# An Incentive Mechanism for Cooperative Data Replication in MANETs

## A Game Theoretical Approach

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*Abstract*—**Wireless ad hoc networks have seen a great deal of attention in the past years, especially in cases where no infrastructure is available. The main goal in these networks is to provide good data accessibility for participants. Because of the wireless nodes' continuous movement, network partitioning occurs very often. In order to subside the negative effects of this partitioning and improve data accessibility and reliability, data is replicated in nodes other than the original owner of data. This duplication costs in terms of nodes' storage space and energy. Hence, autonomous nodes may behave selfishly in this cooperative process and do not replicate data. This kind of phenomenon is referred to as a strategic situation and is best modeled and analyzed using the game theory concept. In order to address this problem we propose a game theory data replication scheme by using the repeated game concept and prove that it is in the nodes' best interest to cooperate fully in the replication process if our mechanism is used.**

***Keywords-MANETs; game theory; repeated games; data replication;***

## I. INTRODUCTION

By emerging advanced wireless computing devices and along that, the notable technological breakthrough in wireless technology, wireless computing has transformed from a faraway dream to a daily reality. Computers now have ample amount of storage space and massive computational power, which, gives new perspective to mobile ad hoc networks (MANETs). A mobile ad hoc network is a wireless peer to peer network which lacks any infrastructure or central server. In MANETs each node acts both as a router and a host. The ultimate goal of these networks is to provide data for other nodes [1]. In recent years a vast range of applications have used this technology, naming in battlefields, search and rescue operations, and many other such applications that are best served by the MANET technology. Network partitioning is a common property of MANETs, because nodes move freely and therefore data accessibility becomes an issue. Data replication is a well-known terminology that addresses the data accessibility problem. It means that data is copied in nodes other than the original owner of data. This mechanism improves the data accessibility and at the same time reduces the request delay [2].

In autonomous MANETs nodes may not be willing to cooperate fully, since, tasks like forwarding the received packets or participating in the replication process is costly from the nodes' initial point of view. However, such selfishness and noncooperation not only deteriorates system efficiency but also reduces nodes' performance. In game theory literature we call this dilemma a strategic situation [3, 4]. In a strategic situation the goal is to enact an equilibrium between gains and losses, which in our case is data accessibility versus nodes' resources. Therefore, design and implementation of a mechanism that motivates the nodes to cooperate in the data replication process is of the utmost importance. Such mechanisms are implemented using the concepts provided by game theory literature [5-8].

In this paper we first discuss the necessity of data replication and then inspired by [2] we introduce a new utility function that incorporates both global parameters and local parameters in the nodes' decision making process and name it self-global benefit (SGB). Since we assume that nodes are rational, it is understandable that each node tries to maximize its own benefit by maximizing its utility function. The problem that arises is that if every node tries to maximize its benefit unilaterally, then no node will cooperate fully in the data replication process and data accessibility deteriorates tremendously. So by using the repeated games concept in game theory, we propose a punishment mechanism that each node punishes its deviating neighbor for a period of time and since we presumed that nodes are rational, the deviating node rectifies its non-cooperative behavior to improve its utility and cooperates with other nodes. We then prove that this mechanism works theoretically.

The remainder of this paper is arranged as follows. In section 2 we will review some of the related works. Section 3 will define and formulate the problem. Section 4 will present the incentive mechanism using repeated games and proves that it works. Finally, in section 5 we conclude the paper and give insights for the future work.

## II. RELATED WORK

There has been tremendous research effort in the area of data replication in wireless environments. Depending on the network management type, ad hoc networks can be divided into two groups: *open networks* and *closed networks* [18]. In a closed network, since the management is unique, the nodes cooperate with each other to achieve the manager's goal in the network. On the other hand, in an open network nodes have autonomous management and therefore each node sees its own benefit. So depending on the application of the network and viewpoint of the authors, selfish behavior might or might not have a role in their approach.

In closed networks some works like [1, 9, 10] pay special attention to grouping nodes for data replica allocation. Other works like [11-13] take on an access frequency approach and try to improve energy consumption and overall response time.

The most recent work in this area [2] is a game theory approach that uses the idea of volunteers' dilemma [3, 4] which in it each player makes a small sacrifice that will benefit the whole network. In their work, Hirsch and Madria [11] propose a method called CADR, where each node calculates a network global benefit NGB for caching a replica of a requested data. Multiple factors are considered in calculating NGB such as nodes' history, transitory window of interest, replica usage, replica TTL and many others that make this method an outstanding one among its rivals.

In open networks there has been various approaches towards addressing selfish nodes' behavior. These techniques, according to [14], can be divided into three categories: *credit based*, *payment based*, and *game theory based* approaches. In credit based techniques each node monitors the behavior of others and uses the corresponding information to measure the degree of node selfishness [17, 18]. In payment approaches, each node, rewards the node that forwards a packet [15-18]. The accumulated credit from these rewards is then used to send data to other nodes. In game theoretic approaches it is presumed that any rational node can find its optimum strategy to maximize its own benefit [7, 19]. Game theory methods usually try to find the Nash equilibrium [3, 4] in order to optimize the system performance. Although much effort has been done in game theory area, most of these solutions are for packet forwarding problem.

Of the most recent works in this scope are the ones in [17, 18]. In their work, Choi *et al*. [17] use the concept of credit risk which every node in a MANET measures the credit risk information in order to estimate a node's degree of selfishness. One particular problem in this method is that the selfish node may become completely isolated and therefore network partitioning occur. In [18] Ryu et al. improve the latter work and consider both node's selfishness and node distance to choose better candidates for replicating data. At the same time the storage space in selfish nodes is also exploited for better efficiency.

Here we briefly provide some differences between our work and some other similar approaches cited above. The primary difference between our work and the group found in [1, 9, 10], and access frequency, found in [11-13], is that these methods take a much localized view to determine replica placement while we try to see both global parameters and local parameters. More than that we consider selfish behavior in our model while the aforementioned works do not consider this type of behavior.

Moreover, game theoretic approaches for replication in mobile environment have not been significantly used. The work in [2] just uses the idea of volunteers' dilemma and the whole approach is based on other parameters and experimental results. Hirsch and Madria in [11], also do not consider selfish behavior in mobile nodes. We try to improve this approach by providing solid formulation of repeated games and prove that our mechanism will work in the presence of selfish nodes.

The main downside in [17, 18] is that they try to persuade the node to tell the truth. Although this is a good way for detecting selfish nodes, but a mechanism to enforce cooperation among nodes seems necessary.

## III. System Model and Punishment Design

In this section we model our solution for data replication using a game theory approach. We first introduce a new utility function, based on [2], and then propose our incentive mechanism. This mechanism holds if nodes act rationally.

### A. *System Model and Formulation*

This work is an extension of [2] with the focus on punishment mechanism design. We expand the aforementioned global benefit (NGB) and propose a self-global benefit (SGB) utility function. In this criteria we try to consider the benefit of each node from the global point of view. Therefore, two local parameters, naming SDC and ODC are introduced. SDC is the cost for self-data caching, meaning the cost incurred for replicating data in a node when the requester is the node itself. On the other hand, ODC is the cost for others' data caching, meaning the cost incurred when replication is done for other nodes' requests. Therefore we introduce our utility function as follows:

$$SGB = \frac{NGB}{SDC + ODC} \tag{1}$$

In (1) the NGB is like what it is defined in [2]. SDC and ODC are as follows:

$$SDC = S_j\,. \tag{2}$$

$$ODC = \alpha_j \sum_{j=1}^{N} S_j \times H_j^k + S_j\,. \tag{3}$$

Which $S_j$ is the size of data item $j$, $\alpha_j$ is the probability that data item $j$ will be replicated in the node, and $H_j^k$ is the request history for data item $j$ requested in node $k$.

The efficiency of this utility function is yet to be proved, but for our purpose we will discuss some parameters that are in direct relationship with the punishment mechanism design.

Of the assumptions that we made was the fact that in our model, nodes have autonomous management and they act rationally. Having the utility function in (1) a node $i$ selects its replicating probability, $\alpha_i$, such that it maximizes the following utility function:

$$U_i(\alpha_i, \alpha_{-i}) = \frac{NGB_i}{SDC_i + ODC_i} \tag{4}$$

It implies that node i will selfishly minimize $ODC_i$, the portion of resources used to replicate data for others. In the game theory literature [3-4, 19-22], Nash

Equilibrium (NE) states that in the equilibrium, every node selects the best response strategy to the other nodes' strategy, the formal definition is given as follows:

*Definition 1*: a Nash Equilibrium of a non-cooperative game $G = (N, (S_i)_{i\in N}, (u_i)_{i\in N})$ is a strategy profile s*∈S such that $\forall i \in N$, we have the following:

$$U_i(s_i^*, s_{-i}^*) \geq U_i(s_i, s_{-i}^*)\ ,\ \forall s_i \in S_i \tag{5}$$

Which in our case $s_i = \alpha_i \in [0, 1]$. Given that every node plays NE, no node can improve its utility by unilaterally changing its own data replication probability. Here $\alpha_{-i}^*$ is the set of all strategies selected by all the nodes other than node i.

In an ongoing relationship the promise of future reward and/or the threat of future punishment sometimes provide incentives for nodes to behave well now. This is best modeled by the concept of repeated games in game theory.

*Definition 2:* let $G = (N, (S_i)_{i\in N}, (u_i)_{i\in N})$ be a strategic game and $\delta \in (0, 1]$ be discount factor. The utility for a player i in the repeated game is given by:

$$U_i(s_i,\ s_{-i}) = \sum_{t=0}^{T} \delta^t g_i(a_i(t),\ a_{-i}(t)) \tag{6}$$

In this equation, $a_i(t)$ is node's *i* action in the repeated game. If $T \rightarrow \infty$ the game is referred to as repeated game with infinite horizon and the utility is normalized as in Eq.7.

$$U_i(s_i,\ s_{-i}) = (1-\delta) \sum_{t=0}^{T} \delta^t g_i(a_i(t),\ a_{-i}(t)) \tag{7}$$

Since having a future motivates the players to behave well in the time being, we model our scenario to an infinite repeated game, where nodes do not know when the game finishes. The details of our punishment mechanism is described in the next section.

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## *B. Punishment Design*

Until now we have just discussed the necessity of a punishment in the case of misbehavior from nodes. In this subsection inspiring from [7] we describe a way of punishing deviating nodes. Firstly we need nodes to monitor each other in a distributed way and more than that we need to provide information for nodes to detect the deed of misbehaving. Therefore, we have two main assumptions:

*1)* Every nodes has perfect awareness of the network. (With this assumption any deviation can be detected).
*2)* Every node has at least one neighbor. (It is necessary to perform punishment task).

With these assumptions we propose the following 3 step rules to ensure that any individually rational utilities can be enforced.

- *Step 1* - The strategy of all nodes is cooperation if there is no deviation in the last stages. After any deviation go to step 2.
- *Step 2* - If a node (j) deviates, the nodes that can punish the deviating node play the punishment strategy for a period called punishment period. The rest of the nodes continue playing cooperation strategy. Any deviation in step 2 causes this condition to restart and punishment continues. If the punishing node does not comply and refuse to play the punishment strategy, the other nodes will punish that particular node. Otherwise after the end of punishment period, go to step 3.
- *Step 3* - Play a strategy that results in $(U_1, \ldots,$ $U_{j-1}, U_j - \varepsilon, U_{j+1}, \ldots, U_N)$. If there is any deviation in step 3, go back to step 2 and punish the deviating node.

We need to mention that Eq.6 and Eq.7 are completely independent of Eq.4, so our proof stands to reason, no matter what the utility function is. In the next section we provide theoretical proof for our method

# IV. System Model and Punishment Design Proof

For a node to be motivated to conform to cooperative strategy, it is necessary that the following holds:

*Profit of deviation – Threat of misbehaving < 0*

In the sequel we show that under our proposition's assumption:

- The profit gained by deviation is less than cooperation profit in any node.
- The profit gained by the punishing node that does not play punishment strategy in punishment period is less than when it conforms to this strategy.

In the following we prove that with the 3 step rules mentioned in the previous section, any rational individual chooses to cooperate in the data replication process [7].

If node *j* deviates in step 1, it gains the immediate profit $\bar{u}_j$ for one period, $\underline{u}_j$ for $T_j$ periods when it is being punished and $U_j - \varepsilon$ after it conforms to the cooperative strategy. This three periods result in the average discounted utility as shown in Eq. 8.

$$\widehat{U_j^\infty} = \bar{u}_j + \frac{\delta(1-\delta^{T_j})}{1-\delta}\underline{u}_j + \frac{\delta^{T_j+1}}{1-\delta}(U_j - \varepsilon) \tag{8}$$

Since if a node cooperates throughout the game the average discounted utility becomes $\frac{1}{1-\delta}U_j$, thus, the gain of deviation is as follows.

$$\Delta U_j = \widehat{U}_j^{\infty} - \frac{1}{1-\delta} U_j \qquad (9)$$

And by subtracting the two values we can see that:

$$\Delta U_j < \bar{u}_j + \frac{\delta(1-\delta^{T_j})}{1-\delta} \underline{u}_j - \frac{1-\delta^{T_j+1}}{1-\delta}(U_j - \varepsilon) \qquad (10)$$

It is obvious that one stage NE is to $\underline{u}_j = 0$. If there exists a $\epsilon$ and the punishment period *Tj* such that

$$\frac{\bar{u}_j}{U_i - \epsilon} < (1 + T_j) \qquad (11)$$

and $\delta \rightarrow 1$, the deviation gain will be strictly less than zero. Hence any rational node will see that the loss of deviation is more that its gain. Therefore, it will not deviate from the cooperative behavior.

During the punishment stage the same logic stands since if the node being punished, continues to deviate it will postpone receiving strictly better utility $U_j - \varepsilon$ in step 3. Therefore it is better not to deviate in the punishment period.

On another hand, if the punishing node *i* deviates from playing the punishment of node *j*, it receives at most:

$$\widehat{U}_i^{\infty} = \bar{u}_i + \frac{\delta(1-\delta^{T})}{1-\delta} \underline{u}_i + \frac{\delta^{T+1}}{1-\delta}(U_i - \varepsilon) \qquad (\mathbf{12})$$

Let $\omega_j^i$ be the utility of node *i* to punish node *j*, then if node *i* plays the punishment strategy, its gain will be

$$\widetilde{U}_i^{\infty} = \frac{(1-\delta^{T})}{1-\delta} \omega_j^i + \frac{\delta^{T+1}}{1-\delta} U_i \qquad (13)$$

Therefore the profit for carrying out the punishment will be

$$\widehat{U}_i^{\infty} - \widetilde{U}_i^{\infty} = \frac{(1-\delta^{T})}{1-\delta} (\omega_j^i - \delta \underline{u}_i) - \bar{u}_i + \frac{\delta^{T+1}\varepsilon}{1-\delta} \qquad (14)$$

Having $\underline{u}_j = 0$ and $\delta \rightarrow 1$ the equation is equivalent to

$$\widehat{U}_i^{\infty} - \widetilde{U}_i^{\infty} = T.\ \omega_j^i - \bar{u}_i + \frac{\varepsilon}{1-\delta} \qquad (15)$$

A $\delta$ close to one makes this expression to be always larger than zero. In fact the closer $\delta$ to *one* the more important the value of future is.

The same argument applies for deviating in condition one and therefore we conclude that deviation in all conditions are not profitable. Therefore, based on the two assumptions mentioned at the beginning of this section, it is proved that any rational node will conform to cooperative strategy.

## V. CONCLUSION

In this paper we proposed a repeated game mechanism to enforce cooperation in data replication between autonomous nodes in MANETs. We first described a utility function (SGB) that incorporated multiple criteria, including local parameters and global parameters. Then we described the incentive mechanism for cooperative data replication and proved that it works. We demonstrated, using the concept of infinite repeated games, that if the nodes are punished when they misbehave, a cooperation strategy can be sustained among nodes. This is because nodes are rational and deviation has the threat of punishment. So any rational node will cooperate in the data replication process.

For future work it is suggested that the utility function be thoroughly tested. We are also interested in testing our findings in simulation and real applications

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