Cooperation Enforcement for Packet Forwarding Optimization in Multi-hop Ad-hoc Networks

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***Abstract*—Ad-hoc networks are independent of any infrastructure. The nodes are autonomous and make their own decisions. They also have limited energy resources. Thus, a node tends to behave selfishly when it is asked to forward the packets of other nodes. Indeed, it would rather choose to reject a forwarding request in order to save its energy. To overcome this problem, the nodes need to be motivated to cooperate. To this end, we propose a self-learning repeated game framework to enforce cooperation between the nodes of a network. This framework is inspired by the concept of "The Weakest Link" TV game. Each node has a utility function whose value depends on its cooperation in forwarding packets on a route as well as the cooperation of all the nodes that form this same route. The more these nodes cooperate the higher is their utility value. This would establish a cooperative spirit within the nodes of the networks. All the nodes will then more or less equally participate to the forwarding tasks which would then eventually guarantee a more efficient packets forwarding from sources to respective destinations. Simulations are run and the results show that the proposed framework efficiently enforces nodes to cooperate and outperforms two other self-learning repeated game frameworks which we are interested in.**

***Index Terms*—Ad-hoc networks, game theory, repeated game, self-learning, cooperation, punishment scheme.**

I. Introduction

In wireless Ad-hoc networks, nodes are self-organizing and autonomous. They manage their own resources and make their own decisions. In order to maintain network connectivity, each node has to forward packets of other nodes. However, since they are known to have limited battery resources, these nodes usually tend to be non-cooperative. Indeed, they might sometimes reject forwarding requests in order to save their proper energy. Thus, nodes are reluctant to participate in routing which may lead the network connectivity to break down. It is then necessary to provide a mechanism that enforces cooperation between nodes and maintains the network connectivity. The problem of forwarding packets in a non-cooperative Ad-hoc network is widely studied, as we highlight afterwards, and many approaches have been proposed. The nodes act selfishly and tend to maximize their own benefits, thus, most of these studies rely on game theory [1] which is a suitable tool to deal with complex interactions between network nodes. From this perspective, the approaches can be classified into two categories depending on the mechanism used to enforce cooperation level between nodes. In the first category, the propositions use the virtual payment scheme. Zhong et al. [2] have proposed Sprite, a credit-based system that makes incentives for nodes to cooperate. Eidenbenz et al. have designed COMMIT [3], a routing protocol based on payment with virtual currencies. The requested intermediate nodes will perceive a compensation that is related to their residual energy level. Ad Hoc-VCG [4] and incentives modeling advanced by Crowcroft et al. [5] also belong to the first category. In the second one, the approaches employ mechanisms to enforce and maintain cooperation between nodes communities. Some works use reputation-based mechanisms. In instance, Kwon et al. [6] who have formulated a Stackelberg game where two nodes sequentially estimate the willingness of each other and decide to cooperate or not according to the opponent reputation score. Also, Buchegger and Le Boudec [7], [8] have defined mechanisms taking into consideration reputation system. Other solutions aim to maintain cooperation by considering punishment threat. In this case, Marti et al. [9] have defined "watchdog" and "pathrater" techniques that improve throughput by excluding misbehaving nodes. Felegyhazi et al. [10] have proposed a scheme that enables the nodes to reach the Nash Equilibrium, under topological conditions (i.e. dependence graph), relying on the "Tit-For-Tat" punishment. Altman et al. [11] have highlighted the "aggressive" punishment in [10] and have proposed milder punishment mechanism which guaranties a Nash Equilibrium and helps nodes to consume less energy. Han et al. [12] have advanced a self-learning repeated framework based on punishment that determines the nodes optimal packet forwarding probabilities to maintain network connectivity. Pandana et al. [13] have considered the same aim as in [12] and have designed three learning schemes with a punishment mechanism under perfect/imperfect local observation and dependence graph conditions.

In this paper, we propose a self-learning repeated game framework inspired by "The Weakest Link" TV game. In our approach, the set of nodes forming a route are considered as the candidates of the chains in the TV game. Each node forwarding probability can be seen as good answer probability for each candidate. Indeed, the maximization of global collective gains depends strongly on the cooperation between the candidates involved in the game. Thereby, we adopt the TV game concept to design our scheme with the objective of motivating nodes to create the longest chains and maximizing their utility values. This would increase the probability that the packets are delivered to the destination and then would optimize packets forwarding. Moreover, the framework relevance lies in the repeated game that enforces collaboration between nodes and a learning scheme that tend to reach better cooperation level. We consider also a punishment mechanism that would discourage nodes from acting selfishly. To asses the efficiency of our proposal, we compare our proposal to two other self-learning repeated game schemes proposed in [12] and [13].

The remainder of the paper is organized as follows: In Section II, the proposed model based on the "Weakest Link" TV game principle is illustrated. The self-learning repeated game framework and punishment scheme are then presented in Section III. Section IV details simulations scenarios used to evaluate our proposal and analyzes the obtained results. Finally, concluding remarks are given in Section V.

II. System Model And Problem Formulation

To optimize packet forwarding in Ad-hoc networks, we strongly believe that applying the concept of the "Weakest Link" TV game is an interesting solution. We explain, firstly, the concept of the game that we want to reproduce and then we detail the proposed model.

A. The "Weakest Link" TV Game Principle

Weakest Link TV game is a game where a group of candidates try to answer correctly, relying on their knowledge, to the questions asked by the TV host. They aim to gather the highest amount of money through successive rounds. In each round, the players try to form a chain of nine correct answers to reach the highest gain. Before answering to a question, a candidate has the possibility to save the collected gain, provided by good answers of precedent candidates, by saying "Bank". It is obvious that the longer the chain is, the higher the gain gets. Nevertheless, a player who gives a wrong answer to a question and did not save the collected gains shall break the good answers chain and reset the gain to zero. Secondly, if the candidates save rapidly the collected gains, the chains will be too short to reach important amounts of money. Thus, answering wrongly or saving collected money return the chain counter to zero. The candidates have to avoid being frequently in these situations if they want to maximize their gains. The earnings scale expresses the potential round gain according to correct answers chain length. For example, if there are four good answers and the current player decides to save collected money, the total gains grow with the amount that corresponds to the chain length. Then, the candidates try to create another chain of good answers. Therefore, the key parameter that influences the maximization of earnings is the probability of giving a correct answer.

B. The Proposed Model: Analogy with the "Weakest Link" TV Game

Our objective is to define an approach that enforces cooperation in a distributed way. The model we propose is inspired by the principle of the TV game. We note interesting analogies between "The Weakest Link" TV game and the Ad-hoc network. The nodes are assumed to be the candidates of the game and forwarding a packet from a node to the next hop is considered as a good answer. We believe strongly that the TV game concept can be used to encourage nodes to cooperate and therefore to optimize packet forwarding. Hence, the nodes, along a route, aim to create the longest chain of successful forwarded packets to get better utility. Despite of the TV game, when a chain of forwarded packet is broken, only the nodes that form the chain and the node which saves the gains will be rewarded. The set of all nodes composing the route is rewarded by the collected gains only if the packet reaches destination. To formulate the expected utility of a node in a route, we propose expressions inspired by [14]. Let α_i and β_i be the forwarding and the saving gain (with chain breaking) probabilities, respectively, for each node i. We assume in our work that $\alpha_i = 1 - \beta_i$. Given a route R with N-1 hops (N nodes), we define in Eq. (1) the average gain that a node i can expect when it plays the role of the n^{th} link of the chain. Let $S(i)$ be the next hop of node i in route R. We mean by $C[n]$ the collected earnings when a chain of (n-1) successful transmissions is transformed in currency and by F the cost of forwarding other's packets. Considering the vector of forwarding probabilities α, the utility of a node i is given by:

$$U_i^R(n,\alpha) = \begin{cases} U_{S(i)}^R(1,\alpha) & if\ n = 0 \\ \begin{array}{c}(1-\alpha_i).C[n]+ \\ \alpha_i.(U_{S(i)}^R(n+1,\alpha) - F)\end{array} & if\ 0 < n < N \\ C[n] & if\ n = N \end{cases} \quad (1)$$

When the node i is an intermediate node and given that it wants to maximize its gains, it has to choose between saving the collected currency or increasing the chain length (relying on the cooperation of the successor(s) to maximize benefits despite of the cost of forwarding). We assume that the source of the packet (i.e. n=0) will send it with the probability equal to 1. Subsequently, the gains depend on the decisions of the next hops. In addition, when the packet reaches the destination (i.e. n=N), the node will save the collected gains with a probability equal to 1. In the latter case, the chain has the length of the route and the gains are maximized.

Therefore, we can formulate this problem as a non-cooperative game where each node will adjust its forwarding probability in order to maximize its own utility. A node i can belong to more than one route, its own utility is then the sum of each route utility, called U_i. To solve this problem, it is necessary to find the Nash Equilibrium of the game.

Definition1: The Nash Equilibrium is some strategy set α^* for all nodes, such that for each node i, the following condition is verified:

$$U_i(\alpha_i^*, \alpha_{-i}^*) \geq U_i(\alpha_i, \alpha_{-i}^*), \forall i, \forall \alpha_i \in [0,1] \quad (2)$$

Where $\alpha_{-i}^* = (\alpha_1^*, \ldots, \alpha_{i-1}^*, \alpha_{i+1}^*, \ldots, \alpha_N^*)$.

This condition emphasizes that no node can increase its utility by operating a unilateral change of its forwarding probability, while all other nodes play the Nash Equilibrium

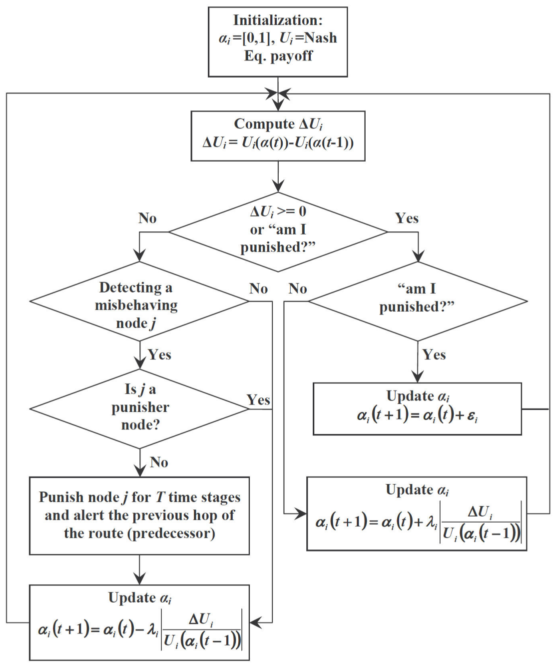

Fig. 1. The self-learning repeated game flowchart

strategy. However, as mentioned in several works as [11]–[13], this equilibrium matches with the strategy where $\alpha_i = 0, \forall i$. To avoid a poor network performance, we propose a self-learning repeated game framework, inspired by the concept of "The Weakest Link" TV game that we call The Weakest Link scheme. The objective of this framework is to enforce cooperation between nodes through learning and punishing threat mechanisms.

III. Self-Learning Repeated Game Framework and Punishment Mechanism

As the Nash Equilibrium corresponds to a non-cooperative strategy, it is more suitable to design cooperation under repetitive game. Applying repeated game scheme match perfectly with our proposed model. Indeed, in each game step, along each route, the nodes try to maximize their utilities and would choose to cooperate. In this paper, we consider an infinite repeated game, where the game duration is unknown to all nodes. Relying on the Folk theorem [15], the outcome of an infinitely repeated game can give better payoffs than those that can be obtained with Nash Equilibrium, especially when permanent punishment threat obliges selfish nodes to be more cooperative. Therefore, we propose a repeated game that enforces cooperation and maintains it through a designed punishment mechanism to encounter misbehaving forwarders. The framework we propose is presented by the flowchart in the Fig. 1.

In the initialization step, all nodes are more or less selfish. They can set their forwarding probabilities to 0 (the Nash Equilibrium strategy played with one stage game). We assume that the routes are determined with a routing protocol and that each node knows all the routes to which it belongs, as considered in [12], [13]. Then, the nodes start playing repeated game strategy. Note that they are rational and want to make benefits. Thus, at each step, each node learns through its utility the cooperation level of other nodes and adjusts its forwarding probability following to the others learnt behavior. It is possible that a node deviates from cooperation, then a punishment scheme is designed to discourage misbehaving nodes and to ask them to be more cooperative in the future. It is applied as soon as a selfish behavior is detected and subsequently the framework satisfies the Folk theorem.

A. The punishment mechanism

In this section, we present the punishment mechanism through a simple scenario. We assume that A and B are two successive nodes along a route. We suppose that the node B is a misbehaving node. The node A as one among the "closest" nodes to node B (i.e. the predecessor of B) is designed to punish it (if B rejects the request of A). We assume that the node A is able to detect the lack of cooperation of B (able to distinguish between a packet drop and a packet loss); the node A can conclude, by listening the channel, that node B is misbehaving when it does not forward the packet to the next node. To punish the selfish node B, the node A fixes its forwarding probability to 0 when the packet has to pass through node B. In this case, the node B will not be able to receive any packet from node A. Thereafter, the node B will be excluded from all chains in which its predecessor is in punishment mode. This punishment cancels the node B benefits for a period T and enforces it to cooperate (as its utility decreases). To avoid the propagation of the punishment mode over all nodes, when the node A is designated to punish the node B, the former one informs its predecessor about the execution of the punishment. Then, the punishment act is not interpreted as a deviation. It is important to mention that we assume that the nodes are not malicious.

B. The self-learning repeated game framework description

At each step of the repeated game, each node compares its current utility value with the former value. If the current utility is better, a cooperation enforcement is concluded. Thereby, the forwarding probability is increased proportionally with the enhancement of the utility to promote the cooperation level. The upgrade of the cooperation level is also led by the coefficient λ_i. It expresses the node sensitivity to the cooperation enforcement. However, when the current utility drops, it is analyzed as a come back to selfishness. Thus, the forwarding probability will decrease (proportionally with the difference). Analogically with "The Weakest Link" TV game, a candidate chooses to break the chain and insures gains if he notices that the following candidate tends to make wrong answers. Hence, cooperative nodes are sensitive to the behavior of the other nodes. As described in the punishment scheme, a node checks if its successor deviates. This deviation can be the result of punishment and an announcement is made to avoid selfishness propagation. The deviation without any

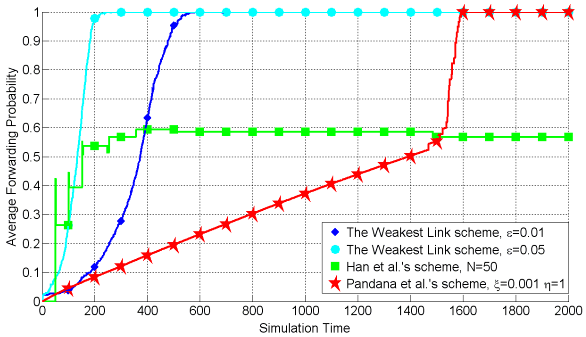

Fig. 2. The evolution of the average forwarding probability for different self-learning repeated game schemes in the case of the ring network

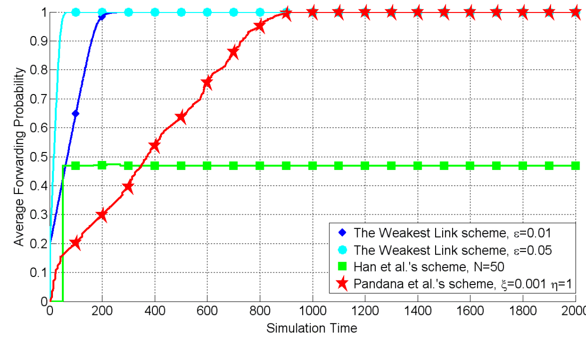

Fig. 3. The evolution of the average forwarding probability for different self-learning repeated game schemes in the case of a random network

notification is considered as a selfish behavior and then the punishment procedure is applied on the misbehaving node. Indeed, during a period T, no packet from its punishing predecessor reaches it. This causes a dramatic utility decrease. Therefore, a punished node is encouraged to be more cooperative in order to avoid longer penalization. Indeed, it increases its forwarding probabilities by a step equal to ε_i. To make possible the cooperation enforcement, another assumption must be considered. In fact, if the maximum gains that can be collected are lower than the forwarding cost, the nodes would not forward any packet even under punishment threat. Finally, it is important to mention that the proposed scheme work well when the mobility is moderate. In other words, transferring all packets on a route must be faster than route breakage due to mobility. We take into consideration this assumption in our simulations.

This framework aims to find the longest chains on a route between source and destination nodes, and routes are provided by a routing protocol to all nodes. If a route is not available at any node in the route, the routing tables must be updated. Moreover, the forwarding probability can be used by the routing protocol to determine better routes or to update routes in order to avoid misbehaving nodes to be a part of a route. Also, it is important to mention that this framework is adapted to scenarios where some nodes can either be only sources and/or destinations of packets as a source node forwards its packets to the next hop with a probability equal to 1 (only if the source node apply the punishment mechanism) and a destination node is not involved in the forwarding process.

IV. Performance Evaluation and Simulations Results

In this section, we evaluate the performances of the proposed approach through two scenarios: the widely used ring network and the random network. We compare our proposal to two other approaches which have inspired us: the scheme proposed by Han et al. [12] and the learning through flooding algorithm designed by Pandana et al. [13]. We implement our framework and do scenarios simulations on MATLAB 7.8.0.

Firstly, we consider a ring network of 25 nodes. The distance between any source and destination is N hops (if a node i is the source, node $mod(i+N, 25)$ is the destination). For each intermediate node, it is imperative that the forwarding cost must be less important than the maximum gain along a route. By the way, the nodes must have benefits in order to maintain a cooperative behavior. In our simulations, each successful forwarding increments by 1 the gain corresponding to the formed chain. In this scenario, we fix N to 6. We consider that one node can be a source or a destination at most one time and an intermediate node at most five times. The nodes initialize their forwarding probabilities at 0 (i.e. the Nash Equilibrium strategy). We choose also to fix the forwarding cost to 3 (i.e. to make benefits possible) and the period of punishment T to 3 time steps.

We represent in Fig. 2 the evolution of the average forwarding probabilities for the considered self-learning repeated game frameworks over 2000 time steps. For our proposal, we depict two different scenarios and each one is characterized by a specific value of ε (where $\varepsilon_i = \varepsilon$ for all nodes and ε takes respectively the values 0.01 and 0.05). The coefficient λ_i is fixed to 0.01 for all nodes. We have also fixed the characteristic parameters of the two other schemes as mentioned in the plot. We invite the reader to refer to [12] and [13] in order to understand the meaning of these parameters (we also assume that each two successive nodes in a route are separated by the same distance in order to simplify the computation of the utility functions when the scheme of Pandana et al. is used).

First of all, we remark that the average forwarding probability observed for the scheme of Han et al. converges to a value that turns around 0.6 and we note that the updates of this average probability become less frequent as time goes on. This finding logically indicates that the cooperation between nodes is limited even if the average cooperation level is rather substantial. The punishment mechanism adopted by the framework of Han et al. is clearly the major cause behind this result and we explain later the reasons behind that. The average forwarding probability obtained for the learning through flooding algorithm designed by Pandana et

TABLE I
EVALUATION METRICS IN THE CASE OF THE RING NETWORK (ALL FORWARDING PROBABILITIES INITIALIZED TO 0)

Schemes \ Metrics	Avg. PDR @ Dest.	Fwd. Pkts / Dlv. Pkts
The Weakest Link (ε=0.01)	75.19%	5.1195
The Weakest Link (ε=0.05)	90.30%	5.0452
Pandana et al.	21.29%	5.7362
Han et al.	0.23%	182.7456

TABLE II
EVALUATION METRICS IN THE CASE OF A RANDOM NETWORK (ALL FORWARDING PROBABILITIES INITIALIZED TO 0)

Schemes \ Metrics	Avg. PDR @ Dest.	Fwd. Pkts / Dlv. Pkts
The Weakest Link (ε=0.01)	92.94%	4.5709
The Weakest Link (ε=0.05)	98.21%	4.5459
Pandana et al.	67.31%	4.7061
Han et al.	1.62%	8.6341

TABLE III
EVALUATION METRICS IN THE CASE OF THE RING NETWORK (ALL FORWARDING PROBABILITIES INITIALIZED TO 0.5)

Schemes \ Metrics	Avg. PDR @ Dest.	Fwd. Pkts / Dlv. Pkts	Avg. Trans. Eff.
The Weakest Link (ε=0.01)	95.24%	5.0555	0.1617
The Weakest Link (ε=0.05)	97.66%	5.0278	0.1639
Pandana et al.	93.84%	5.0492	0.1581

TABLE IV
EVALUATION METRICS IN THE CASE OF THE RANDOM NETWORK (ALL FORWARDING PROBABILITIES INITIALIZED TO 0.5)

Schemes \ Metrics	Avg. PDR @ Dest.	Fwd. Pkts / Dlv. Pkts	Avg. Trans. Eff.
The Weakest Link (ε=0.01)	99.77%	4.4674	0.1832
The Weakest Link (ε=0.05)	99.31%	4.4722	0.1829
Pandana et al.	93.54%	4.525	0.1778

al. converges to 1 but after too many steps (compared to the Weakest Link scheme result). In their evaluation, Pandana et al. have chosen an initial forwarding strategy for nodes (i.e all forwarding probabilities initialized to 0.5) different from the Nash Equilibrium strategy (i.e. non-cooperative strategy). This assumption enables to the nodes of the network that adopt this scheme to reach more rapidly high cooperation levels but leads to a skewed evaluation of the algorithm. Regarding the Weakest Link scheme, the average forwarding probability converges to 1, as the scheme of Pandana et al. but needs less time to reach high cooperation levels. We depict the corresponding evolution for two values of ε: 0.01 and 0.05. We remark that the nodes become cooperative faster as they are more reactive to the punishment mechanisms (i.e. higher increase of the forwarding probability when punishment and utility decrease are detected). Then, the scenario where ε is equal to 0.05 highlights a quicker convergence of the average forwarding probability.

To support these conclusions, we determine for each scheme the average packet delivery rate at the destination and the ratio between the forwarded packets and the delivered packets. Table I lists the corresponding results for the ring network scenario. It is important to remind that the routes have a length of 6 hops. Then, in the ideal case when the nodes fully cooperate, each packet delivered to the destination needs 5 forwards. The found results reflect the efficiency of our scheme. This efficiency is tuned by the input parameters. As we show, the choice of the parameter ε has an important impact on the convergence speed of the average forwarding probability to 1. The scheme of Pandana et al. shows a limited efficiency over the simulation time because of the low convergence to a satisfying cooperation level.

For the two cited schemes, the nodes become cooperative as time goes on. The two algorithms rely on efficient punishment mechanisms. They share the penalty of the misbehaving node instead of all nodes in the network. The values obtained for the ratios of forwarded packets over delivered packets (slightly higher to 5) prove the effectiveness of these solutions to establish cooperation among nodes (even with some delay for the scheme of Pandana et al.). On the contrary, when a node that uses the framework of Han et al. detects a defection, it punishes all other nodes. This reaction engenders the propagation of the non-cooperative strategies and dramatically falls down the network performance.

In the same way, we consider the scenario of a random network consisting of 100 nodes with 1000 source-destination pairs. Fig. 3 depicts the evolution of the average forwarding probability for each scheme and Table II lists the evaluation metrics for the scenario of the random network (the average number of forwarders per route in this scenario is 4.535 nodes). The previous observations and interpretations match with the results obtained for this scenario. We note also that the performance of the Weakest Link and Pandana et al.'s schemes are better. This can be explained by higher opportunities to improve the utility function (i.e. nodes belong to a higher number of routes) compared to the case of the ring network.

Pandana et al. have defined the utility function of a node as its transmission efficiency. The transmission efficiency is the ratio of successful self-transmission power over the total consumed power (self-transmission and forwarding). We aim to compare our proposal to the algorithm of Pandana et al. using the cited criterion. We consider the same scenario of the ring network, as previously, and we initialize the forwarding probabilities of nodes at 0.5 to be as close as possible to the simulation inputs considered by Pandana et al.

We list in Table III the average packet delivery rate, the ratio of forwarded packets over delivered packets and the average transmission efficiency obtained by the Weakest Link scheme and the learning through flooding algorithm for the ring network scenario (the same scenario as previously). We note that the two frameworks highlight high packet delivery rates at destination (i.e. over 93 % with better performance for the Weakest Link scheme) and strong forwarding effectiveness (i.e. ratios of forwarded packets over delivered packets slightly higher than 5). Regarding the comparison based on the transmission efficiency, Table III emphasizes that the Weakest Link scheme (with the different values chosen for ε) reaches higher average transmission efficiency than the algorithm of Pandana et al. and then allows nodes to use better their energy. This finding can be explained be the upper packet delivery rate at the destination obtained for the Weakest Link scheme.

We can in addition emphasize that the behavior of nodes under the Weakest Link scheme enables nodes to have more "elastic" behavior towards defections. Thereafter, it is possible to avoid useless forwards and save energy. In fact, when a node detects a reduction in its utility function, it decreases its forwarding probability and then becomes reluctant to cooperate as the delivery of packets is not accurate. For the algorithm of Pandana et al., the forwarding probability can either increase or remain the same but never decreases. Then, the nodes maintain their cooperation level even if a defection is detected and can uselessly consume their energy.

We compute the same evaluation metrics for the case of a random network which consists of 100 nodes and 1000 source-destination pairs. Each route has at average 4.463 forwarders. We list in Table IV the obtained results for this scenario. We note that the effectiveness of our proposal is verified and that the transmission efficiency provided by the Weakest Link scheme is always better than the one of the algorithm of Pandana et al..

We have to mention that Pandana et al. have also proposed another framework based on utility prediction. It was highlighted in [13] that this latter scheme enables nodes to have better transmission efficiency. Anyway, the behavior of the average forwarding probability follows the same one of the learning through flooding scheme insofar as nodes can only maintain or increase their forwarding probabilities. Nevertheless, a convenient choice of the parameter ε for our scheme enables us to still improve the network performance if necessary.

V. Conclusion

In wireless Ad-hoc networks, nodes are requested to forward traffic. However, because of limited energy resources, they might refuse to collaborate in order to save their energy. This can lead to a significant amount of lost packets and a deterioration of the network performances.

In order to overcome this problem, we have proposed in this paper a self-learning repeated game framework that aims to enforce cooperation between nodes. Our framework is inspired by "The Weakest Link" TV game concept. Indeed, the amount of the global collective gains strongly depends on the cooperation degree between the candidates involved in the game. The candidates try to form the longest chain in order to reach the highest gain. Analogically, the nodes, along a route, would tend to achieve the longest sequence of successful packet forwarding and therefore assure that the packet reaches the destination. Our approach is designed as a self-learning repeated game framework that enables nodes to learn each others cooperation levels. Therefore, nodes that are in a same route and that have a high cooperation level may encourage the other nodes of the route to get more cooperative. For this aim, a punishment mechanism has been considered. Thereby, misbehaving nodes are punished and their utility would dramatically decrease. This allows the network to maintain a relatively satisfying cooperation level.

Simulations have been run and the results have shown that our scheme is efficient for the ring network scenario as well as for the random network scenario. It has been also shown that our proposal outperforms the self-learning repeated game frameworks that we have been interested in in this work.

As future work, it would be challenging to test our framework on real testbeds as smart grids. From this perspective, we want to enhance the Weakest Link scheme framework by considering the different channel characteristics among nodes, relaxing the assumption that a node is able to distinguish between a packet drop and a packet loss and probably taking into consideration the residual energy for each node as a parameter in the utility function. All these perspectives would be helpful to design a real cooperation enforcement framework for multi-hop Ad-hoc networks.

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