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A Dynamic Pricing Approach for Self-Organized Mobile Ad Hoc Networks

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***Abstract*— In self-organized mobile ad hoc networks (MANET) where each user is its own authority, fully cooperative behaviors, such as unconditionally forwarding packets for each other, cannot be directly assumed. The pricing mechanism is one way to provide incentives for the users to act cooperatively by rewarding some payment for cooperative behaviors. In this paper, we model the pricing and routing in self-organized MANETs as multi-stage dynamic games. A dynamic pricing framework is proposed to maximize the sender/receiver's payoff by considering the dynamic nature of MANETs, meanwhile, keeping the forwarding incentives of the relay nodes by providing the optimal payments based on the auction rules. The simulation results illustrate that the proposed dynamic pricing schemes have significant performance gains over the existing static pricing algorithms.**

I. INTRODUCTION

In recent years, mobile ad hoc networks (MANET) have received much attention due to their potential applications and the proliferation of mobile devices. In traditional emergency or military situations, the nodes in a MANET usually belong to the same authority and act cooperatively for the common goals. Recently, emerging applications of MANETs are also envisioned in civilian usage [1]–[3], where nodes typically do not belong to a single authority and may not pursue a common goal. We refer to such networks as self-organized (autonomous) MANETs.

Before MANETs can be successfully deployed in a self-organized way, the issue of *cooperation stimulation* must be resolved first. In the literature, two types of schemes have been proposed to stimulate cooperation among selfish nodes: reputation-based schemes and payment-based schemes. In reputation schemes, such as [1], [2], [4], a node determines whether it should forward packets for other nodes or request other nodes to forward packets for it based on their past behaviors. In the payment-based schemes, such as [3], [5], a selfish node will forward packets for other nodes only if it can get some payment from those requesters as compensation.

In this paper we focus on the payment-based mechanisms. Although the existing payment-based schemes have achieved some success in self-organized MANETs, most of them assume that the network topology is fixed or the routes between the sources and the destinations are known and pre-determined. However, in MANETs, there usually exist multiple possible routes from the source to the destination; furthermore, due to mobility, the available routes between the sources and the destinations may change frequently. In this paper, we refer to *path diversity* as that in general there exist multiple routes between a pair of nodes. We refer to *time diversity* as that due to mobility and dynamic traffic patterns, the routes between two nodes will keep changing over time. Some works have been proposed to exploit the path diversity, such as [6]–[8], in which the authors have introduced some auction-like methods for the cost-efficient and truthful routing in MANETs. In those papers, the sender-centric Vickrey auction has been adopted to discover the most cost-efficient routes. However, none of the existing schemes have addressed how to exploit the time diversity, which we expect can significantly improve the system performance.

In this paper, we consider the pricing and routing as multi-stage dynamic games and propose a dynamic pricing framework to maximize the sender's payoff over multiple routing stages considering the dynamic nature of MANETs, meanwhile, keeping the forwarding incentives of the relay nodes by providing the optimal payments based on the auction rules. The main contribution is as follows: Firstly, by modeling the pricing and routing as a dynamic game, the sender is able to exploit the time diversity in MANET to increase their payoffs by adaptively allocating the packets to be transmitted into different stages. Secondly, an optimal dynamic programming approach based on the Bellman equation is proposed to implement efficient multi-stage pricing for self-organized MANETs. Thirdly, the path diversity of MANET is exploited using the optimal auction mechanism in each stage.

The remainder of this paper is organized as follows: The system model of self-organized MANETs are illustrated in Section II. In Section III, we formulate the pricing process as dynamic games based on the system model. In Section IV, the optimal dynamic auction framework is proposed for the optimal pricing. In Section V, extensive simulations are conducted. Finally, conclusions are drawn in Section VI.

II. SYSTEM DESCRIPTION

An ad hoc network consists of a group of wireless mobile nodes, in which individual nodes cooperate by forwarding packets for each other to allow nodes to communicate beyond direct wireless transmission range. We assume that each node is equipped with a battery with limited power supply, can freely move inside a certain area, and communicates with other nodes through wireless connections. For each node, packets are

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scheduled to be generated and delivered to certain destinations with each packet having a specific delay constraint. In our system model, we assume all nodes are selfish and rational, that is, their objectives are to maximize their own payoff, not to cause damage to other nodes. However, node are allowed to cheat whenever they believe cheating behaviors can help them to increase their payoff. Assume that if a packet can be successfully delivered to its destination, then the source and/or the destination of the packet can get some benefits, and when a node forwards packets for others, it will ask the requesters to provide some compensation, such as virtual money or credits [3], [5], which should at least cover its cost. Without loss of generality, we assume that the source of a packet pays to the intermediate nodes who have forwarded packets for it. Like in [3], we assume that there exist some bank-like centralized management points to handle the billing information. In MANETs, due to the mobility, nodes need to frequently perform route discovery. In this paper, we refer to the interval between two consecutive route discovery procedures as a routing stage, and assume that for each source-destination pair, the quality of the selected route between them will keep unchanged in the same routing stage. Furthermore, to simplify our analysis, we assume that for each source-destination pair, the discovered routes in different routing stages are independent.

After performing route discovery at each stage, multiple forwarding routes can be exploited between the source and the destination. Assume there are ℓ possible routes and let $v_{i,j}$ be the forwarding cost of the jth node on the ith route, which is also referred to as the node type in this paper. Considering possible node mobility in MANET, ℓ and $v_{i,j}$ are no longer fixed values, which can be modelled as random variables. Let the probability mass function (PMF) of ℓ be $\tilde{f}(\ell)$ and the corresponding cumulative density function (CMF) be $\tilde{F}(\ell)$. Similarly, $v_{i,j}$ can be characterized by its probability density function (PDF) $\hat{f}_{i,j}$ and the cumulative density function (CDF) $\hat{F}_{i,j}$. Define the cost vector of the ith route as $\mathbf{v}_i = \{v_{i,1}, v_{i,2}, ..., v_{i,h_i}\}$, where h_i is the number of forwarding nodes on the ith route. Thus, we have the total cost on the ith route $r_i = \sum_{j=1}^{h_i} v_{i,j}$, which is also a random variable. Let the PDF and CDF of r_i be f_i and F_i, respectively.

III. Pricing Game Model

In this paper, we model the process of establishing a route between a source and a destination node as a game. The players of the game are the nodes in the network. With respect to a given communication session, any node can play only one of the following roles: sender, relay node, or destination. In self-organized MANET, each node's objective is to maximize its own benefits. Therefore, the source-destination pair and nodes on the possible forwarding routes construct a non-cooperative pricing game [9]. Since the selfish nodes belong to different authorities, they only have the information about themselves and will not reveal their own types to others. Generally, such non-cooperative game with incomplete information is complex and difficult to study. But based on our game setting, the well-developed auction theory [10] can be applied to formulate and analyze the pricing game. According to the auction game [10], the sender can be viewed as the principle (auctioneer), who attempts to buy the forwarding services from the candidates of the forwarding routes. The possible forwarding routes are the agents (bidders) who compete with each other for serving the source node, by which they may gain extra payments for future use. Thus, because of the path diversity of MANET, the sender is able to lower its forwarding payment by introducing the competition among the routing candidates based on the auction rules. It is important to note that instead of considering each node as a bidder as in [6], [8], we consider each route as a bidder in this paper, which makes it possible for the sender to fully exploit the path diversity to maximize its own payoffs.

We first consider the static pricing game (SPG) model. Specifically, consider an auction mechanism $(\mathbf{Q}, \mathbf{M})$ consisting of a pair of functions $\mathbf{Q} : \mathcal{D} \rightarrow \mathcal{P}$ and $\mathbf{M} : \mathcal{D} \rightarrow R^{\ell}$, where $\mathcal{D}$ is the set of the bidding strategies, $\mathcal{P}$ is the set of probability distributions over the set of routes $\mathcal{L}$. Note that $Q_i(\mathbf{d})$ is the probability that the ith route candidate will be selected for forwarding and $M_i(\mathbf{d})$ is the expected payment for the ith route, where $\mathbf{d}$ is the vector of bidding strategies for all routes, i.e., $\mathbf{d} = \{d_1, d_2, .., d_\ell\} \in \mathcal{D}$. Let d_{-i} denote the strategy vector of route i's opponents. Then, the utility function of the ith forwarding route can be represented as follows

$$U_i(d_i, d_{-i}) = M_i(d_i, d_{-i}) - Q_i(d_i, d_{-i}) \cdot r_i. \qquad (1)$$

Recall that r_i is the forwarding cost of the ith route. Before studying the equilibria of this auction game, we first define the *direct revelation mechanism* as the mechanism in which each route bids its true cost, that is, $d_i = r_i$. The *Revelation Principle* [10] states that given any feasible auction mechanism, there exists an equivalent feasible direct revelation mechanism which gives the auctioneer and all bidders the same expected utilities as in the given mechanism. Thus, we can replace the bids $\mathbf{d}$ by the cost vector of the routes, i.e., $\mathbf{r} = \{r_1, r_2, ..., r_\ell\}$ without changing the outcome and the allocation rule of the auction game. Therefore, the equilibrium of the SPG can be obtained by solving the following optimization problem to maximize the sender's payoff while providing incentives for the forwarding routes.

$$\max_{\mathbf{Q},\mathbf{M}} \left\{ E_{\ell,\mathbf{r}} \left[g \cdot \sum_{i=1}^{\ell} Q_i(\mathbf{r}) - \sum_{i=1}^{\ell} M_i(\mathbf{r}) \right] \right\} \qquad (2)$$

$$s.t. \qquad U_i(r_i, d_{-i}) \geq U_i(d_i, d_{-i}), \forall d_i \in \mathcal{D} \qquad (3)$$

$$Q_i(\mathbf{r}) \in \{0, 1\}, \quad \sum_{i=1}^{\ell} Q_i(\mathbf{r}) \leq 1. \qquad (4)$$

where the constraint (3) is also referred to as the incentive compatibility (IC) constraint, which ensures the users to report their true types, and g is the marginal profit of transmitting one packet.

Considering the dynamic nature of MANET, we will focus on studying the dynamic pricing game (DPG), which is played over many routing stages. Let ℓ_t denote any realization of the route number on the tth stage and $\mathbf{r}_t$ be a realization of the types of all routing candidates on the tth stage. Denote K and B as the total number of packets to be transmitted and the bandwidth constraint, respectively. Let T be the delay constraint of the packets defined as the maximal number of routing stages these packets can wait. Thus, the pricing game needs to be constrained within a T-period time window. Then, consider a T-period dynamic game, the overall utility maximization problem for the source-destination pair can be formulated as follows.

$$\max_{\mathbf{Q},\mathbf{M},\mathcal{K}_1} \left\{ \sum_{t=1}^{T} \beta^t \cdot E_{\ell_t,\mathbf{r}_t} \left[G(\mathcal{K}_t) \cdot \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) - k_t \cdot \sum_{i=1}^{\ell_t} M_i(\mathbf{r}_t) \right] \right\} \quad (5)$$

$$\begin{aligned} s.t. \quad & U_{i,t}(r_{i,t}, d_{-i,t}) \geq U_{i,t}(d_{i,t}, d_{-i,t}), \forall d_{i,t} \in \mathcal{D} \\ & Q_i(\mathbf{r}_t) \in \{0,1\}, \quad \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) \leq 1. \\ & k_t \leq B, \quad \sum_{t=1}^{T} k_t = K. \end{aligned} \quad (6)$$

where k_t is the number of packets transmitted in the tth stage and $\mathcal{K}_t$ is the vector of the numbers of the transmitted packets in the first $T-t+1$ stages, which can be represented as $\mathcal{K}_t = \{k_T, k_{T-1}, ..., k_t\}$. Note that a smaller t in this paper stands for a later time stage. Here, $G(\mathcal{K}_t)$ is the profit function that the sender gains in the tth stage determined by specific applications, which may not only depend on how many packets are transmitted in current stage, i.e., k_t, but also be affected by how many packets have been transmitted in previous stages, $\mathcal{K}_{t+1}$. Without loss of generality, we assume the profit function is concave in k_t. Also, β is the discount factor for multistage games, and the subscript t indicates the tth routing stage.

IV. The Optimal Dynamic Auction Framework for Efficient Pricing in MANET

Considering the optimal auction results in the DPG model formulated in Section III, we further propose the optimal dynamic auction framework for pricing in self-organized MANET. As it is difficult to directly solve (6), we study the dynamic programming approach in our proposed framework to simplify the multistage optimization problem.

Define the value function $V_t(x)$ as the maximum expected profit obtainable from stages $t, t-1, ..., 1$ given that there are x packets to be transmitted within the constraint of time periods. Simplifying (6) using the Bellman equation, we have the maximal expected profit $V_t(x)$ written as follows.

$$\begin{aligned} V_t(x) = \max_{\mathbf{Q},k_t} \Bigg\{ E_{\ell_t,\mathbf{r}_t} \Bigg[\Bigg[G(\mathcal{K}_t) \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) \\ - k_t \sum_{i=1}^{\ell_t} J(v_i) Q_i(\mathbf{r}_t) \Bigg] + \beta \cdot V_{t-1}(x-k_t) \Bigg] \Bigg\}, \end{aligned} \quad (7)$$

$$\begin{aligned} \text{s.t.} \quad & Q_i(\mathbf{r}_t) \in \{0,1\}, \quad \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) \leq 1, \\ & k_t \leq B, k_t \leq x \end{aligned}$$

where $J(r_i) = r_i + 1/\rho(r_i)$, and $\rho(r_i) = f_i(r_i)/F_i(r_i)$ is the hazard rate [11] function associated with the distribution of the routing cost. Note that $J(r_i)$ is also called the virtual type of the ith player. Moreover, the boundary conditions for the above dynamic programming problem are

$$V_0(x) = 0, x = 1, ..., K, \quad (8)$$

Recall that we have the delay constraint T of the maximal allowed time stages and the bandwidth constraint B of the maximal number of packets able to be transmitted for each stage. Based on the principle of optimality in [12], an allocation $\mathbf{Q}$ that achieves the maximum in (7) given x, t and $\mathbf{r}$ is also the optimal solution for the overall optimization problem (6). Note that the above formulation is similar to that of the multi-unit sequential auction [13] studied by the economists.

First, note that from (7) and the monotonicity of $J(\cdot)$, it is clear that if the sender transmits k packets within one time period, these packets should be all awarded to the forwarding route with the lowest cost r_i. Therefore, define the marginal benefits from the tth stage as

$$\begin{aligned} R_t(k_t) = \max_{\mathbf{Q}} \Bigg\{ G(\mathcal{K}_t) \cdot \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) - k_t \cdot \sum_{i=1}^{\ell_t} J(r_i) Q_i(\mathbf{r}_t) : \\ Q_i(\mathbf{r}_t) \in \{0,1\}, \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}_t) \leq 1, k_t \leq B \Bigg\}, \end{aligned} \quad (9)$$

which can also be solved and written as

$$R_t(k_t) = \begin{cases} 0 & if \ k_t = 0, \\ G(k_t, \mathcal{K}_{t+1}) - k_t \cdot J(r_{(1)}) & if \ 0 < k_t < \tilde{k}_t, \\ G(\tilde{k}_t, \mathcal{K}_{t+1}) - \tilde{k}_t \cdot J(r_{(1)}) & if \ k_t \geq \tilde{k}_t, \end{cases} \quad (10)$$

where $\tilde{k}_t = \min(B, x)$ and $r_{(1)}$ represents the lowest cost of the forwarding routes. Thus, the dynamic optimization objective (7) can therefore be rewritten in terms of $R_t(k_t)$ as follows:

$$V_t(x) = \max_{0 \leq k_t \leq \min\{B,x\}} \left\{ E_{\ell_t,\mathbf{r}}[R_t(k_t) + \beta \cdot V_{t-1}(x-k_t)] \right\}, \quad (11)$$

which is also subject to the boundary condition (8). Let $k_t^*(x)$ denote the optimal solution above, which is the optimal number of packets to be transmitted on the winning route at the tth stage given x. Letting $\triangle R_t(i) \equiv R_t(i) - R_t(i-1)$ and $\triangle V_t(i) \equiv V_t(i) - V_t(i-1)$, we can rewrite the maximal expected profit $V_t(x)$ as

$$\begin{aligned} V_t(x) = \max_{0 \leq k_t \leq \min\{B,x\}} \Bigg\{ E_{\ell_t,\mathbf{r}_t} \Bigg[\sum_{i=1}^{k_t} [\triangle R_t(i) - \\ \beta \cdot \triangle V_{t-1}(x-i+1)] \Bigg] \Bigg\} + \beta \cdot V_{t-1}(x). \end{aligned} \quad (12)$$

The above formulation will help us to simplify the optimal dynamic pricing problem. Then, in order to solve the dynamic

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pricing problem (7)-(8), we need to first introduce the following lemmas based on (12).

Lemma 1: If $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$, then $k_t^*(x) \leq k_t^*(x+1) \leq k_t^*(x)+1, \forall x \geq 0$.

Lemma 2: $\triangle V_t(x)$ is decreasing in x for any fixed t and is increasing in t for any fixed x.

The proof of the above lemmas can be found in [14]. Using Lemma 1 and Lemma 2, the optimal allocation of packet transmission for the proposed dynamic auction framework can be characterized by the following theorem.

Theorem 1: For any realization $(\ell_t, \mathbf{r}_t)$ at the tth stage, the optimal number of packets to transmit at state (x,t) is given by

$$k_t^*(x) = \begin{cases} \max\{1 \leq k \leq \min\{x, B\} : \\ \qquad \triangle R_t(k) > \beta \cdot \triangle V_{t-1}(x-k+1)\} \\ \qquad\qquad \text{if } \ R_t(1) > \beta \cdot \triangle V_{t-1}(x), \\ 0 \qquad\qquad \text{otherwise.} \end{cases} \tag{13}$$

Moreover, it is optimal to allocate these $k_t^*(x)$ packets to the route with the lowest cost r_i.

Proof: $V_t(x)$ is the summation of two terms in (12). As the second term is fixed given x, the optimal k_t^* maximizing the first term needs to be studied. Based on the definition (10), $\triangle R(\cdot)$ is decreasing in its argument. Also, $\triangle V_{t-1}(\cdot)$ is decreasing in its argument from Lemma 2. Thus, $\triangle R(k) - \beta \cdot \triangle V_{t-1}(x-k+1)$ is also monotonically decreasing in k. Therefore, the optimal allocation at tth time period with x packets in queue, $k_t^*(x)$, is the largest k for which this difference is positive. ∎

Theorem 1 shows how the source node should allocate packets into different time periods. The basic idea is to progressively allocate the packets to the route with the smallest realization of $J(r_{(1)})$ until the marginal benefit $\triangle R_t(i)$ drops below the marginal opportunity cost $\triangle V_{t-1}(x-i+1)$.

In order to have the optimal allocation strategies using Theorem 1, we first need to know the expected profit function $\triangle V_t(x), \forall t, x$. For finite number of time periods, T, in problem (7), the optimal dynamic programming proceeds backward using the Bellman equation [12] to obtain $\triangle V_t(x)$. Due to the randomness of the route number and its type, it is difficult to obtain the close-form expression of $\triangle V_t(x)$. Thus, we use simulation to approximate the values of $\triangle V_t(x)$ for different t and x, which proceeds as follows: Start from the routing stage 0. For each stage t, generate N samples of the number of available routes and their types, which follow the PDF $\tilde{f}(\ell)$ and $f_i(r_i)$, respectively. For each realization and for each pair of values (x,t), calculate $k_t^*(x)$ using Theorem 1. By using the conclusion of Lemma 1, we simplify the computation of $k_t^*(x)$ and only need $O(NK)$ operations to calculate $V_t(x)$ for all x at fixed t time period. Therefore, $O(NKT)$ operations are required for the whole algorithm. Note that the computation of $V_t(x)$ can be done off-line, which will not increase the complexity of finding the optimal allocation for each realization. We then study the expected profit function for infinite number of routing stages. Such scenario gives the upper-bound of the expected profit, because the source node can wait until low-cost routes being available for transmission. The value iteration [12] method from the dynamic programming can be applied here to obtain the value function of our scheme with infinite time horizon.

Next, our task is to find auction mechanisms that achieve the derived optimal policy. Considering the truth-telling property of the second-price auction, we focus on this mechanism in our paper. In our framework, the source node is trying to find the route with the lowest cost, which implies the application of reverse second-price auction [10]. Considering the sealed-bid auctions require less side-information than open auctions [10] and hence save the network resources, we apply the sealed-bid second-price auction for our optimal allocation policy. Further, in order to guarantee the truth-telling property of the bidders, we use $\tilde{r_t}$ as the reserved price for every stage, which is the highest price that the sender agrees to pay for transmitting one packet within current time period. Note that $\tilde{r}_t = \tilde{J}_t^{-1}(\triangle V_{t-1}(x_t))$, where x_t is the packets to be transmitted from the tth stage and $\tilde{J}_t(r) = G(1, \mathcal{K}_{t+1}) - J(r)$.

V. Simulation Studies

In this section, we evaluate the performance of the proposed dynamic pricing approach in mobile ad hoc networks. In our simulation, $\mathcal{N}$ nodes are randomly deployed inside a rectangular region of $10\gamma \times 10\gamma$ according to the 2-dimension uniform distribution with the maximal transmission range $\gamma = 100m$ for each node, and each node moves according to the random waypoint model [15]. Dynamic Source Routing (DSR) [15] is used as the underlying routing to discover possible routes. Let $\lambda = \mathcal{N}\pi/100$ denote the normalized node density, that is, the average number of neighbors for each node in the network. Note that each source-destination pair is formed by randomly picking two nodes in the network. Without loss of generality, we only consider the minimum-hop routes as the bidding routes for simplicity in the proposed optimal dynamic auction framework. Considering the mobility of each node, its forwarding cost is no longer a fixed value and, without loss of generality, we assume that its PDF $\hat{f}(v)$ follows the uniform distribution $\mathcal{U}[\bar{u}, \underline{u}]$, which has the mean μ and the variance σ^2. Then, using the Central Limit Theorem [16], the cost of a h-hop route can be approximated by the normal distribution with the mean $h \cdot \mu$ and variance $h \cdot \sigma^2$. In our simulation, we consider the performances of three different schemes: our scheme with finite time horizon, our scheme with infinite time horizon and the static scheme. Note that the infinite time horizon cannot be achieved in real application. But it can serve as an upper bound for measuring the performance of our scheme. The static scheme allocates a fixed number K/T of packets into each stage while also using the optimal auction at each stage. This scheme performs static pricing for each stage by exploiting only the path diversity. Assume the cheat-proof profit sharing mechanisms are in place to ensure the cooperation of the forwarding nodes on the same route. Let the benefit function be $G(\mathcal{K}) = g \cdot k$, where g is the benefit of successfully transmitting one packet. Note that the simulation

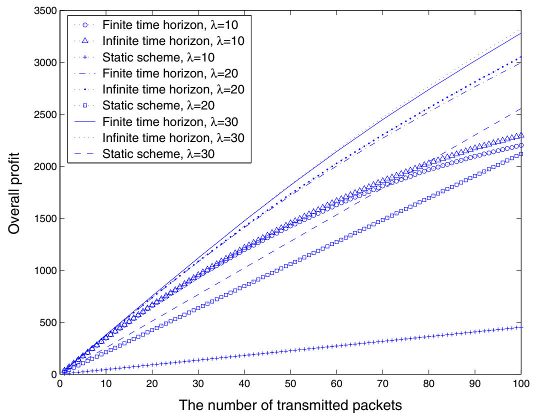

Fig. 1: The overall profits of the fixed scheme, our scheme with finite time horizon and infinite time horizon.

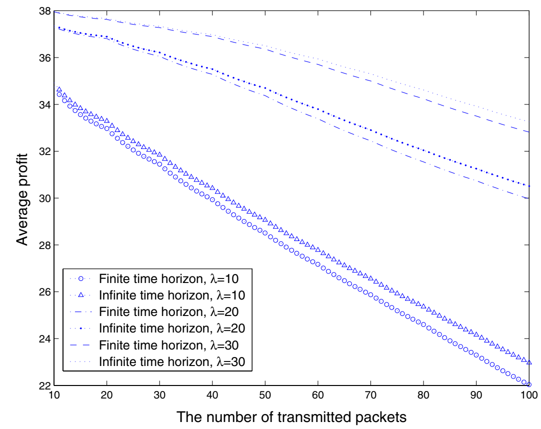

Fig. 2: The average profits of the fixed scheme, our scheme with finite time horizon and infinite time horizon.

parameters are set as $T = 20$, $K = 100$ and $B = 10$. Let $g = 60$, $\bar{u} = 10$, and $\underline{u} = 15$.

In Fig. 1, we compare the overall profits of the three schemes for different node densities with different number of transmitted packets. The concavity of the simulated value functions of our scheme matches the theoretical statement in Lemma 2. It can be seen from the figure that our scheme achieves significant performance gains over the static scheme, which mainly comes from the time diversity exploited by the dynamic approach. For instance, our scheme with $T = 20$ in the scenario of node density being 10 can even achieve similar performance of the static scheme with node density 30. We observe that the performance gap between our scheme with finite time horizon and the static scheme becomes larger when the node density decreases. Thus, in order to increase the profits under the situations of low node densities, it becomes much more important to exploit the time diversity. Also, the total profits of our scheme increases with the increment of the node density due to the higher order of path diversity. Further, since the performance gaps between the schemes with finite and infinite time horizon are all very limited for different node densities when $T = 20$, only a few routing stages are required to fully exploit the time diversity. In Fig. 2, the average profits of the three schemes are shown for different node densities. This figure shows that the average profit of transmitting one packet decreases as the number of packets to be transmitted increases. It is because the packets have to share the limited routing resources from both the time diversity and path diversity. When the node density is 30, the average profit degrades much slower than other cases because the potential of utilizing both the time diversity and path diversity is high.

VI. Conclusions

In this paper, we have investigated the pricing mechanisms for efficient routing in self-organized MANET. We model the pricing procedure as a multi-stage game by considering the dynamic nature of MANET. The proposed dynamic pricing framework can enable the sender to fully exploit the time diversity in MANET, which substantially increases his payoff by dynamically allocating the packets to be transmitted into different stages. The optimal dynamic auction algorithm is developed to achieve optimal packet allocation and route selection. The simulation results illustrate that the proposed scheme achieves significant performance gains over the static one under different simulation settings.

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