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Multi-Hop Data Dissemination with Selfish Nodes: Optimal Decision and Fair Cost Allocation Based on the Shapley Value

Mahdi Mousavi*, Sabrina Müller*, Hussein Al-Shatri*, Bernd Freisleben† and Anja Klein*

∗: Communications Engineering Lab, TU Darmstadt, Germany. {m.mousavi, m.mueller, h.shatri, a.klein}@nt.tu-darmstadt.de
†: Department of Mathematics & Computer Science, University of Marburg, Germany. freisleb@informatik.uni-marburg.de

***Abstract*—We consider a data dissemination scenario in a wireless network with selfish nodes. A message available at a source node has to be disseminated through the network in a multi-hop manner. In order to incentivize a node to forward the source's message to others, a forwarding cost is paid to a forwarder by its respective receiver. In the case of multicast transmission, the cost is shared among the receivers using the Shapley value (SV). Moreover, a node may exploit the maximal ratio combining (MRC) technique to receive the message from multiple transmitting nodes. In this paper, we show that in a game theoretic framework, the optimal decision of a node for receiving the message with minimum cost can be achieved by solving a linear optimization problem. In addition, we propose an algorithm by which truthfulness is a dominant strategy for the nodes and thus, fair cost allocation is guaranteed. Simulation results show that our proposed algorithm shares the cost of data dissemination among the nodes of a network in a fair manner. Compared to previous algorithms, the proposed algorithm can reduce the total cost paid by the nodes in the network for receiving messages.**

I. Introduction

Ad hoc networks attracted much attention over the past decade and researchers studied different problems related to these networks, such as energy consumption or delay minimization [1]. This paper focuses on a multi-hop data dissemination scenario in which a common message available at a source should be distributed throughout the whole network. Since in this scenario, some nodes must forward the source's message to others, incentivizing the nodes to participate in the forwarding process is of high importance. In this network, in order to incentivize a node to act as a forwarder, the forwarding node is paid by its respective receivers. In fact, every node must pay the cost of receiving data. The main goal of this paper is to distribute the source's message through the whole network while under a fair cost allocation, every node pays the least possible cost.

Wireless devices are battery equipped, and energy consumption of such devices is a concern that may prevent the nodes from contributing in the network. The cost in this network is based on the energy that a forwarding node spends for transmitting to its receivers. A receiving node can exploit the maximal ratio combining (MRC) technique to receive the message from multiple forwarders, but it must pay a price to each of its selected forwarding nodes. In other words, the scenario can be viewed as a network with multiple accessible message providers in which a node, in order to receive the message, must pay the price of forwarding the message, e.g., by a virtual currency [2], to each of its providers.

We use game theory to model the nodes' behavior in this network. A non-cooperative game is proposed in which every receiving node chooses one or more nodes among the nodes of the network as its respective forwarders. In addition, from each of its respective forwarders, the receiving node requests the power level that the forwarder should utilize as its transmit power such that the receiving node receives the message with an acceptable signal to noise ratio (SNR). In a multicast transmission where a forwarding node has multiple receivers, the cost paid to the forwarder can be shared among the receiving nodes. In this case, since different receiving nodes may have different power level requests, the fairness of the shared cost is a key issue for the receiving nodes. In our algorithm, we use the Shapley value (SV) [3] as a fair cost allocation method, to determine the cost share of each receiving node. Multicast transmission in such networks may lead to free-riding, i.e., some nodes receive the message without paying the cost of it. We also propose a mechanism that guarantees the truthfulness of the nodes in this network. This results in a completely fair cost sharing among the receivers of a multicast transmission.

The rest of the paper is organized as follows. Section II presents the related work and the main contributions of the paper. Section III describes the network model and states the problem. The proposed algorithm is explained in Section IV. Simulation results and discussions are presented in Section V and finally, Section VI concludes the paper.

II. State of the Art and Related Work

Optimizing the network parameters, such as finding energy efficient algorithms [4] or minimizing the number of transmissions for multihop broadcast [5], was the main challenge in ad hoc networks over the past years. The authors of [4] propose a heuristic algorithm called broadcast incremental power (BIP) that aims at minimizing the energy consumption

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for data dissemination in a wireless ad hoc network. The BIP, like some other algorithms, e.g., proposed in [6] and [7], is based on finding the best connections between the nodes to minimize the energy consumption. Some algorithms propose to reduce the number of transmissions in order to save energy in the network, like [5] in which the authors propose exploiting a sleeping schedule.

Since in ad hoc networks a centralized authority may not be available, game theory has been widely employed in the literature in proposing decentralized algorithms. Particularly, game theory is a powerful tool for studying the problems related to collaboration or conflicts among selfish nodes [7–11]. For instance, the authors in [7] address the energy minimization problem by centralized and decentralized heuristics based on game theory. The authors of [8] study incentivizing the nodes under a game theoretic model. They analyze two main approaches that are used to incentivize the nodes for collaboration in ad hoc networks, namely reputation-based and price-based approaches. They propose an integrated model composed of the two mentioned approaches in order to improve the network performance, such as decreasing the packet drop rate. A framework with a game-theoretic model incorporated with the Q-learning algorithm is proposed in [9] for reputation-based collaboration among the nodes. As the nodes in a network may encounter each other more than once, a node is able to find its optimum strategy against its opponent based on the reputation of its opponent. The scenario considered in [9] is a simple two-source two-destination scenario and the proposed game is based on the iterative prisoners dilemma model [12]. In [10] and [11], we have proposed game theoretic algorithms as a decentralized approach for the energy minimization problem in a single-source data dissemination scenario. In these algorithms, a cost is assigned to every node, assumed to be a player of the game. Then, a node chooses another node in the network to connect to and receive the source's message, in a way to minimize its cost. The MRC technique is exploited in [11] as a technique that can reduce the energy consumption in multihop broadcast networks.

Most of the existing works merely rely on optimization of the network parameters and the fairness issue is usually ignored in multihop data dissemination. In a network in which the nodes can decide by their own whether or not to collaborate with others, incentive mechanisms and fairness of the algorithm are two vital issues that affect the final performance of the network. The objective in [11] is energy minimization and the proposed algorithm does not take fairness into account. More precisely, the cost assigned to a node is not based on the service the node receives in a network, and some nodes may benefit from free riding. This means that some nodes pay nothing for receiving messages while some other nodes pay more than what they really have to. Hence, for networks in which the cost is monetary-based and the fairness of the outcome is important for the nodes, it may not be possible to apply the algorithm suggested by [11].

In this paper we propose a game theoretic model that considers fairness in terms of cost allocation and truthfulness of the nodes in a multihop broadcast scenario. Briefly, our algorithm has the following properties:

- **Incentive**: A nodes is incentivized to be a forwarding node. It is paid by its respective receivers.
- **Fairness**: In a multicast transmission, the total cost that must be paid to a forwarding node is shared among its respective receiving nodes using the SV method. SV is known as a fair cost allocation method in coalition formation games [12]. This is achieved if the nodes truthfully reveal their real power requirement.
- **Truthfulness**: A method will be proposed by which every node must reveal its real power requirement in order to receive data. Therefore, the nodes cannot benefit from free riding, and fairness is guaranteed.
- **Optimal decision**: The optimal decision of a node that minimizes its cost is achieved by solving a linear optimization problem.

III. Network Model and Assumptions

We consider a wireless ad hoc network consisting of $N+1$ nodes: a source S and a set $\mathcal{N} = \{1, \ldots, N\}$ of nodes interested in receiving the source's message. The message is the same for the whole network, e.g., a video with a specific quality and the same length, in a video streaming scenario. Each node has a coverage area that is determined by its maximum transmit power $p^{\max}$. To increase the coverage area, some intermediate nodes must forward the source's message to other nodes.

Every node in this network is assumed to be selfish, that is, not only a node's goal in this network is to maximize its own benefit, but also in order to forward the message to other nodes, it must be incentivized by its respective receiving nodes. It is assumed that any node $j \in \mathcal{N}$ has the potential to act as a forwarder. We call a forwarding node a *parent node* (PN) for the set of its respective receivers. A node served by PN j is called a *child node* (CN) of PN j. Due to the broadcast nature of wireless channels, a PN may serve multiple CNs. The set of CNs served by PN j is denoted by $\mathcal{M}_j$ with cardinality M_j. The set of all nodes that can be a PN for node i is called the candidate parents of node i. The candidate parents of a node i can be the nodes that receive the source's message prior to node i. We define D_i for $i \in \mathcal{N}$ as the distance of node i from the source and thus, $D_{\mathrm{S}} = 0$. The set of candidate parents of a CN i, denoted by $\mathcal{W}_i$ and cardinality W_i, are the nodes that have lower distance to S than that of i, i.e.,

$$\mathcal{W}_i = \left\{ j \,\middle|\, j \in \mathcal{N} \cup \{\mathrm{S}\}, D_j < D_i \right\}. \tag{1}$$

Fig. 1 shows a sample network. In this network, the source's message is disseminated throughout the network by some forwarders including nodes j and l. Nodes j and l are among the set of PNs for node i, i.e., $j, l \in \mathcal{W}_i$. PN j has multiple CNs including CNs i and k.

In this network, PNs are incentivized by a payment from their respective CNs. PNs are paid based on the energy that they spend for message transmission. A CN needs a minimum SNR denoted by $\gamma^{\min}$ in order to decode the message sent

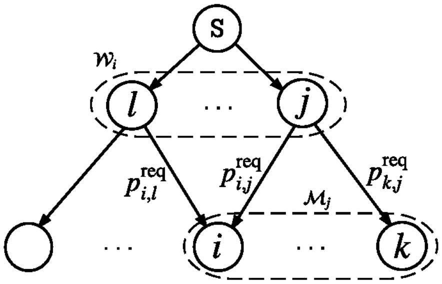

Fig. 1: A sample network. In this network, node i decides to be served by more than one parent nodes including nodes l and j.

from its PN. For a direct link communication between a transmitter and a receiver, the SNR γ at the receiver, given the transmit power p and the channel gain $|h|^2$ between the receiver and the transmitter, is defined as

$$\gamma = \frac{p|h|^2}{\sigma^2} \tag{2}$$

in which σ^2 is the noise power at the receiver.

Every CN $i \in \mathcal{N}$ should request from its candidate parents $j \in \mathcal{W}_i$ the transmit power level that it requires from them to receive the message with minimum SNR of $\gamma^{\min}$. The transmit power that CN i requests from PN j is denoted by $p^{\text{req}}_{i,j}$. Since in such scenarios, a CN may be reached by multiple PNs, it can have more than one PN and use the MRC technique. Using MRC, a CN may constructively combine the signals received from multiple PNs. In this case, the requested powers from the candidate parents must fulfill the SNR requirement at the CN. Using (2), the aggregated SNR at CN i is calculated as

$$\gamma^{\text{req}}_i = \sum_{j \in \mathcal{W}_i} \frac{p^{\text{req}}_{i,j}|h_{i,j}|^2}{\sigma^2} \geq \gamma^{\min} \tag{3}$$

where $|h_{i,j}|^2$ is the channel gain between nodes i and j. Since we do not consider the small scale variations of the channel gain, $|h_{i,j}|^2$ represents an averaged value. We assume that a node knows the average channel gains between itself and the other nodes in its proximity. It is also assumed that the PNs transmit on orthogonal channels and thus, there is no collision in the network.

In Fig. 1, the edges are weighted by the power level that the CNs require from their candidate parents. Note that, in a multicast transmission, i.e., when a PN j has multiple requests from multiple CNs, the transmit power at PN j is determined by the highest requested power by its CNs in $\mathcal{M}_j$ as

$$p^{\text{Tx}}_j(\mathcal{M}_j) = \max_{i \in \mathcal{M}_j} \quad \{p^{\text{req}}_{i,j}\}. \tag{4}$$

In the next section, we define a cost for each CN and propose a game theoretic algorithm by which the CNs can minimize their own cost in the network.

IV. Game Theoretic Algorithm

A. Game Properties

We propose an iterative game consisting of N players. The set of players is shown by $\mathcal{N}$. The action of player $i \in \mathcal{N}$ is a request vector that represents the requested powers of node i from each of its candidate parents. We show the request vector of a node i as $\mathbf{p}^{\text{req}}_i = \left(p^{\text{req}}_{i,1}, \dots, p^{\text{req}}_{i,W_i}\right)$ in which $0 \leq p^{\text{req}}_{i,j} \leq p^{\max}, j \in \mathcal{W}_i$. The requested powers must fulfill the minimum SNR requirement (3), and in the next subsection we discuss the optimal solution for finding $p^{\text{req}}_{i,j}, j \in \mathcal{W}_i$. Then, the action space of the game is defined as $\mathcal{A} = \prod_{i=1}^{N} \mathcal{A}_i$ such that $\mathcal{A}_i \in \mathbb{R}^{W_i}$ is the action space of node i.

Since in our scenario the benefit of every node is the same, that is, the same message is distributed in the whole network, we focus on cost minimization at every node.. Let C_i be the total cost that a node pays in this network. Then, the total cost paid by node i, $C_i(\mathbf{p}^{\text{req}}_i) : \mathcal{A} \to \mathbb{R}^+$ is defined as the summation of the individual costs that node i pays to each of its parent nodes $j \in \mathcal{W}_i$ i.e.,

$$C_i(\mathbf{p}^{\text{req}}_i) = \sum_{j \in \mathcal{W}_i} c_{i,j}(p^{\text{req}}_{i,j}) \tag{5}$$

in which $c_{i,j}(p^{\text{req}}_{i,j})$ is the cost that must be paid to PN j by node i. In a multicast transmission, all the CNs in $\mathcal{M}_j$ benefit from a single transmission while they may have different requests for transmission power at PN j. In this paper, the Shapley value (SV) [3] is used for sharing the cost among the children of a parent. The SV is a budget-balanced cost sharing method that assigns a cost to every member of a set based on its contribution on the final outcome. More precisely in our scenario, SV assigns the cost $c_{i,j}$ to CN i based on the power level that CN i requests from PN j and the final transmit power of PN j according to (4).

A cost sharing rule is budget-balanced if the summation of the cost share of each node $i \in \mathcal{M}_j$ is equal to the transmit power of PN j, i. e., $\sum_{i \in \mathcal{M}_j} c_{i,j}(p^{\text{req}}_{i,j}) = p^{\text{Tx}}_j$. In our case where the transmit power at PN j is equal to the highest requested power of the nodes in $\mathcal{M}_j$, by sorting the requested powers of the nodes in $\mathcal{M}_j$ in the form of $p^{\text{req}}_{1_j,j} \leq, \dots, \leq p^{\text{req}}_{M_j,j}$, the cost of CN $i \in \mathcal{M}_j$ using the SV rule can be calculated as

$$c_{i,j}(p^{\text{req}}_{i,j}) = \sum_{k=1}^{i} \frac{p^{\text{req}}_{k,j} - p^{\text{req}}_{k-1,j}}{M_j + 1 - k} \tag{6}$$

[13] for which $p^{\text{req}}_{0,j} = 0$.

Now, we formally characterize our proposed non-cooperative cost sharing game as $\mathcal{G} = (\mathcal{N}, \{\mathbf{p}^{\text{req}}_i\}_{i \in \mathcal{N}}, \{C_i\}_{i \in \mathcal{N}})$.

B. Decision Making

In this section, the optimal decision of a node is discussed. CN i decides how much power it should request from PN $j \in \mathcal{W}_i$ in order to minimize its cost defined in (5).

Theorem 1: $c_{i,j}(p^{\text{req}}_{i,j})$ can be obtained by a piecewise-linear, increasing function.

Proof: Suppose that $i \notin \mathcal{M}_j$ and the set of sorted requests from PN j is $0 \leq p^{\text{req}}_{1,j} \leq \dots \leq p^{\text{req}}_{M_j,j} \leq p^{\max}$. In this network, a PN j broadcasts the information about the requested powers that it receives from its CNs to its neighboring area. Hence, a node i knows the requested powers of the CNs of PN j prior to joining the multicast group of parent node j. Assume that node i decides to join PN j and $p_{i,j}^{\text{req}}$ is the $(n+1)$th lowest request from PN j such that the sorted requested powers from PN j become $0 \leq \cdots \leq p_{n,j}^{\text{req}} \leq p_{i,j}^{\text{req}} \leq p_{n+2,j}^{\text{req}} \leq \cdots \leq p_{M_j+1,j}^{\text{req}} \leq p^{\max}$, in which $p_{i,j}^{\text{req}} = p_{n+1,j}^{\text{req}}$. Based on (6), $c_{i,j}(p_{i,j}^{\text{req}})$ by considering $i = n+1$ can be written as a function of n as

$$c_{i,j}(p_{i,j}^{\text{req}}, n) = \frac{p_{i,j}^{\text{req}} - p_{n,j}^{\text{req}}}{(M_j+1)+1-(n+1)} + \sum_{k=1}^{n} \frac{p_{k,j}^{\text{req}} - p_{k-1,j}^{\text{req}}}{(M_j+1)+1-k} \tag{7}$$

in which $M_j + 1$ represents the total number of CNs of PN j including i. By expanding the right side of (7) and some transformations, (7) can be written as

$$c_{i,j}(p_{i,j}^{\text{req}}, n) = \frac{p_{i,j}^{\text{req}}}{M_j - n + 1} - \frac{p_{n,j}^{\text{req}}}{M_j - n + 1} + \frac{p_{n,j}^{\text{req}}}{M_j - n + 2} + \cdots - \frac{p_{1,j}^{\text{req}}}{M_j} + \frac{p_{1,j}^{\text{req}}}{M_j + 1}. \tag{8}$$

Eq. (8) can be written in the form of

$$c_{i,j}(p_{i,j}^{\text{req}}, n) = a_i(n) p_{i,j}^{\text{req}} + b_i(n) \tag{9}$$

in which

$$a_i(n) = \frac{1}{M_j + 1 - n} \tag{10}$$

and

$$b_i(n) = \sum_{k=1}^{n \geq 1} \left(\frac{-p_{k,j}^{\text{req}}}{(M_j - k + 1)(M_j - k + 2)} \right). \tag{11}$$

It can be derived form (9) that the cost of node i is obtained by a linear function with slope $a_i(n)$ and y-intercept $b_i(n)$. Both $a_i(n)$ and $b_i(n)$ depend on the interval that $p_{i,j}^{\text{req}}$ falls in. Eq. (9) shows that if $p_{i,j}^{\text{req}}$ increases and falls inside an interval with a higher n, the slope of the function $c_{i,j}$ in (9) increases accordingly. Besides, the y-intercept of $c_{i,j}$ decreases in this case. Therefore, $c_{i,j}$ in (9) forms a piecewise linear function in the interval $[0, p^{\max}]$ with an increasing slope. ∎

Corollary 1: The optimal request vector of node i, i.e., $\mathbf{p}_i^{\text{req}}$ can be obtained by solving a linear optimization problem.

Proof: To minimize its cost, node i has to solve the optimization problem

$$\underset{\mathbf{p}_i^{\text{req}}}{\text{argmin}} \quad \sum_{j \in \mathcal{W}_i} c_{i,j}(p_{i,j}^{\text{req}}), \tag{12}$$

$$\text{s.t.} \quad \sum_{j \in \mathcal{W}_i} \frac{p_{i,j}^{\text{req}} |h_{i,j}|^2}{\sigma^2} \geq \gamma^{\min}, \qquad 0 \leq p_{i,j}^{\text{req}} \leq p^{\max}, \quad \forall j \in \mathcal{W}_i \tag{13}$$

in which the first condition represents the minium SNR requirement at CN i. Knowing the piecewise linearity of $c_{i,j}(p_{i,j}^{\text{req}})$, the problem in (12) can be written as a linear optimization problem. Let us define $t_{i,j} \in \mathbb{R}^+, \forall j \in \mathcal{W}_i$ as an auxiliary scalar variable. Then, the equivalent linear optimization problem of (12) is given by

$$\underset{\{\mathbf{p}_i^{\text{req}}, t_{i,j}\}}{\text{argmin}} \quad \sum_{j \in \mathcal{W}_i} t_{i,j}, \tag{14}$$

$$\begin{aligned} \text{s.t.} \quad & c_{i,j}(\mathbf{p}_{i,j}^{\text{req}}, n) \leq t_{i,j} \qquad \forall j \in \mathcal{W}_i, n = 0, \ldots, M_j, \\ & \sum_{j \in \mathcal{W}_i} \frac{p_{i,j}^{\text{req}} |h_{i,j}|^2}{\sigma^2} \geq \gamma^{\min}, \\ & 0 \leq p_{i,j}^{\text{req}} \leq p^{\max}, \qquad \forall j \in \mathcal{W}_i. \end{aligned}$$

The problem in (14) is a linear optimization problem that can be solved efficiently by a proper solver. ∎

Every node $i \in \mathcal{N}$, iteratively finds its optimum request vector using (14), until none of the nodes updates its action given the action of others. This point is called as the Nash equilibrium (NE) point of the game.

C. Discussion

In this subsection, we discuss the properties of the proposed algorithm.

Proposition 1: The proposed game converges to a NE point.

Proof: A non-cooperative cost sharing game with the SV rule is in the class of potential games for which the convergence of the game to NE point is guaranteed [14]. ∎

Definition: The *social cost* of a game with N players, shown by Q, is defined as $Q = \sum_{i=1}^{N} C_i$ [12].

Theorem 2: Decreasing the cost at the nodes decreases the social cost and the required total transmit power in the network.

Proof: Since the SV cost sharing rule is budget balanced, for every PN $j \in \mathcal{N}$ we have $\sum_{i \in \mathcal{M}_j} c_{i,j}(p_{i,j}^{\text{req}}) = p_j^{Tx}$. This implies that

$$\sum_{j=1}^{N+1} \sum_{i \in \mathcal{M}_j} c_{i,j}(p_{i,j}^{\text{req}}) = \sum_{j=1}^{N+1} p_j^{Tx} \tag{15}$$

in which $j = N+1$ represents the source. The left side of (15) is the total price received by the PNs in the network, which is equal to the total cost paid by CNs. Therefore, the left side of (15) can be written as

$$\sum_{j=1}^{N+1} \sum_{i \in \mathcal{M}_j} c_{i,j}(p_{i,j}^{\text{req}}) = \sum_{i=1}^{N+1} \sum_{j \in \mathcal{W}_i} c_{i,j}(p_{i,j}^{\text{req}}). \tag{16}$$

Since the source does not pay anything to other nodes, $c_{N+1,j}(p_{i,j}^{\text{req}}) = 0$ for all $j \in \mathcal{N}$. Hence, using (15) and (16) we have

$$\sum_{i=1}^{N} \sum_{j \in \mathcal{W}_i} c_{i,j}(p_{i,j}^{\text{req}}) = \sum_{j=1}^{N+1} p_j^{Tx}. \tag{17}$$

Based on the definition in (5), we can rewrite (17) as

$$Q = \sum_{i=1}^{N} C_i(\mathbf{p}_{i,j}^{\text{req}}) = \sum_{j=1}^{N+1} p_j^{Tx}. \tag{18}$$

It can be observed that when the total cost paid by the nodes in the network decreases, the total transmit power in the network decreases accordingly. In other words, what the nodes pay as cost in total is directly related to the amount of energy spent for message forwarding in this network. ■

One of the concerns in cost sharing-based decentralized algorithms is fairness and truthfulness of the nodes. In such networks, a node may benefit by not revealing its real power requirement. More precisely, a node $i \in \mathcal{M}_j$ may request a power much lower than what it really requires, $p_{i,j}^{\text{req}\prime} \ll p_{i,j}^{\text{req}}$, when it finds another node $k \in \mathcal{M}_j$ with higher requested power, i.e., when $p_{i,j}^{\text{req}} < p_{k,j}^{\text{req}}$. By doing so, since p_j^{Tx} is determined by the highest request of CNs in $\mathcal{M}_j$, CN i receives its required SNR from PN j while it pays less than what it really should. Therefore, the cost is not shared between nodes i and j based on their real contribution. This point was not addressed in [11].

In order to overcome this problem, we propose using a unique key for each node for message decoding [15]. More precisely, prior to multicasting the message, PN j generates a unique key for every CN $i \in \mathcal{M}_j$ and transmits the key by a unicast transmission to CN i based on the the power that CN i requested, that is, $p_{i,j}^{\text{req}}$. If CN i cheats and requests a power lower than what it really needs, it cannot decode the key and consequently the message. Therefore, truthfulness becomes the dominant strategy for the nodes.

V. Simulation Results

To experimentally evaluate our approach, we simulated a square region of $1\text{km} \times 1\text{km}$ in which the nodes are randomly deployed. The number of nodes in this network varies between 10 and 40 and the maximum transmit power of a node is set to $p^{\max} = 20$ dBm. The simulation is based on the Monte Carlo method and in each network realization, the source node is chosen randomly. The channel is based on the path-loss model as $|h_{i,j}|^2 = 1/d_{i,j}^{\alpha}$ in which $d_{i,j}$ represents the distance between nodes i and j and α shows the attenuation exponent considered as $\alpha = 3$. The minimum required SNR at the receiving nodes is considered as $\gamma^{\min} = 10$ dB and the noise power is set to $\sigma^2 = -90$ dBm.

Fig. 2 shows the social cost when there are 30 nodes in the network. The nodes join the network one by one by choosing their respective parent nodes and sending them their request given the requests of previous nodes. Joining a new node to the network increases the total cost paid by the nodes until all the nodes join the network. After this step some nodes may update their decision about their parent nodes or requested powers to decrease their own cost. Updating continues until reaching the NE point where none of the nodes can find a lower cost given the action of other nodes. It can be seen that when the nodes are allowed to choose more than one parent, the total cost paid by the nodes in the network to receive the source's message is less than in the case of receiving the message from only one parent. Note that in both cases, the parent nodes are incentivized in the same way, that is a PN is paid by its CNs exactly equal to the energy that it spends, but the total cost that the CNs pay in the network to receive the message decreases when they are allowed to choose more than one parent. In Fig. 2 the game converges to the NE point after about 35 iterations.

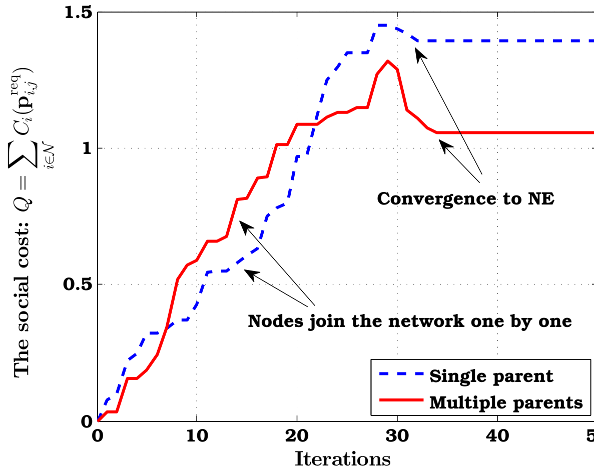

Fig. 2: The social cost normalized to 1 mW when there are 30 nodes in the network.

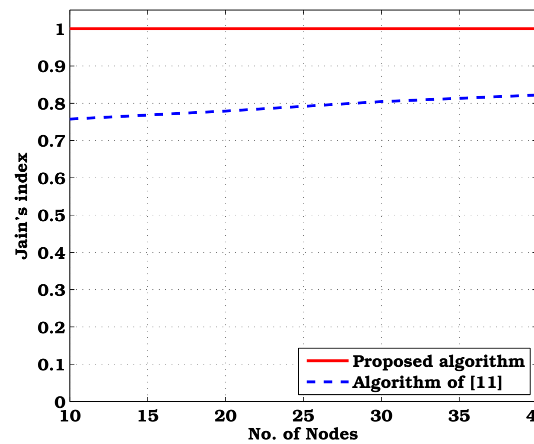

Fig. 3: Comparing the fairness by Jain's index for two algorithms.

Fig. 3 compares the fairness of the proposed algorithm with the one proposed in our previous work [11]. To capture the fair behavior of the nodes, we measure the SNR that an individual node receives in a unicast transmission based on its requested power. More precisely, for each node $\gamma_i^{\text{norm}} = \gamma_i^{\text{req}}/\gamma^{\min}$ shows the SNR at CN i based on its requested power, normalized to the minimum required SNR. With this parameter, we are able to measure the fairness of the algorithm and truthfulness of the nodes in terms of revealing their true power requirements. We use Jain's index [16] as the fairness metric

$$\mathcal{J} = \frac{\left(\sum_{i \in \mathcal{N}} \gamma_i^{\text{norm}}\right)^2}{N \sum_{i \in \mathcal{N}} \left(\gamma_i^{\text{norm}}\right)^2} \tag{19}$$

such that $\frac{1}{N} \le \mathcal{J} \le 1$. The closer $\mathcal{J}$ to 1, the fairer the algorithm performs.

Since in our proposed model, on one hand, the optimization problem at every node is subjected to receiving at least $\gamma^{\min}$ (13), and on the other hand, the objective of a node is to

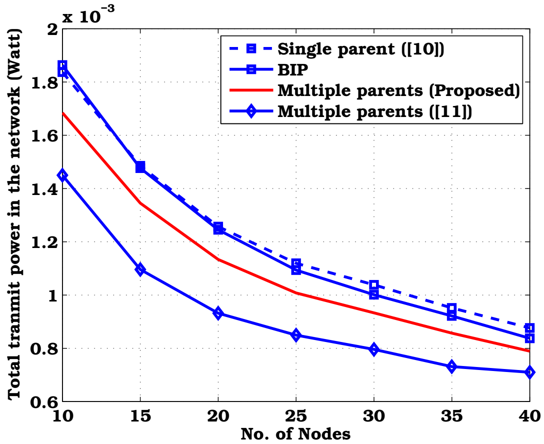

Fig. 4: Total transmit power in the network for different algorithms.

minimize its cost, the power requested by a node i from its candidate parents results in the exact amount of minimum required SNR, i.e., $\gamma_i^{\text{req}} = \gamma^{\text{min}}$. This means that every node reveals its true power requirement to receive the minimum SNR, but it tries to find the best parent and adjust its required power level to minimize its cost. Hence, for every node $i \in \mathcal{N}$, $\gamma_i^{\text{norm}} = 1$ and consequently $\mathcal{J} = 1$. Moreover, using a unique key at every individual node for message decoding, as discussed in subsection IV-C, results in truthfulness of the nodes about their required power. Fig. 3 also shows that based on the algorithm proposed in [11], the nodes may not reveal their true power requirements and benefit from free riding. In fact, in [11] $0 \leq \gamma_i^{\text{norm}} \leq 1$ holds, which means that the request of some nodes is less than what they really require. This leads to an unfair cost allocation among the nodes such that the nodes, usually the nodes with few neighboring nodes or bad channel conditions, pay a larger share of the cost, more than what they really have to.

Fig. 4 compares the performance of different algorithms in terms of total required transmit power in the network for data dissemination. It is evident that by increasing the number of nodes, since the nodes become closer to each other, the total transmit power required for data dissemination decreases. As shown in Fig 4, the proposed algorithm outperforms the BIP algorithm and the game theoretic algorithm of [11]. In both algorithms, the MRC technique is not exploited. Compared to the decentralized algorithm that exploits MRC in [11], the proposed algorithm performs (slightly) worse, but it considers a fair cost allocation among the nodes Although the algorithm of [11] performs better than our proposed algorithm, it does not consider a fair cost allocation among the nodes. That is, in networks where the forwarding nodes must be incentivized and the fairness of the cost is critical for receiving nodes, our proposed algorithm suggests a fair solution with reasonable performance, see Fig. 3. In other words, higher required transmit power for our proposed algorithm compared to [11] is the price that the network pays for achieving a fair result.

VI. Conclusion

We proposed an algorithm for multi-hop data dissemination in a network with selfish nodes. We modeled the nodes' behavior by game theory and proved that the minimum cost of a node based on the Shapley value cost allocation can be found by solving a linear optimization problem. Moreover, the proposed algorithm is fair and has reasonable performance compared to other algorithms.

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