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The flatrate policy is an incentive for saving energy in mobile cooperation networks

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Abstract—In this paper we demonstrate that a flatrate policy is an incentive for saving energy in mobile cooperation networks.

Inspired by the work of Courcoubetis and Weber about peer-to-peer systems, we present a game theoretic incentive mechanism obtained by providing an interpretation in terms of energy efficiency and coverage. The asymptotic properties of the obtained model support the application of a flatrate policy, which requires every participants to commit to the cooperation scheme a fix contribution in energy for reciprocally roaming communication routes and guarantees to every participant a sufficient incentive for cooperation by an individual average energy win from the scheme.

We provide results from simulations which confirm the theory but also show the disrupting effects of actual traffic intensity and routing on game theoretic equilibria, pointing out how these equilibria can be restored.

I. INTRODUCTION

A known way to improve the coverage of mobile networks is to organize a cooperation scheme among network nodes: if these nodes allow each other to “bridge” communication, access points can be reached by terminals without direct coverage. This concept is illustrated in figure 1: a network node, in this case a mobile phone, operates as a relay and transports data between an access point and another remote terminal, which can still reach the access point through one hop, despite of laying outside of the access point’s coverage.

Such schemes require cooperation between nodes of a network because intermediate nodes must yield resources in order to enable the participation of other peers. They do so because they will benefit from the same cooperation scheme when they will become remote peers.

Cooperative communication schemes for energy efficiency have been investigated in [1]–[3]: under certain throughput requirements, cooperative beamforming and distributed space time coding have been shown to dramatically reduce the required transmission power.

Taking for granted that cooperation schemes present overall benefits and that they require participants to commit contributions to the community, a question which immediately arises for every individual participant is whether its own benefit from the overall beneficial scheme is greater than its own contribution to the same scheme. In other words, whether it makes an individual win or a loss.

In economics, such questions are known within the context of a theory of games with incomplete information as mechanism design problems that can be solved by developing incentive compatible mechanisms, i.e. mechanisms which provide the maximum payoff on disclosure of true private preferences rather than on deceiving ones. This mechanism design theory, also known as reverse game theory, includes a revelation principle which states that if the mechanism design problem cannot be solved by an incentive compatible mechanism, it cannot be solved at all. Consequently, the search for a solution can be limited to a set of incentive compatible equilibria, also known as Bayesian Nash equilibria.

We propose and demonstrate that a flatrate policy, as defined in [4], is an incentive for saving energy in mobile cooperation networks. Our main contribution lies on the following: first, we extend the analysis presented in [4] in terms of energy efficiency and coverage by introducing a new parameter ($K$) that represents a contracted win in terms of power. Second, we develop rather detailed discrete-event simulations to validate the proposed scheme under the mathematically intractable effects of network traffic and investigate how equilibria are affected by growth in area or density of the networks.

The rest of the paper is organized as follows. In section II we present the model of cooperation networks: we formulate the mechanism design problem by providing an interpretation for the involved quantities in terms of energy and coverage, then we point to a conclusion which supports the application of a flatrate policy. The business rationale about this policy is briefly presented in section III and section IV reports the setup and the outcomes of our simulated experiments on cooperation schemes.

II. MODEL OF COOPERATION NETWORKS

In this section we define a theoretical model of cooperation networks whose nodes represent, without loss of generality,
within the models. Consist of the definition of the following variables, employed version of such models to energy efficiency. This interpretation provide an interpretation for applying a slightly modified asymptotic behavior relation to their nodes who do not claim any lower benefit than the one they ensure that the highest energy saving can be achieved by which matches its individual benefit, so the scheme must every individual node decides at its own convenience whether circumstances the nodes will cooperate with each other, while actually experiences and every individual node is guaranteed to data through other nodes participating to the same scheme. define a vector in the subspace projected along dimension i, i.e. which excludes the variable \( \theta_i \), as:

\[
\bar{\theta}_i = [\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_n]
\]

\( F(\cdot) \) cumulative probability distribution vector of the utilizations, defined as

\[
F(\cdot) = [F_1(\cdot), \ldots, F_n(\cdot)]
\]

where \( F_i(\cdot) \) is the cumulative probability distribution of \( \theta_i \) and \( f(\cdot) \) is its density. In addition, we define a vector in the subspace projected along dimension i, i.e. which excludes the distribution \( F_i(\cdot) \), as:

\[
\bar{F}_i(\cdot) = [F_1(\cdot), \ldots, F_{i-1}(\cdot), F_{i+1}(\cdot), \ldots, F_n(\cdot)]
\]

and we define a differential operator with the purpose of computing averages as

\[
dF(\theta) = \prod_{i=1}^{n} f_i(\theta_i) d\theta_i
\]

\( \pi_i(\theta) \) probability that the node i participates to the scheme, given the chosen utilization.

\( Q(\theta) \) coverage as access probability to a node within a range depending on the node’s transmit power and sensitivity. The amount of power deployed to the cooperation scheme depends ultimately on the utilization chosen by each individual node.

\( u(\cdot) \) power efficiency curve given a coverage. This curve returns the average saved power on a nominal communication, given the available coverage. For example:

\[
u(x) = \int_{0}^{\infty} area(x) power(x) dx
\]

where

\( area(x) \) average area fraction at \([x, x + dx]\] distance from any node, as shown in figure 2.

\( power(x) \) density of the average saved power when operating at distance \( x \) from a node, for example as reported in [5].

\( p_i(\theta) \) power which a node is willing to make available to the cooperation scheme for participation, ultimately depending on the preference parameters of all participants.

\( c_i(\theta) \) average power required by a node i to sustain the communication routes within the cooperating nodes. It is a function of the traffic characteristics and of the coverage, which are ultimately all determined by the individual utilizations, in particular through the coverage which could be considered also as an explicit argument of this function.

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**Figure 2.** Differential area at distance \( x \) from any node.
Given this interpretation, now we can define the equilibrium which maximizes the efficiency of the network. We define \( \Theta = \times_{n}^{n}[0,1] \) the n-dimensional space of the vector \( \theta \) and \( \Theta_i = \times_{n-1}[0,1] \times_{n+1}[0,1] \), the n-1 dimensional subspace projected along dimension \( i \), i.e. “without” dimension \( i \).

The social welfare is a measure of the global efficiency of the scheme and consists of the average power saved by every individual node \( i (\theta_i, u(Q(\theta))) \) minus the average power required in that individual node to sustain the communication routes defined by other nodes \( (c_i(\theta)) \). The contribution of every individual node to the scheme is determined by its probability of participation \( \pi_i(\theta) \) and the resulting average social welfare must be maximized according to the non-linear optimization problem (1):

\[
\max_{\pi_1(...,\pi_n), Q(\cdot)} \int_{\Theta} \sum_{i=1}^{n} \pi_i(\theta)u(Q(\theta)) - c_i(\theta) dF(\theta) \quad (1)
\]

The maximization of the social welfare presented in problem (1) is subject to three constraints. The first one is known as the weak feasibility constraint, formalized as inequality (2), and it states that the average sum of powers \( p_i(\theta) \), which every node is willing to make available to the cooperation scheme, is higher than the average sum of costs \( c_i(\theta) \) to sustain the same scheme.

\[
\int_{\Theta} \sum_{i=1}^{n} \pi_i(\theta)p_i(\theta) - c_i(\theta) dF(\theta) \geq 0 \quad (2)
\]

The second constraint is known as individual rationality constraint and states that every individual node \( i \) will only participate to the scheme if it can individually expect that the won power \( \theta_iu(Q(\theta)) \) is higher than the power one has to budget for participating to the scheme \( p_i(\theta) \). This difference must be at least a globally contracted power win \( K \), because this is the won benefit which provides an incentive for the flatrate policy presented in section III. This fix benefit is applied only to participants, hence it must be multiplied by the probability of participation \( \pi_i(\theta) \). Inequality (3) presents this constraint in average:

\[
\int_{\Theta} \pi_i(\theta)[\theta_iu(Q(\theta)) - p_i(\theta)]dF(\theta) \geq \pi_i(\theta)K, \forall \theta_i \quad (3)
\]

The last constraint is known as incentive compatibility and states that the power \( \theta_iu(Q(\theta)) \) saved by node \( i \) over the power budget \( p_i(\theta) \) is higher than the one saved over a power budget \( p_i(\theta^*) \) obtained by posting any \( \theta^* \neq \theta_i \). Defining the vector \( \theta^* \) as \( \theta \) with the \( i \)-th element replaced by \( \theta^*_i \):

\[
\theta^* = \theta |_{\theta_i=\theta^*_i} \]

the incentive compatibility constraint is represented by inequality (4).

\[
\int_{\Theta} \pi_i(\theta)[\theta_iu(Q(\theta)) - p_i(\theta)]dF(\theta) \geq \int_{\Theta} \pi_i(\theta^*)[\theta_iu(Q(\theta^*)) - p_i(\theta^*)]dF(\theta), \forall i, \theta^*_i \quad (4)
\]

These constraints can be shown to be equivalent to the constraint presented by inequality (5). The introduction of \( K \) in the inequality (3) requires to rework the analysis presented in the appendix A of [4]: substituting into (3) the expected payment of node \( i \) with the preference parameter \( \theta_i \), indicated in [4] as \( P_i(\theta_i) \), it can be observed that \( P_i(0) + \pi_i(\theta)K \leq 0 \), hence the upper bounds for \( P_i(0) \) is not 0 anymore, but rather \( \pi_i(\theta)K \). The resulting inequality (5) reflects the common sense that the total incentive compatible contribution (first term of (5)) must cover both the required power (second term of (5)) and the contracted benefit \( K \).

\[
\int_{\Theta} \sum_{i=1}^{n} \pi_i(\theta)[g(\theta_i)u(Q(\theta)) - c_i(\theta) - K]dF(\theta) \geq 0 \quad (5)
\]

where

\[
g(\theta_i) = \theta_i - 1 - \frac{F_i(\theta_i)}{f_i(\theta_i)}
\]

The problem (1) under constraint (5) can be shown to be convex (see appendix B in [4]) and solved by Lagrangian methods, which consist of finding \( \pi_1(\cdot), ..., \pi_n(\cdot) \) and \( Q(\cdot) \) which maximize a Lagrangian of:

\[
\sum_{i=1}^{n} \pi_i(\theta_i)[\theta_i + \lambda g(\theta_i)]u(Q(\theta)) - \sum_{i=1}^{n} \pi_i(\theta_i)c_i(\theta_i) + K]
\]

This problem is complex, but [4] shows that it presents simple asymptotic characteristics which make it attractive for devising a business model based on a flatrate policy, described in section III.

### III. Flatrate Policy

Section II has presented a model of cooperation for saving energy over time, expressed in power. The constraint (3) ensures that:

- every node saves \( K \) power in its individual average,
- every node must individually commit a power contribution of \( p_i(\theta) \).

The analysis presented in [4] demonstrates that if the power efficiency \( u(\cdot) \) and power cost \( c_i(\cdot) \) are bounded by exponential laws of the coverage \( Q(\theta) \), increasing the number of participants to the scheme drives individual contributions \( p_i(\theta) \) to converge to a fix value \( p \). This remains true even if participants bear different types of technologies, such as WLAN, WiMAX, UMTS or LTE, which collaborate with different weights on coverage and power.

Since wireless path losses are well approximated by exponential laws, as shown for example in [6], the convergence of \( p_i(\theta) \) holds in the interpretation presented in section II and implies that, with some approximation, an attractive flatrate policy can be introduced: if all participating nodes commit to in forward traffic under a guaranteed flatrate contribution of power \( p \) by sustaining roaming communication routes, then every node can enjoy a power win of at the least \( K \) in average, which can turn into a benefit, for example in terms of battery duration. A participating node can benefit from both coverage
Q(θ) and power saving, which are in fact related to each other by (6).

The model of cooperation presented in section II converges to a higher coverage Q(θ) and a lower flatrate p_i(θ) → p with the increasing number of participants, providing a linear growth of returns in terms of guaranteed power win K per participant. Consequently, this model of cooperation does not maximize profit for a given participation, instead it maximizes participation for a given guaranteed return per participant.

IV. EXPERIMENTAL RESULTS

In the following sections we describe the characteristics of the simulation models we have built and the results obtained from measures of the saved transmit power under multiple configurations and flatrate policies. Our goal has been to investigate the growth of mobile cooperation networks under stationary traffic of their users and under contracted K and p.

A. Characteristics of the simulation models

The simulated networks consist of nodes moving within areas from 50×50 to 100×100 km² with a path loss exponent of 3.24, which is found in [6] to properly represent a suburban environment. The transmit power model is fitted to reach a coverage of 1000 m and as much queue time per hop as experienced at 1 W. Equilibria for both flatrates can be restored reducing the contracted power win to 0.5 W: as shown in figure 3, an energy tolerance buffer of K=5 s, the node exits from the cooperation and it is allowed to “free ride” the other nodes until it eventually returns within the thresholds and participates again to the cooperation. No malicious behavior has been modeled.

B. Results

To begin with, we have simulated one hour of operations for a cooperation network without flatrate constraint: the nodes could join the cooperation as long as their power win was above 1 W, with 5 s of tolerance buffer. The network has converged to the figures reported in the first row of table I. Subsequently, we have tested the convergence by actually enforcing a flatrate with p = 1.1 W and found values rather close to the previous ones, as shown in the second row of table I.

The third row of table I shows that further equilibria exist: a flatrate of 0.5 W halves the contracted power win, but also the packet drop rate, because less hops accept to roam routes by spending power, thus packets reach their destinations through less hops and hence more timely.

If the flatrate drops to 0.375 W, the equilibrium in the cooperation is lost: figure 3 shows that nodes under flatrates of 0.375 W and 0.25 W progressively leave the cooperation because they cannot achieve the contracted power win K of 1 W. Equilibria for both flatrates can be restored reducing the contracted power win to 0.5 W: as shown in figure 3, after some transient time the nodes are given incentives and participation increases.

While the theory calls for an increase in participation, an increase of the nodes’ density on the territory can actually lead to a loss of efficiency in the cooperation. Such a situation is presented by the diagrams of figure 4, which show a loss of 10.5% in participation to a cooperation network whose density is twice the one of a reference network. A closer inspection has revealed that higher density attracts indeed more transmitters must compete to acquire the receivers’ mutually exclusive ownership. Should the transfer fail, either because no route can be found or the destination has moved out of coverage, a backoff procedure regulates subsequent attempts.

The nodes’ mobility is generated from Markov chains which produce patterns for walking (from 3.8 to 4.2 Km/h), transportation (from 50 to 200 Km/h) or just standing.

Every node monitors the power it has delivered for sustaining roamed routes and the power it has saved by participating to the cooperation scheme. If the delivered power p_i(θ) exceeds the flatrate p or the saved power falls below the contracted power win K, with an energy tolerance buffer of K=5 s, the node exits from the cooperation and it is allowed to “free ride” the other nodes until it eventually returns within the thresholds and participates again to the cooperation. No malicious behavior has been modeled.

| Table I 100 MOBILE NODES COOPERATING IN A SUBURBAN AREA OF 50×50 Km² |
|-----------------|---------|--------|------------------|
| p   | K     | drops | hops | saved power |
|     |       |       |      |              |
|     |       | best  | average | worst |
| +∞  | 1 W   | 9.181%| 3.91 | 26.33 W 5.34 W 1.80 W |
| 1.1 W | 1 W | 10.326%| 3.81 | 22.80 W 5.52 W 1.65 W |
| 0.5 W | 1 W | 5.044% | 0.94 | 8.57 W 2.29 W 1.01 W |

The nodes select random destinations and generate Poisson distributions of traffic sessions with average 40 packets and session gaps with average 30 s. Every packet has an average size of 0.5 Kb in a uniform distribution from 1 byte to 1 Kb and an average inter-packet gap of 10 ms under Poisson distribution. The transfer speed is 500 Kbps and packets are given rather tight deadlines which account for a hop every 1000 m and as much queue time per hop as experienced at the source.

The implemented routing algorithm is position-based [7] and searches for an available node which has a sufficiently low load for the packet’s deadline and whose position minimizes the overall transmit power required to reach the destination.

The nodes’ transmitters continuously attempt to transfer packets: every receiver can sustain only one transfer at time, so
nodes, but these nodes are subject to higher traffic: the nodes in the network at double density have sustained in average 16.5% more hops than their counterparts in the single density network and ultimately lost 6% on power savings, driving down participation.

Letting the network grow over a larger area offers more possibilities for saving power, but also requires more power for roaming: the results presented in figure 5 show that the larger area of 100×100 Km² does not elicit more participation than the one presented in figure 4 for 50×50 Km².

Even while keeping density constant, there is no guarantee that efficiency will be maintained: packets will travel longer, affecting power budgets and consequently equilibria of the model. Such a situation is reported in figure 6, which demonstrates how the efficiency during a network expansion drops from 92% to 60% and then raises again to 74%.

V. CONCLUSIONS

In this paper we have demonstrated that participation in a cooperation scheme for saving energy and increasing coverage is successfully elicited by a flatrate policy.

Our simulations quantify mathematically intractable effects like traffic intensity and routing. While confirming the theory, we have shown that such effects can contrast both increase of participants and geographic growth to the point of causing diminishing or actually negative returns.

Disrupted equilibria can be restored by lower guaranteed power wins (K) or higher power flatrates (p) and these parameters are directly linked to the profitability of operators: we can conclude that flatrates indeed elicit participation as predicted by the theory, but operators must accept lower profitability than the maximal achievable one as long as they want to enable further growth in mobile cooperation networks.

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