $u_i^{(k)}$, the total payoff is given by

$$U_i = \sum_{k=0}^{\infty} w^k u_i^{(k)} ,$$

where $w \in (0, 1)$ is the *discount factor*. The infinitely repeated game can also be interpreted as a repeated game that ends after a random number of repetitions. Under this interpretation, the length of the game is a geometric random variable with mean $1/(1-w)$.

In this game a player's strategy specifies the action it will take at each stage, for each possible history of play through previous stages. In our example a strategy for player 1 could be to cooperate until player 2 defects, and then defect forever. Since both players know the previous history, we can view the game starting at stage k with a given history h^k as a new game; this is called a *subgame* of the original game.

Definition 2. *For a given set of strategies that are in Nash equilibrium, history h^k is* on the equilibrium path *if it can be reached with positive probability if the game is played according to the equilibrium strategies, and is* off the equilibrium path *otherwise.*

Definition 3. *A Nash equilibrium is* subgame perfect *if the player's strategies constitute a Nash equilibrium in every subgame.*

Subgame perfection is a stronger concept that eliminates *noncredible* equilibria, since it analyzes the case when a game is on or off the equilibrium path. This will later help us analyze whether a given reputation scheme is robust enough to handle the case when due to inaccurate measurements nodes appear to be out of their predicted behavior.

Definition 4. *A game is* continuous at infinity *if for each player i the payoff U_i satisfies:*

$$\sup_{h,\tilde{h} \ s.t. \ h^k=\tilde{h}^k} \left| U_i(h) - U_i(\tilde{h}) \right| \to 0 \ as \ k \to \infty$$

Under this definition, events in the distant future are relatively unimportant. This holds true if the total payoff of the game is the discounted sum of the per-period payoffs $u_i^{(k)}$, and the per-period payoffs are uniformly bounded. In our example this holds true since $u_i^{(k)} \leq 2$ for all k.

Lemma 1 (One-Stage Deviation Principle). *In an infinite-horizon multi-stage game with observed actions that is continuous at infinity, strategy profile s is subgame perfect if and only if there is no player i and strategy $\hat{s}_i$ that agrees with s_i except at a single stage k and h^k, and such that $\hat{s}_i$ gives a better payoff than s_i conditional on history h^k being reached.*

For a proof see [9]. We say that s satisfies the One-Stage Deviation Principle if no player can gain by deviating from s, either on or off the equilibrium path, in a single stage.

In the rest of this paper we will develop a prisoner's dilemma model for wireless networks. Such an exercise has been carried out before in other papers, but our approach and solution are quite different.

3. NETWORK MODEL

We assume that nodes are selfish but not malicious. A selfish node is a rational user that wants to maximize its own welfare, defined as the benefit minus the cost of its actions. Links are assumed to be bidirectional. Wireless links are often bidirectional, and many MAC layers require bidirectional packet exchanges to avoid collisions, as is the case in IEEE 802.11. Finally, nodes are assumed to operate in promiscuous mode, so they are able to listen to all packets transmitted by their neighbors.

Forwarding a packet consumes resources. We define the normalized relaying cost to be 1. The reward a node receives if its packet is relayed is α, where we assume $\alpha \geq 1$ since the value of a packet should be at least equal to the cost of the resources used to send it. We assume that the interaction among nodes is reciprocal, i.e., any two neighbors have uniform network traffic demands and need each other to forward packets. Thus, we can isolate any pair of nodes and study the interaction between them as a two-player game. In the two-player game, one way to model the nodes is to assume that they send a packet to each other and then simultaneously decide whether to drop or forward their respective packets, and repeat this game iteratively. In this scenario the stage payoffs matrix is given in Table 2. Without loss of generality we normalize the payoff matrix as in Table 3. Using standard game theory notation, we will denote by $i \in \{1, 2\}$ a generic node and by $-i$ its neighbor.

Since the interaction among nodes is asynchronous in nature, we refine the game assuming that time is divided into slots and that slots last long enough to allow each node to send a sufficiently large number of packets. At the end of the slot each node finds the ratio of dropped packets by its neighbor; if the number of packets exchanged is sufficiently large, then this ratio is a good estimate of the probability of dropping a packet. This assumption is implicitly used in other papers on reputation mechanisms as well [10, 11].

Table 2: Payoff Matrix of the Packet Forwarding Game

		Node 2 Forward		Node 2 Drop	
Node 1	Forward	$\alpha-1$	$\alpha-1$	$-\alpha-1$	α
	Drop	α	$-\alpha-1$	$-\alpha$	$-\alpha$

Table 3: Normalized Payoff Matrix of the Packet Forwarding Game

		Node 2 Forward		Node 2 Drop	
Node 1	Forward	1	1	$\frac{-1}{2\alpha-1}$	$\frac{2\alpha}{2\alpha-1}$
	Drop	$\frac{2\alpha}{2\alpha-1}$	$\frac{-1}{2\alpha-1}$	0	0

Due to collisions, it is not always possible to detect whether a node forwarded a packet or not. We define $p_e \in (0,1)$ to be the probability that a packet that has been forwarded was not overheard by the originating node. We also assume that p_e is the same for both nodes. By listening to the channel, node i then estimates the perceived dropping probability $\hat{p}_{-i}^{(k)}$ of its neighbor at time slot $k \geq 0$. It must be noted that a packet is perceived to be dropped if either $-i$ dropped it or if it is not dropped but node i did not overhear the transmission. Thus

$$\hat{p}_{-i}^{(k)} = p_{-i}^{(k)} + (1-p_{-i}^{(k)})p_e = p_e + (1-p_e)p_{-i}^{(k)}, \qquad (1)$$

where $p_{-i}^{(k)}$ is the probability that $-i$ drops a packet.

Thus, using the payoffs of Table 3, the average payoff at time slot k is:

$$u_i^{(k)} = (1-p_i^{(k)})(1-p_{-i}^{(k)}) + \frac{2\alpha}{2\alpha-1}p_i^{(k)}(1-p_{-i}^{(k)}) - \frac{1}{2\alpha-1}(1-p_i^{(k)})p_{-i}^{(k)}.$$

Rearranging terms:

$$u_i^{(k)} = 1 + \frac{1}{2\alpha-1}p_i^{(k)} - \frac{2\alpha}{2\alpha-1}p_{-i}^{(k)}. \qquad (2)$$

The discounted average payoff of player i starting from time slot n is then given by:

$$U_i^{(n)} = \sum_{k=n}^{\infty} w^{k-n} u_i^{(k)}, \qquad (3)$$

where $w \in (0,1)$ is the discount factor. Since node i cannot know for sure $p_{-i}^{(k)}$, it does not know its payoff either. However, we use the actual payoff in the analysis since it tells us whether a given node can gain by deviating from a strategy.

Given this game, each player is allowed to use a strategy to decide whether to drop or forward packets based on the history. We use $\tilde{p}_{i\ S}^{(k)}$ to denote the dropping probability player i should use at time slot k according to strategy S.

As mentioned earlier, we assume symmetric and spatially uniform traffic conditions to derive our model. The robustness of the model is tested in Section 6 using a random network with asymmetric and spatially non-uniform traffic.

4. ANALYSIS OF PRIOR PROPOSALS

To motivate our new protocol which we will present in the next section, in this section we present a few strategies that have been proposed in prior work and show their limitations.

4.1 Trigger Strategies

One idea to provide an incentive for cooperation is to develop a strategy such that the cooperation of a node is measured and if the fraction of packets it has dropped is above a threshold it is consider selfish and is disconnected for a given amount of time. Formally, a *n-step Trigger Strategy* is defined as:

$$\tilde{p}_{i\ nT}^{(0)} = 0$$
$$\tilde{p}_{i\ nT}^{(k)} = \begin{cases} 0 & if\ \hat{p}_{-i}^{(j)} \leq T\ for\ all\ j \in \{k-n,\ldots,k-1\} \\ 1 & else \end{cases}$$

where we define $\hat{p}_{-i}^{(j)} = 0$ for $j \in \mathbb{Z}_-$. From (1) it is easy to see that if node i cooperates then $\hat{p}_{-i}^{(k)} = p_e$ for all k. Hence the optimal value of $T = p_e$. In reality we cannot perfectly estimate p_e, so we have to analyze two cases:

1. If $T < p_e$ then we have that $\tilde{p}_{i\ nT}^{(k)} = 1$ for $k \geq 1$, so cooperation will never emerge.
2. If $T > p_e$ then player $-i$ will be perceived to be cooperative as long as it drops packets with probability:
$$p_{-i}^{(k)} \leq \frac{T-p_e}{1-p_e}.$$

Therefore, since p_e is unknown, any choice of threshold other than $T = p_e$ results in either all packets being dropped or some fraction of packets being dropped. In other words, full cooperation is never the Nash equilibrium point with trigger strategies.

4.2 Tit For Tat

A second alternative is to use a *Tit For Tat* (TFT) strategy [2]. It was generalized in [15] for the wireless context as follows:

$$\tilde{p}_{i\ TFT}^{(0)} = 0$$
$$\tilde{p}_{i\ TFT}^{(k)} = \hat{p}_{-i}^{(k-1)}\ for\ k \geq 1.$$

However, Milan *et al.* [15] proved that this strategy does not provide the right incentive either for cooperation in wireless networks.

4.3 Generous Tit For Tat

The problem with TFT is that it does not take into account the fact that it is not always possible to determine whether a packet was relayed or not due to collisions. A way to deal with this is using a generosity factor g that allows cooperation to be restored. Such a strategy is known as *Generous TFT* (GTFT) [21] and in the case of wireless networks it can be defined [15] as follows:[1]

$$\tilde{p}_{i\ GTFT}^{(0)} = 0$$
$$\tilde{p}_{i\ GTFT}^{(k)} = \max\{\hat{p}_{-i}^{(k-1)} - g, 0\}\ for\ k \geq 1.$$

[1]Note that this definition corresponds to a reputation-based mechanism, not to be confused with the credit-based mechanism proposed in [19] that bears the same name.

LEMMA 2. *If both nodes do not deviate from the GTFT strategy then the generosity factor that maximizes the discounted average payoff is $g^* \geq p_e$.*

PROOF. If $g \geq p_e$ then from (1) we have for all $k \geq 0$ and $i \in \{1, 2\}$ that $p_i^{(k)} = 0$. Using (2) and (3) we obtain:

$$U_i^{(0)} = \frac{1}{1-w}. \tag{4}$$

In the case $g < p_e$ we obtain:

$$p_i^{(0)} = 0$$

and for $k \geq 1$:

$$\begin{aligned} p_i^{(k)} &= (p_e - g) \sum_{n=0}^{k-1} (1-p_e)^n \\ &= (p_e - g) \frac{1-(1-p_e)^k}{p_e}. \end{aligned}$$

So the stage payoffs for $k \geq 1$ are:

$$u_i^{(k)} = \frac{1}{p_e} \left[g + (p_e - g)(1-p_e)^k \right].$$

Therefore the discounted average payoff is:

$$U_i^{(0)} = 1 + \frac{w}{p_e} \left[\frac{g}{1-w} + \frac{(p_e-g)(1-p_e)}{1-w(1-p_e)} \right]. \tag{5}$$

It can easily be checked that the payoff (5) is strictly less than the payoff (4). □

It is important to highlight that in the case $g > p_e$ GTFT is not a Nash equilibrium since for player $-i$ it pays to deviate dropping packets with a probability

$$p_{-i}^{(k)} \leq \frac{g - p_e}{1 - p_e}.$$

The following theorem and corollary tell us that if the interaction between two nodes lasts long enough then GTFT is a robust strategy where no node can gain by deviating from the expected behavior, even if it is not able to achieve full cooperation.

THEOREM 1. *GTFT is subgame perfect if and only if*

$$g \leq p_e \text{ and } w > \frac{1}{2\alpha(1-p_e)}.$$

(See the proof on the appendix.)

COROLLARY 1. *If both nodes use GTFT then cooperation is achieved on the equilibrium path if and only if $g = p_e$.*

Note that in [15] a proof was done for the case $g = p_e$ but only considering the equilibrium path. The subgame perfect region of GTFT is plotted in Fig. 1 for $\alpha = 2$. Fig. 2 shows how the shape of this region is affected by different values of α. Note that when the value of a packet grows larger compared to the actual cost of transmitting it then cooperation has a better chance to emerge since being connected is more important than reducing the cost of helping other nodes. In summary, GTFT is not satisfactory because in order to achieve full cooperation we need a perfect estimate of p_e.

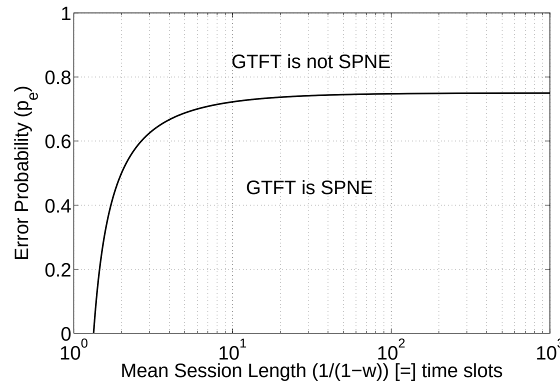

Figure 1: GTFT's Subgame Perfect Nash Equilibrium (SPNE) region for $\alpha = 2$

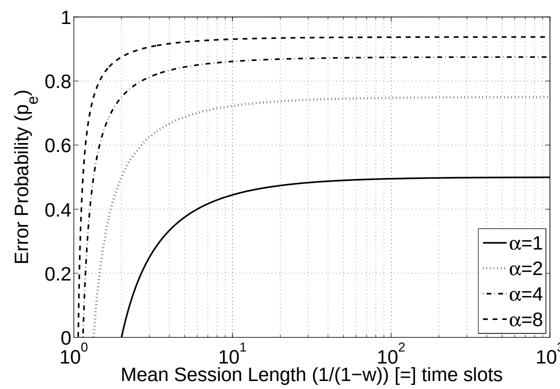

Figure 2: Sensitivity of GTFT's subgame perfect region for different values of α

5. DARWIN

5.1 Definition

Our goal is to propose a reputation strategy that does not depend on a perfect estimation of p_e to achieve full cooperation and that is also more robust than previously proposed strategies. For the iterated Prisoners' Dilemma a modification of TFT known as Contrite Tit For Tat (CTFT) [20, 4] has been proposed based on the idea of contriteness: a player that made a mistake and unintentionally defected should exercise contrition and try to correct the error instead of going into a retaliation situation. This strategy depends on the notion of good standing and is defined as follows. A player is always in good standing on the first stage. It remains in good standing as long as it cooperates when CTFT specifies that it should cooperate. If an individual is in bad standing it can get back in good standing by cooperating on one stage. Then CTFT specifies that a player should cooperate if it is in bad standing, or if its opponent is in good standing; otherwise the individual should defect. Inspired by this strategy, for the case of wireless networks we define the following strategy:

$$\tilde{p}_{i\ DARWIN}^{(k)} = \left[\gamma\left(q_{-i}^{(k-1)} - q_i^{(k-1)}\right)\right]_0^1 \ for\ k \geq 0, \quad (6)$$

where we define for $i = \{1, 2\}$:

$$q_i^{(k)} = \begin{cases} \left[\hat{p}_i^{(k)} - \tilde{p}_{i\ DARWIN}^{(k)}\right]_0^1 & for \quad k \geq 0 \\ 0 & for \quad k = -1. \end{cases} \quad (7)$$

Additionally we define the function:

$$[x]_0^1 = \begin{cases} 1 & if \quad x \geq 1 \\ x & if \quad 0 < x < 1 \\ 0 & if \quad x \leq 0 \end{cases}.$$

Recall that $\hat{p}_i^{(k)}$ denotes the estimated dropping probability and $\tilde{p}_{i\ DARWIN}^{(k)}$ is the dropping probability under DARWIN. Thus, if $\hat{p}_i^{(k)} > \tilde{p}_{i\ DARWIN}^{(k)}$, it means node i is perceived to be dropping more packets than it should under DARWIN. The parameter $q_i^{(k)}$ measures this deviation. In this case $q_i^{(k)}$ acts as a measurement of the bad standing of a node, and only the player that has better standing should proportionally punish its opponent with the *difference* in the two standings instead of the *absolute* value of the standing of its opponent. It must be noted that in the definition of DARWIN it is assumed that nodes share the perceived dropping probability with each other and that users do not lie about this probability; equivalently, we assume that these probabilities can be collected in a secure fashion. An alternative assumption is that most users do not misbehave and only a small number of users do. This allows us to share reputation information among users and the perceived dropping probability would be in this case the average of the received values, so liars have a limited impact.[2]

5.2 Performance Guarantees

The following theorem proves that when the interaction between two nodes lasts long enough DARWIN is a robust strategy where no node can gain by deviating from the expected behavior.

THEOREM 2. *Assuming $1 < \gamma < p_e^{-1}$, DARWIN is subgame perfect if and only if*

$$w > \max\left\{\frac{1}{\gamma}, \frac{1}{2\alpha(1 - p_e\gamma) + p_e\gamma}\right\}. \quad (8)$$

(See the proof on the appendix.)

From (8) it is clear that the optimum value of γ that minimizes this bound is a function of α and p_e. Since you cannot estimate α, a suboptimal strategy could be to choose γ to be the average of the interval $(1, p_e^{-1})$:

$$\gamma = \frac{1 + p_e^{-1}}{2} = \frac{1 + p_e}{2p_e}. \quad (9)$$

In Fig. 3 it is shown the subgame perfect region of DARWIN for different values of α assuming (9) holds, which is not significantly different from the subgame perfect region if we would have used the optimal value of γ.

[2]The reader is referred to [16] where the impact of liars is studied in a different context. The further study of this topic in the case of reputation mechanisms for wireless networks is left as future work.

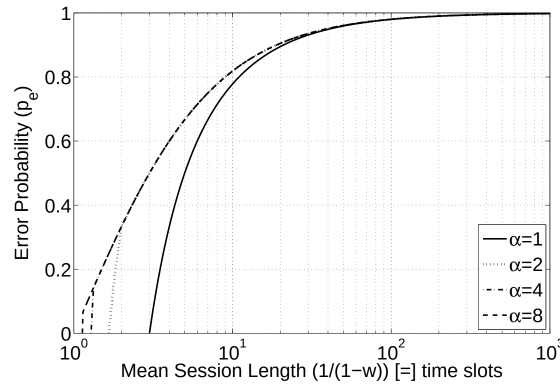

Figure 3: Sensitivity of DARWIN's subgame perfect region for different values of α assuming (9) holds

It must be highlighted that if both nodes use DARWIN then full cooperation is achieved. This can easily be checked using (1) and the definition of DARWIN to observe the game evolution.

LEMMA 3. *If both nodes use DARWIN then cooperation is achieved on the equilibrium path. That is, $p_i^{(k)} = p_{-i}^{(k)} = 0$ for all $k \geq 0$.*

Since this is the best any strategy S can achieve, we have that:

$$U_{i\ S}^{(0)} \leq U_{i\ DARWIN}^{(0)} \ for\ any\ strategy\ S. \quad (10)$$

It is also important to remember that for DARWIN to be subgame perfect we need to estimate p_e in order to achieve the bound $\gamma < p_e^{-1}$. Since we cannot do perfect estimation, we have that the estimated error probability $p_e^{(e)}$ is equal to

$$p_e^{(e)} = p_e + \Delta,$$

where $\Delta \in (-p_e, 1 - p_e)$ is the estimation error. If we choose γ using (9) we have:

$$\gamma = \frac{1 + p_e^{(e)}}{2p_e^{(e)}} = \frac{1 + p_e + \Delta}{2p_e + 2\Delta}.$$

So we have that $\gamma < p_e^{-1}$ if and only if:

$$\Delta > -p_e\left(\frac{1 - p_e}{2 - p_e}\right).$$

Thus, for the DARWIN strategy, one does not need a precise estimate of p_e, an estimator that overestimates p_e is sufficient for Theorem 2 to hold.

5.3 Collusion Resistance

We now consider the case when a group of colluding nodes work together to maximize their own benefit regardless of the social optimum. Define $U_{i\ S_i|S_{-i}}^{(0)}$ to be the discounted average payoff of player i using strategy S_i when it plays against player $-i$ using strategy S_{-i}. Hence (10) can be rewritten as:

$$U_{i\ S|S}^{(0)} \leq U_{i\ D|D}^{(0)} \ for\ any\ strategy\ S. \quad (11)$$

Also, a consequence of Theorem 2 is

$$U^{(0)}_{i\ S|D} < U^{(0)}_{i\ D|D} \tag{12}$$

for any strategy $S \neq$ D=DARWIN. Assume a group of colluding nodes implementing strategy S enters the network. Define $p_S \in (0,1)$ to be the probability that a node that implements DARWIN interacts with a colluding node. Therefore the average payoff to a cooperative node will be:

$$U(D) = p_S U^{(0)}_{i\ D|S} + (1-p_S)U^{(0)}_{i\ D|D}.$$

Similarly, if $p_D \in (0,1)$ is the probability that a colluding node interacts with a node implementing DARWIN we have:

$$U(S) = p_D U^{(0)}_{i\ S|D} + (1-p_D)U^{(0)}_{i\ S|S}.$$

We have that the average payoff is bounded by

$$U(S) < \max\left\{U^{(0)}_{i\ S|D}, U^{(0)}_{i\ S|S}\right\}. \tag{13}$$

So a group of colluding nodes cannot gain from unilaterally deviating if and only if $U(S) < U(D)$. Equivalently,

$$p_S\left[U^{(0)}_{i\ D|D} - U^{(0)}_{i\ D|S}\right] < U^{(0)}_{i\ D|D} - U(S). \tag{14}$$

From (11), (12) and (13) we know that

$$U^{(0)}_{i\ D|D} - U(S) > 0.$$

Define strategy S to be a *sucker strategy* if

$$U^{(0)}_{i\ D|D} < U^{(0)}_{i\ D|S}.$$

If S is a sucker strategy, then (14) is always true. If S is a non-sucker strategy, we have that (14) holds for

$$p_S < \frac{U^{(0)}_{i\ D|D} - U(S)}{U^{(0)}_{i\ D|D} - U^{(0)}_{i\ D|S}},$$

with the understanding that we define the trivial bound $p_S < +\infty$ if

$$U^{(0)}_{i\ D|D} = U^{(0)}_{i\ D|S}.$$

So we have just proved the following theorem:

THEOREM 3. *DARWIN is collusion resistant against a sucker strategy. Furthermore, it is resistant against a non-sucker strategy if and only if*

$$p_S < \frac{U^{(0)}_{i\ D|D} - U(S)}{U^{(0)}_{i\ D|D} - U^{(0)}_{i\ D|S}}.$$

Thus if cooperative nodes mostly interact among each other then DARWIN can resist group attacks.

5.4 Algorithm Implementation

Let $N_i^{(k)}$ denote the set of one hop neighbors that node i has discovered in time interval k by overhearing packet transmissions. For every node $j \in N_i^{(k)}$ node i keeps two counters, one for the number of messages sent to j for forwarding ($S_{ij}^{(k)}$) in time slot k and another for the number of messages j actually forwarded ($F_{ij}^{(k)}$) in time interval k. At the end of the time slot it computes the ratio

$$c_{ij}^{(k)} = \frac{F_{ij}^{(k)}}{S_{ij}^{(k)}}$$

and proceeds to send $c_{ij}^{(k)}$ to its neighbors. With the values gathered node i estimates j's average connectivity ratio

$$\hat{c}_j^{(k)} = \frac{\sum\limits_{\substack{m \in N_i^{(k)} \cup \{i\} \\ m \neq j}} c_{im}^{(k)} \times c_{mj}^{(k)}}{\sum\limits_{\substack{m \in N_i^{(k)} \cup \{i\} \\ m \neq j}} c_{im}^{(k)}},$$

where by definition $c_{ii}^{(k)} = 1$ for all k. It must be noted that the average is weighted with the perceived connectivity ratio that node i measured from node m. This helps to avoid sybil attacks to spread false values with the hope to improve a selfish node's reputation since all its other identities have low connectivity too, so they have a small impact on the average. In a similar way, node i will find $\hat{c}_i^{(k)}$, the average connectivity ratio its one-hop neighborhood perceived from it during time slot k. We define $\hat{p}_j^{(k)} = 1 - \hat{c}_j^{(k)}$ and use (6) and (7) to find the dropping probability that node i will use while forwarding packets for node j in time interval $k+1$.

Since we need $\gamma < p_e^{-1}$, we need to estimate p_e. An interesting solution was proposed in [11] probing a node with anonymous messages, but it increases the overhead of the protocol. Instead, note that p_e is the probability that at least one terminal in $N_i^{(k)}$ transmits when node j transmits. Thus we estimate p_e by measuring the fraction of time at least one node different from j transmits. Call it $\hat{p}_{ej}$. Mathematically, if $T_j^{(k)}$ is the fraction of time node j has transmitted up to time interval k and $T_c^{(k)}$ is the fraction of time a collision occurred up to time interval k we have:

$$\hat{p}_{ej} = T_c^{(k)} + \sum_{\substack{n \in N_i^{(k)} \\ n \neq j}} T_n^{(k)}.$$

In case the MAC layer uses a CSMA/CA protocol, and due to the exposed terminal problem, we will have that $\hat{p}_{ej} \geq p_e$. This overestimation is not a problem for our algorithm since

$$\gamma < \frac{1}{\hat{p}_{ej}} \leq \frac{1}{p_e}.$$

6. SIMULATIONS

6.1 Settings

Our goal is to test the performance of the network in the presence of nodes which deviate from DARWIN. To do that we implemented our algorithm using the network simulator *ns-2*. For the propagation we used the two-ray ground reflection model, while the IEEE 802.11 Distributed Coordination Function (DCF) was used at the MAC layer. Nodes had a physical radio range of 250 m and a raw bandwidth of 2 Mbps. Routing was performed by the Dynamic Source Routing (DSR) protocol. We simulated a network of 50 nodes randomly placed in an area of $670 \times 670\ m^2$, where we randomly selected five nodes that do not implement DARWIN and behave selfishly dropping all packets that are not destined to them. In the rest of this section, a selfish node will be taken to mean a node that does not implement DARWIN and a cooperative node is one which does. There are 14 source-destination pairs and each source transmits at a Constant Bit Rate (CBR) of 2 packets/s, with a packet size of 512 bytes. The simulation time is 800 s, where the time

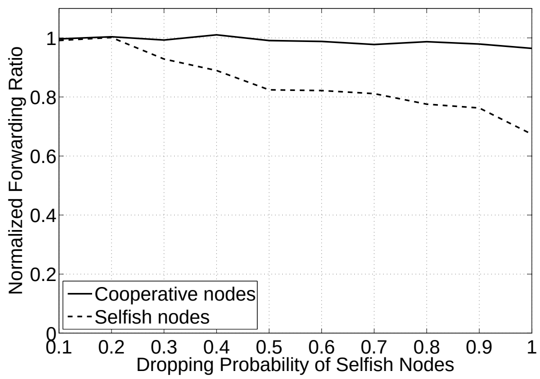

Figure 4: Normalized throughput for different dropping ratio of selfish nodes

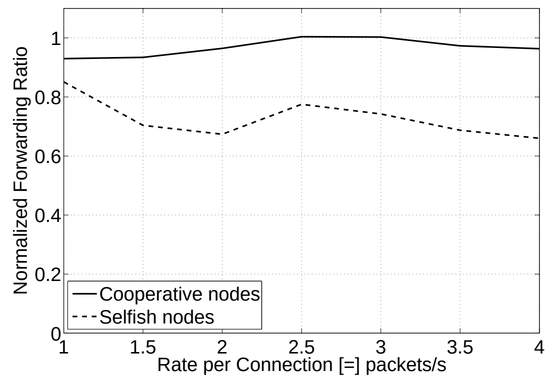

Figure 5: Normalized throughput for different connection rates (for a packet size of 512 bytes)

intervals used by DARWIN were 60 seconds long. Each figure presented is the average of 30 randomly generated runs. In the simulations, γ was set to be 2.

6.2 Results

To evaluate DARWIN's performance, we measure the normalized forwarding ratio for both cooperative and selfish nodes, which is defined to be the fraction of forwarded packets in the network under consideration divided by the fraction of forwarded packets in a network with no selfish nodes.

Figure 4 shows the difference between cooperative and selfish nodes, when selfish nodes probabilistically drop a fraction of the packets they are expected to relay. It can be seen that DARWIN effectively detects selfish behavior and punishes nodes proportionally. The relationship between source rate and the normalized forwarding ratio is presented in Figure 5. It can be noted that the normalized ratio of cooperative nodes remains almost constant for different rates, even at high load when p_e increases and false positives are expected, showing that DARWIN can effectively restore cooperation after false positives. A similar result can be observed if we vary the total number of source-destination pairs. In Figure 6 we explore the impact of the fraction of selfish nodes. Remarkably, even when the fraction is 90%, under DARWIN, cooperative nodes achieve a better forwarding ratio than selfish nodes. The fact that the difference between the normalized ratios is small is less relevant than the fact that selfishness does not improve performance.

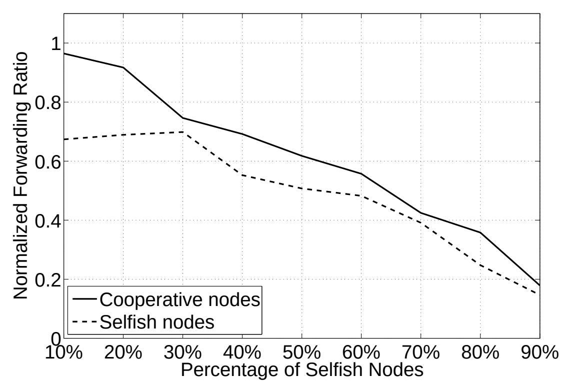

Figure 6: Normalized throughput for different number of selfish nodes

7. CONCLUSIONS

In this paper we have studied how reputation-based mechanisms can help cooperation emerge among selfish users. We first showed the properties of previously proposed schemes, and with the insight gained from such understanding, we proposed a new mechanism called DARWIN. We showed that DARWIN is robust to imperfect measurements, is also collusion-resistant and is able to achieve full cooperation. We also showed that the algorithm is relatively insensitive to parameter choices.

8. APPENDIX

Here we present the proofs of the theorems presented in this paper.

THEOREM 1. *GTFT is subgame perfect if and only if*

$$g \leq p_e \text{ and } w > \frac{1}{2\alpha(1-p_e)}.$$

PROOF. In Section 4.3 we have already seen that if $g > p_e$ then GTFT is not a Nash equilibrium, so for the rest of the proof we will assume $g \leq p_e$. It must be noted that GTFT is a one-stage history strategy because it only needs to take into account what happened in the previous stage. With that in mind, and without loss of generality, let us assume that any history h^n is represented as $p_i^{(0)} = p_i$ for $i \in \{1, 2\}$. If both nodes use GTFT then using (1) we have the following subgame evolution:

k	$p_i^{(k)}$
0	p_i
1	$p_{-i}(1-p_e)+p_e-g$
2	$p_i(1-p_e)^2+(p_e-g)\sum_{n=0}^{1}(1-p_e)^n$
3	$p_{-i}(1-p_e)^3+(p_e-g)\sum_{n=0}^{2}(1-p_e)^n$
$\vdots$	$\vdots$

or equivalently for $k \geq 1$:

$$p_i^{(k)} = \theta_i^{(k)}(1-p_e)^k + \frac{(p_e-g)}{p_e}\left[1-(1-p_e)^k\right]$$

where

$$\theta_i^{(k)} = \begin{cases} p_i & if\ k\ is\ even \\ p_{-i} & if\ k\ is\ odd. \end{cases}$$

Therefore from (2) the stage payoffs for $k \geq 1$ are:

$$u_i^{(k)} = 1 + \frac{1}{2\alpha-1}p_i^{(k)} - \frac{2\alpha}{2\alpha-1}p_{-i}^{(k)}.$$

If player i deviates at stage 1 using

$$p_{i\delta}^{(1)} = \tilde{p}_{i\ GTFT}^{(1)} + \delta$$

for some $\delta > 0$ and later conforms to GTFT, we have the following dropping probabilities:

k	$p_{i\delta}^{(k)}$
0	p_i
1	$p_{-i}(1-p_e)+(p_e-g)+\delta$
2	$p_i(1-p_e)^2+(p_e-g)\sum_{n=0}^{1}(1-p_e)^n$
3	$p_{-i}(1-p_e)^3+(p_e-g)\sum_{n=0}^{2}(1-p_e)^n+\delta(1-p_e)^2$
$\vdots$	$\vdots$

or equivalently:

$$p_{i\delta}^{(2m+1)} = p_{-i}(1-p_e)^{2m+1} + \frac{(p_e-g)}{p_e}\left[1-(1-p_e)^{2m+1}\right] + \delta(1-p_e)^{2m}$$

$$p_{i\delta}^{(2m)} = p_i(1-p_e)^{2m} + \frac{(p_e-g)}{p_e}\left[1-(1-p_e)^{2m}\right].$$

So we have:

$$p_{i\delta}^{(2m+1)} = p_i^{(2m+1)} + \delta(1-p_e)^{2m}\ for\ m \geq 0$$

$$p_{i\delta}^{(2m)} = p_i^{(2m)}\ for\ m \geq 1.$$

Which leads to the following stage payoffs:

$$u_{i\delta}^{(2m+1)} = u_i^{(2m+1)} + \frac{1}{2\alpha-1}\delta(1-p_e)^{2m}\ for\ m \geq 0$$

$$u_{i\delta}^{(2m)} = u_i^{(2m)} - \frac{2\alpha}{2\alpha-1}\delta(1-p_e)^{2m-1}\ for\ m \geq 1.$$

Since the stage payoff received at stage 0 is independent of the action player i takes at stage 1, we are only interested in finding the following discounted average payoff:

$$U_{i\delta}^{(1)} = \sum_{k=1}^{\infty} w^{k-1}u_{i\delta}^{(k)} = U_i^{(1)} + \frac{\delta\left[1-2\alpha w(1-p_e)\right]}{(2\alpha-1)\left[1-w^2(1-p_e)^2\right]}.$$

Where $U_i^{(1)}$ is the discounted payoff received if $\delta = 0$. Since we assume that $\alpha \geq 1$, it does not pay to deviate if:

$$1-2\alpha w(1-p_e) < 0.$$

But this is true if and only if:

$$w > \frac{1}{2\alpha(1-p_e)}.$$

Then by the One-Stage Deviation Principle GTFT is subgame perfect. $\square$

THEOREM 2. *Assuming $1 < \gamma < p_e^{-1}$, DARWIN is subgame perfect if and only if*

$$w > \max\left\{\frac{1}{\gamma}, \frac{1}{2\alpha(1-p_e\gamma)+p_e\gamma}\right\}.$$

PROOF. The line of reasoning is similar to the one presented for Theorem 1. DARWIN is a one-stage history strategy because it only needs to take into account what happened in the previous stage. Hence, and without loss of generality, any history h^n can be represented as $q_i^{(0)} = q_i$ for $i \in \{1,2\}$. If both nodes do not deviate from DARWIN then using (1) we have for $k \geq 1$ the following subgame evolution:

If $q_i \geq q_{-i}$ then:

$p_i^{(k)} = 0$
$p_{-i}^{(k)} = p_e^{k-1}\gamma^{k-1}\min\{1,\gamma(q_i-q_{-i})\}$
$\hat{p}_i^{(k)} = p_e$
$\hat{p}_{-i}^{(k)} = p_e + p_e^{k-1}\gamma^{k-1}(1-p_e)\min\{1,\gamma(q_i-q_{-i})\}$
$q_i^{(k)} = p_e$
$q_{-i}^{(k)} = p_e - p_e^k\gamma^{k-1}\min\{1,\gamma(q_i-q_{-i})\}$

From (2) the stage payoffs for $k \geq 1$ are:

$$u_{i\ a}^{(k)} = 1 - \frac{2\alpha}{2\alpha-1}\left[(p_e\gamma)^{k-1}\min\left\{1,\gamma(q_i-q_{-i})\right\}\right].$$

If $q_i < q_{-i}$ then:

$p_i^{(k)} = p_e^{k-1}\gamma^{k-1}\min\{1,\gamma(q_{-i}-q_i)\}$
$p_{-i}^{(k)} = 0$
$\hat{p}_i^{(k)} = p_e + p_e^{k-1}\gamma^{k-1}(1-p_e)\min\{1,\gamma(q_{-i}-q_i)\}$
$\hat{p}_{-i}^{(k)} = p_e$
$q_i^{(k)} = p_e - p_e^k\gamma^{k-1}\min\{1,\gamma(q_{-i}-q_i)\}$
$q_{-i}^{(k)} = p_e$

From (2) the stage payoffs for $k \geq 1$ are:

$$u_{i\ b}^{(k)} = 1 + \frac{1}{2\alpha-1}p_e^{k-1}\gamma^{k-1}\min\left\{1,\gamma(q_{-i}-q_i)\right\}.$$

If player i deviates at stage 1 using

$$p_{i\delta}^{(1)} = \tilde{p}_{i\ DARWIN}^{(1)} + \delta$$

for some $\delta > 0$ and later conforms to DARWIN, we have the following game evolution:

If $q_i \geq q_{-i}$ then:

$$
\begin{aligned}
p_i^{(1)} &= \delta\\
p_i^{(k)} &= 0\\
p_{-i}^{(1)} &= \min\{1, \gamma(q_i - q_{-i})\}\\
p_{-i}^{(k)} &= (p_e\gamma)^{k-2}\min\{1, \gamma\delta(1-p_e) + p_e\gamma p_{-i}^{(1)}\}\\
\hat{p}_i^{(1)} &= p_e + \delta(1-p_e)\\
\hat{p}_i^{(k)} &= p_e\\
\hat{p}_{-i}^{(1)} &= p_e + (1-p_e)p_{-i}^{(1)}\\
\hat{p}_{-i}^{(k)} &= p_e\\
&\quad +(p_e\gamma)^{k-2}(1-p_e)\min\{1, \gamma\delta(1-p_e) + p_e\gamma p_{-i}^{(1)}\}\\
q_i^{(1)} &= p_e + \delta(1-p_e)\\
q_i^{(k)} &= p_e\\
q_{-i}^{(1)} &= p_e - p_e p_{-i}^{(1)}\\
q_{-i}^{(k)} &= p_e - p_e^{k-1}\gamma^{k-2}\min\{1, \gamma\delta(1-p_e) + p_e\gamma p_{-i}^{(1)}\}
\end{aligned}
$$

Therefore from (2) the stage payoffs are:

$$u_{i\delta}^{(1)} = u_{i\ a}^{(1)} + \frac{\delta}{2\alpha - 1}$$

$$u_{i\delta}^{(k)} = u_{i\ a}^{(k)} - \frac{2\alpha(p_e\gamma)^{k-2}}{2\alpha-1}\min\{1 - p_e\gamma p_{-i}^{(1)}, \gamma\delta(1-p_e)\}.$$

Since the stage payoff received at stage 0 is independent of the action player i takes at stage 1, we are only interested in finding the discounted average payoff

$$
\begin{aligned}
U_{i\delta}^{(1)} = \sum_{k=1}^{\infty} w^{k-1}u_{i\delta}^{(k)} = U_{i\ a}^{(1)} + \frac{1}{2\alpha-1}\,[\delta\\
-\frac{2\alpha w}{1 - wp_e\gamma}\min\{1 - p_e\gamma p_{-i}^{(1)}, \gamma\delta(1-p_e)\}\Big],
\end{aligned}
$$

where $U_{i\ a}^{(1)}$ is the discounted payoff received if $\delta = 0$. It does not pay to deviate if $U_{i\delta}^{(1)} < U_{i\ a}^{(1)}$. Since we assume that $\alpha \geq 1$, we only have to check two cases:

1. If $1 - p_e\gamma p_{-i}^{(1)} < \gamma\delta(1-p_e)$ we need the following condition

   $$\delta - \frac{2\alpha w(1 - p_e\gamma p_{-i}^{(1)})}{1 - wp_e\gamma} < 0$$

   to be true for any δ. Equivalently:

   $$w > \max_{0\leq\delta\leq 1}\left\{\frac{\delta}{2\alpha(1 - p_e\gamma p_{-i}^{(1)}) + p_e\gamma\delta}\right\}.$$

   So we get the bound:

   $$w > \frac{1}{2\alpha(1 - p_e\gamma p_{-i}^{(1)}) + p_e\gamma}. \tag{15}$$

2. If $1 - p_e\gamma p_{-i}^{(1)} \geq \gamma\delta(1-p_e)$ we need the following condition:

   $$\delta - \frac{2\alpha w\gamma\delta(1-p_e)}{1 - wp_e\gamma} < 0.$$

   Thus we have the bound:

   $$w > \frac{1}{2\alpha\gamma(1-p_e) + p_e\gamma}. \tag{16}$$

For the case $q_i < q_{-i}$ the analysis has to be more detailed. In stage 1 according to DARWIN player i has to drop player $-i$'s packets with probability:

$$\tilde{p}_{i\ DARWIN}^{(1)} = \min\{1, \gamma(q_{-i} - q_i)\}.$$

So if $\gamma \geq \frac{1}{q_{-i} - q_i}$ then player i cannot deviate at stage 1 for any value of w. In the case that $\gamma < \frac{1}{q_{-i}-q_i}$ we can only increase δ up to:

$$\delta \leq 1 - \gamma(q_{-i} - q_i).$$

Now the rest of the analysis will consider the following two cases:

$$\delta \leq \min\left\{1 - \gamma(q_{-i} - q_i), \frac{p_e\gamma(q_{-i} - q_i)}{1 - p_e}\right\} \tag{17}$$

$$\frac{p_e\gamma(q_{-i} - q_i)}{1 - p_e} < \delta \leq 1 - \gamma(q_{-i} - q_i) \tag{18}$$

For the case when (17) is true we have the following evolution of the game:

$$
\begin{aligned}
p_i^{(1)} &= \gamma(q_{-i} - q_i) + \delta\\
p_i^{(k)} &= p_e^{k-1}\gamma^k(q_{-i} - q_i) - \delta p_e^{k-2}\gamma^{k-1}(1-p_e)\\
p_{-i}^{(1)} &= 0\\
p_{-i}^{(k)} &= 0\\
\hat{p}_i^{(1)} &= p_e + \gamma(q_{-i} - q_i)(1-p_e) + \delta(1-p_e)\\
\hat{p}_i^{(k)} &= p_e + p_e^{k-1}\gamma^k(q_{-i} - q_i)(1-p_e)\\
&\quad -\delta p_e^{k-2}\gamma^{k-1}(1-p_e)^2\\
\hat{p}_{-i}^{(1)} &= p_e\\
\hat{p}_{-i}^{(k)} &= p_e\\
q_i^{(1)} &= p_e - p_e\gamma(q_{-i} - q_i) + \delta(1-p_e)\\
q_i^{(k)} &= p_e - p_e^k\gamma^k(q_{-i} - q_i) + \delta p_e^{k-1}\gamma^{k-1}(1-p_e)\\
q_{-i}^{(1)} &= p_e\\
q_{-i}^{(k)} &= p_e
\end{aligned}
$$

In this case, and from (2), the stage payoffs are:

$$u_{i\delta}^{(1)} = u_{i\ b}^{(1)} + \frac{\delta}{2\alpha - 1}$$

$$u_{i\delta}^{(k)} = u_{i\ b}^{(k)} - \frac{\delta p_e^{k-2}\gamma^{k-1}(1-p_e)}{2\alpha - 1}.$$

And the discounted average payoff starting from stage 1 is:

$$U_{i\delta}^{(1)} = \sum_{k=1}^{\infty} w^{k-1}u_{i\delta}^{(k)} = U_{i\ b}^{(1)} + \frac{\delta}{2\alpha-1}\left[1 - \frac{w\gamma(1-p_e)}{1 - wp_e\gamma}\right].$$

Since $\alpha \geq 1$ it does not pay to deviate if:

$$1 - \frac{w\gamma(1-p_e)}{1 - wp_e\gamma} < 0.$$

Which leads to the following bound on w:

$$w > \frac{1}{\gamma}. \tag{19}$$

For the case when (18) is true we have the following game evolution:

$$
\begin{aligned}
p_i^{(1)} &= \gamma(q_{-i} - q_i) + \delta \\
p_i^{(k)} &= 0 \\
p_{-i}^{(1)} &= 0 \\
p_{-i}^{(k)} &= p_e^{k-2}\gamma^{k-2}\min\{1, \gamma\delta(1-p_e) - p_e\gamma^2(q_{-i} - q_i)\} \\
\hat{p}_i^{(1)} &= p_e + \gamma(q_{-i} - q_i)(1-p_e) + \delta(1-p_e) \\
\hat{p}_i^{(k)} &= p_e \\
\hat{p}_{-i}^{(1)} &= p_e \\
\hat{p}_{-i}^{(k)} &= p_e + (1-p_e)p_{-i}^{(k)} \\
q_i^{(1)} &= p_e - p_e\gamma(q_{-i} - q_i) + \delta(1-p_e) \\
q_i^{(k)} &= p_e \\
q_{-i}^{(1)} &= p_e \\
q_{-i}^{(k)} &= p_e - p_e p_{-i}^{(k)}
\end{aligned}
$$

From (2), the respective stage payoffs are:

$$u_{i\delta}^{(1)} = u_{i\ b}^{(1)} + \frac{\delta}{2\alpha - 1}$$

$$u_{i\delta}^{(k)} = u_{i\ b}^{(k)} - \frac{(p_e\gamma)^{k-2}}{2\alpha - 1}\left[p_e\gamma^2(q_{-i} - q_i) + 2\alpha\min\{1, \gamma\delta(1-p_e) - p_e\gamma^2(q_{-i} - q_i)\}\right].$$

The discounted average payoff starting from stage 1 is:

$$U_{i\delta}^{(1)} = \sum_{k=1}^{\infty} w^{k-1}u_{i\delta}^{(k)} = U_{i\ b}^{(1)} + \frac{1}{2\alpha - 1}\left\{\delta - \frac{w\left[p_e\gamma^2 Q + 2\alpha\min\{1, \gamma\delta(1-p_e) - p_e\gamma^2 Q\}\right]}{1 - wp_e\gamma}\right\}.$$

Where $Q = q_{-i} - q_i$ and $U_{i\ b}^{(1)}$ is the discounted payoff received if player i does not deviate. It does not pay to deviate if $U_{i\delta}^{(1)} < U_{i\ b}^{(1)}$. Since we assume $\alpha \geq 1$, we have:

1. If $\gamma\delta(1-p_e) - p_e\gamma^2(q_{-i} - q_i) > 1$ we need the condition

   $$\delta - \frac{w[2\alpha + p_e\gamma^2(q_{-i} - q_i)]}{1 - wp_e\gamma} < 0$$

   to be true for any δ. Equivalently:

   $$w > \max_{\delta}\left\{\frac{\delta}{2\alpha + p_e\gamma^2(q_{-i} - q_i) + p_e\gamma\delta}\right\}.$$

   Since δ is bounded by (18) we get:

   $$w > \frac{1 - \gamma(q_{-i} - q_i)}{2\alpha + p_e\gamma^2(q_{-i} - q_i) + p_e\gamma[1 - \gamma(q_{-i} - q_i)]}.$$

   Simplifying:

   $$w > \frac{1 - \gamma(q_{-i} - q_i)}{2\alpha + p_e\gamma}. \tag{20}$$

2. If $\gamma\delta(1-p_e) - p_e\gamma^2(q_{-i} - q_i) \leq 1$ we need the following condition:

   $$\delta - \frac{w\left[p_e\gamma^2 Q + 2\alpha\gamma\delta(1-p_e) - 2\alpha p_e\gamma^2 Q\right]}{1 - wp_e\gamma} < 0.$$

   Where Q was defined above. Thus we have the bound:

   $$w > \max_{\delta}\left\{\frac{\delta}{\delta\left[2\alpha\gamma(1-p_e) + p_e\gamma\right] - (2\alpha - 1)p_e\gamma^2 Q}\right\}.$$

   Since δ is bounded by (18) we get:

   $$w > \frac{1}{\gamma}. \tag{21}$$

So for a given history h^n we have found five bounds that w has to fulfill in order for DARWIN to be a Nash equilibrium in a given subgame. We first start noting that (19) and (21) are identical, so we really have four bounds, two of which are dependent on h^n. In order to find the conditions under which DARWIN is subgame perfect we need to find bounds that are history independent. In the case of (15) the bound is maximized by:

$$w > \frac{1}{2\alpha(1 - p_e\gamma) + p_e\gamma}. \tag{22}$$

Similarly, (20) is maximized by:

$$w > \frac{1}{2\alpha + p_e\gamma}. \tag{23}$$

Comparing (16), (22) and (23) it is easy to check that (22) is the strictest bound since we assumed $\gamma > 1$. In summary, we have the following bound on w for DARWIN:

$$w > \max\left\{\frac{1}{\gamma}, \frac{1}{2\alpha(1 - p_e\gamma) + p_e\gamma}\right\}.$$

Thus if the bound holds true, by the One-Stage Deviation Principle DARWIN is subgame perfect. □

9. REFERENCES

[1] L. Anderegg and S. Eidenbenz. Ad hoc-VCG: A truthful and cost-efficient routing protocol for mobile ad hoc networks with selfish agents. In *Proc. ACM Ninth Annual International Conference on Mobile Computing and Networking (MobiCom '03)*, pages 245–259, San Diego, CA, Sept. 2003.

[2] R. Axelrod. The emergence of cooperation among egoists. *The American Political Science Review*, 75(2):306–318, June 1981.

[3] S. Bansal and M. Baker. Observation-based cooperation enforcement in ad hoc networks. Technical report, Stanford University, Stanford, CA, July 2003.

[4] R. Boyd. Mistakes allow evolutionary stability in the repeated prisoner's dilemma game. *Journal of Theoretical Biology*, 136(1):47–56, Jan. 1989.

[5] S. Buchegger and J.-Y. Le Boudec. Performance analysis of the CONFIDANT protocol (cooperation of nodes: Fairness in dynamic ad-hoc networks). In *Proc. International Symposium on Mobile Ad Hoc Networking & Computing (MobiHoc '02)*, pages 226–236, Lausanne, Switzerland, June 2002.

[6] L. Buttyán and J.-P. Hubaux. Enforcing service availability in mobile ad-hoc WANs. In *Proc. International Symposium on Mobile Ad Hoc Networking & Computing (MobiHoc '00)*, pages 87–96, Boston, MA, Aug. 2000.

[7] L. Buttyán and J.-P. Hubaux. Stimulating cooperation in self-organizing mobile ad hoc networks. *ACM/Kluwer Mobile Networks and Applications*, 8(5):579–592, Oct. 2003.

[8] J. Crowcroft, R. Gibbens, F. Kelly, and S. Östring. Modelling incentives for collaboration in mobile ad hoc networks. In *Proc. WiOpt '03*, France, Mar. 2003.

[9] D. Fudenberg and J. Tirole. *Game Theory*. The MIT Press, Cambridge, MA, Aug. 1991.

[10] Q. He, D. Wu, and P. Khosla. SORI: A secure and objective reputation-based incentive scheme for ad-hoc

networks. In *Proc. IEEE Wireless Communications and Networking Conference (WCNC '04)*, volume 2, pages 825–830, Atlanta, GA, Mar. 2004.

[11] R. Mahajan, M. Rodrig, D. Wetherall, and J. Zahorjan. Sustaining cooperation in multi-hop wireless networks. In *Proc. Second Symposium on Networked Systems Design and Implementation (NSDI '05)*, Boston, MA, May 2005.

[12] S. Marti, T. J. Giuli, K. Lai, and M. Baker. Mitigating routing misbehavior in mobile ad hoc networks. In *Proc. Sixth Annual International Conference on Mobile Computing and Networking (MobiCom '00)*, pages 255–265, Boston, MA, Aug. 2000.

[13] P. Michiardi and R. Molva. CORE: A collaborative reputation mechanism to enforce node cooperation in mobile ad hoc networks. In *Proc. Communications and Multimedia Security Conference (CMS '02)*, Portoroz, Slovenia, Sept. 2002.

[14] P. Michiardi and R. Molva. Analysis of coalition formation and cooperation strategies in mobile ad hoc networks. *Ad Hoc Networks*, 3(2):193–219, Mar. 2005.

[15] F. Milan, J. J. Jaramillo, and R. Srikant. Achieving cooperation in multihop wireless networks of selfish nodes. In *Workshop on Game Theory for Networks (GameNets 2006)*, Pisa, Italy, Oct. 14, 2006.

[16] J. Mundinger and J.-Y. Le Boudec. The impact of liars on reputation in social networks. In *Proc. of Social Network Analysis: Advances and Empirical Applications Forum*, Oxford, UK, July 2005.

[17] M. T. Refaei, V. Srivastava, L. DaSilva, and M. Eltoweissy. A reputation-based mechanism for isolating selfish nodes in ad hoc networks. In *Proc. IEEE Second Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services (MobiQuitous '05)*, pages 3–11, San Diego, CA, July 2005.

[18] V. Srinivasan, P. Nuggehalli, C. F. Chiasserini, and R. R. Rao. Energy efficiency of ad hoc wireless networks with selfish users. In *Proc. European Wireless Conference*, Florence, Italy, Feb. 2002.

[19] V. Srinivasan, P. Nuggehalli, C. F. Chiasserini, and R. R. Rao. Cooperation in wireless ad hoc networks. In *Proc. IEEE INFOCOM '03*, volume 2, pages 808–817, San Francisco, CA, Mar./Apr. 2003.

[20] R. Sugden. *The Economics of Rights, Cooperation and Welfare*. Blackwell Publishing, 1986.

[21] J. Wu and R. Axelrod. How to cope with noise in the iterated prisoner's dilemma. *The Journal of Conflict Resolution*, 39(1):183–189, Mar. 1995.

[22] S. Zhong, J. Chen, and Y. R. Yang. Sprite: A simple, cheat-proof, credit-based system for mobile ad-hoc networks. In *Proc. IEEE INFOCOM '03*, volume 3, pages 1987–1997, San Francisco, CA, Mar./Apr. 2003.