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Cooperative user–network interactions in next generation communication networks

Josephina Antoniou [a,*], Vicky Papadopoulou [b], Vasos Vassiliou [a], Andreas Pitsillides [a]

[a] University of Cyprus, Dept. of Computer Science, 75 Kallipoleos Street, P.O. Box 20537, CY-1678 Nicosia, Cyprus
[b] European University Cyprus, Dept. of Computer Science, 6, Diogenes Street, P.O. Box 22006, CY-1516 Nicosia, Cyprus

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ABSTRACT

Next Generation Communication Networks employ the idea of convergence, where heterogeneous access technologies may coexist, and a user may be served by anyone of the participating access networks, motivating the emergence of a Network Selection mechanism. The triggering and execution of the Network Selection mechanism becomes a challenging task due to the heterogeneity of the entities involved, i.e., the users and the access networks. This heterogeneity results in different and often conflicting interests for these entities, motivating the question of how they should behave in order to remain satisfied from their interactions. This paper studies cooperative user–network interactions and seeks appropriate modes of behaviour for these entities such that they achieve own satisfaction overcoming their conflicting interests.

1. Introduction

Converged Networks [1] allow different access networks, terminals and services to coexist bringing forth a new communication paradigm, which is *user-centric* [2], i.e., the user is no longer bound to only one access network but may indirectly *select* the *best* available access network to support a service session [3]. Upon a new service request or even any dynamic change affecting the session (e.g., mobility) one of the participating access networks needs to be selected in order to support the session. Next Generation Communication Networks – controlled by an IP Core Network – need to be equipped with a *Network Selection mechanism* to assign the *best* access network to handle service activation, or any dynamic session change. Such decision may result in a single access network or even multiple networks cooperating to handle a service (the multiple networks case is treated in [4]). This paper studies the resulting interaction between a user and a network, and seeks the best behaviour for each entity such that their conflicting interests are overcome and satisfaction is achieved.

Interactions between entities with conflicting interests, follow action plans designed by each entity in such a way as to achieve a particular selfish goal and are known as strategic interactions. *Game Theory* is a theoretical framework that studies strategic interactions, by developing models that prescribe actions in order for the interacting entities to achieve satisfactory gains from the situation. In this paper, we utilise Game Theory in order to model, analyze and finally propose solutions for the user–network interactions arising due to the Network Selection mechanism. Initially, we utilise Game Theory in order to model the relationship between the user and the network as a strategic game. Particularly, we utilise the notion of *Present Value* (PV) for a sequence of payoffs in a *repeated game* [5] in order to reach a decision that will be both user-satisfying and network-satisfying.

In an attempt to improve the user–network relationship according to the knowledge acquired during the interaction history, we define a notion of *adaptivity* for the user

* Corresponding author. Tel.: +357 22892686; fax: +357 22892701.
E-mail addresses: josephin@ucy.ac.cy (J. Antoniou), v.papadopoulou@euc.ac.cy (V. Papadopoulou), vasosv@ucy.ac.cy (V. Vassiliou), andreas.pitsillides@ucy.ac.cy (A. Pitsillides).

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as a player in the access network selection decision game, and based on that, we propose a new user strategy for the repeated user–network interaction game. The proposed adaptive strategy, together with the rest of the strategies studied in this paper, are evaluated through simulations that explore their behaviour. The numerical results verify that the players gain more when cooperating, as expected from the theoretical analysis. Moreover, simulations show that the proposed adaptive user strategy results in profitable payoffs, also reinforcing the conclusions of the theoretical analysis.

The paper is organized as follows. Section 2 describes related work and motivates the subsequent work. Section 3 investigates the user–network interaction both as a one-shot and as a repeated interaction. The paper continues by a study of access network selection (Section 4) leading to a proposal of a new adaptive user strategy. A numerical evaluation of all strategies analyzed in the paper is found in Section 5 and finally, conclusions are drawn in Section 6.

2. Related work and motivation

Although network selection is a relatively young research area, it has been extensively studied in recent years [6–8]. The growing popularity of networks that promote technology convergence and allow the co-existence of heterogeneous access networks, has pushed towards the efficient resource management of the overall converged system upon a given dynamic change (e.g., service request, context change, and mobility).

From the earlier works on network selection various approaches describing and analyzing the effects of this new resource management mechanism have been introduced and investigated. Such approaches include fuzzy logic [9,10], adaptive techniques [2,11], utility-based and game-theoretic models [12,13], technology-specific solutions, especially focussing on the inter-operation of cellular systems with wireless LANs [8,14], as well as architectural models focussing on a more comprehensive architectural view [3]. Decision making in these works is either *user-controlled* [10,12,14] or *network-controlled* [3,8,11]. The interaction between them is not considered in detail and the selection decision mainly involves one entity, in some cases involving the other entity indirectly, i.e., decision is taken by the network with the consideration of some user preference [2,13], or the decision is taken by the user with the consideration of some network-specific rankings [9].

In addition to the above techniques, more recent research development explores more dynamic/automated solutions that, similarly to the earlier works, either are based on the user as a decision-making entity [15,16], or are network-controlled solutions proposing improvements to the user-perceived quality during network selection [6,17,18]. Besides the general solutions for network selection, specific solutions handling particular services such as multicast, have been recently proposed [19,20]. These focus on the effect of network selection on the particular service (e.g., multicast) in addition to user and network satisfaction aspects. Again, in these works the decision-making is either user-controlled or network-controlled.

Since network selection is a mechanism involving important decision making, it is essential to take into consideration some strategical planning on behalf of the entities involved in this decision. Game theory is a theoretical framework for strategical decision-making. It has been a very popular approach among recently presented research works [4,7,21,22]. These explore various game theoretic models such as non-cooperative games [21,22], and cooperation schemes where limited resources and/or need for quality guarantees exist [4,7].

Cooperative approaches [4,7] explore the formation of coalitions between the various networks, where a terminal is capable to simultaneously connect to and be served by more than one network. The game selects the best group of networks to serve a new connection or a service demand forecast. In the non-cooperative papers, Cesana et al. [21] study the competition between the mobile users when they are able to select from a set of available access networks, each aiming to minimize the potential selection cost, whereas Cesana et al. [22] consider network selection to be a non-cooperative game between the users and the networks instead of between the users themselves. A user in this game seeks to maximize quality of service and a network seeks to maximize its number of customers. Mathematical programming is used to find the equilibrium in this game.

The current paper is closer to [22] because it models a game where the interacting entities involve the mobile user and the candidate access networks. As in [22], both the user and the network have different payoff functions reflecting their own satisfaction: best predicted quality per unit payment for the user and greatest profit for the network. The current paper improves on the work of Cesana et al. [22] by capturing additional elements (e.g., user payment and network cost), and in addition it identifies and formalizes the cooperative properties instead of the non-cooperative aspects of the user–network interaction addressed in [22]. We utilise the mathematical framework and theoretical tools from Game Theory in order to capture the involvement of both interacting entities in the Network Selection mechanism, i.e., the user and the available networks. The game-theoretic framework enabled us to compute a solution for Network Selection that is both user- and network-controlled, and most importantly, the solution is satisfactory for both the user and the available networks.

3. User–network interaction

In this section we explore, using game theoretical tools, the relationship between the user and the network participating in a converged system. Particularly, we investigate the interaction resulting from the network selection procedure, and we aim through the proposed game model to reach a decision that is both user-satisfying and network-satisfying.

3.1. Incentives

The interaction between a user and a network in a converged system may be viewed as an exchange between two entities. The user gives some kind of *compensation* (most likely monetary) and the network gives a *promise*, in this case of a specific quality level, such that the promise can be evaluated in terms of compensation, i.e., a quality q that corresponds to a compensation c.

Investigating the interaction between entities, we seek to discover the incentives for each entity to select certain strategies, i.e., sets of actions, that result in (i) a cooperative behaviour, and (ii) are such that both entities are satisfied. The incentive function is usually realized by the payoff of each entity involved. Considering a typical scenario situation of the user–network interaction, we assume that the payoffs of the user and the network are the following:

- The payoff of the user is the difference between the perceived *satisfaction*, which is considered to be an increasing function of perceived *quality*, and the *compensation* offered by the user to the network. The perceived quality is based on quality measurements (e.g., the signal strength received by the terminal from the specific access network and the signal alteration rate measured at the terminal). The details of such a function are left for future work.
- The payoff of the network is basically the profit of the network, represented as the difference between the compensation received from the user for the specific service, and the cost of supporting the session, which is considered to be an increasing function of the requested quality level.

Both payoffs are based on the fact that the compensation and the quality level representing satisfaction in the user payoff, as well as the cost of supporting a session in the network payoff are comparable. In the first case, the compensation and satisfaction may be measured by similar *units of satisfaction*, i.e., the more compensation given the less the *units of satisfaction* for the user, and the more quality received the more the *units of satisfaction* for the user. In the second case, quality corresponds to the cost for setting up the resources to support it and again we may view the comparison in terms of *units of satisfaction*, i.e., the more compensation received the more the *units of satisfaction* for the network, whereas the more the quality to be supported, the less the *units of satisfaction* for the network.

3.2. General assumptions and requirements

In order to explore the realization of the above incentives, we proceed to model the user–network interaction as a game, based on the following initial *assumptions*:

(1) The players in the network selection game are heterogeneous players, aiming at different payoffs. This assumption is realistic given the diverse nature of a network and a user.
(2) The modeling of the game assumes a complete game, i.e., one in which players are aware of the available actions and corresponding payoffs of their opponents, but of imperfect information, since the players make decisions without having knowledge of their opponents' moves.
(3) There is a minimum and a maximum compensation as well as a minimum and a maximum quality.
(4) There is always a probability that quality degradation will be perceived by the user. This assumption is justified by the dynamic nature of the network; even if the network decides to offer the requested quality.
(5) At any time the sum of the payoffs of the two players is a constant value, not equal to zero, i.e., a general sum game model; neither player wins as in a zero-sum game. This is a reasonable assumption since we aim to extract conclusions on the cooperation of the two entities.
(6) Both the user and the network have non-negative payoff functions. This assumption is introduced in order to motivate the players to participate in the interaction (reflecting a selection of an appropriate access network during Network Selection).

The above assumptions result in the following specifications, which are imposed by the game model:

- Assumption (6) results in the requirement that the maximum compensation offered by the user is less than or equal to the satisfaction corresponding to the minimum requested quality. Thus, given that compensation and satisfaction from perceived quality are measurable in comparable units, the maximum compensation offered by the user should be defined to be less than or equal to the satisfaction corresponding to the minimum requested quality. In this way, the user *plays* the game without risking to have a negative payoff, satisfying Assumption (6).
- Assumption (6) results in the requirement that the minimum compensation offered by the user is greater than or equal to the cost of the maximum requested quality. Thus, given that the compensation and cost of supporting a requested quality are measurable in comparable units, the minimum compensation offered by the user should be defined to be greater than or equal to the cost for the maximum requested quality. In this way, the network *plays* the game without risking to have a negative payoff satisfying Assumption (6).
- Moreover at any time of the user–network interaction, we require that the network's cost from supporting the requested service is less than the compensation offered by an amount $\epsilon > 0$, such that the network may gain at least marginal profit from this interaction.

Given $\epsilon > 0$, it is better for a network not to reject the user's offer, but accept it and decide whether to cooperate, i.e., offer the requested quality, or cheat, i.e., offer a lower quality than the one requested. On the other hand, we also allow the user to be able to cheat by not giving the amount of compensation, offered as incentive to initiate the user–network interaction.

Initially, we treat this interaction as *one-shot*, in order to derive some fundamental properties of the interaction; however, in practice users and networks interact multiple times. The theoretical analysis of the one-shot model of the game reveals that cooperation between the entities is not achieved. Thus, we move onto investigate whether the knowledge of previous outcomes, when considering a repeated interaction model, results in cooperative behaviour.

3.3. One-shot user–network interaction game

In this subsection, we examine the interaction by considering it first to be a one-shot game, i.e., that it is not affected by outcomes of previous interactions and that it does not affect any future interactions between the two entities.

The user–network interaction model is defined as follows.

Definition 3.1 (*User–network interaction game*). Let the user choose an incentive compensation scheme $\kappa_i \in K$ to offer to the network, where $K = \{\kappa_1, \kappa_2, \ldots, \kappa_n\}$, in order to encourage the network to make and keep a *promise* of offering $q_i \in Q$, where $Q = \{q_1, q_2, \ldots, q_n\}$. The user has the capability to cheat and offer κ'_i, such that $\forall i \in [n],\ \kappa'_i < \kappa_i$, but this will not be known to the network until the end of the game when payoffs are collected. The network makes a decision of whether to accept the user's compensation κ_i and promise to offer q_i or to reject it. If the network rejects the offer, the interaction terminates and the payoff to both players is 0. If the network accepts the offer, it can decide to keep the promise of supporting q_i or to cheat, by offering q'_i, such that $\forall i \in [n],\ q'_i < q_i$. This will be known by the user also at the end of the game, when payoffs are collected.

Regardless of the network's decision, there is a random event, represented by *Nature*, i.e., an event that is not controlled by neither the network nor the user. This random event has two outcomes: the quality offered by the network degrades (the user perceives a lower quality $q'_i < q_i$), or the perceived quality indicates no degradation (quality q_i perceived by the user). A quality degradation might be observed by the user, even when the network takes all the necessary measures to keep the promise for the requested quality. Whether the network cheats, or *Nature's* event is degradation, or whether both occur, the user perceives a quality q'_i without knowing what caused it.

In the rest of the section, we assume a fixed requested quality q_i and corresponding compensation κ_i, so we simplify κ_i to κ, and q_i to q. Table 1 illustrates the possible payoffs of the user and the network in the user–network interaction game, where $\pi(q)$ represents the satisfaction resulting from the perceived quality q, and $c(q)$ represents the cost for supporting quality q. The payoffs are presented by order pairs: the first term is the user payoff and the second term is the network payoff.

Table 1
User and network play the Prisoner's Dilemma, nature's play: no degradation.

	Network accepts and cooperates	Network accepts and cheats
User accepts and cooperates	$\pi(q) - \kappa,\ \kappa - c(q)$	$\pi(q') - \kappa,\ \kappa - c(q')$
User accepts and cheats	$\pi(q) - \kappa',\ \kappa' - c(q)$	$\pi(q') - \kappa',\ \kappa' - c(q')$

3.3.1. Equivalence to Prisoner's Dilemma

Consider the well-known Prisoner's Dilemma Game (Definition 3.2).

Definition 3.2 (*Prisoner's Dilemma type of game [23]*). Consider a one-shot strategic game with two players in which each player has two possible actions: to cooperate with his opponent or to defect from cooperation. Furthermore, assume that the two following additional restrictions on the payoffs are satisfied:

(1) The order of the payoffs is shown in Table 2 for each player $j \in \{1,2\}$ and is such that $A_j > B_j > C_j > D_j$.
(2) The reward for mutual cooperation should be such that each player is not motivated to exploit his opponent or be exploited with the same probability, i.e., for each player it must hold that $B_j > \frac{A_j + D_j}{2}$.

Then, the game is said to be equivalent to a Prisoner's Dilemma type of game.

Consider now the following outcome for the user–network interaction game: the network accepts the user's offer and the outcome of Nature's random event is *no degradation*. We prove that this outcome of the game is equivalent to a *Prisoner's Dilemma type of game*. In the subsequent discussion, we make use of the following fact:

Fact 3.3. *For a set quality q it holds that $\pi(q) - \kappa > 0$, i.e., the difference between the maximum satisfaction perceived by the user and the maximum compensation given by the user is greater than 0. Similarly, the difference between the minimum satisfaction and the minimum compensation is greater than 0, i.e. $p(q^{'}) - \kappa^{'} > 0$.*

We make the following assumptions for the user–network interaction game:

(1) The difference between the maximum and minimum satisfaction, $\pi(q) - \pi(q')$, is greater than the difference between the maximum and minimum compensation, $\kappa - \kappa'$, that may be offered by the user, since the user will always prefer that the maximum compensation offered is set as low as it is allowed by the platform administrator, whereas the satisfaction received from the maximum quality may be evaluated as high as possible, since no such constraints exist.
(2) The network accepts to participate in the interaction in a riskless manner, i.e., only if the range of possible compensations exceeds the range of possible costs, $\kappa - \kappa' > c(q) - c(q')$.

Proposition 3.4. *Consider the user–network interaction game. Assume that the network accepts the user's offer, and the event of Nature does not generate degradation. Then the game is equivalent to a Prisoner's Dilemma game.*

Proof. By Definition 3.1 we immediately conclude that:

Claim 3.5. *There are two possible actions for both players: to cooperate and to cheat (i.e., defect from cooperation).*

Table 2
General payoffs for the Prisoner's Dilemma.

	Player 2 cooperates	Player 2 cheats
Player 1 cooperates	B_1, B_2	D_1, A_2
Player 2 cheats	A_1, D_2	C_1, C_2

Claim 3.5 combined with Definition 3.2 imply that the actions of the players in the user–network interaction game match the actions of the players of a Prisoner's Dilemma game. In particular, Table 3 maps each player's payoffs (for the cases that the network accepts the user's offer), of Table 1 to actions A_j, B_j, C_j, D_j, where $j \in \{1,2\}$, as defined in Definition 3.2.

We proceed to prove:

Lemma 3.6. *Set A_j, B_j, C_j, D_j according to Table 3. Then it holds that: $A_j > B_j > C_j > D_j$ for each $j \in \{1,2\}$.*

Proof. The user–network interaction game satisfies condition 1 of Definition 3.2, when the network accepts the user's offer and no degradation occurs.

Examining the user, we verify straightforward that $\pi(q) - \kappa' > \pi(q) - \kappa$, thus $A_1 > B_1$, and that $\pi(q') - \kappa' > \pi(q') - \kappa$, thus $C_1 > D_1$, since $\kappa > \kappa'$. Given Fact 3.3 and the assumption that $\pi(q) - \pi(q') > \kappa - \kappa'$, it holds that $B_1 > C_1$.

Examining the network, we verify straightforward that $\kappa - c(q') > \kappa - c(q)$, thus $A_2 > B_2$, and that $\kappa' - c(q') > \kappa' - c(q)$, since $c(q) > c(q')$, thus $C_2 > D_2$. Assuming that the network accepts to participate in the interaction in a riskless manner, i.e., only if the range of possible compensations exceeds the range of possible costs, then $\kappa - \kappa' > c(q) - c(q')$, and $B_2 > C_2$. □

We now proceed to prove that:

Lemma 3.7. *The user–network interaction game, satisfies condition 2 of Definition 3.2.*

Proof. To prove the claim we must prove that the reward for cooperation is greater than the payoff for the described situation, i.e., for each player it must hold that $B_j > \frac{A_j + D_j}{2}$.

For the user,

$$\pi(q) - \kappa > \frac{\pi(q) - \kappa' + \pi(q') - \kappa}{2} > \frac{\pi(q) + \pi(q')}{2} - \frac{\kappa' + \kappa}{2}, \tag{1}$$

since $\pi(q) > \pi(q')$ and $\kappa > \kappa'$.

Table 3
The mapping between the user and network payoffs and the payoffs in the Prisoner's Dilemma type of game.

	User payoffs ($j = 1$)	Network payoffs ($j = 2$)
A_j	$\pi(q) - \kappa'$	$\kappa - c(q')$
B_j	$\pi(q) - \kappa$	$\kappa - c(q)$
C_j	$\pi(q') - \kappa'$	$\kappa' - c(q')$
D_j	$\pi(q') - \kappa$	$\kappa' - c(q)$

For the network,

$$\kappa - c(q) > \frac{\kappa - c(q') + \kappa' - c(q)}{2} > \frac{\kappa + \kappa'}{2} - \frac{c(q) + c(q')}{2}. \quad \square \tag{2}$$

Claim 3.5, Lemmas 3.6 and 3.7 together complete the proof of Proposition 3.4. □

The decision of each player in the user–network interaction game is based on the following reasoning [23]: if the opponent cooperates, defect to maximize payoff (A_j in Table 3); if the opponent defects, defect (*payoff C_j instead of payoff D_j*). This reasoning immediately implies:

Corollary 3.8. ([23]) *In a one-shot Prisoner's Dilemma game, for any profile of the game, a best response strategy of both players is to defect.*

Proposition 3.4 combined together with Corollary 3.8 immediately imply:

Corollary 3.9. *In the one-shot user–network interaction game, when the event of Nature is no degradation, a best response strategy of both players is to cheat.*

Corollaries 3.8 and 3.9 give rise to the question of how cooperation could be motivated, since the user and the network must cooperate in order to satisfy their corresponding needs for higher quality levels and higher compensation; if both players are motivated to cheat, then the quality and compensation are kept at minimum levels. A memoryless user–network interaction results in no cooperation between the players. This observation is further investigated next, by modelling this memoryless interaction as a sequential game model, where the moves of the players occur sequentially and not simultaneously. Again, we observe in the sequential game, where neither the future nor the past influence the players' decision, that the resulting payoffs motivate the players to cheat than to cooperate.

3.3.2. Sequential moves game

Here, we present a sequential moves game modeling the user–network interaction, in order to check whether the same conclusions hold. In this game, the two involved entities make sequential decisions, i.e., the user makes a decision first and the network makes the decision second, to check whether the same conclusions hold. The game ends by a random event, which is not controlled by either of the two entities. We utilise a notion from Game Theory to model this sequential decision-making: sequential moves games, a.k.a extensive games.

According to this model, the user is a *first-mover*, the network moves second, and each player has one more move before the event of *Nature*, which randomly sets the outcome of the game to be equal to *degradation*. The payoff functions and the set of actions of the players remain the same as in the one-shot game. Extensive games can be represented as trees, where branches represent decisions and nodes represent decision makers (except the leaves which represent end states). So, the user–network interaction game is modeled in extensive form as illustrated in Fig. 1.

In the case where the network decides to cooperate and keep the promise to the user, degradation might or might not be perceived. If degradation is not perceived, the payoff to the user is the result of the difference between an increasing function of quality q, representing the user's satisfaction, $\pi(q)$, and the offered compensation κ, such that $\pi(q) - \kappa$; the payoff to the network in this case, is the difference between the received compensation κ and an increasing function of quality $q \in Q$, representing the network's cost, $c(q)$, that is $\kappa - c(q)$. On the other hand, if degradation is perceived, the quality perceived is $q' < q$, and the payoff to the user changes to $\pi(q') - \kappa$, where $\pi(q') < \pi(q)$. However, the payoff to the network does not change; we assume that both the compensation offer and the setup for supporting a specific quality level (and consequently the relevant cost), happen at the beginning of a session, whereas any degradation is not observed until the end of the session. In the case that the network decides to cheat, the payoffs to the network also change, since the cost for quality $q' < q$ decreases such that $c(q') < c(q)$. All the payoffs are illustrated at the leaves of the tree in Fig. 1.

Both players want to make choices that maximize their payoff since they are *rational* players. Let us first examine the behaviour of the network. The first choice involves whether to accept or reject a compensation by the user. Since we have considered only the cases where the compensation offered is always greater than or equal to the network's cost, the best choice for the network is to accept the offer made by the user. Given that the network will accept the compensation offer, it knows that the lower the quality for which it reserves resources, the lower its own cost will be. Since, according to the payoffs, the network will not experience any *punishment* for cheating in the one-shot game, and since the current decision of the network has no impact on any future interactions between the two players, the network is motivated to only offer minimum quality, increasing its own payoff but also *cheating* in every case that the quality promised was greater than the minimum. Since *Nature* does not affect the network's payoff, cheating is the decision that will give the highest payoff to the network.

Now, since the user is a rational player and wants to maximize his own payoff, he will choose to offer a payment that in combination with the quality level requested will give him the highest attainable payoff. Using backward induction thinking, i.e., by considering which is the best move for the network, the user may guess that the best response to the network's best behaviour of cheating is to only offer minimum compensation, expecting in return minimum quality. This is done in order to maximize his own payoff as well, by making sure not to experience any losses due to the network's cheating behaviour. Corollary 3.10 summarizes these findings:

Corollary 3.10. *In the sequential moves one-shot game modelling the user–network interaction the outcome of the game is the following:*

The user offers minimum compensation and the network supports minimum quality, with analogous payoffs as in the case where both entities were cheating.

3.3.3. Conclusions

The above discussion on the one-shot game leads to the conclusion that cooperation between the user and the network is not supported for all quality levels. This conclusion motivated our research to move towards a different model for the user–network interaction game, a repeated game model. The result of this study is presented in the next section, where we model the user–network interaction game

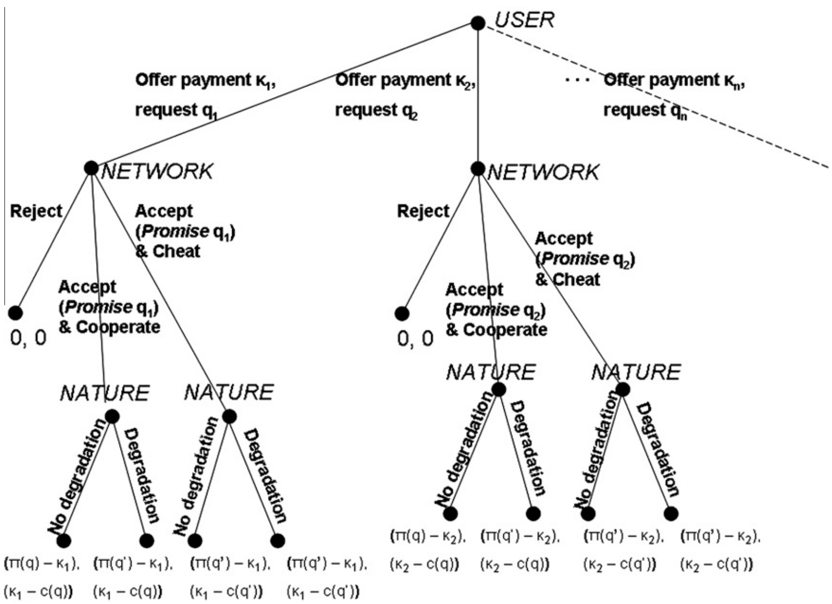

Fig. 1. The one shot sequential moves game of user–network interaction in extensive form.

as a repeated game with infinite horizon [5], particularly as a repeated Prisoner's Dilemma game, with the payoffs for each period as indicated in Table 1.

3.4. Repeated user–network interaction game

If the one-shot game model were an accurate representation of the real interaction, why would networks ever be motivated to satisfy users' requests for higher qualities? The reason is that, in reality, the interactions between networks and users are not one-shot but re-occurring. More importantly, the previous outcomes of their interactions affect their future behaviours. In such relationships, the players do not only seek the immediate maximization of payoffs but instead the long-run optimal solution. Such situations are modelled in Game Theory by repeated games. There are two kinds of repeated games: the finite horizon repeated games and the infinite horizon repeated games, which are actually models of games of unknown length [5]. We categorize the user–network interaction model as an infinite horizon repeated game, since the users keep requesting new sessions from the networks but the number of such requests is not known.

A repeated game makes it possible for the players to condition their moves on the complete previous history of the various stages, by employing strategies that define appropriate actions for each period. Such strategies are called *trigger strategies* [24]. A trigger strategy is a strategy that changes in the presence of a predefined trigger; it dictates that a player must follow one strategy until a certain condition is met and then follow a different strategy, for the rest of the game. One of the most popular trigger strategies is the *grim trigger strategy* [5], which dictates that the player participates in the relationship, but if *dissatisfied* for some known reason, leaves the relationship forever. The grim trigger strategy may be used by the user in the user–network interaction game, such that if degradation is detected by the user in one stage, in the next stage the user may *punish* the network by leaving the relationship (e.g., stop interacting with the specific network). Given such a strategy, the network has a stronger incentive to keep the promise given for a certain quality, since it faces the threat of losing its customer forever. The threat of non-renewal of the user's *contract* to the network, secures compliance of the network to keep the *promise* of quality. Exchanges based on such threats of non-renewing a relationship, which is based on a particular agreement between the two parties, are often referred to as *Contingent Renewal Exchanges* [24]. Therefore, the user employs a grim trigger strategy to elicit performance from the network and the loss of the relationship is costly to the network because it has a negative impact on the user–network relationship. Another popular strategy used to elicit cooperative performance from an opponent, is for a player to mimic the actions of his opponent, giving him the incentive to play cooperatively, since in this way he will be rewarded with a similar mirroring behaviour. This strategy is referred to as *tit-for-tat* strategy [5].

The subsequent study of the repeated user–network interaction employs the grim strategy as a possible strategy for the user and the tit-for-tat strategy as a possible strategy for the network, since the strengths of each strategy mentioned above are considered appropriate for the user–network interaction. Moreover, we define two more strategies for the user and one more strategy for the network. Specifically, for the user we define: (a) the *Cheat-and-Leave* strategy and (b) the *Leave-and-Return* strategy, and for the network we define the *Cheat-and-Return* strategy. The *Cheat-and-Leave* strategy is defined for the user to reflect the user's option to cheat, since the grim strategy is a cooperative strategy. The user leaves after cheating in this case, i.e., does not continue interaction with the particular network, in order to avoid any punishment for cheating. The *Leave-and-Return* strategy is a cooperative strategy similar to the grim strategy but we define it so as to capture the case where the punishment if the network cheats does not involve the user leaving the relationship forever, but leaving for only one period and returning in the subsequent interaction period. Similarly, the *Cheat-and-Return* strategy gives the opportunity to the Network to cheat, and since it cannot in reality leave the user–network relationship (if the user selects to interact with a particular network), it returns to the interaction and accepts the user's punishment, if any. Consequently, the profiles considered in the analysis involve combinations of these strategies.

3.4.1. Present value

Examining the user–network relationship, there is a probability that there will not be an interaction in the future between the particular user and the particular network due to exogenous factors. Therefore, there is always a probability that the game will not continue in the next period. Let this probability be denoted as p. In order to compare different sequences of payoffs in repeated games, we utilize the idea of the *present value of a payoff sequence* [5], and we refer to it as the *Present Value* (PV). PV is the sum that a player is willing to accept currently instead of waiting for the future payoff, i.e., accept a smaller payoff today that will be worth more in the future, similar to making an investment in the current period that will be increased by a rate r in the next period.

Therefore, if the payoff in the next period were equal to 1, today the payoff a player would be willing to accept would be equal to $\frac{1}{1+r}$. If there is a probability that the game will not continue in the next period, equal to $1-p$, then the payoff a player is willing to accept today, i.e., the player's PV, would be equal to $\frac{1-p}{1+r}$, where p gives the probability of termination of interaction, which is not controlled by the network. Let $\delta = \frac{1-p}{1+r}$, where $\delta \in [0, 1]$ and often referred to as the *discount factor* in repeated games [5].

Therefore, given a payoff X in the next period, its PV in the current period equals $\delta \cdot X$. Now, for an infinitely repeated game, a PV should include the discounted payoff of all subsequent periods of the game. Let the payoff from the current period be equal to 1. Then, the additional payoff a player is willing to accept for the next period equals to δ, for the period after that the additional payoff equals to δ^2 and so on. Thus, PV equals to $1 + \delta + \delta^2 + \delta^3 + \delta^4 + \cdots$, which, according to the sum of infinite geometric series, equals to $\frac{1}{1-\delta}$. Therefore, for a payoff X payable at the end of each period, the present value in an infinitely repeated game equals to $\frac{X}{1-\delta}$.

In order to determine whether cooperation is a better strategy in the repeated game for both the network and the user, we utilize PV and examine for which values of $\delta = \frac{1-p}{1+r}$ a given strategy is a player's best response to the other player's strategy. A strategy in an infinitely repeated game, gives the action to take at each decision node. Namely, for each period the network has the choice of two actions: either to take the risk and cooperate with the user offering the requested quality, or to *cheat* and offer the lowest quality. In case the network cheats, and the grim trigger strategy is used, the user will leave the network at the end of the session, because degradation will definitely be perceived.

3.4.2. Equilibria

Since in such a game we have an infinite number of decision nodes, we describe decision nodes in terms of *histories*, i.e., records of all past actions that the players took [25], thus a history corresponds to a path to a particular decision node in the infinitely repeated game tree. When a strategy instructs a player to play the best response to the opponent's strategy after every history, i.e., giving the player a higher payoff than any other action available after each particular history, it is called a *subgame perfect strategy* [5]. When all players play their subgame perfect strategies, then we have an equilibrium in the repeated game, known as a *subgame perfect equilibrium* [5].

Definition 3.11. When a player cheats in one period, and leaves in the next period to avoid punishment by the other player, the strategy employed is referred to as the cheat-and-leave strategy.

Definition 3.12. When a player cheats in one period, and returns to cooperation to accept the punishment by the other player, the strategy employed is referred to as the cheat-and-return strategy.

In repeated games, where histories of previous periods are known and players move simultaneously, and also where, in all periods, the same moves result in the same payoffs, then a subgame perfect equilibrium can be shown to exist by fixing all moves of both players to the proposed equilibrium strategy, and then for one move of any one player, we allow one player to change his action. If no such change can increase the payoff obtained by the proposed equilibrium strategy, then the strategy is a subgame perfect strategy, and if both players employ subgame perfect strategies, then we have a subgame perfect equilibrium. Since, in our game, the above conditions are met we may check for subgame perfect equilibrium by allowing each player to change one move, i.e., from *cooperate* to *cheat*, and keep all other moves fixed to the *conditional-cooperation profile*. The cheat-and-leave period expresses this idea for the user, since the grim strategy, i.e., the user's proposed equilibrium strategy, prescribes leaving once cheating is detected in the last period of the game. The cheat-and-return expresses this idea for the network, since the tit-for-tat strategy, i.e., the network's proposed equilibrium strategy, prescribes returning after own cheating if no cheating from opponent occurs in the last period of the game.

Let the user have a choice between the two following strategies: (i) the *grim* strategy, i.e., offer a compensation κ and keep offering the compensation as long as the network cooperates and no degradation is perceived; if degradation is perceived, then leave the relationship forever, and (ii) the *cheat-and-leave* strategy. Let the network have a choice between the two following strategies: (a) the *tit-for-tat* strategy, i.e., mimic the actions of its opponent, and (b) the *cheat-and-return* strategy. When neither of the two players cheats, the game profile is one of cooperation as identified in Definition 3.13.

Definition 3.13. When the user employs the grim strategy and the network employs the tit-for-tat strategy, the profile of the repeated game is referred to as conditional-cooperation profile of the game.

Next, we formulate Theorem 3.14, which identifies the *conditional-cooperation* profile as a subgame perfect equilibrium for the repeated user–network interaction game.

Theorem 3.14. *In a repeated user–network interaction game, assume* $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$ *and* $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$, *where* δ *is the discount factor of the repeated game. Then, the conditional-cooperation profile is a subgame perfect equilibrium for the game.*

Proof. Since the players' strategies suggest that cheating by either player would eventually result in a termination of the interaction, we assume a history of cooperative moves in the past. Then in the current period, both the user and the network could choose to either cooperate or cheat. Assume that the user plays the grim strategy. If the network cooperates, PV is equal to,

$$PV_{cooperate} = \frac{\kappa - c(q)}{1-\delta}.$$

If the network cheats, PV will be a sum of what the network may get in the current period and what the network may get in the rest of the game beginning in the next period. Thus,

$$PV_{cheat} = \kappa - c(q') + \frac{\delta \cdot 0}{1-\delta}.$$

For the network to be motivated to cooperate with the user instead of cheating, we must show that PV in case of cooperation is preferable for the network than PV in case of cheating. The inequality is given next,

$$PV_{cooperate} > PV_{cheat} = \frac{\kappa - c(q)}{1-\delta} > \kappa - c(q') + \frac{\delta \cdot 0}{1-\delta}.$$

Simplifying, we get $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$. Now, assume that the user plays the cheat-and-leave strategy. If the network cooperates, its PV is equal to,

$$PV_{cooperate} = \kappa' - c(q) + \frac{\delta \cdot 0}{1-\delta}.$$

On the other hand, if the network cheats, its PV is equal to,

$$PV_{cheat} = \kappa' - c(q') + \frac{\delta \cdot 0}{1-\delta}.$$

Clearly, in case the user plays the cheat-and-leave strategy, the network is not motivated to cooperate since:

$$PV_{cheat} > PV_{cooperate}.$$

Next, assume that the network employs a tit-for-tat strategy, and the user may choose to cooperate or cheat. The PV if the user cooperates is the value of the current payoff, $\pi(q) - \kappa$ discounted for the whole infinite game.

$$PV_{cooperate} = \frac{\pi(q) - \kappa}{1-\delta}.$$

The PV if the user cheats, i.e., offers a compensation $\kappa' < \kappa$ and then leave the relationship, is the current payoff $\pi(q) - \kappa'$ plus the forever discounted payoff for leaving the relationship, which is 0

$$PV_{cheat} = \pi(q) - \kappa' + \frac{\delta \cdot 0}{1-\delta}.$$

The inequality of cooperation compared to cheating is given next,

$$PV_{cooperate} > PV_{cheat} = \frac{\pi(q) - \kappa}{1-\delta} > \pi(q) - \kappa' + \frac{\delta \cdot 0}{1-\delta}.$$

Simplifying, we get $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$. Now, assume that the network plays the cheat-and-return strategy. If the user cooperates, its PV is equal to:

$$PV_{cooperate} = \pi(q') - \kappa + \frac{\delta \cdot 0}{1-\delta}.$$

On the other hand, if the user cheats, its PV is equal to,

$$PV_{cheat} = \pi(q') - \kappa' + \frac{\delta \cdot 0}{1-\delta}.$$

Clearly, in case the network plays the cheat-and-return strategy, the user is not motivated to cooperate since:

$$PV_{cheat} > PV_{cooperate}.$$

Thus, it has been shown that as long as $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$ and $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$, the conditional-cooperation profile is the subgame perfect equilibrium for the user–network interaction game. □

Remark 3.15. For the network, cooperation is motivated if $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$. Since $c(q') < c(q) < \kappa$, Theorem 3.14 implies that the bigger $c(q')$ is the more motivated the network is to cooperate; in other words, if the network cannot save a substantial fraction of the cost by cheating, then it is best to cooperate. For the user, cooperation is motivated if $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$; since $\kappa' < \kappa$ and $\kappa < \pi(q)$. Theorem 3.14 implies that the greater κ' is, the better it is for the user to cooperate, in other words; unless the user can lower κ' substantially, he will gain more by cooperating.

Let the strategies selected by the user and by the network, be such that the punishment they impose on their opponent, in case the opponent cheats, lasts only for one period; namely, let the user employ the *leave-and-return* strategy and the network employ the *cheat-and-return* strategy as these are defined below.

Definition 3.16. When a player cooperates as long as the other player cooperates, and leaves for one period in case the other player cheats, returning in the subsequent period to cooperate again, the strategy employed is referred to as the *leave-and-return strategy.*

Based on the newly defined strategy, another profile of the game is defined next.

Definition 3.17. When the user employs the leave-and-return strategy and the network employs the tit-for-tat strategy, the profile of the repeated game is referred to as *one-period-punishment profile of the game.*

It is assumed that when punished, a player accepts the punishment without cheating. This set of strategies is not as strict as the one previously considered, since the punishment lasts for only one period for the player that cheats. It has been proven in [26], that the conditions to sustain cooperation with grim trigger strategies, which are the stricter strategies that may be employed by the players in a repeated Prisoner's Dilemma, are necessary conditions for the possibility of any form of conditional cooperation, i.e., a grim trigger strategy can sustain cooperation in the iterated Prisoner's Dilemma under the least favourable circumstances of any strategy that can sustain cooperation. Motivated by the result in [26], and assuming a history of cooperation between the user and the network, we show that it is easier to impose cooperation in the repeated user–network interaction game under the conditional-cooperation profile elaborated in Definition 3.13, where the imposed punishment ends in the termination of the interaction, rather than under the one-period-punishment profile.

Theorem 3.18. *Consider the repeated user–network interaction game: assuming a history of cooperation, the minimum conditions required to impose cooperation under the conditional-cooperation profile, are also necessary in order to impose cooperation under the one-period-punishment profile, for both the user and the network.*

Proof. Given a history of the game where both players have cooperated in the past, and that the user has decided to cooperate for the current period, the network has two options: to cooperate or to cheat. If the network cooperates, PV will consist of the payoff $\kappa - c(q)$ in the current period, plus a discounted version of this payoff for the next period plus a discounted version of the same payoff for all the rest of the periods. We consider the first two periods separately in order to be able to compare PV when cheating, since the behaviour of the network alternates in these periods of the game. Therefore,

$$PV_{cooperate} = \kappa - c(q) + \delta \cdot (\kappa - c(q)) + \frac{\delta^2 \cdot (\kappa - c(q))}{1-\delta}.$$

If the network cheats, PV is a sum of what the network may get in the current period, what the network may get in the next period (when it is punished) and what it may get in the rest of the game beginning two periods from the current period. Thus,

$$PV_{cheat} = \kappa - c(q') + \delta \cdot 0 + \frac{\delta^2 \cdot (\kappa - c(q))}{1-\delta}.$$

The network's motivation to cooperate is calculated in terms of δ, by showing through an inequality that PV in case of cooperation is preferable for the network than PV in case of cheating as follows:

$$\begin{aligned} PV_{cooperate} &> PV_{cheat} \\ &= \kappa - c(q) + \delta \cdot (\kappa - c(q)) + \frac{\delta^2 \cdot (\kappa - c(q))}{1-\delta} \\ &> \kappa - c(q') + \delta \cdot 0 + \frac{\delta^2 \cdot (\kappa - c(q))}{1-\delta}. \end{aligned}$$

Simplifying, we get $\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$. Now, considering that the network decides to cooperate in the current period, the user has two options as well: to cooperate or to cheat. The PV of the user if he cooperates is the sum of the current payoff, $\pi(q) - \kappa$, the discounted same payoff for the next period, and the discounted same payoff for the rest of the infinitely repeated game. We consider three discounted periods to facilitate the comparison with the user's PV in the case that he cheats.

$$PV_{cooperate} = \pi(q) - \kappa + \delta \cdot (\pi(q) - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}.$$

If the user decides to cheat, PV is a sum of the current payoff $\pi(q) - \kappa'$, the discounted payoff $\pi(q') - \kappa$ in the next period (since the network employs the tit-for-tat strategy), and the cooperation payoff $\pi(q) - \kappa$ discounted for the rest of the game,

$$PV_{cheat} = \pi(q) - \kappa' + \delta \cdot (\pi(q') - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}.$$

We compare PVs for cooperation and cheating in the inequality given next,

$$\begin{aligned} PV_{cooperate} &> PV_{cheat} \\ &= \pi(q) - \kappa + \delta \cdot (\pi(q) - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta} \\ &> \pi(q) - \kappa\prime + \delta \cdot (\pi(q') - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}. \end{aligned}$$

Simplifying, we get $\delta > \frac{\kappa - \kappa'}{\pi(q) - \pi(q')}$. The cooperation thresholds for each player, given its opponent's different strategies, are summarized in Table 4.

The conditions for sustaining cooperation under the conditional-cooperation profile are necessary for sustaining cooperation under the one-period-punishment profile as well. □

Table 4
Cooperation thresholds.

	Conditional cooperation	One-period punishment
Network cooperates If:	$\delta > \frac{c(q)-c(q')}{\kappa - c(q')}$	$\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$
User Cooperates If:	$\delta > \frac{\kappa - \kappa'}{\pi(q) - \kappa'}$	$\delta > \frac{\kappa - \kappa'}{\pi(q) - \pi(q')}$

3.4.3. Conclusions

It appears to be easier to sustain cooperation when strategies that involve harsher punishments are used. For the network, cooperation is motivated if $\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$, which is a similar result with the result for the conditional-cooperation profile. The difference between the two results is the second term in the denominator, $c(q)$ instead of $c(q')$. Therefore, the second result is always greater than the first since $c(q) > c(q')$. For the user, cooperation is motivated if $\delta > \frac{\kappa - \kappa'}{\pi(q) - \pi(q')}$, differing from the result of the conditional-cooperation profile in the second term of the denominator only. Since $\pi(q') < \pi(q)$, and given the initial model assumptions that any compensation offered is less or equal to the minimum satisfaction that could be received, the second result (under the one-period-punishment profile) is always greater than the first result (under the conditional-cooperation profile), since based on the above the denominator is always less.

On a more practical note, in order to be able to enforce these solutions in a real heterogeneous communication network, additional issues must be considered such as the possible architecture that would enable easier management of the heterogeneity of the system, the repeatability of the user–network interaction, and the compensation set. The architecture considered to host such model is envisioned to be a hierarchical system, where a platform administrator (either a centralized or a distributed process) has knowledge of all participating access networks joined to a common core network, which is either IP-based with SIP signalling, or supporting a fully implemented IP Multimedia Subsystem (IMS) infrastructure to ensure multimedia support over all participating networks in an access-agnostic manner. Such architecture would support the existence of several autonomous entities (e.g., content and context providers, and network operators) motivating the overall architecture to be more user-centric instead of network-centric, since all these entities have a common goal of satisfying the user in order to receive the appropriate compensation/payment as in the user–network interaction model.

Furthermore, the existence of several autonomous entities acting independently requires the existence of certain policies which may integrate the interests of these entities by enforcing some rules for the better management and operation of the overall system. Such policies may deal with setting the compensation, i.e., the payment, corresponding to a particular quality level of a requested service. This has to do with the range of qualities in which a particular content (e.g., a video) is available and the corresponding costs and allowable profits.

In addition, policies may have to do with strategy/profile configurations *enforced* onto users and networks by the platform administrator process. To achieve the repeatability, which is a major element in these strategies, there arises the need for the existence of a variable as part of the internal logic of a user terminal or a network gateway node such that both the user and the network may *remember* the previous action of the opponent entity. Thus, ideas of reward and punishment, elaborated in the theoretical model, may be implemented. In any case, the element of repeatability exists, since each user terminal has a number of activated access network interfaces (corresponding to different Radio Access Technologies – RATs) with which it interacts repeatedly; each of these access networks may be under a different profit-seeking network operator who participates in the heterogeneous communication system.

4. Access network selection decision

4.1. The user as an adaptive entity

Having examined the generic relationship between a user and a network through two different types of strategies for each of the players, in this section we propose a model for network selection in a converged environment, which is based on the knowledge obtained from the analysis of these strategies. The Network Selection decision is modelled as a game between one user of the converged environment and the participating access networks that are available to the specific user: the networks play simultaneously as one player (the payoff for the player called *Networks* is given as an array of payoffs corresponding to each of the individual access networks).

The situation we model is the following: the user plays first and offers a compensation to *Networks*, and *Networks* examine the compensation and decide how many networks will accept and how many networks will reject the compensation. Any subset of *Networks* could accept or reject the proposed offer, including all accepting and all rejecting. In the latter case the game terminates with zero payoff to the user and to *Networks*. If one or more networks accept the compensation, then for each network, the user predicts his own satisfaction, in terms of $\pi(q)_{expected}$, and selects the network that is predicted to offer the highest satisfaction, evaluated using several parameters; if only one network accepts, the selection is trivial.

The evaluation of $\pi(q)_{expected}$ is based on an evaluation of user and network context in an attempt to predict the possible satisfaction from the received quality, and is different for each network. Network context includes such parameters as: QoS offered by the network, maximum throughput offered by the network, current signal strength at the terminal, current signal alteration rate at the terminal, current noise/interference, etc. These parameters are compared to the service QoS requirements corresponding to the specific service request, the user terminal capabilities and the user preferences in order to generate an adequately accurate prediction of the possible satisfaction (in terms of perceived quality). Currently, the expected satisfaction is only considered in terms of service quality. However, an interesting enhancement would be to consider service cost as a part of this function and investigate the satisfaction-cost tradeoff. Future work plans to investigate this aspect further.

The user's decision to select one of the networks, induces the specific network to start interacting with the user, having the options to cooperate with the user or to cheat, while the rest of the networks do not interact any further with the user during the game. From then on, the interaction between the user and the network is as previously described in the repeated user–network interaction model. The payoffs for the networks that are not selected are zero, while the payoffs for the user and the selected network are the same as previously discussed. The flow of the network selection game is outlined in Fig. 2.

Within the context of network selection, the user–network interaction may be improved to reflect a user preference towards networks that do not often demonstrate degradation. Perceived degradation could be a Nature-induced random event or could be the result of the network cheating and offering a lower level of quality than the one requested. Nature-induced degradation is a random event with a probability of re-occurring; it is acceptable to assume that such a random event will re-occur in a uniformly random manner. However, such prediction cannot be made for perceived degradation in the case that the network cheats. We employ the idea of an adaptive player, such that the user's decision of which network to select considers a normalized weight of the network's past degradation behaviour, based on the acquired knowledge a user gains over the course of the repeated game [26]. This normalized weight is placed as a coefficient to the $\pi(q)_{expected}$ function, thus it is considered additionally to the parameters previously mentioned to comprise this evaluation function.

Thus, when the user must evaluate his predicted satisfaction from selecting each one of the available networks, the evaluation should also consider this weighted coefficient, calculated dynamically from observing past network behaviour. Being an adaptive player, the user makes a more informed selection decision that considers the past. More specifically, this is achieved by multiplying the predicted satisfaction $\pi(q)_{expected}$ by a variable α (Definition 4.1), representing the normalized weight of past degradation behaviour (the bigger the weight value, the less the degradation observed in the past.[1])

Definition 4.1. In the network selection game, a user possesses an internal state, which, based on a network's history of degradation behaviour, acts as a normalized weight coefficient, $\alpha \in [0,1]$, to its payoff function for better evaluation of the predicted satisfaction from a particular network. Given that the user has an expected satisfaction for a service request, e, such that $\pi(q)_{expected} \geqslant e$, the value of α at the end of an interactive period is modified according to (3)

$$\alpha = \begin{cases} \alpha_{previous} + \left(\alpha_{previous} \cdot \frac{\pi(q)_{final} - e}{\pi(q)_{final}}\right), & \text{if } \pi(q)_{final} \geqslant e,\ \alpha \leqslant 1 \\ 1, & \text{if } \pi(q)_{final} \geqslant e,\ \alpha \geqslant 1 \\ \alpha_{previous} \cdot \frac{\pi(q)_{final}}{e}, & \text{otherwise.} \end{cases} \tag{3}$$

By introducing the variable $\alpha \in [0,1]$, the user considers the network's history, approaching the selection decision in an adaptive manner, i.e., by evaluating $\pi(q)_{expected} \cdot \alpha$ instead of only $\pi(q)_{expected}$.

[1] To achieve this, we assume that the user has an internal state, which modifies α after every interactive period with the network, and that α has a different value for each different network that interacts with the user.

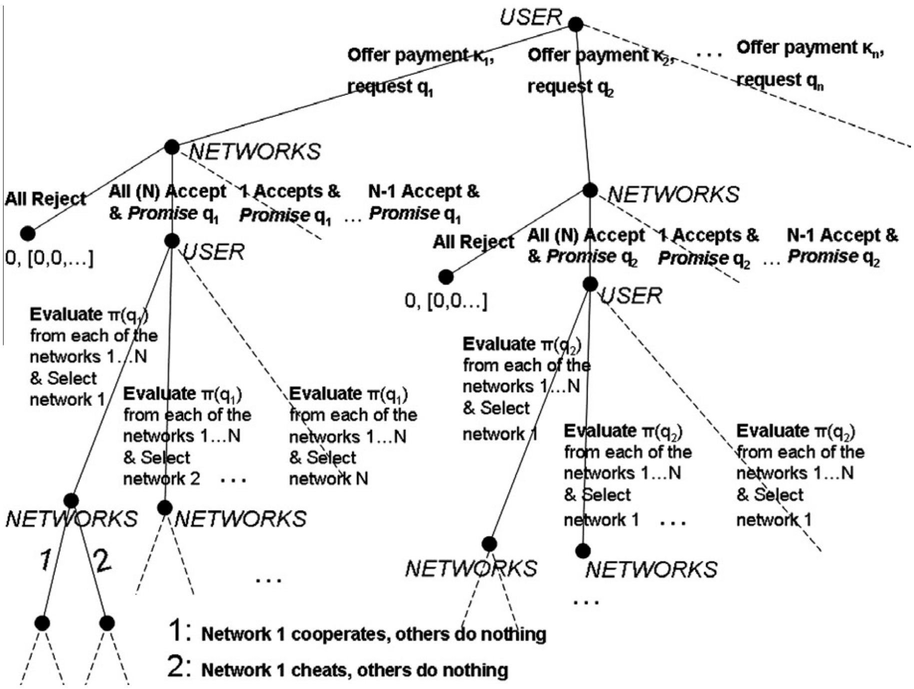

Fig. 2. Network Selection model based on user–network interactions.

4.2. A new adaptive user strategy

Once the user makes a selection decision, he interacts with the selected network by specifying an appropriate strategy for this interaction. In Section 3.4 we have proposed two game profiles; in the *conditional-cooperation* profile, the user punishes the network forever if degradation is perceived even once, while in the *one-period-punishment* profile, the user punishes the network with only one period of absence, even if the network demonstrates degradation frequently.

The *conditional-cooperation* profile involves a harsh punishment to the network in case of cheating, i.e., the user leaves the relationship forever. This strongly motivates the network to cooperate. However, in case of cheating the relationship terminates forever and one could argue that this is costly for both the user and the network, considering the finite and relatively small number of access networks. On the other hand, the *one-period punishment* profile is less motivating for cooperation because punishment is minimum, i.e., leaving for only one period, and this is known to both players. Considering the adaptive way in which the user takes a decision during the selection process, with the use of α, we propose a new strategy for the user to be employed as a means to interact with the selected network. This strategy should select a punishment that adaptively sets the number of periods that the user will leave the network according to the past behaviour of the network in order to motivate the network to keep cooperating, without having to enforce the harsh punishment of the grim strategy.

Let the user's strategy be the following: cooperate as long as the network cooperates; if the network cheats, then leave for an x number of periods; after that, return and cooperate again. Let the number x be equal to 1 if $\alpha = 1$ or $\lceil \frac{1}{\alpha} \rceil$ otherwise; such that a network with a lower value for α suffers a separation of more periods with the user, whereas a network with a higher value for α is punished for less periods (minimum punishment is 1 period).

Definition 4.2. In the network selection game, the *Adaptive-Return strategy* for the user dictates that if the user perceives degradation, he punishes the network by leaving for an x number of periods, before returning back to cooperation. The value of x is a user-generated value as defined in (4)

$$x = \begin{cases} 1, & \text{if } \alpha = 1 \\ \lceil \frac{1}{\alpha} \rceil, & \text{otherwise}. \end{cases} \tag{4}$$

It is important that the network has a motivation to cooperate with the user, when the user employs the *Adaptive Return* strategy. Given that a trigger strategy employing a forever-lasting punishment is the strategy that provides the strongest motivation to cooperate [26], we show that when the user employs the *Adaptive Return* strategy, the network is at least as motivated to cooperate with the user as when the user employs the one-period punishment strategy, because the minimum number of punishment periods imposed by the *Adaptive Return* strategy equals to one. However, the knowledge that the number of punishment periods could increase according to the network's behaviour, increases the motivation of the network to cooperate.

Theorem 4.3. *Assume that $\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$ in the repeated user–network interaction game. Then, when the user employs the Leave-and-Return strategy, i.e., when the profile of the game* *is the one-period-punishment profile, the network is motivated to cooperate. This condition on δ is also necessary to motivate cooperation by the network when the user employs the Adaptive-Return strategy.*

Proof. Given a history of the game where both players have cooperated in the past, and the user employs the Adaptive-Return strategy, the network has two options in the current period: cooperate or cheat. When the network cooperates, the PV is as follows:

$$PV_{cooperate} = \frac{(\kappa - c(q)) \cdot (1-\delta^{x+1})}{1-\delta} + \frac{\delta^{x+2} \cdot (\kappa - c(q))}{1-\delta}.$$

The sum of a finite geometric progression is used to calculate the discounted value for the first $x + 1$ periods. If the network cheats, PV is:

$$PV_{cheat} = \kappa - c(q') + \frac{(1-\delta^{x}) \cdot 0}{1-\delta} + \frac{\delta^{x+2} \cdot (\kappa - c(q))}{1-\delta}.$$

The conditions necessary to impose cooperation are calculated next:

$$\begin{aligned} PV_{cooperate} &> PV_{cheat} \\ &= \frac{(\kappa - c(q)) \cdot (1-\delta^{x+1})}{1-\delta} + \frac{\delta^{x+2} \cdot (\kappa - c(q))}{1-\delta} \\ &> (\kappa - c(q')) + \frac{(1-\delta^{x}) \cdot 0}{1-\delta} + \frac{\delta^{x+2} \cdot (\kappa - c(q))}{1-\delta}. \end{aligned}$$

Since $\delta \in (0,1)$, $x \geqslant 1$, and $\delta^{x+1} \leqslant \delta^2$, such that $\delta_{x+1} - 1 \leqslant \delta^2 - 1$, we may simplify for δ to get $\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$, similarly to the value of δ when employing the one-period punishment strategy. In fact the simplification of $\delta^{x+1} \leqslant \delta^2$, considers the case, that the Adaptive-Return Strategy generates a punishment of only one period, whereas if we consider greater values of x, the motivation for the network to cooperate increases, showing that the conditions for sustaining cooperation by the network when the Adaptive-Return strategy is used by the user are necessary for sustaining cooperation under the one-period-punishment profile. □

5. User and network behaviour with different strategies

This section examines the numerical behaviour of user and network strategies defined and used in the previous sections. The evaluation is based on a Matlab [27] implementation of an iterated user–network interaction game, where all user and network strategies are played against each other multiple times in order to evaluate the behaviour of each strategy in terms of payoff. The implementation of the user–network interaction game was based on a publicly available Matlab implementation of the Iterated Prisoner's Dilemma Game [28], which has been extended to include all the strategies examined in this paper. It is important to note that the payoffs in both sets of simulations presented, obey the two conditions required for equivalency of payoffs to Prisoner's Dilemma game payoff as these are defined in Definition 3.2.

The implementation makes use of the following guidelines, set to reflect the analytical model of the repeated user–network interaction game. In each simulation run, both players play their strategies and get payoffs accordingly. In the first set of simulations the payoffs are the following: when the user leaves, they both get 0 in the specific period, if one cheats and one cooperates, the first gets 4 and the other gets 1, if they both cheat, each gets 2, and if they both cooperate each gets 3. In the second set of simulations, we investigate the behaviour of the players when the numerical difference between cheating and cooperating increases. The payoffs for the second set of simulations are the following: when the user leaves, they both get 0 in the specific period, if one cheats and one cooperates, the first gets 100 and the other gets 1, if they both cheat, each gets 40, and if they both cooperate each gets 60. We use simple numbers as payoffs to help us get some scores for different strategy combinations but these numbers follow the relationships of the payoffs as described in their general case in the repeated game model (Table 3). Furthermore, for the adaptive strategy, the value of α is randomly generated at the beginning of each simulation run but adapted according to the network's behaviour during the actual simulation (since each run simulates an iterative process). A randomly generated perceived quality and a fixed threshold of expected quality are also implemented for the strategies in all simulation runs.

A randomly generated number of iterations was run for each set of simulations to get cumulative user and network payoffs for each combination of a user strategy playing against a network strategy. The user payoffs per strategy and the network payoffs per strategy are eventually added to give the most profitable user and network strategies respectively, for the total number of iterations of a simulation run; then the average cumulative payoffs from all simulation runs are calculated. Although the number of iterations is randomly generated, we still repeat the process 100 times for each set of simulations, i.e., by randomly generating 100 different numbers of iterations, in order to include behaviours when the number of iterations is both small and large.

For the first set of simulations, i.e., with the payoffs ranging from 0 to 4, the payoffs are calculated for an average of 264.38 iterations per simulation run.[2] In both tables we see a score for each strategy combination. The score corresponds to either a user payoff (Table 5) or a network payoff (Table 6).

The results for the first set of simulations, show that the most profitable user strategy is the *Adaptive-Return* strategy, and that the most profitable network strategy is the *Tit-for-Tat* strategy for most payoffs.[3] Furthermore, the combination of these two strategies in the same game profile gives the highest cumulative payoffs to both players.

[2] Minimum iterations generated: 8, maximum iterations generated: 1259.

[3] Except for the payoff received from the combination with the user's *Cheat&Leave* strategy. However, the difference between the payoffs received by the network from playing either the *Tit-for-Tat* strategy or the *Cheat&Return* strategy, in combination with the user's *Cheat&Leave* strategy, is negligible.

Table 5
User payoffs from all strategy combinations (1st simulation set).

User strategies	Network strategies	
	Tit-for-tat	Cheat&Return
Grim	793.14	4.42
Cheat&Leave	6.62	4.65
Leave&Return	793.14	252.92
Adaptive-Return	793.14	355.05

Table 6
Network payoffs from all strategy combinations (1st simulation set).

User strategies	Network strategies	
	Tit-for-tat	Cheat&Return
Grim	793.14	7.42
Cheat&Leave	3.82	4.23
Leave&Return	793.14	617.21
Adaptive-Return	793.14	618.57

Based on these numerical results, we define the *Adaptive-Punishment* profile (Definition 5.1) for the game to consist of the *Adaptive-Return* strategy for the user and the *Tit-for-Tat* strategy for the network.

Definition 5.1 (*Adaptive-Punishment profile*). When the user employs the *Adaptive-Return* strategy and the network employs the *Tit-for-Tat* strategy, the profile of the repeated game is referred to as *Adaptive-Punishment* profile of the game.

For the second set of simulations, i.e., with the payoffs ranging from 0 to 100, the payoffs are calculated for an average of 240.59 iterations per simulation run.[4] As previously, we see in both tables a score for each strategy combination. The score corresponds to either a user payoff (Table 7) or a network payoff (Table 8).

It is interesting to observe that for the second set of simulations, again the most profitable strategy for the user is the *Adaptive-Return* strategy and the network's most profitable strategy is the *Tit-for-Tat* strategy, except for the payoff in combination with the user's *Cheat&Leave* strategy. Overall, however, the preferred profile for the game is still the *Adaptive-Punishment* profile. The increase in the differences between cooperating and cheating payoffs, resulted in higher overall payoffs but has not changed the general payoff trend for the two players. In total, the highest payoffs are experienced by the players when they decide to use cooperating strategies instead of cheating; this result motivates the players to go ahead and cooperate.

Furthermore, it is worth noting that, for both simulation sets, when the user plays the *Leave&Return* strategy, the payoffs received by the user are comparable (though less) to the highest payoffs received, i.e., payoffs for employing the *Adaptive-Return* strategy. The justification for these results is the following: we have shown by Theorem 4.3 that the minimum conditions for the network to cooperate when the user employs the *Adaptive-Return* strategy, are necessary for the network to cooperate when the *Leave&Return* strategy is employed. In fact, the conditions for the two strategies are at least equal, and given this, it is expected to observe payoff values that are numerically closer compared to payoff values for the other user strategies, although it appears that the *Adaptive-Return* strategy manages to achieve slightly higher overall payoffs than the *Leave&Return* strategy.

[4] Minimum iterations generated: 2, maximum iterations generated: 1124.

Table 7
User payoffs from all strategy combinations (2nd simulation set).

User strategies	Network strategies	
	Tit-for-tat	Cheat&Return
Grim	14435.4	47.8
Cheat&Leave	164.2	108.36
Leave&Return	14435.4	4894.76
Adaptive-Return	14435.4	4974.47

Table 8
Network payoffs from all strategy combinations (2nd simulation set).

User strategies	Network strategies	
	Tit-for-tat	Cheat&Return
Grim	14435.4	146.8
Cheat&Leave	65.2	95.49
Leave&Return	14337.4	12850.4
Adaptive-Return	14435.4	12861.8

An additional observation is that the *Leave&Return* strategy is weaker in the case the network decides to cheat, because the user's reaction is a fixed-period punishment. On the other hand, when the user employs the *Adaptive-Return* strategy, the punishment period is not fixed but adapts to the network's past behaviour, appearing to consequently achieve an improvement in the overall user payoff. It is important to note here, that according to the theoretical results when the *Adaptive-Return* strategy is used it is easier to motivate cooperation than when the *Leave&Return* strategy is used. Therefore, it is more likely for the network to decide to cheat when *Leave&Return* is used.

Further, when interpreting the obtained payoffs, we should keep in mind that each simulation investigates a single user–network interaction, thus not considering dependencies that may arise in an evaluation of multiple co-existing interactions, where a user may interact with several networks and vice versa. Future work plans to investigate such aspects.

6. Conclusions

In this paper, we have studied the interaction between a user and a network resulting from Network Selection in Next Generation Communication Networks and we utilized Game-Theoretic tools in order to capture this interaction. This framework enabled us to compute a cooperative solution that is satisfactory for both the user and the network in a repeated interactive situation between the two entities.

Prior to analyzing the repeatability of the interaction, we introduced a model that captures the interaction of the two entities at any time, and does not consider their previous and future actions. The study revealed that the problem in this case is equivalent to the fundamental game theoretic problem of Prisoner's Dilemma. This enabled us to extract previous knowledge from game theory in order to understand our problem. In particular, we concluded that in this model a best response strategy of both players is to cheat.

This conclusion gave rise to the question of how cooperation between the user and the network could be motivated, since it is expected to be beneficial so as to satisfy their corresponding needs for higher quality levels and higher compensation. Our second model addressed this question through a sequential moves game, in order to reflect better the reality that the decisions of the involving entities are taken in sequential time units. The study revealed that the behavior of the two players would be the same as in the previous (one-shot game) model: they will both try to cheat, since repeatability is still not considered.

This undesired behavior of the interacting entities emerges because the network will not experience any punishment for cheating the user. This observation has led to the next model, which successfully solves this inadequacy of previous models: in this model, the interaction between the user and the available networks is represented as a repeated game. Moreover, we utilized some notions from economic game theory, such as the present value, in order to evaluate the profits of the players in case they choose to cheat/cooperate given that their previous actions will affect the other player's future actions. In particular, we assume that the user will punish the network by switching to another network, in the event that he experiences some degradation in the perceived quality of service.

The study has shown that if a harsh punishment is given to the network in case of cheating, i.e., the user leaves the relationship forever, this strongly motivates the network to cooperate. However, in case of cheating the relationship terminates forever. On the other hand, if punishment is minimum, i.e., leaving for only one period, and this is known to both players, it is less motivating for them to engage in cooperation. This motivates a new adaptive user strategy, which is not as harsh as leaving forever, but also not as soft as returning after one period.

This adaptive user strategy feeds on the complete history of the network behaviour. This proposed user strategy as well as the proposed adaptive α component, that affects the network leaving period selection, compose a new, game-theoretic, adaptive network selection approach. The importance of this new strategy lies in the following: the network will only choose to cooperate if it is motivated to do so by its corresponding payoffs. We have shown in the theoretical results that already the motivation for the network is weaker when the *Leave&Return* strategy is used than when the *Grim* Strategy is used, i.e., when the network is threatened with the minimum punishment it is not as motivated to cooperate than when it is threatened with the maximum punishment. However, we must consider that the application of the *Grim* strategy in next generation communication networks, is not realistic because a user may only select from a finite number of access networks; leaving forever would be disastrous for the user in the long run, as could be left with no access network to select. Therefore, the user will choose to employ the *Adaptive-Return* strategy because it offers a solution which theoretically is at least as motivating for cooperation as the *Leave-and Return* strategy, with varying punishments depending on the history of the network's behaviour. In addition, the use of this particular strategy is numerically shown to achieve at least as high payoffs as the other user strategies, thus it is considered a satisfactory solution both theoretically and numerically.

The approach is evaluated both analytically and numerically through Matlab simulations. The theoretical results show that the proposed approach easily motivates cooperation between the user and the network and the simulative results provide supporting evidence that the proposed approach can result in comparatively higher payoffs for both players.

Future work plans to explore further the repeated nature of the interaction between network and user. In particular, we plan to seek additional optimal solutions of the repeated user–network interaction game and identify players' behaviour, as well as overall system performance. Furthermore, future work plans to explore the development of additional tools that enable capturing the effect of the previous outcomes of the interaction between the entities in any future decisions.

The repeated nature of the user–network interaction has been studied with the use of the notion of the discount factor. This notion will be analyzed further as part of future work. Moreover, we aim to discover other such tools that may be able to capture the characteristics of this interaction.

Moreover, this work investigates some repeated profiles which proved to be more probable or reasonable to investigate since they capture rational behaviours of the players. However, an interesting extension to our study concerning repeated profiles is to investigate the outcomes of the interaction between the user and the network when the players employ irrational behaviours. In particular, it is interesting to investigate the outcome of the interaction when the players decide to cheat although their reasoning does not recommend it. Such decisions may be chosen in situations where the players do not have perfect knowledge of the environment, and a rational decision may not finally lead to desired outcomes for them. Studying such irrational behaviors may lead to useful results concerning interactions with imperfect knowledge or unpredictable players. This study constitutes an important future improvement of our current work.

Finally, on the evaluation side, future work plans to implement the proposed theoretical solutions for the selected interactive situations, as enhancements to control infrastructures for heterogeneous communication systems, e.g., IP Multimedia SubSystem (IMS), in order to practically evaluate the effects of the implementation of these theoretical proposals on the performance of a heterogeneous converged network.

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Josephina Antoniou received her B.A. degree (summa cum laude) in Computer Science and Mathematics from Wartburg College, IA, USA in May 2002. She has received her M.Sc degree in Advanced Computer Technologies from the University of Cyprus in June 2004 and is currently working towards her Ph.D. also at the University of Cyprus, in the area of mobile networks. She has been a Research Associate for the University of Cyprus working since June 2002, for the, IST/ICT funded projects: SEACORN, B-BONE, C-MOBILE and C-CAST dealing with Enhanced UMTS, MBMS over UMTS, enhanced MBMS over converged networks and currently context-aware multicasting over converged, next generation networks. Her research interests include radio resource management and session management in mobile networks, specifically Access Network Selection algorithms in next generation mobile networks using game theoretic approaches.

Vicky Papadopoulou has earned her Bachelor Diploma (1998), Master Degree (2001) and Ph.D. degree (2003) in the Department of Computer Engineering and Informatics, University of Patras, Greece. Since then she has held positions as Visiting Lecturer in the Department of Pharmacy, University of Patras (Winter Semester 2003–2004), Visiting Lecturer in the Department of Computer Science, University of Cyprus (Spring Semester 2006–2007), Postdoctoral Researcher in the Laboratory of Foundations of Computer Systems and Theoretical Computer Science, Department of Computer Science, University of Cyprus (2004–September 2008), and is currently an Assistant Professor in the Department of Computer Science and Engineering, European University Cyprus, Cyprus (from October 2008). She has several conference and journal publications and her research interests include Algorithmic Game Theory, Computational Complexity, Graph Theory, Approximation and Combinatorial Algorithms, Networking and Communications.

Vasos Vassiliou is a Lecturer at the Computer Science Department of the University of Cyprus since 2005. He is also the Associate Director of the Networks Research Laboratory (NetRL) at UCY. He held positions as a Visiting Lecturer at the same department (2004–2005) and as an Assistant Professor at the Computer Science Department of Intercollege (2002–2004). He has published several articles in International Conferences and Journals and participates actively in COST actions, local, and European Projects. He holds an M.Sc. (1999) and a Ph.D. (2002) from the Georgia Institute of Technology both in Electrical and Computer Engineering. He is a member of IET (former

IEE), IEEE, ACM, and participates in the Technical Program Committees of several international conferences, such as Globecom, VTC, PIMRC, WNET, EW. He is also an Associate Editor of the Journal of Telecommunication Systems.

Andreas Pitsillides received the B.Sc. (Hns) degree from University of Manchester Institute of Science and Technology (UMIST) and Ph.D. from Swinburne University of Technology, Melbourne, Australia, in 1980 and 1993, respectively. He is a Professor, Department of Computer Science, University of Cyprus, and heads the Networks Research Laboratory (NetRL). Andreas is also a Founding member and Chairman and Scientific Director, of the Cyprus Academic and Research Network (CYNET) since its establishment in 2000. Prior to that he has worked in industry for six years (Siemens 1980–1983, Asea-Brown Boveri, 1983–1986), and from 1987 to 1994 had been with the Swinburne University of Technology (Lecturer, Senior Lecturer 1990–1994, and Foundation Associate Director of the Swinburne Laboratory for Telecommunications Research, 1992–1994). In 1992, he spent a six month period as an academic visitor at the Telstra (Australia) Telecom Research Labs (TRL). Andreas has published over 180 research papers and book chapters, he is the co-editor with Petros Ioannou of the book on Modelling and Control of Complex Systems (CRC Press, ISBN: 978-0-8493-7985-0, 2007), presented invited lectures at major research organisations, has given short courses at international conferences and short courses to industry. Andreas serves/served on the executive committees of major conferences, as, e.g., INFOCOM, WiOpt, ISYC, MCCS, and ICT. He is a member of the IEEE (M'89, SM'2005), of the International Federation of Automatic Control (IFAC) Technical Committee TC 1.5 on Networked Systems and TC 7.3 on Transportation Systems, and of the International Federation of Information Processing (IFIP) working group WG 6.3: Performance of Communications Systems. Andreas is also a member of the Editorial Board of Computer Networks (COMNET) Journal.