On Energy-efficiency in Wireless Networks: A Game-theoretic Approach to Cooperation Inspired by Evolutionary Biology

Zoran Utkovski*, Andrej Gajduk*, Lasko Basnarkov**, Darko Bošnakovski† and Ljupco Kocarev*†§, Fellow, IEEE

Abstract—We develop a game-theoretic framework to investigate the effect of cooperation on the energy efficiency in wireless networks. We address two examples of network architectures, resembling ad-hoc network and network with central infrastructure node. Most present approaches address the issue of energy efficiency in communication networks by using complex algorithms to enforce cooperation in the network, followed by extensive signal processing at the network nodes. Instead, we address cooperative communication scenarios which are governed by simple, evolutionary-like, local rules, and do not require strategic complexity of the network nodes. The approach is motivated by recent results in evolutionary biology which suggest that cooperation can emerge in Nature by evolution, i.e., can be favoured by natural selection, if certain mechanism is at work. As result, we are able to show by experiments that cooperative behavior can indeed emerge and persist in wireless networks, even if the behavior of the individual nodes is driven by selfish decision making. The results from this work indicate that uncomplicated local rules, followed by simple fitness evaluation, can promote cooperation and generate network behavior which yields global energy efficiency in certain wireless networks.

I. INTRODUCTION

The dramatic increase in the number of users and growth in data traffic in the past years pose a significant challenge on all aspects of current communication networks including capacity, signal processing, complexity, and energy consumption. Current communication networks will not be able to answer these demands in near future, which calls for a paradigm shift in the design of network architectures, communication strategies and signal processing tools. The provisioning of energy efficient protocols and communication schemes is one of the main challenges in the design of present and future communication networks. The concept of energy efficiency is particularly relevant to emerging heterogeneous networks which, besides the "classical" communication nodes, include various other devices with low-power capabilities, such as sensors and other nodes producing machine-type traffic [1].

Several recent works show that user cooperation is of fundamental value for increasing both the network throughput and the energy efficiency. The study of the fundamental limits of wireless networks suggests that cooperation among the units can both decrease energy consumption and reduce interference. In this context, techniques such as cooperative diversity [2], [3] and interference alignment [4] have been proposed. Energy efficiency of wireless networks has also been studied in [5], [6] under the assumption that all nodes are interested in minimizing the overall energy consumption of the network. The globally optimal solution, as characterized by the authors, is achieved when the network nodes establish cooperation by relaying packets for other users.

Most of the present approaches which deal with the aspects of cooperative communications, assume that the network nodes act in a pre-defined way, i.e., their behavior is determined by (usually) centralized network rules [7]–[11]. This approach leaves no freedom to the individual nodes to decide about their involvement in the cooperative act. Since cooperation is associated with a cost (usually energy) and requires certain signal processing capabilities (computational complexity), this approach may lead to a "cooperation burden" which can be unreasonably high for some network nodes.

While this "centralized" approach is reasonable in networks with central infrastructure, it is also (somewhat surprisingly) widely adopted in decentralized networks such as ad-hoc networks. One important group of these efforts focuses on designing high-level protocols that prevent users from misbehaving and/or provide incentives for cooperation. To prevent misbehavior, several protocols based on reputation propagation have been proposed in the literature, e.g., [7]–[12]. One general observation is that the proper functioning of these networks is generally maintained either by enforcing cooperation, or by keeping track of the cooperative behavior which demands intensive computation. Other works have used ideas from micro-economy to construct protocols that reward cooperation [13]. Overall, these protocols are based on ideas rooted in game theory, but, in most cases are hard to analyze, due to the complicated underlying network models.

Another group of recent works analyzes energy efficiency from a game theoretic perspective, e.g., [14], [15], where at each time slot, a certain number of nodes are randomly chosen and assigned to serve as relay nodes on the source-destination route. In [15], the authors study the Nash equilibrium of packet forwarding in a static network and derive the equilibrium
conditions for both cooperative and non-cooperative strategies. The works in this thrust utilize the repeated game formulation, where cooperation among users is sustained by punishment for deviating from the cooperation point. In [16], the authors consider wireless networks consisting of both selfish and altruistic nodes. They establish the critical role of the altruistic nodes in encouraging cooperation and elaborate on the sub-optimality of relaying strategies which ignore the game theoretic aspect.

While we also adopt a game-theoretic framework to study energy efficiency, our work differs in several important aspects. First, we do not focus on enforcing cooperation, for example by keeping track of the cooperative behaviour of the users and/or using punishment and reward policies. In addition, we confine our strategies to the physical layer and avoid introducing elements, like virtual currency, which may add significant complexity to the higher layers. Finally, we do not assume presence of altruistic nodes in the network, but rather assume that all nodes are selfish in the sense that they try to minimize their individual energy consumption.

The main essence of the work is that we study cooperative communication scenarios based on simple local rules which mimic evolutionary principles. The approach is motivated by recent results in evolutionary biology which suggest that, if certain mechanism is at work, cooperation can be favored by natural selection, i.e. even selfish actions of the individual nodes can lead to emergence of cooperative behavior in the network. From system point of view, one of the main features of our approach is that we shift from the well accepted paradigm of “engineered” system design, where the system components have known functions and designers maintain separation of concerns. Instead, we look at networks such as biological, social and economic, which evolve over time as a result of the interactions between the system entities and the environment. The motivation behind is the remarkable energy efficiency, information storage and processing capabilities of living organisms, as compared to present communication systems. Based on these observations, we address the mechanisms which lead to the emergence of cooperation in wireless networks and discuss the analogies with evolutionary biology. The results indicate that uncomplicated local rules, followed by simple fitness evaluation, can generate network behavior which yields global energy efficiency.

The rest of the paper is organized as follows. In Section II we present the relation between energy efficiency and cooperation and discuss analogies with biological systems. In Section III we describe the network model and the studied architectures. In Section IV we present a game-theoretic framework for the study of energy-efficiency in wireless networks. The results are presented in Section V. Section VI interprets the obtained results and discusses possible implications on systems other than wireless networks. Section VII concludes the paper and presents directions for future work.

II. Cooperation in Communication Networks: Relations with Biological Systems

A. Biological systems

Cooperation has played a fundamental role in many of the major transitions in biological evolution and is essential to the functioning of a large number of biological systems [17]–[20]. Observations show that cooperative interactions are required for many levels of biological organization ranging from single cells to groups of animals. Human society, as well, is based to a large extent on mechanisms that promote cooperation.

Recent results in evolutionary biology suggest that cooperation can emerge and persist in evolving systems, i.e. cooperation can be favored by natural selection, if certain mechanism is at work [18], [19]. These results may be counter-intuitive since it is well known that in unstructured populations, natural selection favors defectors over cooperators, as shown in Fig. 1.

![Fig. 1. Natural selection favours defectors (red) over cooperators (blue), if no other mechanism is at work. After a random defector is introduced in a network of cooperators, cooperation vanishes over time. Source: [19].](image)

However, while studying evolutionary games in structured populations and on graphs, in [18] the authors observe that in structured populations cooperation may emerge given that a certain mechanism is at work. The approach of capturing this effects is evolutionary graph theory, which allows the study of how spatial structure affects evolutionary dynamics. According to this model, the individuals of a population are assumed to be plain cooperators and defectors without any strategic complexity. The authors show that natural selection can indeed favor cooperation, if the benefit of the altruistic act, \( b \), divided by the cost, \( c \), exceeds the average number of neighbors, \( k \), \( b/c > k \). This simple rule is a good approximation for different graphs, including cycles, spatial lattices, random regular graphs, random graphs and scale-free networks. In this setting, the experiments show that cooperators can prevail by forming network clusters, where they help each other. The resulting network reciprocity is a generalization of spatial reciprocity [19]. The intuition behind is that in this case cooperation can evolve as a consequence of “social viscosity” even in the absence of reputation effects or strategic complexity. It is worth mentioning that, besides network reciprocity, there are several other candidate mechanisms in biology which are able to explain the emergence and stability of cooperation in certain biological systems, such as kin selection, direct reciprocity, indirect reciprocity, and group selection [17], [19]. As we will elaborate later on, among these candidate mechanisms we identify network reciprocity as most relevant to our networks of interest-wireless communication networks.

B. Wireless Networks: Main Features of the Approach

Wireless communication systems have two fundamental properties. The first one is that the receive power decays according to a power law function of the distance between the users, which puts stress on the power consumption; the second one is the broadcast nature of the wireless communication,
which leads to interference between the users. With the increase in the number of subscribers and growth in data traffic in wireless networks, these two features gain on importance and have a strong adverse effect on the network performance in terms of throughput and energy consumption.

The study of the fundamental limits of wireless networks suggests that cooperation among the units could potentially overcome these effects. However, one of the main drawbacks in the performance analysis of general wireless networks is that it is often based on simplifying assumptions. As an example, when deriving the performance limits of different cooperative schemes, the cost of establishing cooperation in the wireless network is not properly taken into account [21]. As result, in some scenarios, the benefits of cooperation might be overshadowed by the cost of establishing cooperation in the first place. As cooperation comes at a cost for the network users, in a network which lacks centralized control, for some users it might be beneficial to defect, instead of to cooperate.

Many of the most fundamental instances of cooperation in biological systems involve simple entities which lack strategic complexity, which prevents them to adopt strategies that take into account the history of their interactions with other entities. Yet, remarkably, cooperation is present in these systems, as supported by evidence [22]–[24]. Similarly, we will be interested in designing rules which are simple enough to be implemented even by network nodes with limited processing capabilities, yet powerful enough to promote cooperation and yield energy efficiency, which is in contrast to the approaches which rely on complex algorithms and reputation tables in order to enforce cooperation in the network [7], [25], [26].

Essentially, we are interested in cooperation which emerges as result of the system evolution. The main question we try to answer is the following: Can cooperation arise in communication networks by evolution? If yes, which mechanism should be at work? We answer this question in the affirmative, by showing that cooperation can be promoted by relying on simple strategies, i.e. by imposing a limited set of rules which mimic the principles of evolution, and let the systems evolve in time. It seems that network reciprocity is the candidate mechanism for promotion of cooperation in some networks. Indeed, if we describe wireless networks as graphs, an analogy can be drawn with populations which are not well mixed. The reason for this is that, given an energy constraint, one user can interact only with the nodes which are in the range of its transmission, thus forming a cluster of potential cooperators.

While we build on the legacies of communication protocols for establishing cooperation in decentralized networks, our approach differs in one important aspect. Namely, we do not assume cooperation to be beneficial "by default", but we rather adopt a game-theoretic approach where the network nodes decide whether to cooperate or not based only on their fitness, which is a quantity related to the individual energy (power) consumption. We propose simple, decentralized strategies for the individual nodes and evaluate their energy efficiency. The individual nodes and evaluate their energy efficiency. We propose simple, decentralized strategies for the individual nodes and evaluate their energy efficiency.

![Fig. 2](image_url)

Fig. 2. Promotion of cooperation in wireless networks with selfish decision-making of the individual nodes. The mechanism behind can be seen as a form of network reciprocity, in the spirit of [18].

### III. Network Model

#### A. Assumptions

In order to investigate the emergence of cooperation in wireless communication networks, we define a network model which aims at capturing both the essence of wireless communication networks and the graph models used in evolutionary game theory. The model is such that it is still rich enough to capture the essence of the energy consumption in the network and the mechanism behind the emergence of cooperation, yet simple enough to be able to interpret the observed phenomena.

We model the network as a graph where the users represent the nodes and the edges are related to interactions between the nodes. A time division multiple access (TDMA) approach is used where the nodes take turns in transmitting their packets (no frequency reuse). We divide the time scale in time slots.
of equal duration and assume that one transmitter/receiver pair is activated at random in each time slot. This multiple access scheme is known to be optimal \[5, 6, 27\], at least in first approximation, from a minimum energy per bit perspective. Although this assumption simplifies the network analysis, it may be regarded as restrictive, as in reality multiple simultaneous transmissions can occur. Nevertheless, we expect that this simple scenario will be able to capture the essence of the cooperative behaviour of the users, by performing simulations over sufficient number of time slots, which averages users activity over time. We are tempted to conclude that, from the perspective of the investigated phenomenon (emergence of cooperation), the simulation results will be a reasonable indicator of the network behaviour in more general scenarios.

We assume that the nodes are selfish in the sense that their objective is to be energy (power) efficient, i.e. to minimize the individual energy spent for transmission. As in game theory, we assume two types of nodes, cooperators and defectors. The assumption of having transmit packets of equal duration establishes equivalence between power and energy and both are used interchangeably throughout the paper.

We address network architectures with either direct (one-hop) communication (in the case when there is no cooperator willing to retransmit the packet), or two-hop communication (one retransmission), in the case of presence of cooperator(s). This is surely a simplification since, in general, information can also be transmitted in a multi-hop fashion where information is relayed from each source to its destination in successive transmissions between intermediate nodes.\(^1\) Although being relatively simple, the architectures we address are rich enough to describe the the network behaviour in the game-theoretic framework.

**B. The role of cooperation**

1) Capturing the essence of the network behavior - A fundamental network unit: Let us look at a network snapshot which is involved in one transmission (one time slot) between two nodes, A and B, as depicted in Fig. 3. Let \( P_D \) be the power A spends for direct transmission to B. As result of the propagation effects, the received power at B is \( P_R = P_D/(Kd_{AB}^\alpha) \), where \( \alpha \) depends on the propagation characteristics of the area (urban, suburban, rural, etc.) and \( K \) is a propagation constant. Typically, \( \alpha \) takes values in the range \( 2 \leq \alpha \leq 4 \). We define the signal-to-noise ratio at the receiver as \( SNR = P_R/\sigma^2 \), where \( \sigma^2 \) is the noise variance. We say that the transmission is successful if the receive SNR exceeds a certain threshold required for reliable reception, \( SNR \geq SNR_0 = P_{R_0}/\sigma^2 \), i.e. A should transmit with power \( P_D \geq Kd_{AB}^\alpha P_{R_0} \). We assume perfect power adaptation and take that node A adjusts the transmit power to the distance \( d_{AB} \), such that it meets the receive SNR requirement exactly.\(^2\)

\(^1\) The optimality of a certain architecture (from perspective of capacity) depends on the operating regime of the network (power-limited or interference limited being two extreme examples). We refer the interested reader to \[28\] for the analysis of the capacity-scaling performance of more general network architectures in different operating regimes.

\(^2\) This is a simplification since for this adaptation to work, A should know the network topology (the distance to B) or to have feedback from B about the receive SNR, in order to adjust the transmit power.

We say that a node C is in range of A, or connected to A, if it can "hear" A's transmission to B. Under the assumed power adaptation, a node C is in the range of A if \( d_{AC} \leq d_{AB} \). Additionally, we assume that C is a potential cooperator only if \( d_{CB} \leq d_{AB} \). This assumption is reasonable, since otherwise the cost of retransmission would be higher than the cost of direct transmission.\(^3\) According to the scenario we address, the region containing potential cooperators is described by

\[ d_{AC} < d_{AB}; \quad d_{CB} < d_{AB}. \]  \( (1) \)

A node C which fulfills \( (1) \) is called intermediate node. As depicted in Fig. 3, potential cooperators are located in the area enclosed with a dashed line. This constellation represents a typical scenario which captures the essence of the communication in the network and can be thus regarded as fundamental network unit. If an intermediate node C decides to help A in the transmission, it will retransmit the signal received from A to B. The benefit that the node A obtains from the cooperative act of C is that, in the presence of the cooperator C, A can decrease the transmit power to a value lower then the power required for direct transmission, \( P_1 \leq P_D \), which defines the benefit of the cooperative act as \( b = P_D - P_1 \).

In general, for a given transmitter/receiver pair A/B there can be more then one cooperator. In this case they can either share the cost for cooperation or let one cooperator pay the overall cost. For simplicity, we only address the case where only the closest cooperator to B retransmits the signal and leave different approaches to cost sharing for future study. At first sight, this simplification might seem suboptimal, since in this way in one time instant the cost of cooperation is paid by a single cooperator. However, this effect will be averaged over time since for different transmitter/receiver pairs, the choice will fall on different cooperators (with high probability).

2) Protocols for establishing cooperation: In order for cooperation to work, the involved nodes should exchange some kind of control messages, i.e. they need to establish a cooperation protocol. We hereby identify two protocol

\(^3\) In general, one could allow for a cooperator C to be found at a distance \( d_{CB} \geq d_{AB} \). In this case cooperation might still be beneficial, if the cost of cooperation is shared between several cooperators. This assumption could influence the network behaviour, particularly in the case of the network architecture with a central infrastructure node, addressed in Section V.
scenarios. For both protocols, we implicitly assume that the nodes have the amount of knowledge of the network topology required for both protocols to work.

**Cooperation protocol 1:** This cooperation protocol assumes that user A sends a low-rate request to relay message within a region of radius $\nu \cdot d_{AB}$, where $0 \leq \nu \leq 1$. The parameter $\nu$ has the role to further reduce the range of A's transmission. With this convention, instead of engaging all cooperators from the area defined with (1) in the retransmission, we account only for those located in the area enclosed by the full line in Fig. 3. By introducing the parameter $\nu$, one avoids sending request to relay messages at large distances. Additionally, it is expected that the cooperative act is most beneficial for the transmitter A when the potential cooperators are found (relatively) near to the transmitter, since this lowers the cost of direct transmission. Although this choice could potentially increase the total cost of cooperation, this will not affect significantly the cost that individual cooperators pay. Indeed, the total cost of cooperation is distributed between the cooperators in the region of interest, either directly (by having more cooperators assisting a single transmitter), or indirectly (by choosing different cooperators over time).

Having received the request to relay message (which besides the sender A, also identifies the destination B), the nodes located in this region will send back an acknowledgement to A that they accept to relay (retransmit). If more than one cooperator is present, A decides which of the cooperators will actually retransmit. The subtle characteristics of this protocol is that node A can be selfish in the decision process in the sense that it can choose only one cooperator-the nearest one, in order to minimize its own transmit power. In that case, in the final phase of the transmission node A will transmit a signal with power adopted to the distance of the nearest cooperator, which will then retransmit the message. We note that this behaviour increases the cost of cooperation and is also suboptimal from the point of view of the total energy consumption of the network.

**Cooperation protocol 2:** In the first phase of this cooperation protocol user A also transmits a request to relay message in the region of radius $\nu \cdot d_{AB}$. In the second phase, the cooperators coordinate among themselves and one of the cooperators sends node A a general confirmation that there are cooperators present in this region (without disclosing their identity). In the case of no response, A assumes that there are no cooperators. If there is a confirmation of cooperators present, in the next phase A will transmit the message with reduced power $P_1 = \nu^n P_D$. Having received the signal from A, it is now on the cooperators to decide which one(s) will retransmit the message. This can be done by a form of coordination between the cooperators. If one cooperator is chosen to retransmit the message, the natural choice falls on the one which is closest to the destination B. The difference with the first protocol is that now the coordination is performed among "trusted nodes", i.e. cooperators. While in the first protocol the transmit node A (which can be a defector in general) dictates the cooperation, in the second one it is the cooperators who decide on the details of the cooperative act.

In the scenarios we address, we adopt the second cooperation protocol, as we expect that it would favor cooperative behavior. The motivation behind is that the adoption of the first cooperation protocol would encourage the transmitter node to save energy by transmitting only to the nearest of the potential cooperators, which would eventually undermine the efforts of the cooperative nodes and discourage spreading of cooperative behavior in the network. On the other hand, the second protocol leaves less room to the transmitter nodes (which are in general not trustworthy) to misbehave, and allows for arrangements among the trustworthy, cooperative nodes.

### IV. A Game-theoretical Framework for Energy-efficiency Analysis in Wireless Networks

Game-theoretic approach to modelling of phenomena assumes existence of some quantity – utility, or benefit – that units in the system try to maximize. In some scenarios the agents may choose to help the others, i.e. to cooperate – this is modeled by the cost they pay for the cooperation. Some agents choose their strategy to be selfish, i.e. they defect, and thus avoid any costs. The cost of cooperative act implies that the cooperators would have smaller fitness than the defectors, i.e. that natural selection of the fittest would favors defectors. However, recent results in evolutionary biology suggest that cooperation can be favored by natural selection, if a certain mechanism is at work. Indeed, there are observations and theoretic analyzes of cases when cooperation persists – there is at least a fraction of cooperators present in the population.

#### A. Definition of Fitness in Wireless Networks

Following the analogy with evolutionary biology, we will define fitness of the individual network nodes. Intuitively, the fitness has to be related with the energy consumption of the individual nodes. Ideally, the appropriate fitness function has to be simple enough to be evaluated locally (possibly without requiring complex processing and memory). On the other hand, it has to be rich enough to capture the essence of wireless transmission and network dynamics. We will define two discrete time scales, according to which the fitness will be evaluated. The fitness function is evaluated at the end of a block of duration $T$ slots. The network performance is observed over $N$ such blocks (iterations). Since we have two time scales, we introduce two indices, $t$ and $n$, where $t \in \{0, 1, \ldots, T\}$ indicates the time slot and $n \in \{0, \ldots, N\}$ indicates the iteration. The fitness is then a function of $n$ and $t$, $F = F(n,t)$. We note that, in order to be consistent with the definition of $t$, we denote the initial iteration (of duration $T$) as 0-th iteration. Additionally, we denote the initial fitness as $F(0,0) = F_0$. Now, let us define

$$\Delta f(n,t) = F(n,t) - F(n,t-1), \quad t = 1, \ldots, T, \quad (2)$$

One such form of coordination is *quorum sensing* which refers to the phenomenon in which the accumulation of signalling molecules in the surrounding environment enables a single cell to assess the cell density so that the population as a whole can make a coordinated response.

$^5$Similar behavior has been observed while studying structured populations. In these populations, once introduced by chance, cooperation persists by the formation of clusters of cooperators which help each other.

$^6$This conjecture has yet to be supported by simulations.
which measures the difference in the fitness evaluated at two consecutive time instants \( t - 1 \) and \( t \), of the \( n \)-th iteration. In our model, \( \Delta f(n, t) \) for the network node \( C \) is defined as
\[
\Delta f(n, t) = -\alpha (1 - \beta) [P_D - P_I] - \gamma \delta P_C(J)
\]
where \( \alpha, \beta, \gamma, \delta \in \{0, 1\} \) are parameters which indicate packet transmission and presence of cooperators and defectors. In particular, \( \alpha = 1 \) when \( C \) has a packet to transmit; \( \beta = 1 \) when \( C \) has at least one cooperator as a neighbor; \( \gamma = 1 \) when \( C \) is connected to at least one active node at that time instant; and \( \delta = 1 \) corresponds to \( C \) being a cooperator (otherwise the parameter values are zeros). We note that the above parameters are also functions of \( n \) and \( t \). However, whenever there is no ambiguity, and in order to simplify the notation, we will skip these indices. Having introduced \( \Delta f(n, t) \), we can define the fitness of the node \( C \) in the following way
\[
F(0,0) = F_0,
F(n, t) = F(n, t - 1) + \Delta f(n, t),
F(n + 1, 0) = F(n, T)
\]
where \( n = 0, 1, \ldots, N - 1 \) and \( t = 0, 1, \ldots, T \). Defined in this way, the fitness reflects both the energy saving of the individual nodes when their transmissions are assisted by cooperators, e. g. the benefit they receive, and their energy expenditure when they assist other nodes in the transmission, i. e. the cost they pay for cooperation. Additionally, we define the quantity
\[
\Delta F(n) = F(n, T) - F(n - 1, T), \quad n = 1, \ldots, N
\]
to be the change of fitness between two consecutive iterations.

B. Game-theoretic Strategies

In this work we study four different strategies of cooperative behavior in wireless networks. In the present approach we assume that all network nodes adopt the same strategy during the simulations. This approach certainly does not cover some more general scenarios, for example the one when the individual nodes are able to choose their strategy at random, or according to some rule. Nevertheless, we expect that the results from our analysis will fairly well indicate the general trend and, as such, will be useful in the evaluation of the fundamental limits on energy efficiency in decentralized networks.

The first strategy addresses the trivial case when there is no cooperation between the nodes, i. e. all nodes are defectors. We denote this strategy by DEF. The second strategy addresses the case where all nodes cooperate and will be denoted as COOP. It corresponds to a scenario where cooperation is "enforced" in the network. Besides these "trivial" cases, we will concentrate on strategies which where the individual nodes are essentially selfish and decide whether to cooperate or not based solely on their individual fitness. In the scenario that we propose, at the end of the \( n \)-th iteration the network nodes make a simple decision whether to cooperate or defect in the next iteration, based on the change in the fitness \( \Delta F(n) = F(n, T) - F(n - 1, T) \), as defined in Eq. 5.

We will distinguish between two simple and intuitive strategies for this scenario. According to the first one, if the node observes an increase in the fitness, \( \Delta F(n) > 0 \), it will retain the previous status in the next iteration. If, on the other hand, the node observes decrease in the fitness \( \Delta F(n) < 0 \), the node will change its behavior, i. e. a cooperator will become a defector and vice versa. We observe that from the perspective of a single node, the game resembles the repeated prisoner’s dilemma [17]. In this regard, the above described strategy corresponds to the well known win-stay, lose-shift (WSLS) and is based on the simple idea of retaining the previous status when the node is doing well, but changing otherwise. According to the other strategy for this scenario, the node will decide to cooperate in the next iteration if it observes an increase in the fitness, \( \Delta F(n) > 0 \). Otherwise, it will defect. According to this strategy, a defector will become cooperator and a cooperator will stay cooperator, if \( \Delta F(n) > 0 \). Otherwise, the node will choose to defect. We note that the increase in fitness reflects the average behavior of the adjacent nodes, in the sense that the reason for the fitness increase is the cooperative behavior of some of the adjacent nodes. In the context of the repeated prisoner’s dilemma, this strategy resembles the tit-for-tat (TFT) strategy which is based on the idea of mimicking the other node(s) behavior in the previous turn. This means that the node will become cooperator only if it observes cooperative behavior of other nodes which is reflected in the increase in the fitness.

V. Examples of Network Architectures: Description of the Experiments

A. Network Architectures

We investigate the cooperative behavior in two wireless network architectures, wireless ad hoc network and network with a central infrastructure node. A graphical representation for the two network architectures is given in Fig. 1.

Wireless ad hoc network: A wireless ad hoc network represents a collection of wireless nodes that self-configure to form a network without the aid of any established infrastructure. Immediate applications of ad hoc networks include emergency and battlefield networks, metropolitan mesh networks for broadband Internet access, and sensor networks. In addition to these pending applications, ad hoc networks are closely related to the science of networks in other fields, including biology, economics, and air and automobile transportation.

Network with central infrastructure node: The second architecture we address is asymmetric and assumes that the users in one area (circle for example) transmit their signals to a central infrastructure node, e. g. access point, relay, or base station. This architecture is particularly relevant in the context of the emerging trends in the design of future wireless networks, which rely on dense and heterogeneous deployment of the wireless network infrastructure. Dense deployment means pairing traditional macrocells with pico or femtocells in densely populated urban environments; heterogeneous deployment means combining the current cellular network infrastructure with a parallel offloading infrastructure, based on multiple radio-access technologies (such as GSM, UMTS, WiFi, and device-to-device communication) [30]. The simulation set up for both network architectures is as follows.
Fig. 4. Network architectures where cooperative behavior is considered: a) wireless ad hoc network; b) network with central infrastructure node.

We place $M$ wireless nodes uniformly at random in a circle of unit radius $r$ (we are interested only in the relative performance of the different strategies and not in the absolute value of the consumed energy). The nodes send their messages during time slots of fixed duration (same for all nodes), where in each time slot exactly one transmitter/receiver pair is activated at random. We group the time slots in a block of length $T$, which denotes one iteration. The network behaviour is observed over $N$ iterations. Additionally, $N_t$ different network configurations are tested. The parameters selected for our simulations are: $M = 30$, $\alpha = 4$, $T = 1000$, $N = 1000$ and $N_t = 1000$.

Assuming the aforementioned strategies for the behavior of the individual users, the aim of the analysis/simulations will be to investigate the cooperative behaviour in the network and to evaluate the performance of the different strategies in terms of individual and global energy consumption, for both network architectures. As we will see, although both architectures share certain similarities, the adoption of the same game-theoretic architecture introduces the same qualitative differences in network behavior.

While simulating the performance of TFT and WSLS, we will assume that in the initial iteration all users are defectors. At the end of the initial iteration we choose one user at random to become cooperator. According to the change in the fitness defined in (5), the users determine their behaviour during the next iteration (cooperate or defect) according to the TFT or the WSLS strategy. The performance will be compared with COOP (all cooperators) and DEF (all defectors), which serve as upper respectively lower bound for the performance.

**B. Simulations: Wireless ad hoc network**

In this set up we assume peer-to-peer communication where each transmitter/receiver pair is equally likely.

1) Cooperative behaviour: In the case of TFT and WSLS, simulation results indicate that, once a single cooperator is introduced in the network (by chance), the network evolves such that cooperation spreads through the network, even though the decision making of the individual nodes is based on a (rather simple) evaluation of the individual fitness. Fig. 5 depicts the effect of spreading of cooperation over time. In addition, the simulation results show that the emergence and stability of cooperation is fairly robust to the random placement of the initial cooperator. This, as we believe, is mainly due to the assumption that each transmitter/receiver pair is equally likely, which brings symmetry to the problem. We note that the effect of spreading of cooperation, in general, also depends on the activity of the users and the duration (length) of one iteration.

We recall that in our scenario we assume that in each time slot (at least) one transmission takes place in the network, and that one iteration involves a long number of time slots. This means that during the first iteration there will almost certainly exist network node(s) which will benefit from the cooperative act of the initial cooperator, which is exactly the prerequisite for cooperation to spread in the network. If this is not the case, cooperation is expected to vanish in the next iteration.

**2) Energy consumption:** Before proceeding, we first evaluate the influence of the choice of the parameter $\nu$, defined in Section III. The simulations show that the value of $\nu$ for which the total energy consumption is minimal varies slightly with the choice of strategy, but can be located close to 0.39. This value is used in the rest of the simulations.

When the users adopt the DEF strategy, a transmitter $A$ communicates with a receiver $B$ by direct transmission. In the case when the users adopt the COOP strategy, for a transmitter/receiver pair $A/B$, user $A$ receives benefit from the cooperators located in the area defined by (1), reflected in the fact that it can decrease the transmit power. The simulations show that when all nodes cooperate the total (average) energy consumption is reduced by 60% as opposed to the case when all nodes defect, as indicated in Table I which illustrates the standard deviation of the individual energy consumption as a function of the network geography (distance from the center).

![Fig. 5. Emergence of cooperation in wireless ad hoc networks. Red circles–defectors; blue circles–cooperators. After the introduction of a single cooperator, cooperative behavior spreads in the network and persists over time.](image)

**TABLE I**

| strategy | mean($E\psi$) | std($E\psi$) |
|----------|---------------|--------------|
| DEF      | 0.70000       | 0.05000      |
| COOP     | 0.00000       | 0.10000      |
| TFT      | 0.01000       | 0.10000      |
| WSLS     | 0.02000       | 0.10000      |

Apart from the reduction in average energy consumption, cooperation leads to a more-fair energy consumption among the individual nodes. Indeed, when there is no cooperation the nodes which are located further from the center are at a disadvantage as the average distance to the rest of the nodes is larger compared to the nodes which are located near the center, leading to increased energy consumption for transmission. The introduction of cooperation lessens this imbalance to some extent. An illustration of this effect is shown in Fig. 6. As we can see, the introduction of cooperation balances the amount of energy spent by the individual nodes, and decreases the effect of the network topology on the individual energy consumption.

While simulating the performance of the TFT and WSLS strategy, we start by assuming that in the initial iteration...
all users are defectors. At the end of the initial iteration we choose one user at random to become a cooperator. The simulation results show that COOP yields a minimal total energy consumption among all four strategies (which is expected), followed by TFT, as shown in Table II.

Fig. 7. Individual energy consumption with COOP, TFT and WSLS.

However, the results also indicate that the COOP might not be the optimal strategy from the perspective of the energy consumption of the individual nodes, as Fig. 6 and Fig. 7 indicate. For example, when the network nodes follow the WSLS strategy, the nodes closer to the center are characterized by lower individual energy consumption compared to the other strategies. Further, the WSLS strategy yields a more balanced energy consumption as function of the geographical distribution of the nodes, as presented in Table II.

C. Simulations: Network with Central Infrastructure Node

The second network architecture we address corresponds to a cellular (infrastructure) scenario as it assumes that the users located in one area transmit their signals to a central infrastructure node, e.g. access point, relay, or base station.

1) Cooperative behaviour: Due to the specific network geometry (central infrastructure node which receives all packets), the mechanism of spreading of cooperation in this network shows significant difference with the wireless ad hoc network. To see why this is the case, let us take that a cooperator is placed at distance $r_0$ from the center. Due to the specific network configuration, only nodes which are at distance $r > r_0$ (i.e. further away from the center) can benefit from the cooperative act. As result, only these nodes can change their behavior from defectors to cooperators. In other words, spreading of cooperation is sensitive to the location of the initial cooperator. This is a major difference from the previous case, where no such constraint has been observed.

This observation has the implication that, in order to quantify correctly the effect of cooperation on the energy consumption in the network, one has to average over all different placements of the initial cooperator. Fig. 8 depicts the total energy consumption for the TFT strategy (averaged over the number of nodes), presented as a function of the location of the initial cooperator. We observe that the overall energy consumption is minimal when the initial cooperator is approximately at distance $r_0 = 0.26$ from the center. This behavior is somewhat surprising, since one would expect that the most beneficial set up is when the initial cooperator is located as close as possible to the center.

Fig. 8. Total energy consumed with TFT depending on the location of the initial cooperator.

2) Energy consumption: As result of the network configuration, the behaviour of the TFT and the WSLS strategy in this network architecture shows significant difference. The most important observation is that when the nodes adopt the WSLS strategy, cooperation does not persist in the network on long term. Namely, after the introduction of the initial cooperator, the cooperation behavior spreads in the network, but fades out over a finite number of iterations. In the case when the nodes adopt the TFT strategy, on the other hand, simulation results show that cooperation persists over time (although the region where cooperators are found) depends on the placement of the initial cooperator. The TFT strategy also yields a fairly low total energy consumption in the network (second best, right after the COOP strategy), as shown in Table II.

Additionally, it can be observed that WSLS and DEF have almost identical energy consumption. This is expected, since after the initial cooperation frenzy, the number of defectors gradually increases leading to extinction of cooperation. The individual energy consumption as function of the distance from the center, when different strategies are applied, is displayed in Fig. 9. When the nodes act accordingly to the WSLS

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7Since the cooperative behaviour vanishes in the case of the WSLS strategy, only the result for the TFT strategy is illustrated.
8The total energy consumption depends on the location of the individual cooperator. The values in the table are shown for cooperator locations which lead to the minimal possible energy consumption.
strategy, the energy consumption increases polynomially with the distance, due to the extinction of cooperation. The energy consumption with TFT increases gradually up to 0.8 distance units from the center, and decreases for the nodes over this point. We can conclude that TFT leads to a reduction in the individual energy consumption for all nodes when compared to DEF. This is different from the COOP strategy where some nodes (for example those at distance 0.4) spend more energy as cooperators as opposed to when they are defectors.

![Graph showing individual energy consumption vs distance from center]

**Table II**

| Strategy | mean($\mathcal{E}$) | std($\mathcal{E}$) |
|----------|----------------------|---------------------|
| DEF      | 1.00000              | 1.34355             |
| COOP     | 0.29348              | 0.78187             |
| MINIMAL  | 0.11021              | 0.92921             |
| TFT      | 0.46329              | 0.81327             |
| WSLS     | 0.99534              | 1.33419             |

Distance $r$ from the central node thus reads

$$\mathcal{E}_T(r) = K \int_0^r P(r,y)(r - y)^\alpha dy,$$

where $K$ is a normalization constant which accounts for all propagation factors, apart from the signal path loss.

The density $P(x,y)$ corresponds to all pairs transmitter-cooperator which are located in some infinitesimal regions (see Fig. 10), where the area of such infinitesimal region is proportional to its distance from the central node. We assume that the retransmissions of messages originating from the infinitesimal area around A are shared equally by the cooperators from the infinitesimal area around C (we consider only the messages targeting the cooperators in this area according to the probability distribution). From the proportionality of the areas, it follows that the average number of messages (per node) to be retransmitted by a cooperator C at distance $y$ from the central node, and originating from a sender A at distance $x$, is larger for a factor $x/y$ than the average number of generated messages (targeting at C’s neighbourhood). Hence, the average energy spent for cooperation of a node at distance $r$ from the central node reads

$$\mathcal{E}_C(r) = K \int_r^R P(x,r)x^{\alpha} y dx.$$  

The average energy consumed by a node at distance $r$ from the central node (including both the energy for transmission of own messages and the energy for cooperation) is given by

$$\mathcal{E}(r) = K \int_0^r P(r,y)(r - y)^\alpha dy + K \int_r^R P(x,r)x^{\alpha} y dx.$$  

By using (8), one can calculate the total energy consumption in the network as

$$\mathcal{E}_{\text{total}} = K \int_0^R dx \int_0^x P(x,y)Q(x,y)dy,$$

where

$$Q(x,y) = (x - y)^\alpha + y^{\alpha - 1}x.$$  

Ideally, the optimal choice of the distribution $P(x,y)$ would minimize the total energy consumption and balance the individual energy consumption simultaneously. However, since both requirements might be contradictory, we first address each issue separately.

**D. A special case: Dense homogeneous network with central infrastructure node and full cooperation**

This case addresses the scenario where the network is dense enough so that at least one cooperator is present in every (sufficiently small) area. This assumption is not only convenient as it simplifies the analysis, but is also realistic to some extent since it covers the case of large networks spreading over a region of fixed area. Additionally, we consider that all nodes are cooperators. Hence, the performance of the system in this setting can be seen as the ultimate performance bound for any strategy (or a set of mixed strategies) in terms of the total energy consumption in the network.

In a typical communication scenario, node A (located at distance $x$ from the center) transmits to the central node B with the help of a cooperator C (located at distance $y < x$ from B). The high-density assumption allows to assume that the node C lies on the line AB, or at least very close to it (see Fig. 10). In order to distribute the cost of cooperation, we assume that A can choose among all cooperators between it and B (which are close to the line AB), with some probability. Let the probability density function for choosing (targeting) the cooperator at distance $y$, when the sender is at distance $x$, be $P(x,y)$. The average transmission energy for a node at
Minimizing the total energy consumption: Here we derive the distribution of $P(x,y)$ which minimizes $\mathcal{E}_{\text{total}}$, and also present the resulting minimal energy.

**Lemma 1:** The distribution $P(x,y)$ which minimizes $\mathcal{E}_{\text{total}}$ is given by

$$P(x,y) = \delta (y - y(q(x))), \quad (11)$$

where $Q_{\text{min}}(x,y) \equiv q(x)$ denotes the minimal value of $Q$ for fixed $x$ - the minimization is done by varying $y$, and $\delta(\cdot)$ is the Dirac $\delta$ function.

**Proof:** The proof is given in Appendix A.

Having the optimal $P(x,y)$, the minimal total energy reads

$$\mathcal{E}_{\text{min}} = K \int_0^R dx \int_0^\pi \delta (y - y(q(x))) Q(x,y) dy$$

$$= K \int_0^R q(x) dx. \quad (12)$$

Clearly, the last integral depends on $\alpha$, since $q(x)$ depends on $\alpha$, $q(x) = q_\alpha(x)$. Singularity of distributions implies that the transmitters from the ring with radius $x$ should send their messages to their peers at the ring with radius $y(q(x))$. We denote the cooperation strategy associated strategy with the minimal total energy consumption as MINIMAL. The total energy consumption of this strategy is illustrated in Table I.

Balancing the individual energy consumption: While the distribution (12) minimizes the total energy consumption in the network, it is not the optimal solution when it comes to the energy consumption of the individual nodes. Indeed, as Fig. 9 shows, the individual energy consumption depends on the node location. For example, nodes at distance 0.5 (approximately) from the center consume more energy than other nodes. Perfect balancing would require that the distribution $P(x,y)$ is such that the individual energy consumption is independent on the distance $r$

$$\mathcal{E}(r) = K \int_0^r P(r,y)(r-y)^\alpha dy + K \int_r^R P(r,y)r^\alpha \frac{y}{r} dx$$

$$= \text{const.} \quad (13)$$

Analytical solution of (13) (if it exists at all), seems to be out of reach. In order to simplify the analysis, one can relax the demand for equal energy spending and search for a solution with as balanced as possible individual consumption. This means finding the coordination pattern among the nodes which leads to smallest possible variation of the consumed energy. To make the problem more tractable one can divide the circle into $N$ rings of width $r$, such that $R = Nr$. This discretization of the problem would allow for deployment of some optimization techniques. The directions for solving the problem in the discrete case are presented in Appendix B.

VI. DISCUSSION

A. Interpretation of the results

The results clearly indicate that cooperation can spread in wireless networks, even in networks with selfish nodes which adopt simple strategies and update their behavior only based on the individual fitness. In addition, there are several other important conclusions, which arise as result of the analysis.

B. Relevance to systems other than communication networks

Although this work addresses energy efficiency in wireless communication systems, it is possible that the results have implications on the understanding of certain biological and social phenomena. We recall that the main feature of wireless networks which justifies cooperative behaviour is the fact that the cost of communication (transmission) is a function which is polynomial in the distance. However, similar functions (although not always well understood) may be objects to optimization in biological systems as well. As an example we can take the neural system, where neurons differentiate from...
multipotent stem cells and migrate to their final residence in the system. When these neurons reach their residence, they extend an axon which needs to travel a certain distance to attach to other neurons (forming a synapse) and enable inter-neuronal communication. Since axons may travel long distances, axonal trajectories appear to be broken up into a series of smaller movements, where the axon finds intermediate targets that act as choice points (also called guidepost cells) [31]. This behaviour has clear analogy in the relaying (retransmissions) addressed in the wireless network scenario. In this particular example, the insights gained from the analysis of wireless networks where the behaviour of the nodes is determined by evolutionary-like rules, could be applied to access the benefits and costs associated with growing axons directly to the target, and using intermediate targets, i.e. guidepost cells.

VII. CONCLUSIONS AND FUTURE WORK

We investigated the mechanisms for promotion of cooperation in decentralized wireless networks. The approach was motivated by recent results in evolutionary biology which suggest that cooperation can be favoured by natural selection, if a certain mechanism is at work. We modelled the wireless network as a graph, where benefits and costs were associated with the strategy that the network users follow. In game-theoretic spirit, the nodes based their behavior on calculations of their energy spending. We presented numerical study of cooperative communication scenarios based on simple local rules, which is in contrast to most of the approaches in the literature which enforce cooperation by using complex algorithms and require strategic complexity of the network nodes. The simulations show that even selfish decision making (such as one based on TFT or WSLS strategy) of the nodes can lead to emergence of cooperation. These observations serve as indicator that uncomplicated local rules, followed by simple fitness evaluation, can generate network behavior which yields global energy efficiency. We identify several major directions for future work, as formulated in the following.

Individual strategy selection: We recall that in this work we adopted the convention that the same strategy was used by all users in all iterations. In a future version of the work, we will consider the case where each of the individual users is allowed to choose its own strategy at every iteration. As discussed, the results from the simulations indicate that, depending on the node distance from the center, distinct nodes could find optimal to follow different strategies. It is expected that this analysis will bring valuable insights in the dependencies between the choice of optimal strategy for the individual users and the network topology.

Nodes with finite energy buffers, energy harvesting: In addition, it will be interesting to evaluate the network behaviour in the case when the nodes have buffers with limited energy capacity, under a particular random arrival process. This is in contrast to the here addressed scenario which assumes nodes with infinite-length buffers. We expect that the adoption of this more realistic assumption will influence both the behaviour of the individual nodes and the way energy is consumed in the network. Additionally, it is expected that will yield qualitatively different performance of the here addresses strategies, as indicated in Section [VI]. This more general approach also includes the energy harvesting scenario where the nodes harvest energy quanta from the environment according to some arrival process.

Implication on other systems: While this work was motivated by observations in biological systems and social systems, it is possible that the results have implications on the understanding of certain biological and social phenomena. This would establish a connection in the other direction, where lessons from artificial systems (such as wireless communication networks) can be applied to natural systems.

APPENDIX A
PROOF OF LEMMA [1]

Since the function \( Q(x,y) \) is non-negative, the following inequality holds

\[
\int_0^R dx \int_0^x P(x,y)Q(x,y)dy \geq \int_0^R dx \int_0^x P(x,y)q(x)dy,
\]

where \( q(x) = Q_{\min}(x,y) \) denotes the minimal value of \( Q \) for fixed \( x \) – the minimization is done by varying \( y \). The right hand side of the last inequality then simplifies

\[
\int_0^R dx \int_0^x P(x,y)q(x)dy = \int_0^R q(x)dx,
\]

due to the normalization of the distribution, \( \int P(x,y)dx dy = 1 \). The equality in (14) will hold only if one chooses a singular distribution

\[
P(x,y) = \delta \left( y - y(q(x)) \right),
\]

located at the point \( y(q(x)) \) which corresponds to the minimum of the function \( Q(x,y) \) for fixed \( x \).

APPENDIX B
BALANCING THE INDIVIDUAL ENERGY CONSUMPTION: DISCRETE APPROXIMATION

When the number of rings \( N \) is large, for the purpose of energy calculation, one can assume that the nodes are located in the middle of the rings. Furthermore, we assume that every node sends its message with some probability to some peer in some inner ring, or with some probability directly to the relay. For the node in the ring \( i \) the set of those probabilities is \( p_{i,j} \), where \( j = 0,1,...,i-1 \), and \( p_{i,0} \) is the probability for sending the message to the relay. The energy for transmission for that node will be

\[
E_t(i) = \sum_{j=0}^{i-1} p_{i,j} [r(i-j)]^\alpha = r^\alpha \sum_{j=0}^{i-1} p_{i,j} (i-j)^\alpha .
\]

On the other hand, the cooperation will consume energy

\[
E_c(i) = \sum_{k=i+1}^N p_{k,i} (ir)^\alpha \frac{k}{i} = r^\alpha \sum_{k=i+1}^N p_{k,i} \frac{k}{i} ,
\]

where \( r \) is the transmission rate and \( \alpha \) is the energy consumption per unit of data.

\( [1] \)
where the factor $k/i$ appears for the same reason as in (7). Total energy thus consists of two sums

$$
\mathcal{E}(i) = r^\alpha \left[ \sum_{j=i}^{N-1} \beta_{i,j} p_{i,j} + \sum_{j=1}^{N} \gamma_{j,i} p_{j,i} \right].
$$

(19)

The last expression could be written more neatly as

$$
\mathcal{E}(i) = r^\alpha \sum_{j=0}^{N} (\beta_{i,j} p_{i,j} + \gamma_{j,i} p_{j,i}),
$$

(20)

where the non-zero coefficients are $\beta_{i,j} = (i-j)^\alpha$ for $j = 0, 1, \ldots, i-1$ and $\gamma_{j,i} = j^{\alpha-1}$ for $j = i+1, i+2, \ldots, N$. This means that for particular $i$ and $j$ only one of $\beta_{i,j}$ and $\gamma_{j,i}$ is non-zero. The average energy is

$$
\langle \mathcal{E} \rangle = \frac{r^\alpha}{N} \sum_{i=1}^{N} \mathcal{E}(i) = \frac{r^\alpha}{N} \sum_{i=1}^{N} \sum_{j=0}^{N} (\beta_{i,j} p_{i,j} + \gamma_{j,i} p_{j,i})
$$

$$
= \frac{r^\alpha}{N} \sum_{i=1}^{N} \sum_{j=0}^{N-1} \delta_{i,j} p_{i,j},
$$

(21)

where $\delta_{i,j} = \beta_{i,j} + \gamma_{j,i}$. As a measure of the balance is the mean squared deviation

$$
\sigma^2 = \langle (\mathcal{E} - \langle \mathcal{E} \rangle)^2 \rangle = \frac{1}{N} \sum_{i=1}^{N} \langle \mathcal{E}(i) - \langle \mathcal{E} \rangle \rangle^2.
$$

(22)

Since the optimal parameters $p_{i,j}$ are probabilities, the normalization puts a constraint

$$
\sum_{j=0}^{N-1} p_{i,j} = \sum_{j=1}^{N} p_{j,i} = 1.
$$

(23)

Hence, in the discrete case, if one searches for a solution which balances the individual energy consumption in the network, one should minimize (22), subject to the constraint (23). This can be performed, for example, by using certain modeling systems for convex optimization.

REFERENCES

[1] B. Bandyopadhyay, Q. Tian, and E. J. Coyle, “Spatio-temporal sampling rates and energy efficiency in wireless sensor networks,” IEEE/ACM Transactions on Networking (TON), vol. 13, no. 6, pp. 1339–1352, 2005.

[2] A. Sendonaris, E. Erkip, and B. Aazhang, “User cooperation diversity, part i: System description,” IEEE Transactions on Communications, vol. 51, no. 11, pp. 1927–1938, 2003.

[3] ———, “User cooperation diversity, part ii: Implementation aspects and performance analysis,” IEEE Transactions on Communications, vol. 51, no. 11, pp. 1939–1948, 2003.

[4] V. R. Cadambe and S. A. Jafar, “Interference alignment and degrees of freedom of the $K$-user interference channel,” IEEE Transactions on Information Theory, vol. 54, no. 8, pp. 3425–3441, 2008.

[5] Q. Zhao and L. Tong, “Energy efficiency of large-scale wireless networks: proactive versus reactive networking,” Selected Areas in Communications, IEEE Journal on, vol. 23, no. 5, pp. 1100–1112, 2005.

[6] A. El Gamal and J. P. Mammen, “Optimal hopping in ad hoc wireless networks,” in INFOCOM, 2006.

[7] S. Zhong, J. Chen, and Y. R. Yang, “Sprite: A simple, cheat-proof, credit-based system for mobile ad-hoc networks,” in Twenty-Second Annual Joint Conference of the IEEE Computer and Communications, INFOCOM 2003, vol. 3. IEEE, 2003, pp. 1987–1997.

[8] S. Buchegger, J. Le Boudec, et al., “The effect of rumor spreading in reputation systems for mobile ad-hoc networks,” in WoOpt’03: Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, 2003.

[9] Y. Liu and Y. R. Yang, “Reputation propagation and agreement in mobile ad-hoc networks,” in Wireless Communications and Networking, WCNC 2003, vol. 3. IEEE, 2003, pp. 1510–1515.

[10] T. Anantvanee and J. Wu, “Reputation-based system for encouraging the cooperation of nodes in mobile ad hoc networks,” in IEEE International Conference on Communications, ICC’07. IEEE, 2007, pp. 3383–3388.

[11] J. Munding and J.-Y. Le Boudec, “Analysis of a reputation system for mobile ad-hoc networks with liars,” Performance Evaluation, vol. 65, no. 3, pp. 212–226, 2008.

[12] P. Marbach and Y. Qiu, “Cooperation in wireless ad-hoc networks: A market-based approach,” IEEE/ACM Transactions on Networking (ToN), vol. 13, no. 6, pp. 1325–1338, 2005.

[13] L. Buttyan and J.-P. Hubaux, “Nuglets: a virtual currency to stimulate cooperation in self-organized mobile ad hoc networks,” 2001.

[14] V. Srinivasan, P. Nuggehalli, C. Chiasserini, and R. R. Rao, “An analytical approach to the study of cooperation in wireless ad hoc networks,” Wireless Communications, IEEE Transactions on, vol. 4, no. 2, pp. 722–733, 2005.

[15] M. Felegyhazi, J.-P. Hubaux, and L. Buttyan, “Nash equilibria of packet forwarding strategies in wireless ad hoc networks,” Mobile Computing, IEEE Transactions on, vol. 5, no. 5, pp. 463–476, 2006.

[16] L. Lai and H. El Gamal, “On cooperation in energy efficient wireless networks: the role of altruistic nodes,” Wireless Communications, IEEE Transactions on, vol. 7, no. 5, pp. 1868–1878, 2008.

[17] R. Axelrod and W. D. Hamilton, “The evolution of cooperation,” Science, vol. 211, no. 4489, pp. 1390–1396, 1981.

[18] H. Ohtsuki, C. Hauert, E. Lieberman, and M. A. Nowak, “A simple rule for the evolution of cooperation on graphs and social networks,” Nature, vol. 441, no. 7092, pp. 502–505, 2006.

[19] M. A. Nowak, “Five rules for the evolution of cooperation,” Science, vol. 314, no. 5805, pp. 1560–1563, 2006.

[20] J. Cremer, A. Melbinger, and E. Frey, “Growth dynamics and the evolution of cooperation in microbial populations,” Scientific reports 2, Article number 281, no. doi:10.1038/srep00281, 2012.

[21] A. Lozano, R. W. Heath Jr., and J. G. Andrews, “Fundamental limits of cooperation,” http://arxiv.org/abs/1204.0011v1, 2012.

[22] M. C. Soares, I. M. Côté, S. Cardoso, and R. Bshary, “The cleaning goby mutualism: a system without punishment, partner switching or tactile stimulation,” Journal of Zoology, vol. 276, no. 3, pp. 306–312, 2008.

[23] N. J. Mehliaibadi, C. N. Jack, T. T. Farnham, T. G. Platt, S. E. Kalla, G. Shaulsky, D. C. Queller, and J. E. Strassmann, “Social evolution: kin preference in a social microbe,” Nature, vol. 442, no. 7105, pp. 881–882, 2006.

[24] J. Faaborg, P. Parker, L. DeLay, T. De Vries, J. Bednarz, S. M. Paz, J. Naranjo, and T. Waite, “Confirmation of cooperative polyandry in the galapagos hawk (buteo galapagoensis),” Behavioral Ecology and Sociobiology, vol. 36, no. 2, pp. 83–90, 1995.

[25] S. Buchegger and J.-Y. Le Boudec, “Performance analysis of the contact protocol,” in Proceedings of the 3rd ACM international symposium on Mobile ad hoc networking & computing. ACM, 2002, pp. 226–236.

[26] P. Michiardi and R. Molva, “Core: a collaborative reputation mechanism to enforce node cooperation in mobile ad hoc networks,” in Advanced Communications and Multimedia Security. Springer, 2002, pp. 107–121.

[27] G. Caire, D. Tuninetti, and S. Verdú, “Suboptimality of tdma in the low-power regime,” Information Theory, IEEE Transactions on, vol. 50, no. 4, pp. 608–620, 2004.

[28] A. Özgür, O. Lévêque, D. Tse et al., “Operating regimes of large wireless networks,” Foundations and Trends® in Networking, vol. 5, no. 1, pp. 1–107, 2011.

[29] S. Lasaulce and H. Tembine, Game theory and learning for wireless networks: fundamentals and applications. Academic Press, 2011.

[30] S. Zhao and D. Raychaudhuri, “Scalability and performance evaluation of hierarchical hybrid wireless networks,” Networking, IEEE/ACM Transactions on, vol. 17, no. 5, pp. 1536–1549, 2009.

[31] K. Shen, R. D. Fetzer, and C. I. Bargmann, “Synaptic specificity is generated by the synaptic guidepost protein syg-2 and its receptor, syg-1,” Cell, vol. 116, no. 6, pp. 869–881, 2004.