Empathy and Berge equilibria in the Forwarding Dilemma in Relay-Enabled Networks

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***Abstract*—Device-to-device communications aim to enhance service coverage, particularly at cell edges or in black spots within a neighborhood through relaying and forwarding. In this context, each device is free to move independently, and will therefore change its links to other devices frequently due to connectivity issues. During these movements, a device may be requested to forward traffic unrelated to its own use, and therefore be a temporary router or a relay. This paper analyses the forwarding dilemma from different perspective using psychological game theory. It also provides different approaches that try to solve the forwarding problem in multi-hop relay-enabled networks by means of empathy, mutual support and partial altruism.**

***Index Terms*—device-to-device communication, forwarding dilemma, game theory, wireless networks**

I. Introduction

Wireless technology is proliferating rapidly, and the vision of pervasive wireless networking, computing and communications offers the promise of many industrial and individual benefits. This explosion of wireless applications creates an ever-increasing demand for more radio spectrum. The presence of Device-to-Device (D2D)-enabled mobile users defines an extended network coverage and its co-existence with device-to-infrastructure networks is not without challenges. D2D communication appears also in a context of mobile ad hoc networks, which is a decentralized type, self-configuring, infrastructure-less network of mobile devices connected without wires. In this context, each device can move independently, and will therefore change its links to other devices frequently due to connectivity issues. Relay-enabled wireless device may be requested to forward traffic unrelated to its own use, and therefore be a temporary router or a relay. D2D is a promising technique for offloading local traffic from cellular base stations by allowing local devices, in physical proximity, to communicate directly with each other. Furthermore, the resulting short-range communications can enable local devices to realize higher data rates, lower communication latency, and reduced power consumption. Through relaying and forwarding, D2D is also a promising approach to enhancing service coverage, particularly at cell edges or in black spots within the cell. In addition to improving network performance and service quality, D2D can open up opportunities for new proximity-based services and applications for cellular users. With 5G expected to be an important carrier for the internet-of-everything (IoE) traffic, the potential role of D2D and its scalability to support massive IoE devices and their machine-centric and human-centric communications need to be investigated. New challenges have also arisen from new enabling technologies for D2D communications, such as millimeter-wave and distributed massive MIMO (multiple-input and multiple-output) systems, which call for new solutions to be proposed. The presence of high priority primary users (PUs) and the requirement that the cognitive users should cause only limited interference with them define an access paradigm called cognitive access. Cognitive access control is relevant to both the cognitive radio and the coexistence community. Cognitive access control protocols play an important role to exploit the spectrum opportunities, manage the interference to primary users, and coordinate the spectrum access amongst cognitive users. D2D communication allows us to avoid some of the communication range occupied by PUs and hence improves the probability of success of secondary users. However, the devices are low-powered and have limited battery. Forwarding the data of others in wireless ad hoc networks may quickly become critical issue in terms of remaining energy, leading to the so-called Forwarding Dilemma. The goal of this paper is to analyze the forwarding problem from different point of view and propose methodologies for improving users' participation.

Structure

This paper is structured as follows. We start with an introduction to how to route and forward data in mobile ad hoc networks by means of incentives. It focuses on individual power-limited mobile devices and explores how they can communicate together and how their forwarding decisions shape the connectivity of the network. The first section presents a background on access control and relay-enabled forwarding schemes. Then, a one-shot forwarding game model is presented. Several solution concepts are introduced to solve the decision-making problem. When the network environment is dynamic and users can move independently, it is critical to capture the variability of the channel state in device-to-device communication. A forwarding game with random

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payoffs, which is random matrix game, is introduced and analyzed, with both complete and incomplete information, with incentives, empathy, mutual support and berge solution approach.

Data Forwarding as a Game

When a D2D link is not occupied by PUs data, the secondary or cognitive users can opportunistically share the spectrum in a distributed and autonomous manner. However, simultaneous transmissions around the same range will generate an aggregate interference that could be potentially high and thus reduces the performance of the wireless devices. This interaction falls down clearly in a strategic decision-making problem, also called game. Game theory is a tool aimed at understanding and modelling both cooperative and competitive situations, which imply the interaction of decision makers (which can be altruistic, irrational, altruistic or rational) with mutual and possibly conflicting interests. In the data forwarding setting, the decision is on, when to transmit/forward and with which transmit power. The decision policy is based on location, queue, remaining energy, channel state and resource availability. In order to forward the data, the connection between the devices is established by the flooding of data packets or route discovery part of the reactive routing protocol with minimal interference to the PU communication ranges. Considering a certain number of participating wireless devices (players of the game), each of them may play the role of relay node or regular node. They can decide to forward or not the message. If the channel gain of the all the intermediary forwarding nodes are good enough and the data is successfully decoded at all the intermediary nodes and forwarded the message till the destination device, then the source device gets an end-to-end successful transmission with the expense of the energy consumption at all the participating devices in the multi-hop routing path. In the context of next generation networks, the term cognitive D2D communication is sometimes used when spectrum sensing is performed at each D2D transmitter before transmission to make sure that the channel designated for D2D transmission is not being used for future cellular communication in the uplink or downlink. Since an end-to-end transmission requires the involvement and participation from all the intermediary devices between the source and the destination, it is crucial that the intermediary nodes help the source by forwarding the data. However, forwarding a data is costly in the sense it consumes power and these wireless devices are power limited. Therefore a wireless device is facing to a sort of dilemma between focusing only its own data and forwarding the data of others.

Literature review

Cognitive access control coupled with state estimation and detection for identifying and exploiting instantaneous spectrum opportunities is one of the central challenges. In addition, the opportunistic spectrum access needs to the take into consideration battery lifetime and energy constraints of sensing, exploration, exploitation and transmission, see for example [6], [9]. Then the question is, how to develop cognitive sensing and access strategies that learn from observations and offer improved fairness and performance over time without central controllers or dedicated communication/control channels (see [1], [8]). The question of spectrum access and transmissions is an important issue and has been addressed by many authors. The work in [10] proposed a memory management for distributed spectrum sharing under limited spectrum sensing. The authors in [2] examine the question of asynchronicity in ad hoc networks. The work in [5] examines cognitive medium access and the relation to competitive multi-armed bandit problem. The arm bandit problem is well understood for single cognitive user, who wishes to opportunistically exploit the availability of resources in the spectrum. For multiple users however the outcomes are not clear. This difficulty is in particular due to the interactive behavior of the underlying processes of decision making in dynamic environment. The authors proposed a Bayesian approach to identify a tradeoff metric between exploring the availability of other free channels/time slots and exploiting the opportunities identified. In [8], a game theoretic learning and pricing have been proposed. The authors in [15] examine how efficient allocation can be done with multiple channels in mobile ad hoc networks. The authors in [12] consider cooperative packet forwarding in self-organized mobile ad hoc networks under unreliable channel which results in loss of packets and noisy observation of transmissions. The authors propose an indirect reciprocity framework based on evolutionary game theory, and enforce cooperation of packet forwarding strategies. The works in [3], [4], [7] develop a framework to from coalition between wireless devices using evolutionary coalitional game theory in wireless networking and communications. The work in [11] deals with the problem of joint sensing and medium accessing in cognitive radio networks. The authors design a non-cooperative two-step game to describe the Sense-Transmit-Wait paradigm in an opportunistic point of view.

Main Focus of this paper

Relay-Enabled Cognitive Access Control: D2D communication between secondary users will be allowed only when it does not interfere with PU communications. Each device can therefore sense the channel. If the channel is free then the access protocol is initiated. The problem is that several secondary D2D communications can interfere when they are in intersecting ranges. This may create collisions, packets losses and the end-end transmission delay increases.

Relay-Enabled Data Forwarding: If the receiving device can also play the role of relay then it will forward the data to the next hop after sensing the channel again. For given routing path, the data need to be forward at each intermediary hop until the end destination. The intermediary nodes are relays or regular nodes that are willing to forward. If many nodes are participating in the forwarding, every node can benefit from that service, and hence it is a public good, which we refer to as mobile crowdforwarding. By analogy with crowdfunding, crowdsourcing, crowdsensing, the concept of mobile crowdforwarding consists to call for contributors (mobile devices) who willing to forward data in mobile ad hoc networks by means incentive schemes. However, most of the current smart devices are battery-operated mobile devices that suffer from a limited battery lifetime. Hence, a user who is forwarding a data needs also to balance with the remaining energy by limiting the energy consumptions. When decision-makers are optimizing their payoffs, a dilemma arises because individual and social benefits may not coincide. Since nobody can be excluded from the use of a public good, a user may not have an incentive to forward the data of others. One way of solving the dilemma is to give more incentive to the users. It can be done by slightly changing the game, for example, by adding a second stage in which a reward (fair) can be given to the contributors (non-free-riders).

II. One-Shot Forwarding Game

We consider two source nodes (S1 and S2) and two destination nodes (D1 and D2) with the network configuration as depicted in Figure 1.

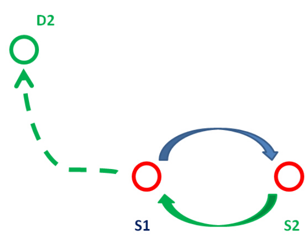

Fig. 1: Example of two source-destination pairs with forwarding dilemma configuration.

In order to reach the destination device D1, the source device S1 needs help from S2 to forward his data to D1. Similarly, the source device S2 needs help from S1 to forward his data to D2. Wireless devices S1 and S2 have limited power and limited battery lifetime. Each wireless device can decide to forward (F) or not to forward (nF) the data of the other wireless source device. If the wireless device S2 forward the data of source device S1 to the destination D1 and if the data is successfully received at D1 then S1 has a successful transmission. However, all the participating wireless devices S1, S2 had consumed energy to reach the destination D1. Thus, energy consumption cost cannot be neglected in the formulation even if it is in the low-power regime. Let $c_i = c(p_i)$ be the energy cost of device Si for forwarding the data where p_i is the transmission power of device S_i. We choose c_1 and c_2 to be between 0 and 1.

A. Simultaneous moves

A simultaneous move forwarding game between two source-destination pairs is a forwarding game where each source node chooses his action without knowledge of the actions chosen by other wireless device. Table I represents the payoff matrix of the simultaneous-move forwarding game. Notice that simultaneous-move game does not mean that the wireless devices act simultaneously.

TABLE I: Strategic form representation for two source-destination pairs

		Player II	
		F	nF ($\bar{F}$)
Player I	F	$(1-c_1, 1-c_2)$	$(-c_1, 1)$
	nF	$(1, -c_2)$	$(0, 0)$

B. Sequential moves representation

A sequential move forwarding game is a forwarding game where one wireless source device chooses their action F or nF before the others choose theirs. Importantly, if the later devices do not have any information of the first's choice, the difference in time would have no strategic effect and the information set is as large as the set of possible action profile of the others.

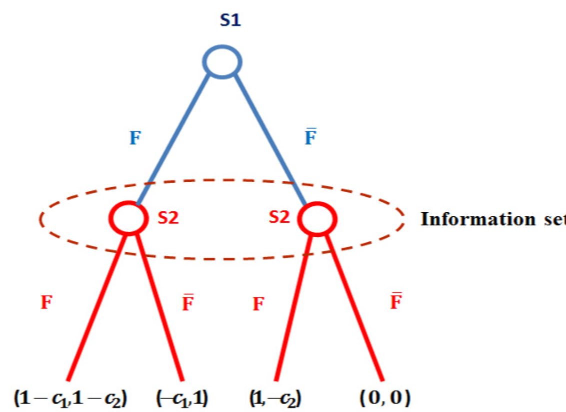

Fig. 2: Sequential forwarding game

C. Solution concept

A Nash equilibrium of the one-shot forwarding game is a strategy profile in which no wireless device has anything to gain by changing only his own strategy unilaterally. To find a Nash equilibrium, we proceed by unilateral comparison from each of the outcomes in Table I or equivalently in Figure 2. For example the strategy profile (F,F) is not a Nash equilibrium because the wireless device 1 can get payoff of 1 instead of $1 - c_1$ by just changing its choice. It turns out that for any $c_1 > 0, c_2 > 0$ the strategy nF is a dominant strategy and the one-shot forwarding game has a unique equilibrium given by (nF, nF). The corresponding equilibrium payoff is (0,0).

In the sequential moves with action knowledge setting, if S1 moves first, her action will be known by S2 and S2 will decide her choice knowing the choice of S1. This type of game is known as Stackelberg game or hierarchical game. In this setting, the Stackelberg solution is easily obtained by backward induction: S2 who is the follower will optimize and decide not to forward in both branches of the tree. Therefore, S1 who is the leader will decide not to forward as well. The Stackelberg solution is (nF, nF).

D. Forwarding game with sensing cost

The forwarding game involves not only a transmission cost but also a sensing cost ($cs >= 0$), which occurs when the secondary senses the channel before forwarding the data.

TABLE II: Forwarding game with sensing and energy cost

		Player II	
		F	nF ($\bar{F}$)
Player I	F	$(1-c_1-cs_1, 1-c_2-cs_2)$	$(-c_1-cs_1, 1)$
	nF	$(1, -c_2-cs_2)$	$(0,0)$

By resetting the numbers $c_1 + cs_1$ and $c_2 + cs_2$ we get a similar game as in Table II.

The next section explains how to reach a near Nash equilibrium through learning and imitation.

III. Learning Algorithm for Nash equilibria

We propose an imitative combined distributed payoff-and-strategy learning algorithm (CODIPAS, see [3], [13]) to find the solution of the forwarding game. The basic idea of CODIPAS is based on the following observations:

- Consequences influence the behaviour of the wireless nodes: if a wireless node realizes that its payoffs are not as high as expected, and sees that he is expending lot of energy, the device will change its decision and will try to save energy.
- The behaviors influence the outcomes: the choice of devices to participate or not affect the payoff as displayed in Table I.

Let $x_{1,t}(F)$, (respectively $x_{2,t}(F)$) be the probability of the row player (column player) to choose the action F at time iteration t. The parameter $l_{1j,t}$ is a positive real number and represents the learning rate for strategy-dynamics of device j. $l_{2j,t}$ is a positive real number which represents the learning rate for payoff-dynamics. The estimated payoff per action of wireless device j at time t is denoted by the vector $(\hat{r}_{j,t}(F), \hat{r}_{j,t}(\bar{F}))$. The realized payoff at time t by wireless device pair j is $r_{j,t}$. In the CODIPAS scheme each wireless device tries to learn her payoff functions as well as the associated optimal strategies.

Initialization

$$\hat{r}_{1,0} = (\hat{r}_{1,0}(F), \hat{r}_{1,0}(\bar{F}))$$
$$x_{1,0} = (x_{1,0}(F), x_{1,0}(\bar{F}))$$
$$\hat{r}_{2,0} = (\hat{r}_{2,0}(F), \hat{r}_{2,0}(\bar{F}))$$
$$x_{2,0} = (x_{2,0}(F), x_{2,0}(\bar{F}))$$

Define the sequences up to $T:\ l_{1j,t}, l_{2j,t}$ for $t \in \{1, 2, \ldots, T\}$

Learning pattern of the row player

$$x_{1,t+1}(F) = \frac{x_{1,t}(F)(1+l_{11,t})^{\hat{r}_{1,t}(F)}}{x_{1,t}(F)(1+l_{11,t})^{\hat{r}_{1,t}(F)} + (1-x_{1,t}(F))(1+l_{11,t})^{\hat{r}_{1,t}(\bar{F})}}$$
$$\hat{r}_{1,t+1}(F) = \hat{r}_{1,t}(F) + l_{21,t}\mathbb{1}_{\{a_{1,t}=F\}}(r_{1,t} - \hat{r}_{1,t}(F))$$
$$\hat{r}_{1,t+1}(\bar{F}) = \hat{r}_{1,t}(\bar{F}) + l_{21,t}\mathbb{1}_{\{a_{1,t}=\bar{F}\}}(r_{1,t} - \hat{r}_{1,t}(\bar{F}))$$

Learning pattern of the column player

$$x_{2,t+1}(F) = \frac{x_{2,t}(F)(1+l_{12,t})^{\hat{r}_{2,t}(F)}}{x_{2,t}(F)(1+l_{12,t})^{\hat{r}_{2,t}(F)} + (1-x_{2,t}(F))(1+l_{12,t})^{\hat{r}_{2,t}(\bar{F})}}$$
$$\hat{r}_{2,t+1}(F) = \hat{r}_{2,t}(F) + l_{22,t}\mathbb{1}_{\{a_{2,t}=F\}}(r_{2,t} - \hat{r}_{2,t}(F))$$
$$\hat{r}_{2,t+1}(\bar{F}) = \hat{r}_{2,t}(\bar{F}) + l_{22,t}\mathbb{1}_{\{a_{2,t}=\bar{F}\}}(r_{2,t} - \hat{r}_{2,t}(\bar{F}))$$

Interpretation of the learning scheme

The payoff-learning at time t is given by $\hat{r}_t = (\hat{r}_{1t}, \hat{r}_{2t})$ and it estimates the expected payoffs for each of the actions F and nF. When the length of the horizon T is sufficiently large and the actions sufficiency explored, each user will be able to learn the expected payoff via these estimations. However a user does not need to wait till the end of the exploration phase. Each wireless device adapts its strategy simultaneously with a recent experience r_{jt}. Then, the strategy-learning x_t is used to learn the optimal strategies. The strategies are imitative in the sense the next probabilities are proportional to the previous ones. The probability of strategies that result in higher average payoff will increase and the other probabilities will decrease by normalization. As we can see in the above analysis and as illustrated in Figures 3 and 4, the outcome of the game is not satisfactory in terms of rate of end-to-end successful transmissions. This is because the other node is not willing to forward the data. A successful transmission is still possible when the source and the destination nodes move around and becomes close to each other within s short range so that direct D2D transmission is possible. However, the process is slow and the packet may be expired. In order to improve successful transmission rate, one needs the nodes to participate or to play temporarily the role of a relay. However, the relaying behavior is energy consuming. One important issue is to design protocols that give more incentive to users to participate in forwarding by rewarding them. Another issue is to design the learning rates $l_{1j,t}$, $l_{2j,t}$, since they play an important role in the convergence behavior of CODIPAS.

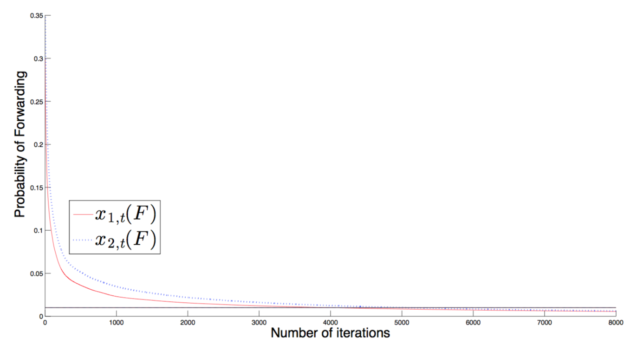

Fig. 3: Converge to optimal strategies using CODIPAS

Constant learning rate: Figure 5 illustrates the evolution of the probability of forwarding using constant rate $l_{1j,t}, l_{2j,t} = 0.1$. Diminishing learning rate: We choose the strategy-learning rate in the order of $1/(1+t)^{3/4}$ and the payoff-learning rate as $1/log(t+6)$. The number of iterations to converge is around 89 (no relay nodes). We observe that the number of iterations has significantly reduced by choosing these parameters. In Figure 6, we plot the evolution of strategies when the network is only composed of selfish nodes. The number of iterations changes from 5079 to be around 89 to reach a neighborhood the equilibrium. When we increase the percentage of altruistic nodes to 20%, the number of iterations goes to 55, which is 100 times faster than the scenario illustrated in Figure 5.

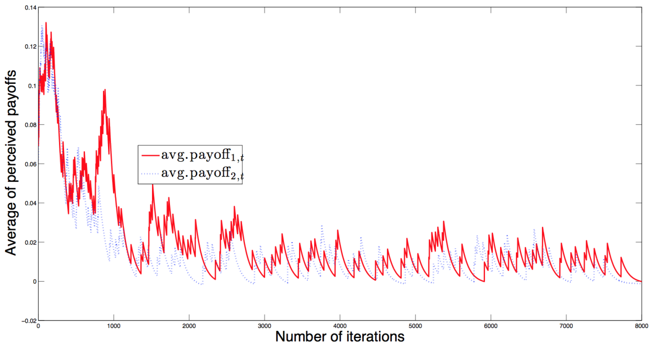

Fig. 4: Converge to equilibrium payoffs using CODIPAS

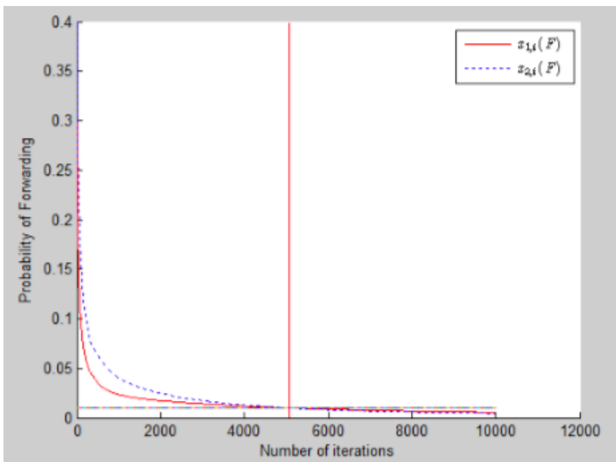

Fig. 5: 5079 iterations to converge without relay nodes

IV. Random matrix forwarding game

We now introduce finite forwarding games in which the realized payoffs are influenced by the actions of the wireless devices and a random variable representing the channel state. Such games are called random matrix forwarding games. Given random payoff matrices, the question arises as what is meant by playing the random matrix game (RMG) in an optimal way. Different approaches have been proposed: expectation approach, which consists to replace the random payoffs by their corresponding mathematical expected values. variance reduction approach consists to optimize not only the expected payoffs but also to minimize the variance of payoffs. mean-variance approach consists to find a tradeoff between the expected payoffs and their corresponding variances. multi-objective approach consists to analyze the random payoffs with difference objectives: mean, variance, skewness, kurtosis and risk among the others. The signal-to-interference-plus-noise ratio (SINR) for transmission from node S1 to S2 is given by $SINR_{S1S2} = \mathbb{1}_{\{a_1=F\}}.(p_1|h_{S1S2}|^2)/(N_0 + I_{S2})$, where $p_1 > 0$ is the transmission power from S1, $N_0 > 0$ is the background noise, h_{S1S2} is channel state between S1 and S2, and $I_{S2} \geq 0$ is the interference at the receiver in S2, and a1 denotes the action picked by device S1. The notation $\mathbb{1}_{\{SINR_{S1S2} \geq \beta\}}$ indicates the indicator function on the event $\{SINR_{S1S2} \geq \beta\}$, i.e., it is equal to 1 if $SINR_{S1S2} \geq \beta$, and 0 otherwise. Let

$$
\begin{aligned}
m_{11} &= \mathbb{1}_{SINR_{S1S2}>\beta} \cdot \mathbb{1}_{SINR_{S2D1}>\beta} \\
n_{11} &= \mathbb{1}_{SINR_{S2S1}>\beta} \cdot \mathbb{1}_{SINR_{S1D2}>\beta} \\
n_{12} &= \mathbb{1}_{SINR_{S2S1}>\beta} \cdot \mathbb{1}_{SINR_{S1D2}>\beta} \\
m_{21} &= \mathbb{1}_{SINR_{S1S2}>\beta} \cdot \mathbb{1}_{SINR_{S2D1}>\beta}
\end{aligned}
$$

Since $h = (h_{S1S2}, h_{S2S1}, h_{S1D2}, h_{S2D1})$ is a random vector, the coefficients $m_{11}, n_{11}, n_{12}, m_{21}$ are random. This leads to a random matrix forwarding game between wireless devices S1 and S2 as described in Table III.

TABLE III: Random matrix forwarding game

		S2	
		F	nF (F)
S1	F	$(m_{11} - c_1, n_{11} - c_2)$	$(-c_1, n_{12})$
	nF	$(m_{21}, -c_2)$	$(0, 0)$

We describe below the expectation approach. It consists to replace the coefficients of payoff matrix in Table III by the corresponding mathematical expectation where the expectation is taken with the respect to h. We denote by $a_{ij} := E[m_{ij}]$ and $b_{ij} := E[n_{ij}]$. Note that the numbers a_{ij} and b_{ij} are non-negative. The expected payoff matrix is given in Table IV.

TABLE IV: Expected matrix forwarding game

		S2	
		F	nF (F)
S1	F	$(a_{11} - c_1, b_{11} - c_2)$	$(-c_1, b_{12})$
	nF	$(a_{21}, -c_2)$	$(0, 0)$

We analyze the normal form game of Table IV. If $a_{11} - c_1 < a_{21}$ then the row player will not forward, and hence the column player will not forward. This leads to Nash equilibrium strategy (nF, nF). If $a_{11} - c_1 > a_{21}$ and $b_{11} - c_2 > b_{12}$ then (F, F) is a Nash equilibrium. Note that the configurations (F, nF) and (nF, F) are not equilibria whenever $c_i > 0$.

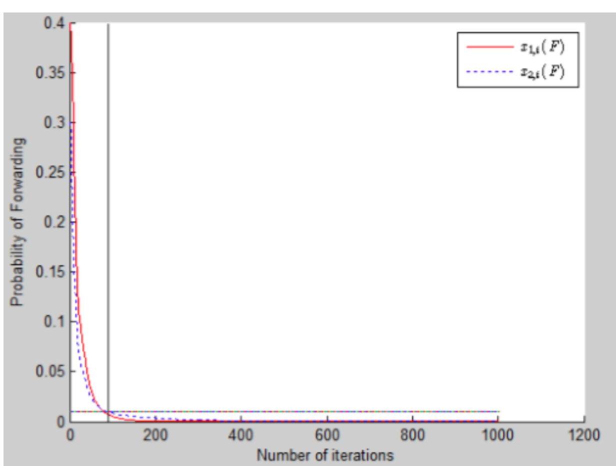

Fig. 6: 89 iterations to converge without relay nodes

V. Random matrix game with incomplete information

This section presents two types of wireless nodes with random payoffs. The random matrix game is of incomplete information in the sense that each wireless device knows its own type but does not know the type of the other. Therefore a strategy is conditioned on the knowledge of the type.

TABLE V: Random matrix game in strategic form representation with incomplete information

		Altruistic
		F
Altruistic	F	$(m_{11}-c_1, n_{11}-c_2)$

		Selfish	
		F	nF (F)
Altruistic	F	$(m_{11}-c_1, n_{11}-c_2)$	$(-c_1, n_{12})$

		Altruistic
		F
Selfish	F	$(m_{11}-c_1, n_{11}-c_2)$
	nF	$(m_{21}, -c_2)$

		Selfish	
		F	nF (F)
Selfish	F	$(m_{11}-c_1, n_{11}-c_2)$	$(-c_1, n_{12})$
	nF	$(m_{21}, -c_2)$	$(0,0)$

The equilibrium of random matrix game in Table V is not systematic. It depends on the realized of the random variables. In an A-A interaction, there is no other alternative. The equilibrium structure is therefore to forward whenever the channel is good enough. In a Se-A or A-Se interaction, the selfish wireless node has to compare. For example, in a Se-A interaction, if $m_{11}-c_1 > m_{21}$ then the selfish node 1 will forward (F) otherwise he will not forward (nF). The equilibrium structure of Se-A interaction is (F, F) if $m_{11}-c_1 > m_{21}$, (nF, F) if $m_{11}-c_1 < m_{21}$, (any mixed strategy, F) if $m_{11}-c_1 = m_{21}$.

Similarly, the equilibrium structure of A-Se interaction is (F, F) if $n_{11}-c_2 > n_{12}$, (F, nF) if $n_{11}-c_2 < n_{12}$, (F, any mixed strategy) if $n_{11}-c_2 = n_{12}$. In a Se-Se interaction, the equilibrium structure is described in a similarly way as in S1-S2 in Table IV. The action profile (nF, nF) is an equilibrium, and there is another additional equilibrium (F, F) when $m_{11}-c_1 > m_{21}$ and $n_{11}-c_2 > n_{12}$. Note that the latter event may happen with non-zero probability. To summarize, the strategy consisting to forward (F) if the type is "Altruistic" and the channel is good enough, and not to forward (nF) otherwise, is an equilibrium strategy of random matrix forwarding game with incomplete information.

Creating a Public Good By means of users' Incentives

Data forwarding is crucial for the viability of mobile networks. It extends the coverage and improve connectivity by mobility and multihop forwarding. Thus, it is public good. However, there is critical need to incentivize the users to participate in data forwarding. This section discusses how to incentive users and create a public good with reasonable end-to-end multi-hop delay. There are several rewarding designs. Here, we illustrate a probabilistic rewarding. When a wireless device forwards successfully the data of another, he will be rewarded with a certain probability. There are two basic schemes for the reward: Step-by-step probabilistic reward, which consists to reward the forward with a certain well-designed probability. End-to-End probabilistic reward consists to reward (with a certain probability) only after reaching final destination of the data.

When the rewarding is not limited to intermediary nodes on a specific path that forwarded, It concerns any node who is participating. Thus, one gets an interaction between all the nodes of the devices in the network.

TABLE VI: Forwarding game with rewarding scheme

		S2	
		F	nF (F)
S1	F	$(1+r1-c_1, 1+r2-c_2)$	$(r1-c_1, 1)$
	nF	$(1, r2-c_2)$	$(0,0)$

Nash Equilibrium Analysis: When $ri < ci$ for $i \in 1, 2$ then (nF,nF) is an equilibrium, and one gets a similar configuration as the game in Table I. When $r_1 > c_1$ and $r_2 < c_2$ then forwarding more rewarding from wireless device 1 than device 2 and (F, nF) is a Nash equilibrium. When $r_1 < c_1$ and $r_2 > c_2$ then forwarding is more rewarding to wireless device 2 than device 1 and (nF, F) is a Nash equilibrium. When the difference $r_i - c_i$ is positive for any $i \in \{1, 2\}$ then (F, F) is a Nash equilibrium. (nF,nF) is not an equilibrium anymore because forwarding is more rewarding than the energy consumption cost. This means that rewarding scheme may help to increase the number of contributors to mobile crowdforwarding. However, in the probabilistic rewarding scheme, not all contributors will be rewarded at a time. The reward is given to the winners of a probabilistic selection (lottery) designed for the contributors.

Mean-Field Forwarding Game: Interaction: Following the methodology presented in [14], we model the interaction as a mean-field-type forwarding game. We choose $r_j = r, c_j = c$. Each device has a certain type. The type can be A or Se. The payoff is a function of the proportion of forwarders (pf) of the networks. The payoff function increases with the mean-field term pf. However, when the pf is high, a generic player is not interested in forwarding if there is no incentive. In presence of incentives, the player will participate with higher probability and the resulting expected will be positive for every node. However, forwarding is costly in terms of energy consumption. Energy consumption dynamics: If node j starts with initial energy level $E_j(0)$ at time 0. Then, the remaining energy dynamics is given by: $E_j(t+1) = E_j(t) - p_j(t).\mathbb{1}_{\{a_j(t)=F\}}$, where $a_j(t)$ denotes the action chosen by node j at time t. There is a positivity constraint on E. Constraint on actions: It is possible to forward only when the remaining energy is above a certain threshold. Cumulative payoff: After T time units, the cumulative payoff of device j is $r_j(a_j(0), pf(0)) + r_j(a_j(1), pf(1)) + r_j(a_j(T-1), pf(T-1))$. The equilibrium of the mean-field forwarding game can be obtained by backward induction. If there is any energy left at time $T-1$, then the device $j$will decide on a one-shot basis so-called a single deviation principle, anticipating that the future will be the terminal payoff. At any time t, the same reasoning can be used. However, a decision taken at time t will affect the energy dynamics for the future and hence the next action. The device has therefore to optimize the sum of the current payoff and the future payoff. The resulting proportion of devices, which are forwarding should coincide with pf by consistency.

VI. Empathy in Forwarding Dilemma

Deviation to the material payoff outcomes: What if participants in a one-shot forwarding dilemma game know before making their decision that the other device has already decided not to forward (defected)? From the perspective of classic game theory with material payoff, a dilemma no longer exists because of dominating strategy. It is clearly in their best interest to defect too. The empathy-based test predicts, however, that if some of them feel empathy for the other, then a forwarding dilemma remains: self-interest counsels *not to forward* (defection); empathy-induced behavior may counsel not. The several previous test revealed that empathy seems far more effective than most other techniques that have been proposed to increase cooperation in one-shot forwarding dilemma games. We introduce a psychological payoff that is not only self-interested but also other-regarding through the two random variables λ_{12} and λ_{21}.

TABLE VII: Random matrix forwarding game

S1\ S2	F	nF
F	$(m^{\lambda}_{11}, n^{\lambda}_{11})$	$(m^{\lambda}_{12}, n^{\lambda}_{12})$
nF	$(m^{\lambda}_{21}, n^{\lambda}_{21})$	$(0,0)$

$$m^{\lambda}_{11} = m_{11} - c_1 + \lambda_{12}(n_{11} - c_2)$$
$$n^{\lambda}_{11} = \lambda_{21}(m_{11} - c_1) + n_{11} - c_2$$
$$m^{\lambda}_{12} = -c_1 + \lambda_{12}n_{12},\; m^{\lambda}_{21} = m_{21} - \lambda_{12}c_2$$
$$n^{\lambda}_{12} = -\lambda_{21}c_1 + n_{12},\; n^{\lambda}_{21} = \lambda_{21}m_{21} - c_2$$

- Case 0: $\lambda_{12} = \lambda_{21} = 0$
  In absence of empathy, it is equivalent to the self-regarding payoffs case. The game leads to the outcome (nF, nF) when $m_{11} - c_1 < m_{21}$ and $n_{11} - c_2 < n_{12}$.
- Case 1: $\lambda_{12} > 0,\ \lambda_{21} > 0$
  (F, F): If $m^{\lambda}_{11} \geq m^{\lambda}_{21}$ or $n^{\lambda}_{11} \geq n^{\lambda}_{12}$ then the strategy nF is not dominating anymore. In this case, forwarding is a good candidate for Nash equilibrium of the psychological one-shot forwarding game. In addition, if $m_{ii} \geq 0$ and $\lambda_{12} \geq \frac{c_1+m_{21}-m_{11}}{n_{11}}$ and $\lambda_{21} > \frac{c_2+n_{12}-n_{11}}{m_{11}}$ then full cooperation (F, F) becomes a Nash equilibrium. If $\frac{c_1+m_{21}-m_{11}}{n_{11}}$ and $\frac{c_2+n_{12}-n_{11}}{m_{11}}$ belongs to $(0, 1)$ and then a mixed strategy equilibrium emerges in addition to the pure ones, which explains the observed variation of percentages of cooperators depending on the empathy index measured from the experiment.
  (Fn, F) is an equilibrium if $m^{\lambda}_{12} \geq 0$ and $n^{\lambda}_{12} \geq n^{\lambda}_{11}$. This means $\lambda_{12}n_{12} \geq c_1,\ \lambda_{21}m_{11} + n_{11} - n_{12} - c_2 \leq 0$, i.e., λ_{12} is positively high enough and λ_{21} is low.

TABLE VIII: Summary of the outcomes

S1 \ S2	λ_{21} Negative	Low	Medium	High
λ_{12} High	FnF	FnF	F F	FF
λ_{12} Medium	nFnF	nFnF	FF,nFnF, mix	FF
λ_{12} Low	nFnF	nFnF	nFnF	nFF
λ_{12} Negative	nFnF	nFnF	nFnF	nFF

  Similarly when λ_{12} is low and λ_{21} positively high enough then (nF, F) becomes an equilibrium.
  (nF, nF) is an equilibrium when $\{m^{\lambda}_{12} \leq 0, n^{\lambda}_{21} \leq 0\}$ which means $\lambda_{12}n_{12} \leq c_1, \lambda_{21}m_{21} \leq c_2$.
  If $\lambda_{12} \in (\frac{c_1+m_{21}-m_{11}}{n_{11}}, \frac{c_1}{n_{12}})$, $\lambda_{21} \in (\frac{c_2+n_{12}-n_{11}}{m_{11}}, \frac{c_2}{m_{21}})$ then there are three equilibria: (F, F), (nF, nF) and a mixed equilibrium.
  If $\lambda_{12} > \frac{c_1}{n_{12}}$, $\lambda_{21} > \frac{c_2}{m_{21}}$ then (F, F) is the unique equilibrium as F is a dominating strategy for both users.
  If both users have low empathy $\lambda_{12} < \frac{c_1+m_{21}-m_{11}}{n_{11}}$, $\lambda_{21} < \frac{c_2+n_{12}-n_{11}}{m_{11}}$ then nF is a dominating strategy for both users, hence (nF, nF) is an equilibrium.
- Case 2: $\lambda_{12} < 0,\ \lambda_{21} < 0$: Both users have a dominating strategy which is nF. Then, (nF, nF) is the outcome.
- Case 3: $\lambda_{12} > 0,\ \lambda_{21} < 0$: Player 2 has a dominating strategy which is nF. Thus, (F, nF) is the outcome if the empathy of player 1 is high enough and (nF, nF) otherwise. At the threshold value of λ such that $m^{\lambda}_{12} = 0$, every partially mixed strategy profile $(y\delta_F + (1-y)\delta_{nF}, nF)$ with $y \in [0, 1]$ is an equilibrium.
- Case 4: $\lambda_{12} < 0,\ \lambda_{21} > 0$: (nF, F) is the outcome if the empathy of 2 is high enough and (nF, nF) otherwise.

When the parameters lead to an equality of payoff, there may be infinite number of (mixed) equilibria. We have omitted these degenerate cases since λ will be a continuous random variable. Table VIII summarizes the outcomes when the entries m, n are non-zero depending on the affective empathy level of the users: negative (spiteful), low (positive), medium, and high when $\frac{c_1+m_{21}-m_{11}}{n_{11}} < \frac{c_1}{n_{12}}$ and $\frac{c_2+n_{21}-n_{11}}{m_{11}} < \frac{c_2}{m_{21}}$. For user 1, low empathy means $\lambda_{12} \in (0, \frac{c_1+m_{21}-m_{11}}{n_{11}})$, medium empathy means $\lambda_{12} \in (\frac{c_1+m_{21}-m_{11}}{n_{11}}, \frac{c_1}{n_{12}})$ and High empathy means $\lambda_{12} > \frac{c_1}{n_{12}}$. For user 2, low empathy means $\lambda_{12} \in (0, \frac{c_2+n_{21}-n_{11}}{m_{11}})$, medium empathy means $\lambda_{21} \in (\frac{c_2+n_{21}-n_{11}}{m_{11}}, \frac{c_2}{m_{21}})$ and high empathy means $\lambda_{21} > \frac{c_2}{m_{21}}$.

Clearly, when the distribution of empathy across the population is of full support, the probability to end up with (F, F) as an outcome is positive.

VII. Berge solution and mutual support

The Berge solution concept was introduced in [23, page 20]. See also [16]–[22] for recent investigation of Berge solution.

If the players have chosen a strategy profile that forms a Berge solution, and i sticks to the chosen strategy but some of other players change their strategies, then i's payoff will not increase. This is a resilience to deviation by other players or other teams. The strategy profile a^* is a Berge solution if

$$r_i(a^*) = \max_{a_{-i}} r_i(a^*_i, a_{-i}).$$

Berge strategy yields the best payoffs to the others' players who also play Berge strategies. In Berge solution, a deviation by one or more other players can reduce the payoff to a player who does not deviate. In forwarding dilemma game one has:

$$r_i(F, F) = 1 - c_i > -c_i = r_i(F, nF), \ \forall i.$$

This means the strategy profile (F, F) is the unique Berge solution in the forwarding dilemma game.

This result is important because the outcome (F, F) appears as a mutual support between the relay nodes. Note that such an outcome is not possible in the Nash forwarding dilemma game. The Nash equilibria is not able to predict observed outcomes in practice in the unmodified game while the Berge solution is predicting a better outcome as (F, F) is observed in many experimental setups even in the one-shot game case. Berge solution occurs when players are mutually supportive in the forwarding game. It means S1 supports data from S2 and S2 supports data from S1. It increases connectivity and coverage in the network.

VIII. Conclusion

In this paper we have studied forwarding dilemma in relay-enabled networks. It turns out that increasing the number of empathetic-altruistic nodes who help in forwarding data and will increase the probability of success of end-to-end multi-hop transmissions in mobile networks. The question is, how to increase such number of participants?

There are several ways of doing it. We described two of them. The first one is a direct approach, which consists to deploy or to enable a certain number of relay devices in the network. The second approach consists to incentivize users to forward the data by means of probabilistic rewarding.

Each of these two schemes has a cost to the operator of the network. The deployment has a direct cost of injecting these relays. In the probabilistic rewarding scheme, no extra deployment is required. However, there is a need of a crowd forwarding requires a significant reward to who participate. A natural question is: who will fund the reward? For those who will be interacting with each other for a long time, there is no need of extra incentives. There is an endogenous reward which occurs when the corresponding node's data is forwarded by the others. In order to get that endogenous reward, he will forward many time its data will not be forwarded by the others. Thus, the reward is the help that the node will receive from the others. In short-term interaction or in highly dynamic networks, there is a need of an exogenous reward which needs to be designed by the network operator. This reward could be, for example, bonus in terms of connection or renewable energy sources powered batteries. These incentives will increase the number of contributors to the forwarding scheme leading to a more "sustainable mobile crowd-forwarding" in the internet-of-everything.

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