Intervention with Complete and Incomplete Information: Application to Flow Control

Luca Canzian, *Member, IEEE*, Yuanzhang Xiao, William Zame, Michele Zorzi, *Fellow, IEEE*, and Mihaela van der Schaar, *Fellow, IEEE*

***Abstract*—Most congestion control schemes are based on user cooperation, i.e., they implicitly assume that users are willing to share their private information and to take actions such that the network operates efficiently. However, a self-interested and strategic user might exploit such schemes to obtain an individual gain at the expenses of the other users, misrepresenting its private information and overusing the resources. We first quantify the inefficiency of the network in the presence of selfish users for two different scenario: in the *complete information* case – in which the users have no private information – and in the *incomplete information* case – in which the users have private information. Then, we ask whether the congestion control scheme can be designed to be robust to self-interested strategic users. To reach this objective, we use an *intervention* scheme. For the complete information scenario we describe a scheme that is able to give the users an incentive to optimally use the resources. For the incomplete information scenario we describe two schemes that provide the users with an incentive to report truthfully and to use the resources efficiently, although not always optimally. Illustrative results show that the considered schemes can considerably improve the efficiency of the network.**

***Index Terms*—Flow control, congestion control, game theory, intervention, mechanism design, incomplete information.**

I. Introduction

NOWADAYS, most of the devices connected to a network are smart, autonomous and highly programmable, and they mutually interact in a lot of different situations. For this reason, the design of network schemes able to handle selfish and strategic behaviors, exploiting the tools offered by game theory [1], has gained increasing attention in the recent years and has led to numerous tutorials [2]–[4] and books [5], [6] outlining game-theoretic concepts and their usage in wireless networks.

In this paper, we consider the congestion problem in a store-and-forward node of a network, namely, the server. Each user connected to the server, represented by a traffic flow that enters the server, sends its packets according to a Poisson process. The server serves the packets following a First Come First Serve (FCFS) scheme with exponentially distributed service time. The system can be modeled as an M/M/1 queue. We take into account the possibility that users belong to different classes of traffic, requiring different quality of service. The class of traffic a user belongs to is represented by a parameter, called the *type* of the user. We assume that each user can independently set its transmission rate to maximize its own *utility* represented by the *power*[1], defined in [7] as the ratio between the throughput and the delay and later extended in [8] to take into account multiple classes of traffic.

In this context, we use a game theoretic approach to study the interaction between users in two different scenarios: (1) in the *complete information* scenario every user is aware of the types of the other users and their interaction can be modeled with a complete information game [1]; (2) in the *incomplete information* scenario the users are not aware of the types of the other users, but a common probability distribution of the types of the other users exists, and the interaction can be modeled with a *Bayesian* game [1]. We show that the self-interested and strategic nature of the users leads to the overuse of the resources and to substantial inefficiencies in both cases, which are quantified using as performance criterion the geometric mean of the users' utilities. To improve the efficiency of the network, we design incentive schemes following the theoretical framework of *intervention* introduced by [9] and extended by [10] to deal with private information, imperfect monitoring and costly communication – in addition to intervention. That is, we allow the manager of the network to deploy an *intervention device* that can communicate with the users, monitor the users' actions and send an additional flow of packets to the server, i.e., it can *intervene* in the network. By designing the *intervention rule* – the rule that describes the selection of the intervention device's transmission rate – we are able to show that the intervention scheme can achieve the goal of providing the users with an incentive to adopt the optimal transmission rates in the complete information scenario. For the incomplete information scenario the situation is more complicated since the private information of the users – their types – is useful to optimally operate the network. If communication is possible, the intervention device may ask users to report their private information and then, using this information, adopt the optimal intervention rule derived for the complete information scenario. However, since the users are strategic, they might lie about their private information, if it is in their individual interests to do so. Following the theoretical framework proposed in [10], we design a system of reports, recommendations and intervention that is able to provide

Manuscript received August 4, 2012; revised January 7 and March 28, 2013. The editor coordinating the review of this paper and approving it for publication was A. MacKenzie.

L. Canzian, Y. Xiao, and M. van der Schaar are with the Department of Electrical Engineering, UCLA, Los Angeles CA 90095, USA. William Zame is with the Department of Economics, UCLA, Los Angeles CA 90095, USA (e-mail: luca.canzian@gmail.com).

M. Zorzi is with the Department of Information Engineering, University of Padova, Via Gradenigo 6/B, 35131 Padova, Italy.

The work of Luca Canzian, Yuanzhang Xiao and Mihaela van der Schaar was partially supported by the NSF grant CCF 1218136.

The work of Michele Zorzi was partially supported by Fondazione Cariparo through the program "Progetti di Eccellenza 2011-2012."

Digital Object Identifier 10.1109/TCOMM.2013.061013.120559

[1] Please note that this concept of power has nothing to do with the standard definition of power as energy per unit of time.

the users with an incentive to report truthfully and follow the instructions, despite the fact that they are self-interested. Since the computation of the optimal scheme is hard, we also describe an algorithm that converges to a suboptimal scheme. Moreover, since in some situations it may not be possible for the users to communicate with the intervention device, we describe also a scheme that does not require the users to make reports. Illustrative results show, among other things, that intervention can considerably increase the efficiency of the network in the incomplete information scenario as well.

Flow control[2] is a necessary operation to make a service accessible to many users. Several metrics have been considered as performance indicators. The power was proposed in [7] as a way to trade-off between throughput and delay. This concept was later extended in [8] to take into account multiple classes of traffic. To obtain distributed flow control algorithms, [11]–[14] model the flow control problem as a network utility maximization problem, and interpret the Lagrangian multipliers as prices. The users in these works need only to observe the aggregate information of the system state, keeping the information exchange lighter than in our approach. However, since real monetary transfers are not required and information in not exchanged strategically, users in these works are implicitly assumed to be compliant, hence the considered scenarios are very far from ours. The earlier applications of game theory to flow control problems with strategic users were limited to the computation of the inefficient Nash equilibria of existing congestion schemes. Examples of this approach include [15]–[17] which use the power as the performance metric, and [18] that shows that most congestion control schemes used, such as TCP, encourage a behavior that leads to congestion. [19] characterizes the Nash equilibrium and the Pareto Boundary for linearly coupled communication games, leading to the same result as [16] for the particular case of the flow control game. Later, with the same philosophy of our work, game theory was used to design practical schemes to deal with selfish and strategic users. [20] considers pricing schemes in routing problems, in which users are charged based on their resource usage, and show that if appropriate cost function and pricing mechanism are used, one can find an efficient Nash equilibrium. [21]–[23] design pricing schemes in flow control problems that maximize the service provider's revenue instead of the users' satisfaction. In particular, [22], [23] deal also with incomplete information settings, adopting a Bayesian approach in which the expected utilities are maximized. [24] uses a packet-dropping scheme – a particular instance of intervention schemes – to improve the efficiency of the Nash equilibrium, allowing to arbitrarily approach the optimal social welfare. Table I summarizes the differences between the approaches in the described literature.

What differentiates our paper from the above works is the strategic aspect associated to the information acquisition. We consider an incomplete information scenario in which the users have private information which is important to operate efficiently the system, and we introduce the ideas of mechanism design [25]–[30] and intervention [9] to create protocols that elicit the private information of the users. Because the proposed methodology is novel in the literature, we illustrate its abilities using a simple and clear to understand deployment scenario, focusing on a single link of a network. However, our new methodology is general, and can be applied in many settings.

[2]In this article, in order to be consistent with most of the cited literature on this topic, we use the expression "flow control" to denote a policy which limits the transmission rates of certain nodes to prevent congestion in a network. Hence, throughout the paper we will use congestion control and flow control interchangeably.

TABLE I
COMPARISON AMONG DIFFERENT FLOW CONTROL APPROACHES

	[11]–[14]	[15]–[19]	[20]–[24]	our work
Obedient users	X			
Strategic users		X	X	X
Incentive scheme			X	X
Strategic info				X

The contribution of this work is as follows. First, we analytically compute the Bayesian Nash Equilibrium (BNE) of the incomplete information flow control game without intervention, quantifying its inefficiency. Then, we apply the intervention scheme in the complete information setting and we design the device that can achieve the optimal performance. Finally, we apply the theoretical framework described in [10] to design schemes able to deal with the incomplete information scenario as well. Illustrative results show that the considered schemes can considerably improve the efficiency of the network.

The remainder of this paper is organized as follows. In Section II, we formulate the flow control problem. In Section III, we study flow control games without incentive schemes and show their inefficiency. In Section IV, we introduce the intervention device, we design the incentive schemes for the complete and incomplete information scenarios, and we quantify the improvement in the network efficiency. Also, we discuss how this work can be extended to multi–hop networks and some future research directions. Section V concludes with some remarks.

II. Formulation of the Flow Control Problem

We consider n flows with Poisson arrival rates of a_1, a_2, $\ldots$, a_n that are serviced by a single server with exponentially distributed service times with mean $\frac{1}{C}$. Since we assume that all packets have the same length, we will talk interchangeably of arrival rate ($\frac{pkt}{s}$) and transmission rate ($Mbps$), and C can be seen as the channel capacity, in $\frac{pkt}{s}$, after the server.[3] We refer to each stream of packets as a user, and $N = \{1, \ldots, n\}$ as the set of users. We assume that each user i can control its own traffic (e.g., by adjusting the coding quality of its communication), i.e., it can select its transmission rate (action) $a_i \in A_i = [0,\ C]$. The system is an M/M/1 queue with a total input arrival rate $\lambda = \sum_{i=1}^{n} a_i$.

In most cases a user is faced with two conflicting objectives, i.e., to maximize its throughput[4] and to minimize its average delay. The conflict between throughput and delay is obvious

[3]We consider packets of the same length to keep a simple notation and because the qualitative results do not critically depend on this assumption. However, the model and the analysis can be extended to take into account packets of different lengths.

[4]Here the throughput is defined as the average traffic served per unit time, and ignores the fact that some packets may be corrupted or lost due to physical layer effects.

since as more traffic enters the server queue the delays become larger. In order to incorporate these two measures in a single performance metric, the concept of power was proposed in [7] and later extended in [8]. It is defined as the ratio between the throughput and the average delay, where the exponent of the throughput is a positive constant. We can therefore write i's utility as

$$U_i(a,t_i) = a_i^{t_i}\,(C-\lambda) = a_i^{t_i}\left(C - \sum_{k=1}^{n} a_k\right) \qquad (1)$$

where $a = (a_1, \ldots, a_n) \in A = A_1 \times \ldots \times A_n$ denotes the transmission rate (action) profile and the parameter $t_i > 0$ represents user i's type.

The value of t_i may depend, for example, on the quality of service of the application corresponding to the i-th stream of packets. As we will see in Eqs. (2) and (3), that consider compliant users and strategic users respectively, the rate adopted by a user is increasing in its type. This consideration suggests the idea that the higher the type of a user, the higher the importance of the rate, with respect to the delay, for that user. As an example, streams of packets associated to delay dependent applications should have a low type while streams of packets associated to delay tolerant applications should have a high type.

In general, the applications a server has to deal with may change over time. For this reason it is useful to define the type set T_i, for every user i, whose elements represent all the possible types user i may have. We assume that the type set is the same for all users and is finite, i.e., $T_i = T_1 = \{\tau_1, \tau_2, \ldots, \tau_v\}$, $v \in \mathbb{N}$, $\tau_k \in \mathbb{R}$, $\tau_1 < \tau_2 < \ldots < \tau_v$, for every user $i \in N$. Suppose that at the beginning of a communication session the types of the users connected to the system are unknown. We assume that a common probability distribution exists and that user types are independent and identically distributed (i.i.d.) with $\pi(t_i)$ denoting the probability that a user has type t_i, $t_i \in T_1$, and $\pi(t) = \prod_{i=1}^{n} \pi(t_i)$ the probability that the type profile is t, $t \in T = T_1^n$. $\pi(t_i)$ can be thought as the average fraction of applications having type t_i that require services to the server. We use the notation a_{-i} and t_{-i} to denote the users' actions and the users' types except those of user i, while A_{-i} and T_{-i} denote the sets of all possible combinations of users' actions and users' types except those of user i.

The network must be designed to operate efficiently following the manager's objective, which can be quantified by a utility function. We assume that the manager's utility is the geometric mean of the users' utilities:

$$U(a,t) = \sqrt[n]{\prod_{i=1}^{n} U_i^+(a,t_i)} = (C-\lambda)^+ \prod_{i=1}^{n} a_i^{\frac{t_i}{n}}$$

where $(x)^+ = \max\{x\ ,\ 0\}$.[5] This choice allows to maintain a balance between two competing interests a benevolent manager might have: to maximize the social welfare of the network (defined as the sum utility) and to allocate resources fairly, giving to users similar utilities. Notice that maximizing $U(a,t)$ with respect to the users' actions is equivalent to maximizing a proportional fairness of the users' utilities, i.e., $\sum_{i=1}^{n} \ln U_i^+(a,t_i)$, and the optimal solution $g^M(t) = \left(g_1^M(t), \ldots, g_n^M(t)\right)$, as a function of the users' types, is given by (see [19])

$$g_i^M(t) = \frac{t_i C}{n + \sum_{k=1}^{n} t_k} \qquad (2)$$

We denote by $EU_i(g,t_i)$ and $EU(g)$ the expected (with respect to the types) utilities of user i having type t_i and of the manager, where $g(t) = (g_1(t), \ldots, g_n(t))$ represents the actions adopted by the users when the type profile is t, i.e.,

$$EU_i(g,t_i) = \sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) U_i(g(t),t)$$

$$EU(g) = \sum_{t \in T} \pi(t) U(g(t),t)$$

The benchmark optimum for the manager – the maximum expected utility he could achieve if users were compliant to a prescribed scheme – is therefore equal to $EU^{ben} = EU(g^M(t))$.

III. The Flow Control Games without Intervention

In this section we compute the outcome of a flow control problem considering self-interested and strategic users, for both the complete and the incomplete information scenarios. Moreover, we quantify the loss of efficiency of the manager's utility with respect to the maximum efficiency utility.

A. Complete information scenario

We define the complete information game

$$\Gamma_t^0 = (N, A, \{U_i\}_{i=1}^n)$$

where each user i selects its action $g_i(t)$ strategically, knowing the types t_{-i} of all the other users.

We denote by $g^{NE^0}(t) = \left(g_1^{NE^0}(t), \ldots, g_n^{NE^0}(t)\right)$ a *Nash Equilibrium* (NE) of the game Γ_t^0, which is an action profile so that each user obtains its maximum utility given the actions of the other users, i.e., $\forall i \in N$ and $\forall g_i : T \to A_i$,

$$U_i\left(g^{NE^0}(t), t\right) \geq U_i\left(g_i(t), g_{-i}^{NE^0}(t), t\right)$$

The NEs represent a solution concept for a complete information game. The unique NE $g_i^{NE^0}(t)$ of Γ_t^0 is, $\forall\, i \in N$, (see [19])

$$g_i^{NE^0}(t) = \frac{t_i C}{1 + \sum_{k=1}^{n} t_k} \qquad (3)$$

Notice that strategic users use the resources more heavily with respect to compliant users, i.e., $g_i^{NE^0}(t) > g_i^M(t)$, $\forall\, i \in N$ and $\forall\, t \in T$ (excluding the trivial case $n = 1$).

The manager's expected utility in the complete information scenario is equal to $EU(g^{NE^0}(t))$.

[5]We consider U_i^+ instead of U_i for mathematical reasons, because utilities as defined in Eq. (1) may also be negative, and the geometric mean would lose meaning with negative quantities. Anyway, notice that it is in the interest of both the users and the manager to have $\lambda \leq C$, i.e., working in the sub-space of the original domain such that $U_i^+ = U_i$.

B. Incomplete information scenario

We define the incomplete information game

$$\Gamma^0 = (N, A, T, \pi, \{U_i\}_{i=1}^n)$$

where each user i selects its action $g_i(t_i)$ strategically, knowing its own type t_i and the probability distribution of the types of the other users, $\pi(t_{-i})$.

We denote by $g^{BNE}(t)$ a *Bayesian Nash Equilibrium* (BNE) of the game Γ^0, which is an action profile so that each user obtains its maximum expected utility given the actions of the other users, i.e., $\forall\, i \in N$ and $\forall g_i : T_1 \to A_i$,

$$EU_i\left(g^{BNE}(t), t_i\right) \geq EU_i\left(g_i(t_i), g_{-i}^{BNE}(t_{-i}), t_i\right)$$

If each user acts to maximize its expected utility given the beliefs it has about the other users, the incomplete information game is called *Bayesian game* and the $BNEs$ represent a solution concept.

Proposition 1. *There exists a unique Bayesian Nash Equilibrium $g^{BNE}(t)$ of Γ^0 which can be obtained by solving a linear system $\mathbf{A}g^{BNE} = b$. In addition, the inverse of $\mathbf{A}$, $\mathbf{A}^{-1}$, can be computed analytically.*[6]

Proof: See Appendix A. ■

The manager's expected utility in the incomplete information scenario is equal to $EU(g^{BNE}(t))$.

C. Illustrative results

Fig. 1 shows the manager's expected utility as a function of the number of users, considering $C = 5\,Mbps$ and a type set $T_1 = \{0.1,\, 1\}$ with uniformly distributed types. The upper curve represents the benchmark optimum, while the dashed and the dotted lines represent the manager's expected utility when users are strategic, in the complete and incomplete information cases, respectively. The manager's utility when users act strategically, for both the complete and the incomplete information scenarios, is far below the benchmark optimum. Notice that the manager can obtain a higher utility in the incomplete information scenario with respect to the complete information scenario, at least when there are more than three users in the system. This agrees with the results of [32], [33] where, in a strategic setting, the less closely related the agents' goals the lower the quantity of information they prefer to exchange. In our case, the objective of the manager becomes less closely related to the objective of a single user as the total number of users increases. In fact, the manager's objective is to increase the utility of all users in a fair way, while the goal of a user is to improve only its own utility, at the cost of the utility of all the other users. Hence, as the number of users increases, the selfishness of a single user has a higher negative impact on the manager's objective.

IV. The Flow Control Games with Intervention

Fig. 1 shows that the manager's expected utility in strategic settings (for both the complete and the incomplete information scenarios) is much lower than the benchmark optimum. Here we ask whether the manager can do something to make the system robust against strategic users, filling, at least partially, the gap between the benchmark optimum and the manager's expected utility in strategic settings.

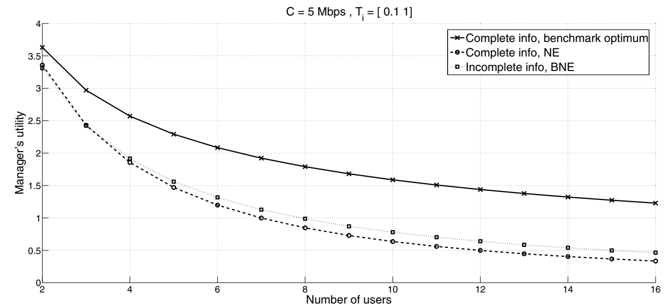

Fig. 1. Manager's utility as a function of the number of users.

We assume that the manager can choose and deploy an *intervention device* in the system that (1) can receive communications from users, (2) can send communications to users, (3) can monitor the actions of users, and (4) can transmit a stream of packet $x \in X = [0,\, \overline{x}]$ to the server, which we interpret following [9] as an *intervention*. The intervention action increases the incoming traffic of the server to $\lambda = \sum_{i=1}^n a_i + x$, and the users' and the manager's utilities change accordingly:

$$U_i^I(a, t_i, x) = a_i^{t_i}\,(C - \lambda) = a_i^{t_i}\left(C - \sum_{k=1}^n a_k - x\right) \quad (4)$$

$$U^I(a, t, x) = \sqrt[n]{\prod_{i=1}^n U_i^{I+}(a, t_i, x)} = (C - \lambda)^+ \prod_{i=1}^n a_i^{\frac{t_i}{n}}$$

It is straightforward to check that the users' and the manager's utilities satisfy assumptions **A1**-**A6** of [10]. In particular, the manager's preferred action is $x^* = 0$ (i.e., no intervention), and the game Γ_t^0 defined in [10] coincides with the game Γ_t^0 defined in Subsection III-A.

In the complete information scenario, the intervention device is a tool the manager employs to instruct the users on how to behave, giving them the incentive to adopt efficient actions by *threatening punishments* which are *not executed* if users follow the recommendations (we will return on this later). In addition, in the incomplete information scenario, the device is also used to retrieve the relevant information from the users, i.e., their types. First, we formalize a device in the more general scenario of incomplete information, and we will then discuss the natural simplifications for the complete information scenario.

A device is a tuple $D = \langle \mu, \overline{x}, \Phi \rangle$ where[7]

- $\mu : T \to A$ is the *message rule*, which specifies the profile of messages to be sent to the users as a function of the reports received from all users. The users report (possibly strategically) their types and the intervention device sends to each user a message representing the recommended action for that user. If r are the observed

[6]The expressions of b and $\mathbf{A}$ can be found in Appendix A, the expression of $\mathbf{A}^{-1}$ can be found in [31].

[7]We restrict our study to devices that ask the users to report their types and recommend them the actions to adopt, assuming that reports, messages and actions are perfectly observed and that communication is costless. A more general definition of the intervention device is given by [10].

reports we write $m = \mu(r)$ for the recommended actions, $m = (m_1, \ldots, m_n) = (\mu_1(r), \ldots, \mu_n(r))$; [8]
- $\overline{x}$ represents the maximum rate at which the intervention device is able to transmit;
- $\Phi : T \times A \times A \to X$ is the *intervention rule*, which specifies the transmission rate the device will adopt given the received reports, the transmitted messages and the observed actions. If r are the observed reports, m the transmitted messages and a the observed actions, we write $\Phi(r, m, a)$ for the adopted intervention action.

In the incomplete information scenario, a strategic user i selects its report r_i and its action a_i in order to maximize its expected utility given the information and the beliefs it has. Specifically, a strategy for user i consists of a pair of functions (f_i, g_i), in which $f_i : T_1 \to T_1$ specifies the report of user i based on its type, and $g : T_1 \times A_i \to A_i$ specifies the action of user i based on its type and on the recommendation received (note that the recommendation can carry information about the types of the other users, that can be exploited by i to select the most appropriate action). As usual, we denote by f and g the profiles of the two strategies.

In the following, we summarize the different stages of the interaction between the users and the intervention device in the incomplete information scenario.

1: each user i sends the report $r_i = f_i(t_i)$ to the intervention device

2: the intervention device sends the recommended action $m_i = \mu_i(r)$ to each user i

3: each user i takes the action $a_i = g_i(t_i, m_i)$

4: the intervention device monitors the users' action profile[9] a and adopts the intervention action $x = \Phi(r, m, a)$

In this paper we restrict our attention to the class of *affine intervention* devices $\mathcal{D}$, in which the intervention level increases linearly with the users' actions. It may seem restrictive to only consider such a simple class of devices. However, $\mathcal{D}$ will turn out to be optimal, i.e., it is not possible to increase the manager's expected utility by considering more complex devices.

$D = \langle \mu, \overline{x}, \Phi \rangle$ is an affine intervention device if the intervention rule Φ is of the form

$$\Phi(r, m, a) = \left[\sum_{i=1}^{n} c_i(r, m) \left(a_i - \tilde{a}_i(r, m) \right) \right]_0^{\overline{x}} \quad (5)$$

where $\tilde{a}_i(r, m) \geq 0$ represents a target action for user i, $c_i(r, m) \geq 0$ is the rate of increase of the intervention level due to an increase of i's action, and $[\cdot]_a^b = \min\{\max\{a, \cdot\}, b\}$. Though in this abstract definition $\tilde{a}_i(r, m)$ might be different from the recommended action $m_i = \mu(r)$, in the schemes we will propose in the following we will have $\tilde{a}_i(r, m) = m_i$, $\forall\, r$, m_{-i}, i.e., $\tilde{a}(r, m)$ will represent the recommended action profile.

[8]Differently from [10], here we do not consider *randomized* rules because, as we will see, *pure* rules are sufficient to obtain optimal results in the complete information case and to satisfy the conditions we need to use the algorithm proposed by [10] in the incomplete information case.

[9]The device can estimate the users' rates by counting in real time the number of packets that each user has sent since the beginning of the communication session. Such estimates may be inaccurate, in particular in the first phases of the session. Here we neglect this issue, implicitly assuming that the session is long enough (with respect to the users' rates) to converge very soon to accurate estimates. We will take into consideration an extension of this work in which we analyze in more detail the impact of imperfect monitoring.

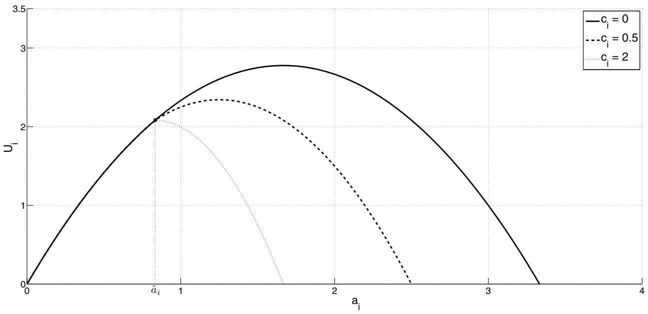

Fig. 2. User i's utility as a function of user i's action for different intervention rules.

Fig. 2 shows how the intervention rule Φ changes the relation between i's utility and i's action, for given type, report and message profiles and assuming that the other users adopt the target action profile $\tilde{a}_{-i}(r, m)$. The utility of user i is plotted for three different values of the parameter $c_i(r, m)$ ($c_i(r, m) = 0$ means that the intervention device never intervenes). For an action a_i lower than the target action $\tilde{a}_i$, i's utility is as if the device did not exist. However, for an action a_i higher than the target action $\tilde{a}_i(r, m)$, i's utility is lower compared to the utility it would have obtained without the device, and the gap increases as c_i increases. In fact, if the users adopt the target action profile $\tilde{a}(r, m)$ the intervention level is 0, but if a single user i deviates from the recommendation adopting an action $a_i > \tilde{a}_i(r, m)$, the intervention device reacts transmitting a flow of packets with a positive rate $x = \Phi(r, m, a)$ that is increasing in $c_i(r, m)$, and affects the utilities of all users. This agrees with our view of intervention as a threat of punishments that are not executed if all users follow the recommendations.

As noted before, in the complete information scenario the interaction between the users and the device can be simplified, because the type profile t is known by everybody. In particular, since the device already knows t, the reports do not play any role and we can consider $f_i(t_i) = t_i$, $\forall\, i$ (or, alternatively, we can skip stage **1**). Moreover, the users know in advance the messages they will receive because messages are a deterministic function of the type profile (hence, also stage **2** can be skipped). Finally, since reports and messages are given, the intervention rule can simply be written as a function of the users' actions: $\overline{\Phi}(a) = \Phi(t, \mu(t), a)$. In particular, for an affine device the parameters $c_i = c_i(t, \mu(t))$ and $\tilde{a}_i = \tilde{a}_i(t, \mu(t))$ are constant. Thus, in the complete information scenario a device is simply described by $\overline{x}$ and $\overline{\Phi}$. In this context, each user i has to select an action a_i to maximize its utility.

Given a device D, in both the complete and the incomplete information cases, the interaction among users can be modeled as a game. Note that the device is not strategic: it follows the pre-programmed rules. However, *the manager behaves strategically in committing to a choice of a device*. In the following we provide the tools for the manager to choose a device in the class $\mathcal{D}$, for both the complete and the incomplete information scenarios.

A. Complete information scenario

In the complete information scenario, given a device $D = \langle \overline{x}, \overline{\Phi} \rangle$, the interaction among users is modeled with the game

$$\Gamma_t = \left(N, A, D, \{U_i^I\}_{i=1}^n\right)$$

in which each user i strategically selects the action $g_i(t)$ (the dependence on t shows that if the type profile t changes, the game Γ_t changes as well and the users may decide to take different actions) to maximize its utility U_i^I, see Eq. (4).

The outcome of such interaction is represented by the NE. We say that the device D *sustains* an action profile $g(t)$ in Γ_t if $g(t)$ is a NE of Γ_t. We say that the device D sustains an action profile $g(t)$ in Γ_t *without intervention* if D sustains $g(t)$ and $\overline{\Phi}(g(t)) = 0$. If such a device exists, we say that $g(t)$ is sustainable without intervention in Γ_t. The manager faces the problem of choosing a device D so that there exists a NE of the game Γ_t that gives it the highest utility U^I among what is achievable with all possible NEs.

Lemma 1. *Consider the affine device D such that, $\forall\, i \in N$,*

$$c_i \geq \frac{t_i\,(C - \sum_{k=1}^n \tilde{a}_k) - \tilde{a}_i}{\tilde{a}_i}$$
$$\overline{x} \geq \frac{c_i\,[t_i\,(C - \sum_{k=1}^n \tilde{a}_k) - \tilde{a}_i]}{1 + t_i(1 + c_i)} \tag{6}$$

If $\tilde{a} \leq g^{NE^0}$, then $\tilde{a}$ is a NE of Γ_t.[10]

Proof: See Appendix B ■

Interpretation: If a c_i high enough is selected, and if the device is able to transmit with a large enough transmission rate, the utility function decreases for an action greater than $\tilde{a}_i$ (this situation is shown in Fig. 2 for $c_i = 2$), i.e., the threat of punishment discourages the users from adopting actions higher than the target. Hence, if the utility of user i is increasing before the target action $\tilde{a}_i$ (in particular, this is valid if $\tilde{a}_i \leq g_i^{NE^0}$), as in Fig. 2, then user i's utility has a maximum in $\tilde{a}_i$, which becomes the best response action for user i.

Proposition 2. $\forall\, t \in T$, *the optimal profile $g^M(t)$ is sustainable without intervention in Γ_t, adopting the device $\overline{x} \geq \dfrac{C}{1+\tau_1}$, $\tilde{a} = g^M(t)$ and $c_i \geq n-1$, $i \in N$.*

$\forall\, t \in T$, *every strategy profile $a \leq g^{NE^0}(t)$ is sustainable without intervention in Γ_t, adopting the device $\overline{x} \geq C$, $\tilde{a} = a$ and c_i high enough (i.e., $c_i \geq \frac{\tau_v(C - \sum_{k=1}^n \tilde{a}_k) - \tilde{a}_i}{\tilde{a}_i}$), $i \in N$.*

Proof: First, consider the second affirmation. The condition of Eq. (6) on $\overline{x}$ is automatically satisfied if the right hand side is lower than 0. Moreover, if it is higher than 0, the right hand side is increasing in c_i. In fact, the function $h(c_i) = \frac{a c_i}{b + a c_i}$, with $a, b > 0$, is increasing in c_i, because $h'(c_i) = \frac{ab}{(b + a c_i)^2} > 0$. Thus, the condition of Eq. (6) on $\overline{x}$ becomes stricter as c_i increases. Taking the limit for $c_i \to +\infty$ we can find the following stricter condition on $\overline{x}$ that does not depend on c_i:

$$\overline{x} \geq \frac{t_i\,(C - \sum_{k=1}^n \tilde{a}_k) - \tilde{a}_i}{t_i} = C - \sum_{k=1}^n \tilde{a}_k - \frac{\tilde{a}_i}{t_i}$$

In order to obtain conditions that are independent of users' types and action profiles to sustain, which will be useful for the incomplete information scenario, we can consider the following stricter conditions:

$$\overline{x} \geq C - \sum_{k=1}^n \tilde{a}_k - \frac{\tilde{a}_i}{\tau_v} \quad , \quad \overline{x} \geq C - \sum_{k=1}^n \tilde{a}_k \quad , \quad \overline{x} \geq C \tag{7}$$

As for c_i, we can find a stricter condition independent of users' types substituting t_i with τ_v. Thus, once the action profile to sustain is fixed, it is sufficient to select a c_i satisfying

$$c_i \geq \frac{\tau_v\,(C - \sum_{k=1}^n \tilde{a}_k) - \tilde{a}_i}{\tilde{a}_i} \tag{8}$$

Now consider the first affirmation. Substituting $\tilde{a} = g^M(t)$ we obtain

$$c_i \geq \frac{t_i\,(C - \sum_{k=1}^n \tilde{a}_k)}{\tilde{a}_i} - 1 = n - 1$$

As to $\overline{x}$, substituting $\tilde{a} = g^M(t)$ into the second condition of Eq. (7) we obtain

$$\overline{x} \geq \frac{nC}{n + \sum_{k=1}^n t_k}$$

Finally, since the right hand side is decreasing in $\sum_{k=1}^n t_k$, a stricter condition can be obtained substituting $t_k = \tau_1$, $\forall k \in N$, obtaining

$$\overline{x} \geq \frac{C}{1 + \tau_1}$$

■

If the device is able to transmit a stream of packets with a rate higher than a certain threshold (that is upper-bounded by C), if $\tilde{a} = g^M(t)$ and if $c_i \geq n-1$, the threat of punishments is an incentive for the users to adopt the optimal action profile $g^M(t)$. Note that, in this case, the *punishments are not executed*. Thus, the manager can extract the maximum utility from the game Γ_t. The following corollary is an implication of this consideration.

Corollary 1. *The class of affine intervention rules $\mathcal{D}$ is optimal (i.e., it is not possible to gain more by considering more complex devices) in the complete information scenario.*

Finally, the manager's expected utility for the complete information scenario with the intervention device is equal to the maximum efficiency utility $EU(g^M(t))$.

B. Incomplete information scenario

In the incomplete information scenario, given a device $D = \langle \mu, \overline{x}, \Phi \rangle$, the interaction among users is modeled with the Bayesian game

$$\Gamma = \left(N, A, T, \pi, D, \{U_i^I\}_{i=1}^n\right)$$

in which each user i strategically adopts the functions $f_i : T_1 \to T_1$ (which specifies the report of user i based on its type) and $g_i : T_1 \times A_i \to A_i$ (which specifies the action of user i based on its type and on the recommendation received) to maximize its expected utility

$$EU_i^I(f, g, t_i, D) = \sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) U_i^I(a, t_i, x)$$

[10]Throughout the paper, inequalities between vectors are intended component-wise.

where, $\forall\, k \in N$,

$$r_k = f_k(t_k)\ ,\ m = \mu(r)\ ,\ a_k = g_k(t_k, m_k)\ ,\ x = \Phi(r, m, a)$$

The outcome of such interaction is represented by the BNE. We say that the device D *sustains* a strategy profile (f, g) in Γ if (f, g) is a BNE of Γ. We say that the device D sustains a strategy profile (f, g) in Γ *without intervention* if D sustains (f, g) and $\Phi(r, m, a) = 0$, $\forall\, t \in T$. The manager faces the problem of choosing a device D so that there exists a BNE of the game Γ that gives it the highest expected utility

$$EU^I(f, g, D) = \sum_{t \in T} \pi(t) U^I(a, t, x)$$

among what is achievable with all possible $BNEs$.

We say that a device is *incentive compatible* if it sustains the *honest and obedient* strategy profile, in which users report truthfully their types and adopt the suggested actions, i.e., $f_i(t_i) = t_i$ and $g_i(t_i, \mu_i(t)) = \mu_i(t)$, $\forall\, i, t$.

In the following we apply the results derived in [10] to find the conditions for the existence and the computability of a device – which we call *maximum efficiency device* – that allows the manager to achieve its benchmark optimum. In case such device does not exist, the network cannot operate as efficiently as in the compliant users scenario. Moreover, in this case the optimal device is hard to compute. For this reason, we consider two suboptimal devices which are easier to compute than the optimal device.

1) Existence and calculation of a maximum efficiency device: We wonder if there are some conditions under which the manager can select a device to obtain the same utility it would achieve with compliant users. The following result provides an answer to this question.

Proposition 3. *If* $\forall\, l = \{1, \ldots, v-1\}$ *and* $\forall\, t_{-i} \in T_{-i}$,

$$\left(\frac{n + \sum_{j \neq i} t_j + \tau_{l+1}}{n + \sum_{j \neq i} t_j + \tau_l}\right)^{\tau_l + 1} \left(\frac{\tau_l}{\tau_{l+1}}\right)^{\tau_l} \geq 1 \qquad (9)$$

then the affine device $\mu(t) = g^M(t)$, $\overline{x} \geq \dfrac{C}{1+\tau_1}$, $\tilde{a}_i(r, m) = m$ *and* $c_i \geq n-1$, $i \in N$, *is a maximum efficiency incentive compatible device.*

Proof: See Appendix C ■

Notice that all maximum efficiency incentive compatible devices must recommend the optimal action profile, i.e., $\mu(t) = g^M(t)$, and provide an incentive for the users to adopt it by threatening severe enough punishments. However, if condition (9) is not satisfied, the device might not be able to give to the users the incentive to report truthfully.

2) Algorithm that converges to an incentive compatible device: Here we specialize, for the flow control application, the general algorithm proposed in [10, Sec VI] that converges to an incentive compatible device. Such an algorithm is used off-line by the manager to select an efficient incentive compatible device. Prop. 2 guarantees that, at each step of the algorithm, the considered device sustains without intervention (i.e., in the equilibrium path punishments are never executed) the suggested action profile $\mu(r)$ in Γ_r (note that the suggested action profile will never be higher than $g^{NE^0}(t)$).

In the algorithm text $W_i(t_i, t_i')$ denotes the expected utility that user i, with type t_i, obtains reporting type t_i' and adopting the suggested action, when the other users are honest and obedient and the intervention device does not intervene, i.e.,

$$W_i(t_i, t_i') = \sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) U_i(\mu(t_i', t_{-i}), t)$$

The algorithm has been designed with the idea of minimizing the distance between the optimal action profile $g^M(t)$ and the suggested action profile $\mu(t)$, for each possible type profile t. If a maximum efficiency device exists, the initialization of the algorithm corresponds to a maximum efficiency incentive compatible device and the algorithm stops after the first iteration. If a user i having type τ_s can benefit by pretending to be of type τ_l (i.e., $W_i(\tau_s, \tau_s) < W_i(\tau_s, \tau_l)$), for each type profile $\tau = (\tau_l, t_{-i})$ the algorithm increases the recommended action for user i – if it is lower than $g_i^{NE^0}(\tau)$ – or the recommended actions for the other users. In both cases, the new device is selected such that the new suggested action profile $\mu(\tau)$ is sustained without intervention in Γ_τ. Proceeding in this way, the algorithm will converge to a device in which no user can benefit by pretending to be of another type. In fact this is of course true if, $\forall\, t$, $\mu(t) = g^{NE^0}(t)$, because in this situation each user is always adopting its best action given the types and the actions of the others. Since at each step of the algorithm the recommended action of a user i is increased by a finite amount ϵ_i toward $g_i^{NE^0}(t)$, the condition $\mu(t) = g^{NE^0}(t)$ will be reached after a finite number of iterations, in case the algorithm does not stop before. The bigger the steps ϵ_i, $i \in N$, the quicker the convergence of the algorithm. On the other hand, the smaller the steps, the closer the final suggested action profile to the optimal one.

Algorithm 1 Flow control algorithm.

1: **Initialization**: $\forall\, r \in T$, $\overline{x} \geq C$, $\mu(r) = g^M(r)$, $\tilde{a}(r, \mu(r)) = \mu(r)$, $c_i(r, \mu(r)) \geq n-1$
2: **For** $s = 1 : v$ and $l = 1 : v$
3:   **If** $W_i(\tau_s, \tau_s) < W_i(\tau_s, \tau_l)$
4:     **For** $t_{-i} \in T_{-i}$
5:       $\tau \leftarrow (\tau_l, t_{-i})$
6:       **If** $\mu_i(\tau) < g_i^{NE^0}(\tau)$
7:         $\mu_i(\tau) \leftarrow \min\left\{\mu_i(\tau) + \epsilon_i,\ g_i^{NE^0}(\tau)\right\}$
8:         $\tilde{a}(\tau, \mu(\tau)) = \mu(\tau)$, $c_i(\tau, \mu(\tau))$ satisfying (8)
9:       **Else for** $k = 1 : m$, $k \neq i$
10:         $\mu_k(\tau) \leftarrow \min\left\{\mu_k(\tau) + \epsilon_k,\ g_k^{NE^0}(\tau)\right\}$
11:         $\tilde{a}(\tau, \mu(\tau)) = \mu(\tau)$, $c_k(\tau, \mu(\tau))$ satisfying (8)
12: Repeat from 2 until 3 is unsatisfied $\forall\, s, l$

3) Communication-free device: In this Subsection we define a new type of device, called *communication-free device*, in which reports do not play any role for the final outcome, i.e., the message and intervention rules do not depend on reports. This is particularly useful in situations where it is not possible for the users to communicate with the device, or where communication is very expensive. However, also for scenarios where users can send reports, a communication-free device might represent a good sub-optimal device that is efficient and easy to compute.

Consider the communication-free device D that, independently of users' types, suggests action profile $\overline{a}$,

$$\overline{a} = \underset{a \in A}{\text{argmin}} \left[-\ln\left(C - \sum_{i=1}^{n} a_i\right) \mathbb{E}_t \left[\prod_{i=1}^{n} a_i^{\frac{t_i}{n}} \right] \right]$$
$$a_i \geq 0 \ , \ \ a_i \leq C \ , \ \ \forall i \in N \tag{10}$$

Proposition 4. *Eq. (10) defines a convex problem if $\tau_v \leq n$. Moreover, if the device D sustains $\overline{a}$ without intervention in Γ, then D is an optimal communication-free incentive compatible device and the manager's expected utility is $EU(\overline{a})$.*

Proof: See Appendix D ■

Corollary 2. *Consider the communication-free device D such that, $\forall\, r \in T$ and $\forall\, i \in N$,*

$$\mu(r) = \overline{a} \ , \ \ \Phi(r, \overline{a}, a) = \left[\sum_{i=1}^{n} c_i(\overline{a})(a_i - \overline{a}_i) \right]_0^{\overline{x}}$$
$$c_i(\overline{a}) \geq \frac{\tau_v \left(C - \sum_{k=1}^{n} \overline{a}_k\right) - \overline{a}_i}{\overline{a}_i} \ , \ \ \overline{x} \geq C \tag{11}$$

If $\overline{a} \leq g^{NE^0}(t)$, $\forall\, t \in T$, then D is an optimal communication-free incentive compatible device and the manager's expected utility is $EU(\overline{a})$.

Proof: It is sufficient to show that D sustains $\overline{a}$ without intervention in Γ. Notice that $\overline{\Phi}(r, \overline{a}, \overline{a}) = 0$, so it is sufficient to show that $\overline{a}$ is an equilibrium in Γ. Notice that D satisfies the conditions of Lemma 1, $\forall\, t \in T$, therefore D sustains $\overline{a}$ in Γ_t, i.e., $\forall\, t \in T \ , \ \forall\, i \in N \ , \ \forall\, \hat{a}_i \in A_i$,

$$U_i\left(\overline{a}, t, x\right) \geq U_i\left(\hat{a}_i, \overline{a}_{-i}, t, \hat{x}\right)$$

where $x = \Phi(r, \overline{a}, \overline{a})$ and $\hat{x} = \Phi(r, \overline{a}, \hat{a}_i, \overline{a}_{-i})$. As a consequence, $\forall\, i \in N \ , \ \forall\, t_i \in T_1 \ , \ \forall\, \hat{a}_i \in A_i$,

$$\sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) U_i\left(\overline{a}, t, x\right) \geq \sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) U_i\left(\hat{a}_i, \overline{a}_{-i}, t, \hat{x}\right)$$

Hence, $\overline{a}$ in an equilibrium in Γ. ■

Notice that $\overline{a} \leq g^{NE^0}(t)$, $\forall\, t \in T$, is a sufficient condition for D to be an optimal communication-free incentive compatible mechanism, but it is not necessary. In fact, D might sustain $\overline{a}$ without intervention in Γ even if $\overline{a} \nleq g^{NE^0}(t)$ for some $t \in T$.

C. Illustrative results

In the following we are going to quantify the manager's expected utility and the expected throughput and delay for each type of user in different scenarios. We consider $C = 5\,Mbps$ and a common type set $T_1 = \{0.1, 1\}$. Except for Fig. 4, we assume that the types are uniformly distributed, i.e., $P(0.1) = P(1) = 0.5$, and we plot the results varying the number of users from 2 to 16.

We first look at how the manager's expected utility varies increasing the number of users, in the complete and incomplete information scenarios. The left side of Fig. 3 refers to the complete information scenario. The overlapped upper lines represent the manager's expected utility when users are compliant and when they are strategic with the device derived in Subsection IV-A. The manager's expected utility is decreasing in the number of users because, as the number of users increases, the total congestion experienced by every user increases as well. However, it is remarkable that with the intervention scheme the manager can completely fill the gap between the benchmark optimum and its expected utility when the users are strategic but no incentive scheme is adopted (dotted line). The reason behind this result is that the device threatens punishments which *are not executed* if the users follow the recommendations, and in the complete information scenario such threats are strong enough to deter deviations from the recommendations.

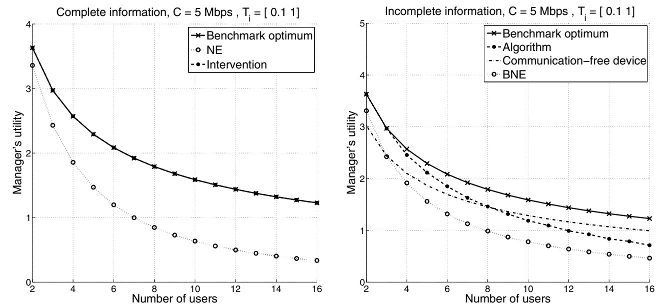

Fig. 3. Manager's expected utility vs. number of users for the complete and incomplete information scenarios.

The right side of Fig. 3 refers to the incomplete information scenario. In this scenario the manager is guaranteed to achieve the benchmark optimum using the device derived from the algorithm (dashed line) if the number of users is sufficiently small. In fact, for a number of users less than or equal to 3, it is straightforward to check that the sufficient condition (9) is satisfied, hence, a maximum efficiency device exists and the algorithm converges to it. For a larger number of users, there is no guarantee of optimality, and in fact the results of Fig. 3 show that in this case the manager's expected utility is lower than what could be obtained with compliant users. However, the manager can still considerably increase its expected utility compared to the case of strategic users and no incentive scheme (dotted line), by adopting the device derived from the algorithm for a number of users lower than 8 and the communication-free device (dash-dot line) for a number of users greater than or equal to 8 (the device defined by (11) turns out to sustain the solution of (10) without intervention in Γ). It is not surprising that the communication-free device is able to obtain good performance for a large number of users, in fact in this situation the manager is able to foresee more accurately the fraction of users of a certain type, hence the information about users' types becomes less important.

Now we investigate how the results depend on the type probability distribution for the incomplete information scenario. In Fig. 4 we fix the number of users to 4 and we vary the probability of the low type, $P(0.1)$, from 0 to 1, which is equivalent to varying $P(1)$ from 1 to 0. We can see that the gap between the benchmark optimum and the manager's expected utility achievable with the device derived from the algorithm is not strongly dependent on the type probability distribution. In fact, such a mechanism provides incentives for each type of user to be honest and obedient, even though some user types rarely occur. Notice that in the algorithm the recommended action profile for a certain type profile is increased by a finite amount ϵ if the users do not have an

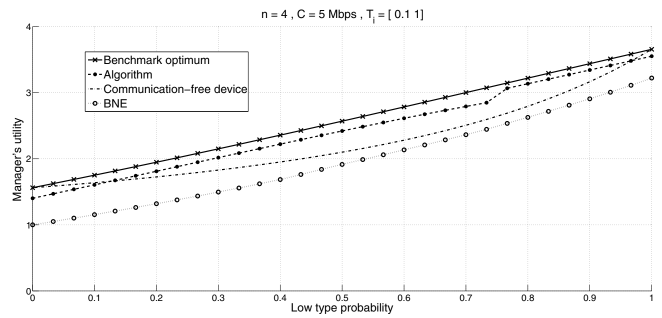

Fig. 4. Manager's expected utility vs. low type probability for the incomplete information scenario.

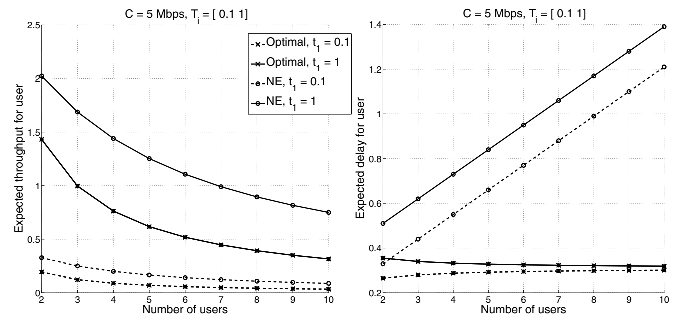

Fig. 5. Total expected throughput and delay vs. number of users for the complete information scenario.

incentive to report truthfully, which has the effect to produce the little step visible in Fig. 4 (the lower ϵ, the smoother the step). On the contrary, the performance penalty incurred by the communication-free device is strongly dependent on the probability distribution of user types. In fact, the recommended and enforced action profile depends exclusively on the type probability distribution. As an example, if the low type occurs rarely, the device will suggest the users to adopt an action profile that is close to the objective of the users with high type, that will probably be the majority of the users in the network. In the extreme case, if low type users are for sure not present in the network (i.e., P(0.1) = 0), then the adopted action profile will maximize the interests of the users having high type and the communication-free device is able to achieve the benchmark optimum. Notice that in this situation the manager has no uncertainty about the types of the users in the network, which is the reason why it is able to extract the maximum utility. In some sense, the uniform probability distribution represents the worst case for the communication-free device because the manager has the highest uncertainty over the types of the users in the network.

So far we have only considered the utility as performance indicator. However, the utility includes the two real performance metrics, throughput and delay. Now we investigate the expected throughput and delay achievable with the considered schemes in the complete and incomplete information scenarios, for each type of user.[11] Fig. 5 shows the expected throughput (left-side) and delay (right-side) for the complete information scenario. Continuous lines refer to the high type users, while dashed lines refer to the low type users. Notice that the high type users obtain a higher expected throughput and a higher expected delay compared to the low type users (this will be true also for the incomplete information scenario), since the higher the type the higher the user's preference for throughput with respect to delay. In both pictures, the upper (continuous and dashed) lines refer to the strategic scenario without intervention device, in which the users adopt the NE action profile, while the overlapped lower (continuous and dashed) lines represent the optimal action policy, obtainable with compliant users or with strategic users with the device derived in Subsection IV-A. With no incentive scheme, strategic users tend to overuse the resources of the network, transmitting with higher rates compared to the optimal ones. This translates into much higher delays, that increase quickly as the number of users increases. Conversely, the optimal transmission policy is such that the expected delay is almost constant with respect to the number of users. This means that also the aggregate throughput is almost constant, and the rate of each user scales as n^{-1}.

Fig. 6 shows the expected throughput (left-side) and delay (right-side) for the incomplete information scenario. Continuous lines refer to the high type users, while dashed lines refer to the low type users, with the exception of the performance obtainable adopting the communication-free device, represented by the dash-dot line, in which different types of users adopt the same action and experience the same throughput and delay. In both pictures, the upper (continuous and dashed) lines refer to the strategic scenario without intervention device, in which the users adopt the BNE action profile, while the lower (continuous and dashed) lines represent the optimal action policy. The performance obtainable adopting the device derived from the algorithm lies in between. The lines that represent the expected delay for the BNE action profile are truncated for a number of users equal to 3 and 5 because for more users the system might become unstable. In fact, in the BNE the expected utility of a user is maximized, given that the other users adopt the BNE. However, for some type profile instances, the utility might be equal to 0, i.e., the delay might diverge. Thus, the expected delay diverges as well, since there is a positive probability that the network becomes congested. The device derived from the algorithm allows to improve this situation, limiting the delay experienced by each user. However, such a delay increases almost linearly as the number of users increases. This is the reason why the communication-free device, at a certain point, even though it is not able to differentiate the service given to different classes of traffic, is able to obtain a better performance (from the manager's utility point of view) than the mechanism derived from the algorithm. In the communication-free device each user, independently of its type, adopts a rate which is between the optimal rates adopted by the low type users and the high type users, and this situation reflects in the expected delay. This results in a very low and constant delay with respect to the number of users.

[11]Notice that all users in the network experience the same delay. However, such delay depends on the type profile: the higher the number of high type users with respect to the number of low type users, the higher the delay. Thus, the expected delay for a low type user is lower than the expected delay for a high type user.

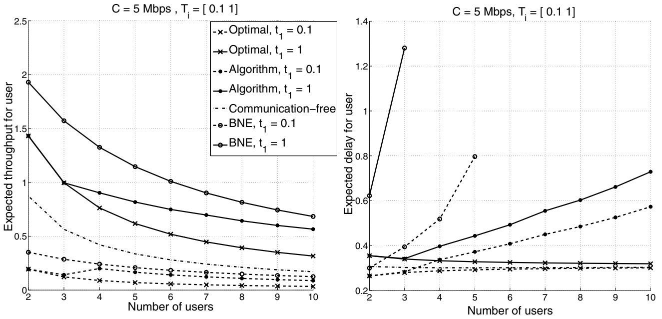

Fig. 6. Expected throughput and delay per user vs. number of users for the incomplete information scenario.

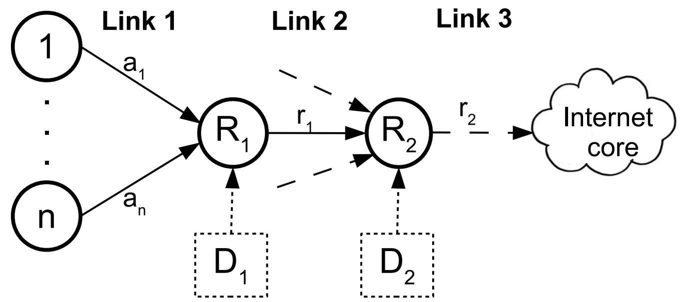

Fig. 7. Representation of a flow control problem in a multi–hop network.

D. Discussion and future work

In this work we have proposed a new methodology to create protocols that elicit the private information of the users, and we have illustrated its abilities using a simple and clear to understand deployment scenario, focusing on a single link of a network. Here we discuss how this work can be extended to multi–hop networks and some future research directions.

Consider the multi–hop scenario represented in Fig. 7, in which the final users are directly connected to the router R_1, the router R_1 is connected to the router R_2, and R_2 is connected to the Internet core. We focus on Links 1 and 2, but similar considerations apply to the subsequent hops. The rate r_1 between routers R_1 and R_2 may depend on physical constraints (i.e., the channel capacity), on regulations, and on the network state (e.g., the rate r_2 and the traffic load entering router R_2). If the manager of router R_2 has reasons to suspect that R_1 (or the other entities connected to R_2) may inject too much traffic, it can adopt the same approach we considered in this paper, i.e., it may use an intervention device D_2 designed with a rule which provides R_1 with an incentive to communicate truthfully its relevant information (e.g., the type of traffic it is serving) and adopt an efficient rate r_1. Once the rate r_1 is determined, the router R_1 has to guarantee that Link 1 is shared efficiently among users. This can be done using the device D_1 and adopting the methodology considered in this work. That is, our approach can be independently applied in each link of the network, whenever there are reasons to suspect that the involved entities may behave selfishly and strategically.

A possible extension to this work involves a different type of utilities, in which users are interested in maximizing a trade–off between end–to–end throughput and delay, instead of focusing only on the throughput and delay of the single link. In this case the intervention at router R_1 is coupled with the intervention at router R_2, and these interventions may affect each other, like in a leader–follower game, where one intervention needs to consider the effect of the other interventions downstream. This study is left for future research.

V. Conclusion

In this paper we have analyzed the performance of a congestion control scheme in the presence of self-interested and strategic users, both when the users have private information and when they do not have private information. We have quantified the inefficiency of the NE of the complete information game and the BNE (which is analytically computed) of the incomplete information game. To improve the efficiency of the network, we have deployed in the system an intervention device. For the complete information scenario, we have designed a device able to provide the incentive for the users to adopt the optimal transmission rate, by threatening punishments if they deviate. Such a scheme is able to obtain the optimal performance achievable when the users act cooperatively. For the incomplete information scenario, we have designed two devices: the first one is able to retrieve the private information from the users giving them the incentive to report it truthfully; the second one is based only on the a priori information that the device has about the users. Illustrative results show that these devices can considerably increase the efficiency of the network in the incomplete information scenario as well.

Appendix A
Proof of Proposition 1

Proof: We want to find the value of $g_i(t_i)$ that maximizes $EU_i(g, t_i)$.

$$EU_i(g,t_i) = \mathbb{E}_{t_{-i}}\left[U_i(g(t),t_i)\right] = g_i(t_i)^{t_i}\mathbb{E}_{t_{-i}}\left[(C-\lambda)\right] = $$
$$= g_i(t_i)^{t_i}\left[\left(C - g_i(t_i) - \sum_{j=1,j\neq i}^{n}\mathbb{E}_{t_j}\left[g_j(t_j)\right]\right)\right]$$
$$\frac{\partial \ln EU_i}{\partial g_i(t_i)} = \frac{t_i}{g_i(t_i)} - \frac{1}{C - g_i(t_i) - \sum_{j\neq i}^{n}\mathbb{E}_{t_j}\left[g_j(t_j)\right]}$$
$$\frac{\partial^2 \ln EU_i}{\partial g_i^2(t_i)} = -\frac{t_i}{g_i^2(t_i)} - \frac{1}{\left(C - g_i(t_i) - \sum_{j\neq i}\mathbb{E}_{t_j}\left[g_j(t_j)\right]\right)^2}$$

Because the second derivative is negative, we impose the first derivative equal to 0, obtaining that the Bayesian Nash Equilibrium g^{BNE} must satisfy, $\forall\, i \in N$ and $\forall\, l = 1, \ldots, v$,

$$(1+\tau_l)\, g_i^{BNE}(\tau_l) + \tau_l \sum_{j=1,j\neq i}^{n}\sum_{k=1}^{v}\pi(\tau_k) g_j^{BNE}(\tau_k) = C\tau_l \tag{12}$$

The system of equations defined by (12) can be written as a matrix equation of the form

$$\mathbf{A}g^{BNE} = b$$

where

$$g^{BNE} = \begin{bmatrix} g_1^{BNE} \\ \vdots \\ g_n^{BNE}\end{bmatrix}, \quad g_i^{BNE} = \begin{bmatrix} g_i^{BNE}(\tau_1) \\ \vdots \\ g_i^{BNE}(\tau_v)\end{bmatrix},$$

$$b = \begin{bmatrix} \hat{b} \\ \vdots \\ \hat{b} \end{bmatrix}, \quad \hat{b} = \begin{bmatrix} C\tau_1 \\ \vdots \\ C\tau_v \end{bmatrix},$$

$$\mathbf{A} = \begin{bmatrix} \boldsymbol{\Lambda} & \tau \cdot \mathbf{P} & \cdots & \tau \cdot \mathbf{P} \\ \tau \cdot \mathbf{P} & \boldsymbol{\Lambda} & \cdots & \tau \cdot \mathbf{P} \\ \vdots & \vdots & \ddots & \vdots \\ \tau \cdot \mathbf{P} & \tau \cdot \mathbf{P} & \cdots & \boldsymbol{\Lambda} \end{bmatrix},$$

$$\boldsymbol{\Lambda} = \mathrm{diag}\,(1+\tau_1, \ldots, 1+\tau_v)\,, \quad \tau = \begin{bmatrix} \tau_1 \\ \vdots \\ \tau_v \end{bmatrix},$$

$$\mathbf{P} = \begin{bmatrix} \pi(\tau_1) & \ldots & \pi(\tau_v) \end{bmatrix}.$$

$\mathbf{A}^{-1}$ can be analytically computed applying the matrix inversion lemma to

$$\mathbf{A} = \begin{bmatrix} \boldsymbol{\Lambda} - \tau \cdot \mathbf{P} & & \\ & \ddots & \\ & & \boldsymbol{\Lambda} - \tau \cdot \mathbf{P} \end{bmatrix} + \\ + \begin{bmatrix} \mathbf{I} \\ \vdots \\ \mathbf{I} \end{bmatrix} \cdot \begin{bmatrix} \tau \cdot \mathbf{P} & \ldots & \tau \cdot \mathbf{P} \end{bmatrix}$$

where $\mathbf{I}$ is the identity matrix in $\mathbb{R}^{v \times v}$. Due to space limitations, we avoid to write down such computations and the final expression of $\mathbf{A}^{-1}$. They can be found in [31]. ■

APPENDIX B
PROOF OF LEMMA 1

Proof: For a generic user i, we want to prove that $\tilde{a}_i$ is the best action given that the other users adopt $\tilde{a}_{-i}$. We study the sign of the derivative of the logarithm of i's utility with respect to i's action

$$\frac{\partial \ln U_i^I(a_i, \tilde{a}_{-i}, t_i, x)}{\partial a_i} = \begin{cases} \dfrac{t_i}{a_i} - \dfrac{1}{C - \sum_{k \neq i} \tilde{a}_k - a_i} & a_i < \tilde{a}_i \\ \dfrac{t_i}{a_i} - \dfrac{1 + c_i}{C - \sum_{k \neq i} \tilde{a}_k - a_i - c_i(a_i - \tilde{a}_i)} & \tilde{a}_i < a_i < \tilde{a}_i + \dfrac{\overline{x}}{c_i} \\ \dfrac{t_i}{a_i} - \dfrac{1}{C - \sum_{k \neq i} \tilde{a}_k - a_i - \overline{x}} & a_i > \tilde{a}_i + \dfrac{\overline{x}}{c_i} \end{cases}$$

We denote by $a_i^{BR}(a_{-i})$ the best response function of user i, i.e., i's action that maximizes i's utility when the action vector of the other users is a_{-i}. Since the users' utilities satisfy the assumptions **A4-A6** of [10], $\dfrac{\partial U_i^I(a_i, \tilde{a}_{-i}, t_i, x)}{\partial a_i} \geq 0$ for $a_i < \tilde{a}_i$. In fact $U_i^I(a, t_i, x)$ is increasing with respect to a_i in $\left[0,\ a_i^{BR}(\tilde{a}_{-i})\right)$ and $\tilde{a}_i \leq g_i^{NE^0} = a_i^{BR}(g_{-i}^{NE^0}) \leq a_i^{BR}(\tilde{a}_{-i})$, where the first inequality is an assumption of the Lemma and the last inequality is valid because of the submodularity of the game. Hence, a sufficient condition for $\tilde{a}_i$ to be the best action for user i is $\dfrac{\partial U_i^I(a_i, \tilde{a}_{-i}, t_i, x)}{\partial a_i} \leq 0$ for $a_i > \tilde{a}_i$.

Consider first the case $\tilde{a}_i < a_i < \tilde{a}_i + \dfrac{\overline{x}}{c_i}$. In this interval we have that $\dfrac{\partial U_i^I(a_i, \tilde{a}_{-i}, t_i, x)}{\partial a_i} \leq 0$ if and only if

$$c_i \geq \frac{t_i \left(C - \sum_{k=1, k \neq i}^{n} \tilde{a}_k - a_i\right) - a_i}{t_i\left(a_i - \tilde{a}_i\right) + a_i}$$

The right hand side term is decreasing in a_i, therefore the condition is valid in $\tilde{a}_i < a_i < \tilde{a}_i + \dfrac{\overline{x}}{c_i}$ if and only if it is valid in $\tilde{a}_i$, obtaining

$$c_i \geq \frac{t_i\left(C - \sum_{k=1}^{n} \tilde{a}_k\right) - \tilde{a}_i}{\tilde{a}_i} \tag{13}$$

Notice that (13) is also a necessary condition for $\tilde{a}_i$ to be the best action (and hence for $\tilde{a}$ to be a NE). In fact, if it is not satisfied then $U_i^I(a_i, \tilde{a}_{-i}, t_i, x)$ is strictly increasing in $\tilde{a}_i$ and, for the continuity of $U_i^I(a_i, \tilde{a}_{-i}, t_i, x)$ with respect to a_i, we can find an action $\hat{a}_i > \tilde{a}_i$ such that $U_i^I(\hat{a}_i, \tilde{a}_{-i}, t_i, x) > U_i^I(\tilde{a}_i, \tilde{a}_{-i}, t_i, x)$.

Consider now the case $a_i > \tilde{a}_i + \dfrac{\overline{x}}{c_i}$. In this interval we have that $\dfrac{\partial U_i^I(a_i, \tilde{a}_{-i}, t_i, x)}{\partial a_i} \leq 0$ if and only if

$$\overline{x} \geq \frac{c_i\left[t_i\left(C - \sum_{k=1}^{n} \tilde{a}_k\right) - \tilde{a}_i\right]}{1 + t_i(1 + c_i)}$$

Given the condition (13) on c_i, this last condition is sufficient (but not necessary) for $\tilde{a}_i$ to be a global maximizer. In fact in this way $U_i^I(a_i, \tilde{a}_{-i}, t_i, x)$ becomes quasi-concave in a_i: increasing for $a_i < \tilde{a}_i$ and decreasing for $a_i > \tilde{a}_i$. ■

APPENDIX C
PROOF OF PROPOSITION 3

Proof: Conditions **1**, **3** and **4** of [10, Prop.2] are satisfied. It remains to verify that **2** is satisfied, i.e., $\forall\, t_i, \hat{t}_i \in T_1$,

$$\sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) a_i^{t_i} \left(C - \sum_{k=1}^{n} a_k\right) \geq \sum_{t_{-i} \in T_{-i}} \pi(t_{-i}) \hat{a}_i^{t_i} \left(C - \sum_{k=1}^{n} \hat{a}_k\right) \tag{14}$$

where, $\forall j \neq i$,

$$a_i = \frac{t_i C}{n + \sum_{k \neq i} t_k + t_i}\ ,\quad a_j = \frac{t_j C}{n + \sum_{k \neq i} t_k + t_i}\ ,$$
$$\hat{a}_i = \frac{\hat{t}_i C}{n + \sum_{k \neq i} t_k + \hat{t}_i}\ ,\quad \hat{a}_j = \frac{t_j C}{n + \sum_{k \neq i} t_k + \hat{t}_i} \tag{15}$$

In particular, Eq. (14) is valid if, $\forall\, t_{-i} \in T_{-i}$,

$$a_i^{t_i} \left(C - \sum_{k=1}^{n} a_k\right) \geq \hat{a}_i^{t_i} \left(C - \sum_{k=1}^{n} \hat{a}_k\right) \tag{16}$$

Substituting Eq. (15) into Eq. (16) we obtain:

$$\left(\frac{n + \sum_{k \neq i} t_k + \hat{t}_i}{n + \sum_{k \neq i} t_k + t_i}\right)^{t_i + 1} \left(\frac{t_i}{\hat{t}_i}\right)^{t_i} \geq 1 \tag{17}$$

We use the notation $b = n + \sum_{k \neq i} t_k$, and $y = \frac{\hat{t}_i}{t_i}$. We want to find the condition on t_i and y such that

$$h(y) = \left(\frac{b + t_i y}{b + t_i}\right)^{t_i + 1} y^{-t_i} \geq 1$$

Notice that $h(1) = 1$. We take the derivative of h with respect to y

$$h'(y) = t_i y^{-t_i-1}\left(\frac{b+t_i y}{b+t_i}\right)^{t_i}\left(\frac{y-b}{b+t_i}\right)$$

$h'(y) \geq 0 \Leftrightarrow y \geq b \Leftrightarrow \frac{\hat{t}_i}{t_i} \geq n + \sum_{k\neq i} t_k$.

$f(\frac{\hat{t}_i}{t_i})$ is decreasing in $\hat{t}_i$ until $\hat{t}_i = t_i\left(n + \sum_{k\neq i} t_k\right)$, then it is increasing. This implies that for $\hat{t}_i < t_i$ Eq. (16) is satisfied, i.e., user i has no incentive to report a lower type. However, if $\hat{t}_i \to t_i^+$, since $h'(1) < 0$, then user i has an incentive to communicate a higher type (this result is linked to [10, Prop.2]). In fact Eq. (16) is not satisfied $\forall\, t_{-i} \in T_{-i}$, and therefore Eq. (15) is unsatisfied. Since the function $h(\frac{\hat{t}_i}{t_i})$ increases for $\hat{t}_i > t_i\left(n + \sum_{k\neq i} t_k\right)$, the only way for Eq. (16) to be satisfied is that the function $f(y)$ will eventually reach the value 1 for a value $x^{th} = \frac{\tau^{th}}{t_i}$ and all the types higher than t_i are higher than the threshold value τ^{th}. Notice that it is sufficient that this condition is verified by the type that follows t_i. Substituting t_i with τ_l and $\hat{t}_i$ with τ_{l+1} into Eq. (17) we obtain Eq. (9). ■

Appendix D
Proof of Proposition 4

Proof: First, we demonstrate that Eq. (10) describes a convex problem if $\tau_v \leq n$. The constraints describe a convex set. We can rewrite the objective function in the following way

$$\begin{aligned}
f(a) &= -\ln\left[\left(C - \sum_{i=1}^{n} a_i\right)\sum_{t\in\mathcal{T}}\pi(t)\prod_{i=1}^{n} a_i^{\frac{t_i}{n}}\right]\\
&= -\ln\left[\left(C - \sum_{i=1}^{n} a_i\right)\prod_{i=1}^{n}\sum_{l=1}^{v}\pi(\tau_l) a_i^{\frac{\tau_l}{n}}\right] =\\
&= -\ln\left(C - \sum_{i=1}^{n} a_i\right) - \sum_{i=1}^{n}\ln\sum_{l=1}^{v}\pi(\tau_l) a_i^{\frac{\tau_l}{n}}
\end{aligned}$$

We calculate the partial derivatives of $f(a)$

$$\frac{\partial f(a)}{\partial a_j} = \frac{1}{C - \sum_{i=1}^{n} a_i} - \frac{\sum_{l=1}^{v}\pi(\tau_l)\frac{\tau_l}{n} a_j^{\frac{\tau_l}{n}-1}}{\sum_{l=1}^{v}\pi(\tau_l) a_j^{\frac{\tau_l}{n}}}$$

$$\frac{\partial^2 f(a)}{\partial a_j^2} = \frac{1}{\left(C - \sum_{i=1}^{n} a_i\right)^2} + \frac{\left(\sum_{l=1}^{v}\pi(\tau_l)\frac{\tau_l}{n} a_j^{\frac{\tau_l}{n}-1}\right)^2}{\left(\sum_{l=1}^{v}\pi(\tau_l) a_j^{\frac{\tau_l}{n}}\right)^2} + - \frac{\left(\sum_{l=1}^{v}\pi(\tau_l)\frac{\tau_l}{n}\left(\frac{\tau_l}{n}-1\right) a_j^{\frac{\tau_l}{n}-2}\right)\left(\sum_{l=1}^{v}\pi(\tau_l) a_j^{\frac{\tau_l}{n}}\right)}{\left(\sum_{l=1}^{v}\pi(\tau_l) a_j^{\frac{\tau_l}{n}}\right)^2}$$

$$\frac{\partial^2 f(a)}{\partial a_j \partial a_k} = \frac{1}{\left(C - \sum_{i=1}^{n} a_i\right)^2}$$

We have $\frac{\partial^2 f(a)}{\partial a_j^2} \geq \frac{\partial^2 f(a)}{\partial a_j \partial a_k} \geq 0$, where the first inequality is valid if $\tau_v \leq n$.

Before concluding, we state and prove the following Lemma.

Lemma 2. *The matrix*

$$H = \begin{bmatrix} \alpha_1 & \beta & \dots & \beta \\ \beta & \alpha_2 & \dots & \beta \\ \vdots & & \ddots & \vdots \\ \beta & \beta & \dots & \alpha_n \end{bmatrix}$$

where $\alpha_i \geq \beta \geq 0$, $\forall\, i = \{1, 2, \cdots, n\}$, is positive semidefinite. If the first inequality is strict, it is also positive definite.

Proof:

$$H = \beta\begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix} + \begin{bmatrix} \alpha_1 - \beta & 0 & \dots & 0 \\ 0 & \alpha_2 - \beta & \dots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \dots & \alpha_n - \beta \end{bmatrix}$$

Therefore

$$w^T \cdot H \cdot w = (\alpha_1 - \beta)\, w_1^2 + \cdots + (\alpha_n - \beta)\, w_n^2 + \beta\left(\sum_{i=1}^{n} w_i\right)^2$$

$w^T \cdot H \cdot w \geq 0\;\forall\, w$ if $\alpha_i \geq \beta \geq 0\;\forall\, i$. $w^T \cdot H \cdot w > 0\;\forall\, w \neq 0$ if $\alpha_i > \beta \geq 0\;\forall\, i$. ■

Applying Lemma 2 to the Hessian of the function $f(a)$ we obtain that the Hessian is positive semidefinite, therefore the function $f(a)$ is convex.

As for the optimality of the communication-free incentive compatible device D, we have

$$\begin{aligned}
&\max_{a\in A}\mathbb{E}_t\left[\sqrt[n]{\prod_{i=1}^{n} U_i^{I+}(a, t_i, \Phi(r, m, a))}\right]\\
&\leq \max_{a\in A}\mathbb{E}_t\left[\sqrt[n]{\prod_{i=1}^{n} U_i^{I+}(a, t_i, x^*)}\right] =\\
&= \max_{a\in A}\left(C - \sum_{i=1}^{n} a_i\right)^{+}\mathbb{E}_t\left[\sqrt[n]{\prod_{i=1}^{n} a_i^{t_i}}\right] =\\
&\max_{a\in A}\left(C - \sum_{i=1}^{n} a_i\right)\mathbb{E}_t\left[\prod_{i=1}^{n} a_i^{\frac{t_i}{n}}\right]
\end{aligned}$$

Thus, if D sustains $\overline{a}$, D is an optimal communication-free incentive compatible device. ■

References

[1] G. Owen, *Game Theory*, 3rd ed. Academic, 2001.

[2] V. Srivastava, J. Neel, A. B. MacKenzie, R. Menon, L. A. DaSilva, J. E. Hicks, J. H. Reed, and R. P. Gilles, "Using game theory to analyze wireless ad hoc networks," *IEEE Commun. Surveys Tuts.*, vol. 7, no. 4, pp. 46–56, 2005.

[3] E. Altman, T. Boulogne, R. El-Azouzi, T. Jimenez, and L. Wynter, "A survey on networking games in telecommunications," *Computers and Operations Research*, vol. 33, no. 2, pp. 286–311, Feb. 2006.

[4] M. Felegyhazi and J. P. Hubaux, "Game theory in wireless networks: a tutorial," EPFL, Tech. Rep., 2006. Available: http://infoscience.epfl.ch/record/79715/files/FelegyhaziH06tutorial.pdf

[5] A. B. MacKenzie and L. A. Dasilva, *Game Theory for Wireless Engineers*. Morgan & Claypool Publishers, 2006.

[6] Q. Huang, *Game Theory*. Sciyo, 2010.

[7] A. Giessler, J. Hanle, A. Konig, and E. Pade, "Free buffer allocation—an investigation by simulation," *Comput. Networks*, vol. 2, no. 3, pp. 191–208, Jul. 1978.

[8] L. Kleinrock, "Power and deterministic rules of thumb for probabilistic problems in computer communications," in *Proc. 1979 IEEE ICC*, vol. 2, no. 4, pp. 43.1.1–43.1.10.

[9] J. Park and M. van der Schaar, "The theory of intervention games for resource sharing in wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 1, pp. 165–175, Jan. 2012.

[10] L. Canzian, Y. Xiao, W. Zame, M. Zorzi, and M. van der Schaar, "Intervention with private information, imperfect monitoring and costly communication," to appear in *IEEE Trans. Commun.*, 2013.

[11] F. P. Kelly, "Charging and rate control for elastic traffic," *European Trans. Telecommun.*, vol. 8, no. 1, pp. 33–37, Sep. 1997.

[12] F. P. Kelly and A. K. Maulloo, "Rate control for communication networks: shadow prices, proportional fairness and stability," *J. Operational Research Society*, vol. 49, no. 3, pp. 237–252, 1998.

[13] S. H. Low and D. E. Lapsley, "Optimization flow control—I: basic algorithm and convergence," *IEEE/ACM Trans. Netw.*, vol. 7, no. 6, pp. 861–874, Dec. 1999.

[14] T. Alpcan and T. Basar, "Distributed algorithms for Nash equilibria of flow control games," *Annals of Dynamic Games*, vol. 7, 2003.

[15] C. Douligeris and R. Mazumdar, "A game theoretic perspective to flow control in telecommunication networks," *J. Franklin Institute*, vol. 329, no. 2, pp. 383–402, Mar. 1992.

[16] Z. Zhang and C. Douligeris, "Convergence of synchronous and asynchronous greedy algorithm in a multiclass telecommunications environment," *IEEE Trans. Commun.*, vol. 40, no. 8, pp. 1277–1281, Aug. 1992.

[17] E. Altman, T. Basar, and R. Srikant, "Nash equilibria for combined flow control and routing in networks: asymptotic behavior for a large number of users," *IEEE Trans. Autom. Control*, vol. 47, no. 6, pp. 917–930, 2002.

[18] R. Garg, A. Kamra, and V. Khurana, "A game-theoretic approach towards congestion control in communication networks," *SIGCOMM Comput. Commun. Rev.*, vol. 32, no. 3, 2002.

[19] Y. Su and M. van der Schaar, "Linearly coupled communication games," *IEEE Trans. Commun.*, vol. 59, no. 9, pp. 2543–2553, Sep. 2011.

[20] E. Altman, T. Basar, T. Jimenez, and N. Shimkin, "Competitive routing in networks with polynomial costs," *IEEE Trans. Autom. Control*, vol. 47, no. 1, pp. 92–96, Jan. 2002.

[21] T. Basar and R. Srikant, "Revenue-maximizing pricing and capacity expansion in a many-users regime," in *Proc. 2002 IEEE INFOCOM*, pp. 23–27.

[22] H. Shen and T. Basar, "Optimal nonlinear pricing for a monopolistic network service provider with complete and incomplete information," *IEEE J. Sel. Areas Commun.*, vol. 25, no. 6, pp. 1216–1223, Aug. 2007.

[23] ——, "Incentive-based pricing for network games with complete and incomplete information," *Annals of Dynamic Games*, vol. 9, pp. 431–458, 2007.

[24] Y. Gai, H. Liu, and B. Krishnamachari, "A packet dropping-based incentive mechanism for M/M/1 queues with selfish users," in *Proc. 2011 IEEE INFOCOM*, pp. 2687–2695.

[25] L. Hurwicz, "Game theory," in *Decision and Organization: A Volume in Honor of Jacob Marshak*, 1972, pp. 297–336.

[26] P. Dasgupta, P. Hammond, and E. Maskin, "The implementation of social choice rules: some results on incentive compatibility," *Review of Economic Studies*, vol. 46, no. 2, pp. 185–216, Apr. 1979.

[27] B. Holmstrom, "Moral hazard and observability," *Bell J. Economics*, vol. 10, pp. 74–91, Aug. 1979.

[28] R. B. Myerson, "Incentive-compatibility and the bargaining problem," *Econometrica*, vol. 47, no. 1, pp. 61–73, Jan. 1979.

[29] ——, "Optimal auction design," *Mathematics of Operations Research*, vol. 6, pp. 58–73, Dec. 1981.

[30] ——, "Optimal coordination mechanism in generalized principal-agent problems," *J. Mathematical Economics*, vol. 10, no. 1, pp. 67–81, Jun. 1982.

[31] L. Canzian, Y. Xiao, W. Zame, M. Zorzi, and M. van der Schaar, "Designing information revelation and intervention with an application to flow control, technical report. Available: http://arxiv.org/abs/1207.4044, 2012.

[32] B. Holmstrom, "On the theory of delegation," Northwestern University, Center for Mathematical Studies in Economics and Management Science, Discussion Papers, 1980. Available: http://www.kellogg.northwestern.edu/research/math/papers/438.pdf

[33] V. P. Crawford and J. Sobel, "Strategic information transmission," *Econometrica*, vol. 50, no. 6, pp. 1431–1451, Nov. 1982.

Luca Canzian [M'13] received the B.Sc., M.Sc., and Ph.D. degrees in Electrical Engineering from the University of Padova, Italy, in 2005, 2007, and 2013, respectively. From 2007 to 2009 he worked in Venice, Italy, as an R&D Engineer at Tecnomare, a company providing design and engineering services for the oil industry. From September 2011 to March 2012 he was on leave at the University of California, Los Angeles (UCLA). Since January 2013, he has been a PostDoc at the Electrical Engineering Department at UCLA. His research interests include resource allocation, game theory, online learning and real-time stream mining.

Yuanzhang Xiao received the B.E. and M.E. degree in Electrical Engineering from Tsinghua University, Beijing, China, in 2006 and 2009, respectively. He is currently pursuing the Ph.D. degree in the Electrical Engineering Department at the University of California, Los Angeles. His research interests include game theory, optimization, communication networks, and network economics.

William Zame William Zame (Ph.D., Mathematics, Tulane University 1970) is Distinguished Professor of Economics and Mathematics at UCLA. He previously held appointments at Rice University, SUNY/Buffalo, Tulane University and Johns Hopkins University, and visiting appointments at the Institute for Advanced Study, the University of Washington, the Institute for Mathematics and its Applications, the Mathematical Sciences Research Institute, the Institut Mittag-Leffler, the University of Copenhagen, VPI, UC Berkeley and Einaudi Institute for Economics and Finance. He is a Fellow of the Econometric Society (elected 1994) and a former Guggenheim Fellow (2004-2005).

Michele Zorzi [F'07] received the Laurea and the PhD degrees in Electrical Engineering from the University of Padova, Italy, in 1990 and 1994, respectively. During the Academic Year 1992/93, he was on leave at the University of California, San Diego (UCSD) as a visiting PhD student, working on multiple access in mobile radio networks. In 1993, he joined the faculty of the Dipartimento di Elettronica e Informazione, Politecnico di Milano, Italy. After spending three years with the Center for Wireless Communications at UCSD, in 1998 he joined the School of Engineering of the University of Ferrara, Italy, where he became a Professor in 2000. Since November 2003, he has been on the faculty at the Information Engineering Department of the University of Padova. His present research interests include performance evaluation in mobile communications systems, random access in mobile radio networks, ad hoc and sensor networks, energy constrained communications protocols, broadband wireless access and underwater acoustic communications and networking.

Dr. Zorzi was the Editor-In-Chief of the *IEEE Wireless Communications Magazine* from 2003 to 2005 and the Editor-In-Chief of the IEEE TRANSACTIONS ON COMMUNICATIONS from 2008 to 2011, and currently serves on the Editorial Board of the Wiley *Journal of Wireless Communications and Mobile Computing*. He was also guest editor for special issues in the *IEEE Personal Communications Magazine* (Energy Management in Personal Communications Systems), *IEEE Wireless Communications Magazine* (Cognitive Wireless Networks), and the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS (Multi-media Network Radios, and Underwater Wireless Communications Networks). He served as a Member-at-large of the Board of Governors of the IEEE Communications Society from 2009 to 2011.

Mihaela van der Schaar [F'10] is Chancellor's Professor of Electrical Engineering at University of California, Los Angeles. Her research interests include network economics and game theory, online learning, multimedia networking, communication, processing, and systems, real-time stream mining, dynamic multi-user networks and system designs. She is an IEEE Fellow, a Distinguished Lecturer of the Communications Society for 2011-2012, the Editor in Chief of IEEE TRANSACTIONS ON MULTIMEDIA and a member of the Editorial Board of the IEEE JOURNAL ON SELECTED TOPICS IN SIGNAL PROCESSING. She received an NSF CAREER Award (2004), the Best Paper Award from IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY (2005), the Okawa Foundation Award (2006), the IBM Faculty Award (2005, 2007, 2008), the Most Cited Paper Award from *EURASIP: Image Communications Journal* (2006), the Gamenets Conference Best Paper Award (2011) and the 2011 IEEE Circuits and Systems Society Darlington Award Best Paper Award. She received three ISO awards for her contributions to the MPEG video compression and streaming international standardization activities, and holds 33 granted US patents. For more information about her research visit: http://medianetlab.ee.ucla.edu/