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Reputation-based network selection mechanism using game theory

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ABSTRACT

Current and future wireless environments are based on the coexistence of multiple networks supported by various access technologies deployed by different operators. As wireless network deployments increase, their usage is also experiencing a significant growth. In this heterogeneous multi-technology multi-application multi-terminal multi-user environment users will be able to freely connect to any of the available access technologies. Network selection mechanisms will be required in order to keep mobile users "always best connected" anywhere and anytime. In such a heterogeneous environment, game theory techniques can be adopted in order to understand and model competitive or cooperative scenarios between rational decision makers. In this work we propose a theoretical framework for combining reputation-based systems, game theory and network selection mechanism. We define a network reputation factor which reflects the network's previous behaviour in assuring service guarantees to the user. Using the repeated Prisoner's Dilemma game, we model the user–network interaction as a cooperative game and we show that by defining incentives for cooperation and disincentives against defecting on service guarantees, repeated interaction sustains cooperation.

1. Introduction

The next generation of wireless networks is already making its way into our daily lives. Because of the ease of use, affordability, and power of the new mobile devices and the wide range of new mobile applications, mobile users' demands are increasing. According to Cisco [1], the compound annual growth of mobile data traffic is approximately 108%, and expected to reach 3.6 exabytes per month by 2014. More than 90% of the entire mobile broadband traffic is generated by laptops, netbooks, and smartphones. The advances in mobile devices enable people to connect to the Internet from anywhere at any time while on the move (e.g. on foot, in the car, on the bus, stuck in traffic, etc.) or stationary (e.g., at home/office/airport/coffee bars, etc.). Moreover, with the popularity of video-sharing websites like: YouTube, social networks (Twitter, Facebook, Linkedin, MySpace, etc.), mobile TV, entertainment services, etc., there is an exponential growth in video traffic. According to [1], video traffic is expected to reach 66% of the overall wireless data traffic by 2014.

In order to cope with this explosion in data traffic, network operators have started to deploy different radio access technologies in overlapping areas, such as: WLAN, WiMAX, UMTS, and the most recent, LTE. In this way they can accommodate more and more subscribers increasing their revenue.

The coexistence of multiple access technologies deployed by different operators has come to play a very important role, seeking to offer always best connectivity [2] to the Internet for mobile users. Mobile users want to be on the best value network that best satisfies their preferences for their current application(s), while the network operators want to maximize revenue by efficiently using their networks to satisfy and retain the most users possible. Challenges for the operators include network optimization especially for video traffic, if it represents two-thirds of the overall wireless traffic. Uninterrupted, continuous, and smooth video streaming, minimal delay, jitter, and packet

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loss, must be provided in order to avoid degradation in video quality and user experience. The main challenge for the users' multi-mode terminal is to be on the best available radio access network (RAN). The network selection decision is a complex one, with the challenge of trading-off different decision criteria, (e.g. service class type, user's preferences, mobile device being used, battery level, network load, time of day, price, etc.) this is further complicated by the combination of static and dynamic information involved, the accuracy of the information available, and the effort in collecting all of this information with a battery, memory, and processor limited device. This selection decision needs to be made once for connection initiation and subsequently as part of all handover decisions.

Game theory is a mathematical tool aimed at understanding and modelling competitive situations which imply the interaction of rational decision makers with mutual and possibly conflicting interests. In this article we extended our previous work presented in [3] and propose a novel reputation-based network selection mechanism. In [3] we proposed a power-friendly access network selection strategy which selects the least power consuming network in order to avoid the mobile device running out of battery. In this work we focus on the user–network interaction and we define a network reputation factor obtained as a result of the repeated cooperative game. The network reputation factor is integrated then in the network selection decision. To our knowledge no other work combines reputation-based systems with game theory in order to build a reputation-based network selection mechanism.

We start in Section 2 by providing a classification of game theory approaches which focus on resource allocation and network selection. The related works in the area of reputation-based systems are also discussed. In Section 3 we propose a combined network selection and game theory solution. In Section 4 a two-player repeated cooperative game is formulated using the model of repeated Prisoner's Dilemma and the main components of the game are described. Using the cooperative approach, it is assumed that players will cooperate in order to maximize their payoffs. In a realistic scenario, players may choose to cheat or to behave selfishly by seeking to optimize their own payoffs. In Section 5 we analyse the equilibrium of the game. We show that, by defining incentives for cooperation and disincentives against cheating or selfish behaviour, repeated interaction leads to cooperation. Considering the heterogeneous scenario where users have a pool of choices with different RANs (Radio Access Networks) belonging to different operators and users are able to freely choose between them without any contractual agreement. In this situation there is a need for an assurance of service guarantees from both parties. The repeated user–network interaction can be seen as an ongoing relationship in which by using cooperative game theory we demonstrate that we can sustain cooperation without a contract. Section 6 details the computation of the network reputation factor and in Section 7 we present the numerical analysis and simulation results. Conclusions and future work are detailed in Section 8.

2. Related work

One of the first published works on network selection strategies was in 1999 by Wang et al. [4] in which they described a policy-enabled network selection function that uses a cost function defined as the sum of a weighted normalized form of three parameters: bandwidth, power consumption and price. The network with the lowest value for the cost function is chosen as the target network. This cost or score function can be formally classified as a Simple Additive Weighted (SAW) method. Other papers offering variations of the SAW method include [5]. The SAW method can be inaccurate, as shown in [6]. In order to scale different characteristics of different units to a comparable numerical representation, different normalized functions have been used, such as: exponential, logarithmic and linear piecewise functions [6]. Other classical multiple attribute decision-making (MADM) methods have also been used in order to find a solution to the network selection problem. These methods include: TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [7], GRA (Grey Relational Analysis) and AHP (Analytic Hierarchy Process) [8].

Recently game theory has been widely adopted in telecommunication environment, especially in wireless sensor networks [9], cognitive radio networks [10], and ad hoc networks [11]. Game theory is used as a tool in studying, modelling, and analysing the interactions between individuals strategically. In the wireless environment, game theory has been used in order to solve many distributed power control [12], resource management and allocation, and dynamic pricing [13] related problems. A more comprehensive survey on game theory application in wireless networks is offered by Charilas et al. in [14]. In this review, we focus on network selection and resource allocation approaches.

2.1. Game theory

Usually a game consists of a set of players, a set of actions, and a set of payoffs. The players seek to maximize their payoffs by taking actions (also known as strategies) depending on the available information at the time of the action decision. The combination of best strategies for each player is known as equilibrium. When each player cannot benefit anymore by changing his/her strategy while keeping the other players' strategies unchanged, then we say that the solution of the game represents a Nash equilibrium. The payoff for each player can be represented as the actual or expected utility a player receives by playing the current strategy. In general, two kinds of games are used: (1) Cooperative games, which imply the joint considerations of the other players. Usually cooperative games explore the formation of coalitions between various players using a characteristic function to describe the maximum expected total income of the coalition. The core represents the solution concept of a cooperative game, and is usually used in order to obtain the stability region. It gives the set of all feasible outcomes that cannot be improved by the coalition individuals when acting independently. (2) Non-cooperative games in which each player selects his/her strategy individually.

We classify the existing works into three broad categories based on players' interactions:

- *Users vs. Users*—in the non-cooperative approach users compete against each other seeking to maximize

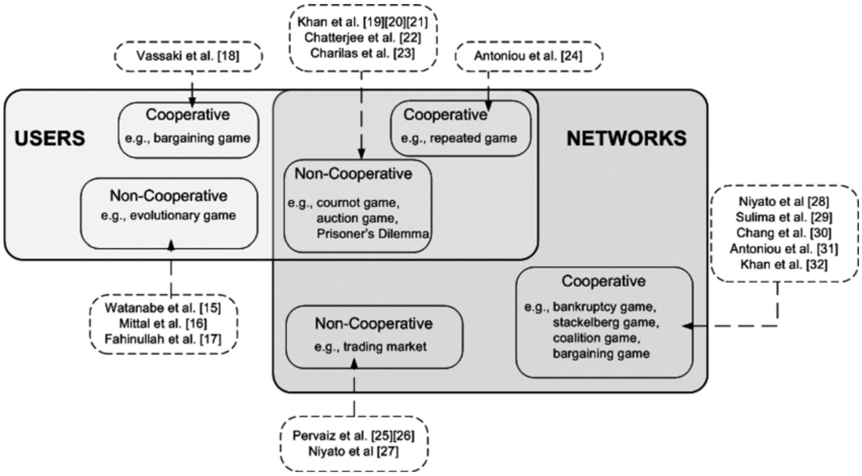


Fig. 1. Selected related work—classified based on players' interactions.

their own utility [15–17]. In the cooperative approach users cooperate in order to obtain mutual advantage (maximize social welfare) [18].

- *Networks vs. Users*—in the non-cooperative approach, users compete against networks, each seeking to maximize their own utility [19–23]. On one side the users try to maximize their cost-benefit performance. On the other side the networks aim to maximize the profit for the provided services. In the cooperative approach, both sides cooperate in order to achieve mutual satisfaction [24].
- *Networks vs. Networks*—in the non-cooperative approach, the networks compete against each other seeking to maximize their individual revenues [25–27]. In the cooperative approach, networks cooperate in order to achieve global welfare maximization [28–32].

As illustrated in Fig. 1, most of the related works formulate the resource allocation and network selection problems as non-cooperative games. Few of the works look at cooperative behaviour, of those that do, most of them are based on cooperation between networks.

Table 1 summarizes the considered approaches. When using game theory in the heterogeneous wireless environment, a set of challenges can be identified. One challenge is to identify the game type to use for the problem e.g. cooperative game or a non-cooperative game. Next, the players of the game, the strategies available to each player and their objectives must be clearly defined as they represent the main components of the game.

Various types of games were used in the literature. For example in the users vs. users scenario Watanabe et al. [15] make use of the *non-cooperative evolutionary game-theory* model in order to study the behaviour of selfish users. They show that equilibrium close to optimal, from the system perspective can be reached, but that the equilibrium is very unfair when users can freely choose their transmission rate for receiving VoIP traffic. In [18] Vassaki et al. model the resource allocation problem as a *cooperative N-person bargaining* problem and the Nash bargaining solution is found. The users' strategies are the bandwidth demands, and they are assumed to be free to bargain in order to achieve mutual advantage.

The *non-cooperative auction game* is used by Khan et al. in [19–21] in order to study the interaction between networks and users while Chatterjee et al. [22] use the *non-cooperative cournot game*, Charilas et al. [23] propose the use of *non-cooperative Prisoner's Dilemma game* in order to address the admission and load control problems, whereas Antoniou et al. [24] look at the network selection problem and model the user–network interaction as a *cooperative repeated game*.

In order to solve the bandwidth allocation problem in cooperative networks vs. networks scenarios Niyato et al. [28] use a *bankruptcy game*, Sulima et al. [29] use a *Stackelberg game*, Antoniou et al. [31] use a *coalition game* and Khan et al. [32] use a *bargaining game*.

Most of the presented solutions used non-cooperative game theory in order to define the interaction between players. Using game theory we can model realistic scenarios in which players compete against each other, each of them seeking to maximize their own profit. On the other side, in cooperative games, players collaborate in order to maximize their payoffs.

Another challenge, evident in Table 1, when designing a cooperative or a non-cooperative game comes when considering a single or multiple operators. Some of the cooperative games in the literature explore the formation of coalition between various networks' operators [29,31]. The networks within a coalition collaborate in order to meet the users' service requirements. The feasibility of such a scenario in the real world where competition among operators is fierce is questionable. Moreover, information regarding the coverage range and operational characteristics of the APs or BSs is considered to be highly confidential to the operators. For example, in [17] the authors assume the existence of an information service deployed in the system which provides information about the available APs and their associated users. It would be unusual for an operator to be willing to provide such information.

Another important aspect is considering the monetary cost incurred by the user as one of the decision parameters. Most of the works consider a flat rate pricing scheme [17,19,25,22] considers differentiated pricing. Considering

Table 1
Summary of the surveyed approaches.

Ref.	Game type	Objective	Players	Strategy set	Payoffs	Resource	RAT	Operator
Watanabe et al. [15]	Non-cooperative evolutionary game	*Resource sharing*—study the behaviour of selfish users who compete for medium access in a WLAN.	Users vs. users	Available transmission rates	Utility function	Bandwidth	WLAN	Single
Mittal et al. [16] Fahimullah et al. [17]	Non-cooperative	*Network selection*—fair users' distribution among the APs.	Users vs. users	All available APs in the network	Utility function	bandwidth	WLAN	Single [16]/multiple [17]
Vassaki et al. [18]	Cooperative bargaining game	*Resource allocation*—optimal bandwidth distribution.	Users vs. users	Requested bandwidth	Utility function	Bandwidth	Cellular	Single
Khan et al. [19–21]	Non-cooperative auction game	*Network selection*—select the network which fulfils the user requirements.	Networks vs. users	Requested bandwidth with associated attributes	Utility function	Bandwidth	HSDPA, WLAN	Multiple
Chatterjee et al. [22]	Non-cooperative cournot game	*Resource allocation*—allocate the available resources among users within user classes.	Networks vs. users	Subscription plan (Premium, Gold, or Silver)	Utility function	power	CDMA	Single
Charilas et al. [23]	Non-cooperative Prisoner's Dilemma	*Resource management*—admission and load control.	Networks vs. users	**Network**: admit or reject; **user**: stay or leave;	Utility function	Bandwidth	Not specified	Multiple
Antoniou et al. [24]	Cooperative repeated game	*Network selection*—achieve a user-satisfying and network-satisfying solution.	Networks vs. users	**Network**: tit-for-tat or cheat-and-return; **user**: Grim, Cheat-and-Leave, Leave-and-Return, or Adaptive return	Utility function	Bandwidth	Not specified	Multiple
Pervaiz [25,26]	Non-cooperative	*Network selection*—select the network which fulfils the user requirements.	Networks vs. networks	Offered prices	Utility function	Bandwidth	WiMAX, WLAN	Multiple
Niyato et al. [27]	Non-cooperative trading market	*Resource allocation*—allocate bandwidth from each available RAN to an incoming connection in a fair manner.	Networks vs. networks	Amount of offered bandwidth	Utility function	Bandwidth	WLAN, CDMA, WMAN	Single
Niyato et al. [28]	Cooperative bankruptcy game	*Admission control*—guarantee the total transmission rate requested by the new connection; *bandwidth allocation*— allocate bandwidth from each network in a fair manner.	Networks vs. networks	Coalition form	Characteristic function	Bandwidth	WLAN, CDMA, WMAN	Single
Sulima et al. [29]	Cooperative Stackelberg game	*Resource allocation*—allocate resources by splitting the user's application over the available networks.	Networks vs. networks	Coalition form	Characteristic function	Bandwidth	Not specified	Single
Chang et al. [30]	Cooperative	*Network selection*- compute the preference value from the network point of view, seeking to decrease the number of handoffs and achieve load balancing.	Networks vs. networks	Preference value for each network	Utility function	Bandwidth	Not specified	Single
Antoniou et al. [31]	Cooperative coalition game	*Resource allocation*—allow individual access networks components to cooperate and share resources.	Networks vs. networks	Coalitions	Characteristic function	Bandwidth	Not specified	Multiple
Khan et al. [32]	Cooperative bargaining game	*Resource allocation*—allocate bandwidth from each network in a fair manner.	Networks vs. networks	Offered bandwidth	Utility function	Bandwidth	Not specified	Multiple

the competitive market, most wireless operators followed the 'all you can eat' model by adopting flat rate pricing schemes. Flat rate pricing works well as long as the usage on the network is reasonable. However, with the exponential increase in data traffic, more wireless operators have had to start adopting usage-based pricing schemes (e.g., AT&T moved to a tiered model). If most wireless operators adopt the usage-based model, then the remaining flat rate wireless operators will attract the heaviest data users.

Involving the user in the decision mechanism is based on the idea that in order to provide a useful solution if not the best one to the customer, service providers should know what each customer really needs and where the real problem lies. As the user preferences play an important role in the decision mechanism another important aspect is the degree of the user's implication. There are many ways of collecting data from the user. Some of the proposed solutions probe the user for some required settings that are transformed afterwards in weightings for the networks parameters [25]. The solution proposed in [19] integrates a GUI in the user's mobile terminal in order to collect the user preferences on the following inputs: Service request class (Data, Video, Voice); Service preferred quality (Excellent, Good, Fair); and Service price preferences (Always Cheapest, Maximum service price). Asking the user for data can be annoying or even invasive to the user as the decision mechanism is no longer transparent. It is very important to find a trade-off between the cost of involving the user and the decision mechanism. One solution for minimizing the user interaction may be implementing an intelligent learning mechanism that could predict the user preferences over time.

As illustrated in Table 1, the existing solutions can be applied to single or multiple types of access network technologies. For example, [15–17] apply only to WLAN networks, [18] applies to cellular, [22] applies only to CDMA networks, while the rest apply to two or even three different technologies.

When considering the energy consumption of a multi-interface mobile device, an important aspect is the connectivity. For example, in [27–29] the authors consider that the multi-interface mobile device has simultaneous connections, with the bandwidth requirements split among multiple networks. In terms of energy consumption, simultaneous connections will drain the battery of the mobile device even faster than a single connection. In terms of monetary cost, simultaneous connections involve more complicated billing for operators running multiple RANs.

2.2. Reputation-based systems

Reputation systems have been studied and applied in the wireless environment [33], especially in mobile ad hoc networks, wireless mesh networks, and Internet-based peer-to-peer, being useful in cooperation scenarios and decision-making problems. For example, reputation systems are used in order to help peers decide with whom to cooperate or not. Peers with good reputation are favoured.

Seigneur et al. in [34] use a reputation system in a telecommunication environment where the users share their QoE information in a peer-to-peer fashion. The authors consider the possible attack from the telecommunication operator that might want to try to influence their QoE levels in order to maintain market position. In this context they present their work in progress towards an attack-resistant computational reputation model by introducing a trust engine for reputation-based network selection. The trust engine is used to manage trust and reputation of different entities. Trust values are computed by the trust engine and assigned to potential networks before the network selection is done. Any mobile terminal can have its own integrated local trust engine that communicates in a peer-to-peer fashion with other trust engines. The main objective is to avoid false information propagation and to facilitate the choice of the best network available.

Salem et al. in [35] look at the problem of selecting a Wireless Internet Service Provider (WISP) when multiple providers are available. The authors propose the integration of a Trusted Central Authority (TCA) into a Wi-Fi environment. All the WISPs will be registered with the TCA which will periodically collect feedback about each WISP in order to update the reputation records. The authors also provide a detailed threat analysis. They have identified eight specific attacks: Publicity, Selective Publicity, Denigration, Flattering, Report Dropping, Service Interruption, Refusal to Pay and Repudiation attacks. They have considered also several general attacks such as: Packet Dropping, Filtering and Replay attacks.

In [36] Zekri et al. propose a reputation system to speed up vertical handover in a complex wireless environment. The proposed reputation system is denoted by the Overlay Reputation Manager (ORM) and is based on the analysis of past connections between mobile terminals and available access networks. The ORM collects information about the individual scores given by users and computes a global rating which represents the network reputation. In the case of a handover the mobile terminal will send a request to the ORM for the available networks' reputations.

Satsiou et al. in [37] propose the use of a reputation-based system in the context of neighbourhood wireless communities. The main objective of a neighbourhood wireless community is to provide free Internet access to its members. The Internet sharing community is formed with a number of APs whose owners are members of the community willing to share their available capacity. Any user who is a member of the community can access the Internet as he/she passes through the neighbourhood. The authors propose a reputation-based allocation framework that based on the reputation of the visiting users decides on how to allocate the available resources. The reputation is computed based on the offered quality of the Internet connection and the past ten transactions. In this way cooperation is induced inside the Internet sharing community and members can enjoy free Internet access.

Most of the reputation-based systems compute a global reputation based on the information gathered from multiple entities. In this context the trust level of each entity is addressed in order to avoid fraudulent behaviour, by providing false information which could increase or decrease the reputation of an entity. In our case, considering the fact that different users have different preferences, different

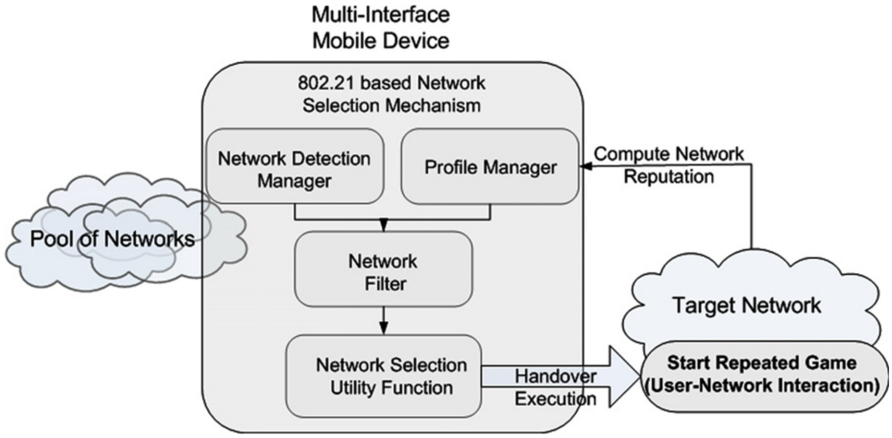


Fig. 2. Network selection mechanism.

device requirements, different application requirements; each mobile terminal will store its own list of reputations for the visited networks, avoiding possible fraudulent behaviour in this way.

3. Network selection mechanism

3.1. System architecture

In this work we propose a reputation-based network selection mechanism based on an extended version of the IEEE 802.21 model [3]. The proposed mechanism makes use of the repeated cooperative game from Game Theory in order to model the user–network interaction and to compute the reputation of the network. Fig. 2 illustrates the system architecture of the proposed network selection mechanism.

The role of the *Network Detection Manager* is to scan the surrounding area and to provide a list of the available networks and their characteristics to the *Network Filter*. A basic minimum/maximum threshold is defined for the main criteria for each application type. The *Network Filter* eliminates the networks which do not meet the minimum criteria for the essential parameters, therefore reducing the computational load. In this way only the networks that pass these thresholds will be considered as candidate access networks for further processing in the network selection algorithm.

In order to compare different RANs we define a score function based on the weighted multiplicative method, which has previously been shown to be useful in [6]. A generic model of our score function is as given in Eq. (1):

$$U_i = \varphi_i \cdot \left[\prod_p u_{p_i}^{w_p} \right] \tag{1}$$

where Ui is the user utility of RAN i; φ_i is the reputation factor of RAN i; p is the number of parameters considered; u_{p_i} is the utility function for parameter p for RAN i; w_p is the weight of parameter p, where $\sum_p w_p = 1$.

In this work the proposed network selection algorithm takes three parameters into consideration: the energy consumption of the mobile device when running real-time applications, the monetary cost of the network, application requirements and estimated network conditions in terms of average throughput. The network selection decision is designed for a user device which is running only one application (video streaming) at a time using a single link connection with one of the available RANs.

The *Profile Manager* module keeps track of the user profile, device profile, application requirements, and operator profile which includes information about its reputation. The user profile collects information about the user preferences used to weight the network parameters. In this work we do not focus on the definition of the weights but, as we mentioned before, there are many ways of collecting data from the user. For example, in [38,39] the authors propose probing the user while the authors in [40] obtain the weights through questionnaires on user and service requirements. Another solution makes use of a GUI in the user's mobile terminal in order to collect the user preferences. One solution could be taking the user preferences at start-up time of the mobile terminal, and trying to minimize the user interaction by integrating an intelligent learning mechanism that could predict the user preferences over time. Of course the user will still have the possibility to manually set his/her preferences. All these gathered parameters are then used in evaluating the network selection utility function. The network with the highest score is selected as the target network and the *Handover Execution* module will setup the connection to the selected network for call initiation. If the setup is unsuccessful, due to the target RAN's admission control mechanism, the next highest ranking RAN is chosen. After the call initiation process the mobile user will be fully served by the new network and the *Two-Player Repeated Cooperative Game* starts. The network is considered to be Defecting when its offered utility goes below the minimum acceptable utility of the user. At the end of each user–network interaction a reputation factor is computed and the operator's profile is updated in the *Profile Manager*.

3.2. Score function

The proposed network selection score function is a multiplicative multi-criteria utility function as defined in Eq. (2):

$$U_i = \varphi_i \cdot [u_{e_i}^{w_e} \cdot u_{q_i}^{w_q} \cdot u_{c_i}^{w_c}] \quad (2)$$

where U is the overall utility for RAN i; $\varphi_i \in [0, 1]$ is the network reputation factor of the RAN i, u_e, u_q, and u_c are the utility functions defined for energy, quality in terms of received bandwidth, and monetary cost for RAN i respectively. Also $w_e + w_q + w_c = 1$, where w_e, w_q, w_c are the weights for the considered criteria, representing the importance of a parameter in the decision algorithm. The network reputation factor (ref. Section 6), α_i, represents the degradation observed by the user in his/her past interactions with the network, the higher the value of the network reputation factor the smaller the observed degradation. The overall score function is computed for each of the selected candidate networks and the network with the highest score is selected as target network.

- *Energy utility—u_e*

The estimated energy consumption for a real-time application is computed using Eq. (3) as defined in [41].

$$E = t(r_t + Th_{\text{req}} r_d) + c \quad (3)$$

where t represents the transaction time (s), r_t is the mobile device's energy consumption per unit of time (W), Th_{req} is required throughput (kbps), r_d is energy consumption rate for data/received stream (J/Kbyte), c is a constant, and E is the total energy consumed (J).

The transaction time can be predicted from the duration of the video stream. The parameters r_d and r_t can be determined by running different simulations for various amounts of data and defining a power consumption pattern for each interface.

Having calculated the estimated energy consumption, E using Eq. (3), and following the principle "the smaller the better", we define the energy utility, u_e, as in Eq. (4):

$$u_e = \begin{cases} 1, & E < E_{\min} \\ \dfrac{E_{\max} - E}{E_{\max} - E_{\min}}, & E_{\min} <= E < E_{\max} \\ 0, & otherwise \end{cases} \quad (4)$$

where $E_{\min}$ is the minimum energy consumption and $E_{\max}$ is the maximum energy consumption needed for the current video streaming application to run until completion. Both $E_{\min}$ and $E_{\max}$ are computed using Eq. (3) for $Th_{\min}$ and $Th_{\max}$ respectively.

- *Quality utility—u_q*

In order to map the received bandwidth to user satisfaction we define a zone-based quality sigmoid utility function which is illustrated in Fig. 3. The utility is computed based on: the minimum throughput ($Th_{\min}$) needed to maintain the multimedia service at a minimum acceptable quality, values below this threshold result in unacceptable quality levels; the required minimum throughput (Th_{req}) in order to ensure high quality levels for the multimedia service; the maximum throughput ($Th_{\max}$), values above this threshold result in quality levels which are higher than humans need or can distinguish between. The buffer is setup

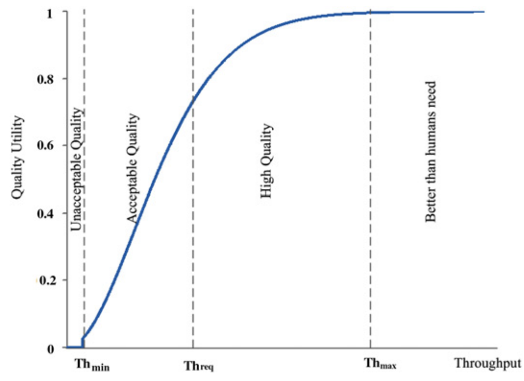


Fig. 3. Zone-based quality sigmoid utility function.

to cover any delay variation. The mathematical formulation of this quality utility function is given in Eq. (5).

$$u_q = \begin{cases} 0, & Th < Th_{\min} \\ 1 - e^{\frac{-\alpha * Th^2}{\beta + Th}}, & Th_{\min} <= Th < Th_{\max} \\ 1, & otherwise \end{cases} \quad (5)$$

where α and β are two positive parameters which determine the shape of the utility function and Th is the predicted average throughput for each of the candidate networks.

- *Cost utility—u_c*

Because the monetary cost also follows the principle "the smaller the better", the cost utility u_c is defined as given in Eq. (6):

$$u_c = \begin{cases} 1, & C < C_{\min} \\ \dfrac{C_{\max} - C}{C_{\max} - C_{\min}}, & C_{\min} <= C < C_{\max} \\ 0, & otherwise \end{cases} \quad (6)$$

where C is the monetary cost for the current network, $C_{\min}$ is the minimum cost that the user is willing to pay and $C_{\max}$ is the maximum possible cost that the user can afford to pay.

The computational efficiency is an important concern when dealing with network selection algorithms. In our particular case a number of different processes are executed. For example, let us consider the case of one mobile user with the network selection algorithm enabled on his/her mobile device and located in the coverage area of a number of available wireless networks. First, the algorithm will start an elimination process and from the list of available wireless networks only the networks that pass the required thresholds will be selected and further processed. The elimination process will reduce a good amount of the computational load. For each candidate network we compute the energy consumption, the quality utility, the energy utility, the payoff function, the reputation factor, and the overall utility. The network that has the maximum score is selected as the target network. The process is repeated every time the current network fails to fulfil the user requirements or another better network is available.

4. Two-player repeated cooperative game formulation and components

In order to study the interaction between the user and the network, we make use of game theory and formulate the problem as a cooperative repeated Prisoner's Dilemma game. The user and the network cooperate in order to achieve Nash equilibrium. The outcome of the game seeks to reach both the user and the network satisfaction. The game can be defined as follows:

- *Players*: The players in this game are the user and the network.
- *Strategies*: Following the model of the repeated Prisoner's Dilemma game, we define a set of three strategies for each player.
  The user's strategies are:
  - *Cooperate*: the user accepts the network's offer and stays;
  - *GRIM*: always cooperate as long as the network cooperates;
  - *Defect*: the user decides to leave the network if the network does not offer the minimum requested QoS, or a better offer is available.

  The network's strategies are:
  - *Cooperate*: the network accepts to maintain the QoS at the required level for the user;
  - *GRIM*: always cooperate as long as the user cooperates;
  - *Defect*: the network decides not to fulfil the QoS requirements of the user anymore, acting selfishly by trying to increase its own revenue and admitting new users to a crowded cell, attempting to accommodate more users at the cost of a reduced level of quality for some/all existing users.

The *GRIM* strategy is the one in which the players *Cooperate* as long as the opponent does the same. If one of the players fails to reciprocate, the opponent will switch to *Defect* permanently or temporarily. If the network *Defects* then the value of the network reputation factor α is decreased. This will impact the network's score next time the Network Selection Decision takes place.

- *Payoffs*: We define payoff functions for the user and the network as follows:
  - *User's payoff function*

Each player's gain when playing the repeated cooperation game is defined through payoff functions. The user satisfaction and the perceived quality of the service are two directly proportional factors. As we have seen in Fig. 3, the quality of the service is an increasing function of the average throughput received. In order to have a non-zero utility for the user satisfaction a minimum amount of throughput is needed. At the other extreme, if the received throughput is more than the maximum needed for the service, the improvement in the quality is unnoticeable for humans. When the received throughput is in between the two thresholds, $Th_{\min}$ and $Th_{\max}$, the utility presents significant changes. In order to avoid brutal changes in the quality by jumping from a high quality level to a low quality level, which can be disturbing for the user, an adaptive multimedia mechanism is integrated. The adaptive mechanism can smoothly change from one quality level to another with reduced impact on the user satisfaction.

We define the user's payoff (π_M) as in Eq. (7). π_M for the user can be expressed as the difference between the benefit obtained in terms of service quality and the cost incurred, as the price paid by the user for the specific service.

$$\pi_M = U_i * B - C_i + P_{\text{new}} - C_{\text{HO}} \tag{7}$$

where π_M is the user's payoff, U_i is the user overall utility for the current network i, B is the user's budget, C_i is the cost of the current network i, P is the user's payoff if he/she would handover to a new network (is 0 when the user Cooperates), C_{HO} is the cost of handover to a new network (is 0 when the user Cooperates).

- *Network's payoff function*

On the network operators' side we can identify the operator's attitude towards long-term and short-term gains in profit. If the network acts selfish by trying to maximize its own revenue, then the immediate maximization of its payoff would be the increase in the number of customers. However, admitting a large number of users into one network is not always the best option when trying to maximize the profit for the service. By admitting more and more users into one cell or AP generates the risk of degrading the service quality of experience (QoE) for the already connected users. As the number of admitted users increases, the quality of the service decreases which leads to users leaving the network and a corresponding decrease in revenue for the operator.

We define the network's payoff as in Eq. (8):

$$\pi_N = G - C_{\text{QoS}} - L_{\text{rev}} \tag{8}$$

where π_N is the network's payoff, G is the network gain (money gained from user payments for the services used in the network), C_{QoS} is the cost paid by the network for the current QoS provisioning, L_{rev} is the loss of revenue in case the user decides to defect/leave the network (is 0 if the user Cooperates).

5. Analysis of equilibrium

After the network selection decision takes place, and the target network is selected, the two-player repeated cooperative game starts. We assume that the game starts with the network's *Cooperate* strategy. If the user's response will be *Cooperate*, then the network will switch to playing *GRIM*. Even though the network's strategy is *Cooperate*, it might happen that the user perceives degradation in the quality of service. This is because of the wireless environment where connections are prone to interference, high data loss rates, and/or disconnection. In general, the errors in the wireless environment are random and can be represented by the Nature player. Fig. 4 illustrates an example of an extensive form of the one-shot user–network game where the Nature player is integrated.

Nash Equilibrium (NE) represents the steady state of the play of the game where no player can benefit by changing his/her strategy while the other players keep their strategies unchanged.

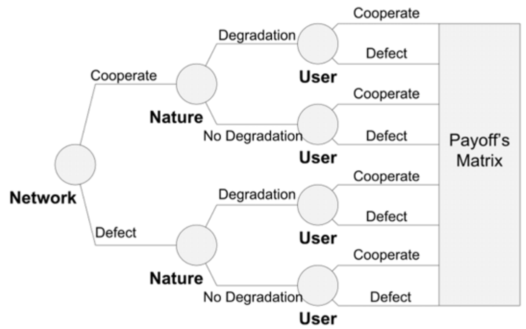


Fig. 4. Extensive form of the one-shot user–network game.

Table 2
General payoffs user–network repeated game.

	Player 2—network			
		Cooperate	GRIM	Defect
	Cooperate	B_1B_2	B_1B_2	D_1A_2
Player 1—user	GRIM	B_1B_2	$\boxed{B_1B_2}$ NE	C_1C_2
	Defect	A_1D_2	C_1C_2	C_1C_2 NE

Definition 1. By definition, a pair of strategies is said to be the *Nash Equilibrium* of the game if and only if each player's strategy is the best response to the other's strategy.

When dealing with cooperative games, a standard assumption is that a rational agreement will be Pareto efficient.

Definition 2. By definition, an agreement is said to be *Pareto efficient* if and only if there is no other feasible agreement that all the players prefer.

An approach on explaining how cooperation can survive in long-term relationships without the need for external enforcement is finding *a Pareto-efficient Nash Equilibrium* in the user–network repeated game.

Usually a repeated game has a huge number of strategies, leading to an infinite number of Nash equilibrium. In this work, following the model of repeated Prisoner's Dilemma, we look at three strategies: *Cooperate*, *Defect*, and *GRIM*. Considering that the game starts with the network playing *Cooperate*, then the user has two options to *Cooperate* or to *Defect*. If the user decides to *Cooperate* in the first stage, then the game will continue by playing *GRIM* in the next stages. The general payoff table of the game is illustrated in Table 2. Each player $k \in \{1, 2\}$ has a payoff such that $A_k > B_k > C_k > D_k$.

Observing the payoff's table, we notice that the user gets the highest payoff if the network *Cooperates* and he/she *Defects*. This can happen when another better offer is available and the user decides to switch to that network. On the other side, the network gets the highest payoff when the user decides to *Cooperate* but the network *Defects*. This happens when the network operator acts selfishly, trying to maximize the short-term increase in its own payoff by squeezing in extra users which finally will lead on low QoS for the user. The meaning of the general payoffs is illustrated in Table 3.

From the payoff Table 2 we notice that if the user–network repeated game would have had only *Cooperate* and *Defect* strategies it would be reduced to one-shot version of the game. Two *Nash Equilibrium* can be identified from the payoff table, one for punishment when both players *Defect*, and one for reward when both players play *GRIM*. Usually if a repeated game has more than one NE, then the prospect of playing different equilibria in the next stage is used, in order to provide incentives (rewards and punishments) for cooperation in the current stage.

In order to sustain NE in the game we have to show that the user would earn more if he/she plays *Cooperate* rather than *Defect*. If the user selects to *Cooperate* in the first stage then his/her payoff would be B1 plus the payoff from the next stage when both will play *GRIM* which is B1, leading to a total payoff of 2B1. If the user decides to *Defect* in the first stage, then his/her payoff would be A1 plus the payoff from the next stage when both players *Defect*, leading to a total payoff of $A_1 + C_1$. In order to sustain NE we need $2B_1 > A_1 + C_1$.

Another way of showing this is by comparing the temptation to *Defect* in the current stage with the value of rewards and punishment in the next stage. We have to show that

$$\text{temptation to Defect in the } \textbf{\textit{current stage}} \leq \text{the value of reward–value of punishment in the } \textbf{\textit{next stage}}. \tag{9}$$

The temptation to *Defect* in the current stage is given by the difference between the payoff the user gets by playing *Cooperate* and the payoff the user gets by playing *Defect*: A_1–B_1. The value of reward in the next stage is given by the payoff the user gets when both players play *GRIM*, which is B_1. The value of punishment in the next stage is given by the payoff the user gets when both players *Defect*, which is C_1. Putting all together we have:

$$A_1 - B_1 \leq B_1 - C_1$$
$$\Leftrightarrow$$
$$A_1 - B_1 \geq -B_1 + C_1$$
$$\Leftrightarrow$$
$$A_1 \geq C_1$$

but we know that $A_1 > B_1 > C_1 > D_1$
$\Rightarrow$ *True* $\rightarrow$ *enables us to sustain* ***Cooperation***.

Using the two NE, one for punishment and one for reward, enables us to sustain *Cooperation*.

Usually, when the duration of the game is known, the players tend to play *Defect* in the last period. In this work the game between the user and the network has no known end, but we define a probability of continuity δ. In order to sustain NE in a game with unknown end, we have to demonstrate the same as in (9). The value of temptation to *Defect* in the current stage is the same as before, but the value of reward in the next stage is given by the payoff earned when playing *Cooperate* for the entire period of the rest of the game, till the game ends. The value of punishment in the next stage is given by the payoff earned when playing *Defect* till the game stops. The difference of the two values is multiplied by δ, where $\delta < 1$ as the game may end and the next period might not happen.

Table 3
Mapping table.

User's payoffs	
A1	The payoff the user gets when the network *Cooperates* but another better offer is available, expressed as the difference between the benefit the user gets from the service and the cost incurred in the new network (*the payoff of the new network* > *the payoff of the current network*).
B1	The payoff the user gets when both players *Cooperate* or play *GRIM*, expressed as the difference between the service quality and the cost of the current network.
C1	The payoff the user gets when both players *Defect* or one plays *GRIM* and the other one *Defects*, expressed as the difference between the service utility when the network does not offer the requested QoS and the cost incurred when the user decides to leave.
D1	The payoff the user gets when he/she *Cooperates* but the network acts selfishly by trying to maximize its own payoff and *Defects*, expressed as the difference between the quality utility when the network is not offering the requested QoS to the user and the cost utility charged as for receiving the requested QoS.
Network's payoffs	
A2	The payoff the network gets when the user *Cooperates* but the network *Defects* seeking short-term maximization of its own revenue, expressed as the difference between the compensation received by accepting other users, and the cost incurred in supporting the requirements.
B2	The payoff the network gets when both players *Cooperate* or play *GRIM*, expressed as the difference between the compensation received from the user and the cost incurred in supporting the requirements.
C2	The payoff the network gets when both players *Defect* or one plays *GRIM* and the other one *Defects*, expressed as the difference between the compensation received after the user decides to leave the network and the cost incurred in supporting lower QoS requirements.
D2	The payoff the network gets when *Cooperates*but the user decides to leave the network as a better offer is available, expressed as the difference between the compensation received after the user decides to leave and the cost incurred on offering the requirements.

$$A_1 - B_1 \le [B_1\,\textit{for the rest of the game} - C_1\,\textit{for the rest of the game}] \times \delta;$$
$$B_1\,\textit{for the rest of the game} = B_1 + B_1\delta + B_1\delta^2 + \cdots = B_1/(1-\delta);$$
$$C_1\,\textit{for the rest of the game} = C_1 + C_1\delta + C_1\delta^2 + \cdots = C_1/(1-\delta);$$
$$\Leftrightarrow$$
$$A_1 - B_1 \le [B_1/(1-\delta) - C_1/(1-\delta)] \times \delta$$
$$\Leftrightarrow$$
$$\text{if } \delta > (A_1 - B_1)/(A_1 - C_1)\ \textit{enablesus to sustain}\ \boldsymbol{Cooperation}.$$

This analysis shows that we can get cooperation by using the GRIM trigger as a sub-game perfect equilibrium provided $\delta > (A_1 - B_1)/(A_1 - C_1)$. For continuous interactions, to provide incentives for cooperation, it helps to have a future, meaning that the probability that the interaction will continue in the next period is high. The continuity probability represents the weight we put on the future interactions. We need that the probability of interaction to continue to be reasonable high in order to overcome the temptation to *Defect*.

6. Network reputation factor

In our work, in order to strengthen the cooperation between users and networks by keeping track of past behaviour, we define a network reputation factor, φ which is considered in the network selection decision. φ is computed based on the user's past interactions with the network. We assume that at the first contact between user and network, $\varphi = 1$, meaning that the network reputation factor will not have any impact on the selection as there is no history between the user and the network.

Assuming a mobile user which had a number of n past interactions with a network i, a simple computation of φ_i can be given by Eq. (10):

$$\varphi_i = \sum_{j=1}^{n} \pi_{M_{ji}} \Big/ n \qquad (10)$$

where, $\pi_{M_{ji}}$ represents the user's average payoff at the end of interaction j with network i.

In Eq. (10), both the most recent interaction as well as the oldest are given same importance. Considering the fact that people tend to remember recent experience more than the past ones [42], we choose to define a weight for each interaction. In this way the reputation computation becomes more dynamic preventing the case in which an operator, after getting high reputation in the past, can change his/her attitude by acting selfish, in the recent times. For this reason the present interactions will have a higher weight which will reduce smoothly as the interaction becomes older.

We define the network reputation factor, φ for a network i, based on the age of the interaction as given in Eq. (11):

$$\varphi_i = \sum_{j=1}^{n} w_{ji}\pi_{M_{ji}} \Big/ n \qquad (11)$$

where w_{ji} represents the weight assigned to interaction j with network i.

The weight of the interaction is computed using Eq. (12):

$$w_{ji} = (e^{(j-n)/\rho} - 1)/(e^{-n/\rho} - 1) \qquad (12)$$

where j is the interaction with network i, n is the total number of interactions, ρ (Rho) is the importance tolerance of the weights. The values of w_{ij} are between 0 and 1, meaning that recent interactions are given higher importance which is reduced with time passing.

7. Simulation results

7.1. Impact of different strategies on the payoffs

In this section we examine the impact of different strategies and payoffs on the user–network interaction. In order to do this we implemented an analytical model of the repeated game in Matlab. There are three strategies for the network: GRIM—the network cooperates as long as the user cooperates, Always Defect—the network defects in each round, and Random Behaviour—there is a random chance for the network to defect of to cooperate. On the other side, the user can make use of four strategies:

Table 4
Payoffs.

		Simulation set 1		Simulation set 2	
		Network		Network	
		Cooperate	Defect	Cooperate	Defect
User	Cooperate	3/3	1/4	60/60	1/100
	Defect	4/1	2/2	100/1	40/40

GRIM—the user cooperates as long as the network does the same, Tit for Two Tats—the user will defect if the network defects two consecutive times, Tit for Random Tats—the user will defect if the network defects a random number of consecutive times, and Always Cooperate—the user will cooperate in each round. The payoffs were selected in order to simplify the analysis of different strategies and they are based on the previously mentioned relationship: $A > B > C > D$. We ran two sets of simulations using different payoffs and the same combination of strategies. The payoffs are illustrated in Table 4.

For example, in the first simulation set if the user Cooperates and the network Defects, the user will get 1 while the network gets 4. In the second simulation set we increased the gap between the payoffs received when Cooperating and the payoffs received when Defecting. In this case the cooperating user will get 1 and the defecting network 100. When the user Defects, it means that the user leaves the network for a random number of rounds. We assume that another better network that fulfils his/her requirements is available. The user's total accumulated payoff will include the payoff for the current round and previous rounds. The payoff for the rest of the rounds (where he/she has left the network) is zero. A new random number is generated every time the user comes back, and is different for each of the strategies and simulation sets.

For each simulation set and strategy combination we ran 100 simulations with random number of rounds per simulation so that we could cover the behaviour when the user–network interaction is both short-term and long-term. The minimum number of rounds generated was 3 and the maximum number was 935. Based on the cumulative user and network payoffs per simulation we computed the average cumulative payoffs from all the simulations runs, for an average of 258.46 rounds. Table 5 illustrates the results of both simulation sets.

We see that in both cases the Network gets the best score when it plays Always Defect and the user plays Always Cooperate. This means that the Network offers a quality to the user, which is below the minimum acceptable threshold, and the user accepts it. This will not happen in real life, as users expect to usually get the service quality they are paying for. When the network plays Random we can see the different behaviour of the user for each strategy. For example, when the user plays GRIM, the network defects (ND) 49.9% of the rounds and the user cooperates (UC) only 20.2% of the rounds, getting a smaller payoff. This payoff reflects only the payoff the user gets from this particular user–network interaction, without considering the payoff he/she gets from the other network that he/she connects to when leaving the current network. This means that his/her actual payoff is greater. In this case, when the user plays GRIM and the network defects almost 50% of the rounds, the situation in which the user is not willing to accept poor quality is reflected. If the user plays Tit for Random Tats, even though his/her payoff will be higher by cooperating 95.13% of the rounds, the network still defects 49.9% of the rounds. So the user is suffering the poor service quality offered by the network.

The situation that satisfies both parties, and is the most convenient for both the network and the user is when the network plays GRIM and the user plays any of his/her strategies. Only then they will both gain from the user–network interaction.

7.2. *Impact of user preferences on the network reputation*

Different users, having different preferences will generate different reputation factors for the networks that they visit. The network reputation depends on a particular user profile and whether they are using the current application for business or for personal use. For example, a network that generally offers good quality levels for a reasonable price can have a better reputation for a user that prefers quality over energy conservation or cost, than for a user that can accept a lower quality level for a cheaper price. In this section we study the impact of different user preferences on the network reputation. The user's and network's payoffs are computed using Eqs. (7) and (8), respectively, as defined in Section 4.

The quality utility is computed based on Eq. (5). $Th_{\min}$, Th_{req}, and $Th_{\max}$ were selected considering the case of a client–server adaptive multimedia streaming system, where at the server side there will be located a number of different quality levels. For example, there can be five quality levels: 120, 240, 480, 960, and 1920 kbps. In case

Table 5
Average cumulative payoffs from all strategy combinations.

			Network			
			GRIM	Always defect	Random	
Simulation set 1	User	GRIM	**775.38**/**775.38**	3/6	131.29/209.71	49.9% ND & 20.2% UC
		Tit for 2 Tats	**775.38**/**775.38**	4/10	233.6/396.35	49.8% ND & 41.8% UC
		Tit for R Tats	**775.38**/**775.38**	8.37/27.6	493.59/861.78	49.9% ND & 95.13% UC
		Always Cooperate	**775.38**/**775.38**	258.46/**1030**	515.98/905.08	50.17% ND & 100% UC
Simulation set 2		GRIM	**15 500**/**15 500**	41/140	2170/4765	49.6% ND & 20.49 UC
		Tit for 2 Tats	**15 500**/**15 500**	42/240	3600/8980	49.8% ND & 41.49% UC
		Tit for R Tats	**15 500**/**15 500**	45.81/660.60	7640/19 900	49.7% ND & 96% UC
		Always cooperate	**15 500**/**15 500**	258.46/**25 846**	7900/20 700	49.9% ND & 100% UC

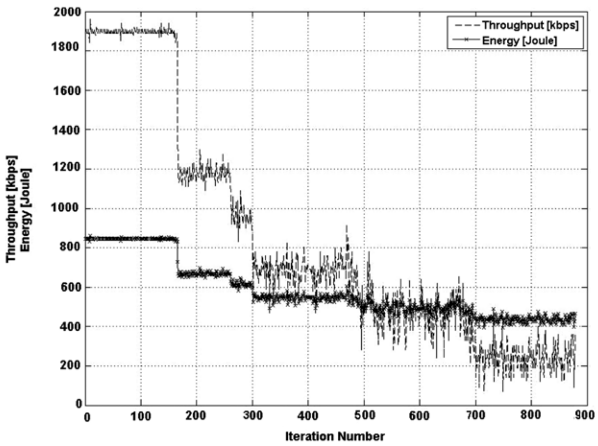


Fig. 5. Throughput trace and energy consumption.

of a WLAN network, depending on the network conditions one of the five quality levels can be streamed. In case of a cellular network (e.g., HSDPA), depending on the network conditions one of the first three streams can be streamed, as the downlink rate is much lower in a cellular network. Assuming that we have a WLAN network we compute u_q for $Th_{\min} = 120$ kbps, $Th_{\text{req}} = 480$ kbps, and $Th_{\max} = 1920$ kbps as:

$$u_q = 1 - e^{\frac{-5.72*Th^2}{2.66+Th}}.$$

The energy utility is based on and computed with Eq. (4), as defined in Section 3, and making use of the data provided in [39]. We compute $E_{\min}$, E_{req}, and $E_{\max}$ based on $Th_{\min}$, Th_{req}, and $Th_{\max}$ and assuming that the user is streaming a 10 min video clip. We assume that the user has a budget of 10 c/KB, meaning that he/she is willing to spent up to $B = 10$ c/KB. We assume a flat rate cost and we select the cost of the network based on the current offers on the market for pay as you go option: $C = 2$ c/KB (Meteor Ireland).

The cost paid by the network for the current QoS provisioning is computed using: $C_{\text{QoS}} = u_q * 40\% * G$. We assume that as the network offers a lower QoS, its cost for provisioning is decreasing, therefore increasing the revenue. For example, considering that the network advertises data rates of 2 Mbps for a price of 2 c/KB while actually offering 0.48 Mbps for the same price, its payoff will be $2 - 0.34 * 0.4 * 2 = 1.728$. For the purpose of the study we assume the values for the C_{HO} and L_{rev} are random values in the [0, 1] interval. The payoff of the user in case he/she handovers to a new network, P_{new} is assumed to be the payoff the user gets for U_{req}, having the same budget and same network cost.

In order to study the impact of different user preferences, we considered three cases:

- First case (quality-oriented user)—the user prefers high quality over low energy and cost: $w_q = 0.6$, $w_e = 0.2$, $w_c = 0.2$.
- Second case (energy-oriented user)—the user prefers low energy over high quality and low cost: $w_q = 0.2$, $w_e = 0.6$, $w_c = 0.2$.

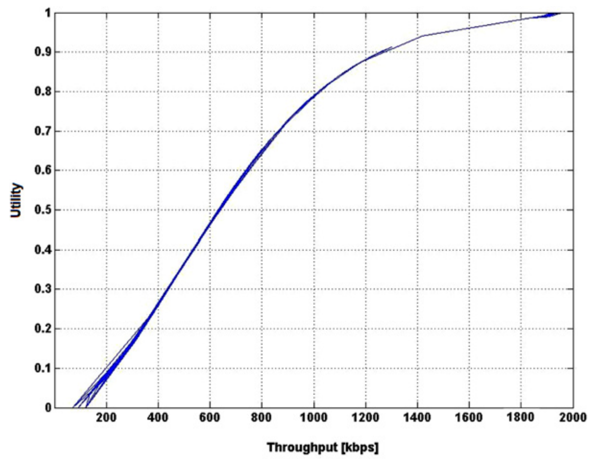
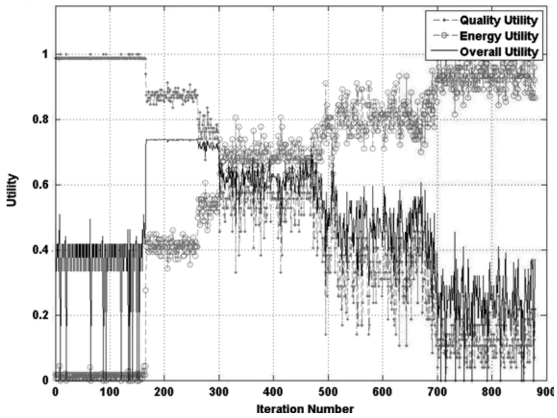


Fig. 6. Quality utility.

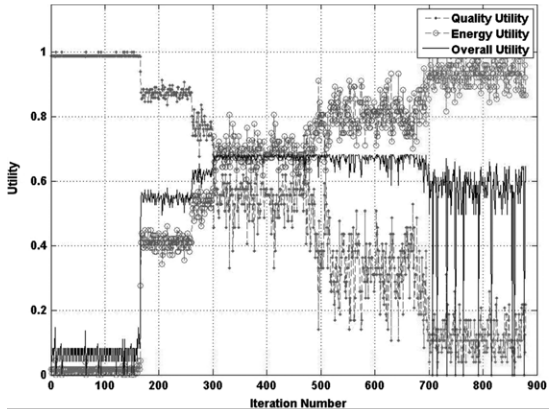
- Third case (quality & energy focused user)—the user equally prefers quality and energy over cost: $w_q = 0.4$, $w_e = 0.4$, $w_c = 0.2$.

We implemented the repeated game in Matlab as proof of concept. A CBR (1920 kbps data rate) throughput trace file generated from NS-2, was delivered over WLAN network that becomes overloaded in time. The throughput trace file contains throughput values that range from very high values to very low values, for simulation purposes in order to cover all different possible network loads. Note that in real scenarios the throughput does not vary as much as in this trace file. The same trace file was used for all three cases. Based on the throughput trace file we compute the energy consumption and the quality utility as illustrated in Figs. 5 and 6.

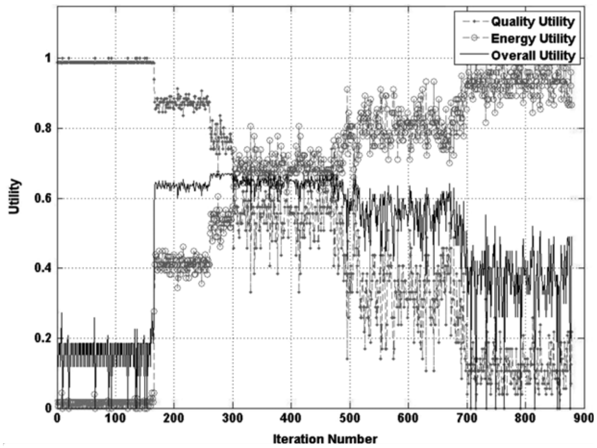
For each of the three cases we compute the overall user utility for WLAN as $U = u_e^{w_e} \cdot u_q^{w_q} \cdot u_c^{w_c}$. The quality utility ($u_q$), energy utility ($u_e$) and overall utility ($U$), for all three cases considered in our simulation, are illustrated in Fig. 7. It is clear that the quality utility is high when the throughput is high and decreases as the throughput decreases; on the other side, the energy utility is low when the throughput is high, as the energy consumption will



(a) First case ($w_q = 0.6$, $w_e = 0.2$, $w_c = 0.2$).



(b) Second case ($w_q = 0.2$, $w_e = 0.6$, $w_c = 0.2$).



(c) Third case ($w_q = 0.4$, $w_e = 0.4$, $w_c = 0.2$).

Fig. 7. Quality utility, energy utility, and overall utility for the three cases.

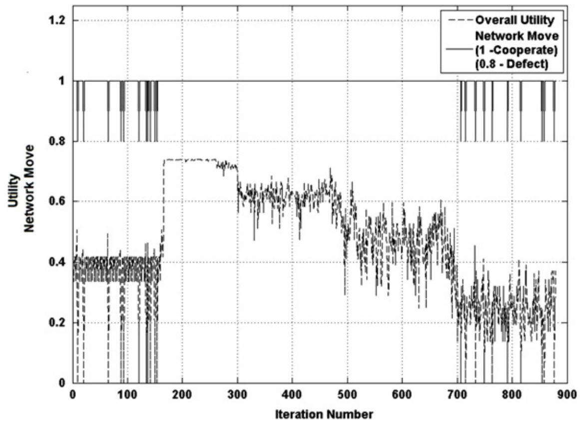
also be high, and increases as the throughput decreases. By varying user preferences we can see that when the user prefers the quality (first case) although the quality utility is high, the overall utility is low because the energy consumption is very high and this does not represent a good trade-off for the user. If the throughput is very high, better quality is supported but more energy is consumed, and if the user will not be able to watch the full multimedia stream due to possible battery depletion then, it is not worth to the user that the quality was high.

A good trade-off between the energy and throughput is needed, and this is obtained through the utility function as illustrated in Fig. 7(a), (b), and (c). In Fig. 7(b), when the user prefers the energy conservation, the overall utility is very low for high values of quality utility as the energy consumption is significant.

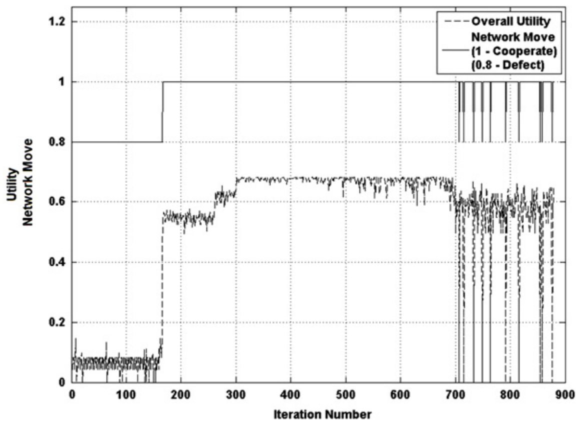
For the three different cases the Network will have different reputation factors. We consider that the network Defects when its offered utility goes below the minimum acceptable utility of the user. Because user preferences are different, every user will have different minimum acceptable utilities. When the user prefers higher quality (first case), its minimum acceptable utility and the required utility are: $U_{\min} = 0.1167$ and $U_{\text{req}} = 0.4786$, respectively. For the second case $U_{\min} = 0.4743$ and $U_{\text{req}} = 0.6737$ and for the third case $U_{\min} = 0.2350$ and $U_{\text{req}} = 0.567$. The Overall Utility and the network's move (1 denotes Cooperation and 0.8 denotes Defection) are illustrated in Fig. 8.

As mentioned before, for the first case even though the network offers high quality utility, the trade-off quality-energy represented by the overall utility is not acceptable, therefore the network is considered by the user to be Defecting. In the Second case, when the user prefers more the energy conservation, for the high values of the quality utility the network will be defecting for this user, only when its overall utility goes above $U_{\min} = 0.4743$, the network starts Cooperating.

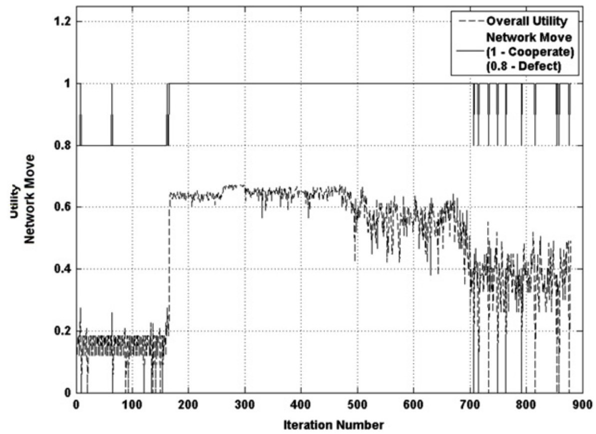
Of course, in a real scenario even though the network offers high throughput values, and the user prefers more the energy conservation meaning lower throughput, adaptive mechanisms can be integrated in order to reduce



(a) First case ($U_{\min} = 0.1167$ and $U_{\text{req}} = 0.4786$).



(b) Second case ($U_{\min} = 0.4743$ and $U_{\text{req}} = 0.6737$).



(c) Third case ($U_{\min} = 0.2350$ and $U_{\text{req}} = 0.567$).

Fig. 8. Overall utility and network moves (1 for Cooperation and 0.8 for Defection) for the three cases.

the received throughput based on the user preferences. As mentioned, in this work we used this example only as proof of concept.

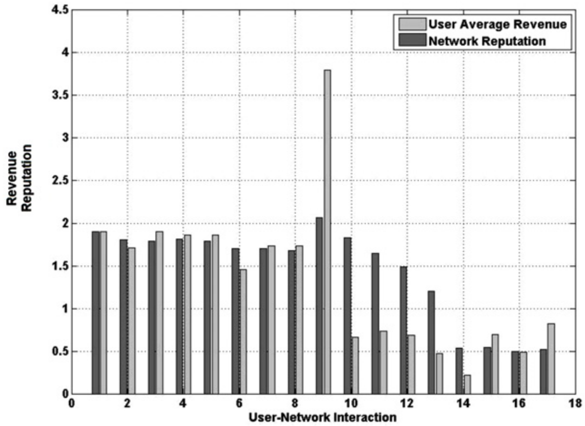
In all the above cases the network cooperates only when a good trade-off quality-energy is reached. This is based on the user preferences. In all the cases the user plays GRIM.

We consider a user–network interaction as the period in which the user and the network are cooperating. The average revenue for each interaction is computed as well as the reputation factor of the network at the end of each interaction. The network reputation factor is computed using Eq. (11) considering the history of five past interactions with the network. The weight of each interaction is computed using Eq. (12) with $\rho = 2.5$. The recent interactions are given higher importance, and reducing with time passing. The average user's revenues and the network reputation factor variation for the three networks are illustrated in Fig. 9.

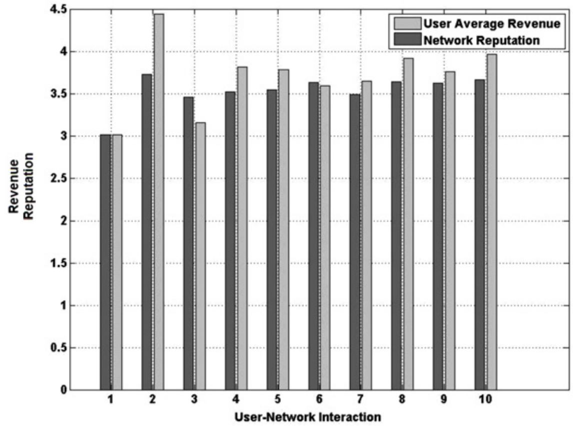
The results show that for the same network, considering different user preferences, each user will score the network different, and they will have different reputation factors based on their requirements. In all three cases, as the average revenue of the user is increasing so is the reputation. If user's average revenue is decreasing, the reputation is decreasing as well.

8. Conclusions and future work

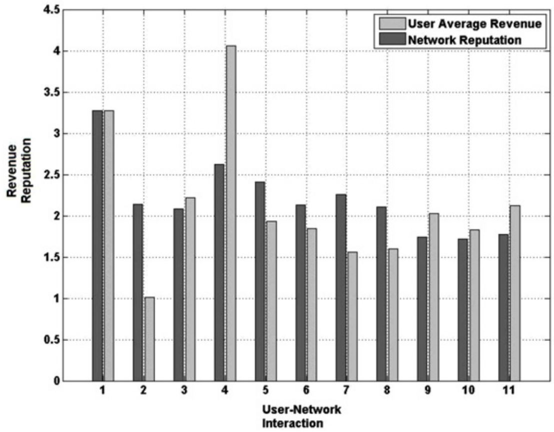
In this paper we study the interaction between user and network and we propose a novel reputation-based network selection mechanism. The mechanism combines the reputation-based systems and game theory in order to strengthen the cooperation between users and networks. We model the interaction between user and network as a two-player cooperative game using the model of repeated Prisoner's Dilemma game. We define the network reputation factor based on the output of the repeated game, in order to keep track of network past behaviour in the network selection decision. By defining incentives for cooperation and disincentives against fraudulent behaviour, we show that repeated interaction sustains cooperation. The use of game theory in combination with the network selection mechanism enables us to create a reputation-based system for the heterogeneous network environment. We showed that by considering reputation



(a) First case ($w_q = 0.6$, $w_e = 0.2$, $w_c = 0.2$).



(b) Second case ($w_q = 0.2$, $w_e = 0.6$, $w_c = 0.2$).



(c) Third case ($w_q = 0.4$, $w_e = 0.4$, $w_c = 0.2$).

Fig. 9. User average revenue and network reputation for the three cases.

in the network selection mechanism is useful in cases of cooperation and when making decisions.

We think that the reputation-based system is a valuable tool to make next generation heterogeneous environment work well. We plan to extend the proposed reputation mechanism by incorporating data from different sources. For example, by considering feedback received from other users, which have already interacted with that specific operator. The network reputation factor will be then computed based on user past interaction with the network, and also based on feedback received from other users. Of course a credibility factor will be considered for the feedback users. As part of the future work, a study of the network operators' attitude towards profit gains could be considered.

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References

[1] Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2009–2014.

[2] E. Gustafsson, A. Jonsson, Always best connected, IEEE Wireless Communications (1) (2003) 49–55.

[3] R. Trestian, O. Ormond, G.-M. Muntean, Power-friendly access network selection strategy for heterogeneous wireless multimedia networks, in: IEEE International Symposium on Broadband Multimedia Systems and Broadcasting, BMSB, March 2010.

[4] H.J. Wang, R.H. Katz, J. Giese, Policy-enabled handoffs across heterogeneous wireless networks, in: Proceedings of Second IEEE Workshop on Mobile Computing Systems and Applications, WMCSA, 1999, pp. 51–56.

[5] E. Adamopoulou, Intelligent access network selection in heterogeneous networks—simulation results, in: 2nd International Symposium on Wireless Communication Systems, 2005, pp. 279–283.

[6] Q.-T. Nguyen-Vuong, Y. Ghamri-Doudane, N. Agoulmine, On utility models for access network selection in wireless heterogeneous networks, in: IEEE Network Operations and Management Symposium, NOMS, 2008, pp. 144–151.

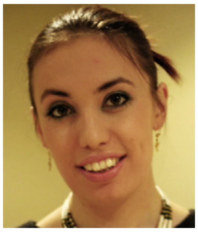
[7] W. Zhang, Handover decision using fuzzy MADM in heterogeneous networks, in: IEEE Wireless Communications and Networking Conference, WCNC, vol. 2, 2004, pp. 653–658.

[8] Q. Song, A. Jamalipour, An adaptive quality-of-service network selection mechanism for heterogeneous mobile networks, Wireless Communications and Mobile Computing 5 (6) (2005).

[9] R. Machado, S. Tekinay, A survey of game-theoretic approaches in wireless sensor networks, Elsevier Computer Networks 52 (16) (2008) 3047–3061.

[10] B. Wang, Y. Wu, K.J. Ray Liu, Game theory for cognitive radio networks: an overview, Elsevier Computer Networks 54 (14) (2010) 2537–2561.

[11] V. Srivastava, et al., Using game theory to analyze wireless ad hoc networks, IEEE Communications Surveys & Tutorials 7 (4) (2005) 46–56.
[12] T. Alpcan, T. Başar, S. Dey, A power control game based on outage probabilities for multicell wireless data networks, IEEE Transactions on Wireless Communications 5 (2006) 890–899.
[13] S. Sengupta, et al., Dynamic pricing for service provisioning and network selection in heterogeneous networks, Elsevier Physical Communication 2 (1) (2009) 138–150.
[14] D.E. Charilas, A.D. Panagopoulos, A survey on game theory applications in wireless networks, Elsevier Computer Networks 54 (18) (2010) 3421–3430.
[15] E.H. Watanabe, et al. Modeling resource sharing dynamics of VoIP users over a WLAN using a game-theoretic approach, in: The 27th IEEE Conference on Computer Communications, INFOCOM, 2008.
[16] K. Mittal, E.M. Belding, S. Suri, A game-theoretic analysis of wireless access point selection by mobile users, Computer Communications 31 (10) (2008).
[17] K. Fahimullah, S. Hassan, Game-theory based wireless access point selection scheme, in: IEEEP Silver Jubilee International Multi-topic Symposium, SIMTS, 2010.
[18] S. Vassaki, A.D. Panagopoulos, P. Constantinou, Bandwidth allocation in wireless access networks: bankruptcy game vs cooperative game, in: International Conference on Ultra Modern Telecommunications & Workshops, ICUMT, 2009, pp. 1–4.
[19] M.A. Khan, et al. Game-theory based user centric network selection with media independent handover services and flow management, in: Eighth Annual Research Conference on Communication Networks and Services, CNSR, 2010.
[20] M.A. Khan, et al. Auction based interface selection with media independent handover services and flow management, in: European Wireless Conference, EW, 2010.
[21] M.A. Khan, et al. Auction based interface selection in heterogeneous wireless networks, in: Wireless Days, WD, 2nd IFIP, 2009.
[22] M. Chatterjee, H. Lin, S.K. Das, Non-cooperative games for service differentiation in CDMA systems, Mobile Networks and Applications 10 (6) (2005).
[23] D.E. Charilas, A.D. Panagopoulos, P. Vlacheas, O.I. Markaki, P. Constantinou, Congestion avoidance control through non-cooperative games between customers and service providers, in: MOBILIGHT, 2009, pp. 53–62.
[24] J. Antoniou, et al., Cooperative user-network interactions in next generation communication networks, Elsevier Computer Networks 54 (13) (2010) 2239–2255.
[25] H. Pervaiz, J. Bigham, Game theoretical formulation of network selection in competing wireless networks: an analytic hierarchy process model, in: Third International Conference on Next Generation Mobile Applications, Services and Technologies, NGMAST, 2009.
[26] H. Pervaiz, A Multi-Criteria Decision Making (MCDM) network selection model providing enhanced QoS differentiation to customers, in: International Conference on Multimedia Computing and Information Technology, MCIT, 2010.
[27] D. Niyato, E. Hossain, A noncooperative game-theoretic framework for radio resource management in 4G heterogeneous wireless access networks, IEEE Transactions on Mobile Computing (3) (2008).
[28] D. Niyato, E. Hossain, A cooperative game framework for bandwidth allocation in 4G heterogeneous wireless networks, in: IEEE International Communications Conference, ICC, 2006.
[29] I.M. Suliman, C. Pomalaza-Raez, I. Oppermann, J. Lehtomaki, Radio resource allocation in heterogeneous wireless networks using cooperative games, in: Nordic Radio Symposium I Finnish Wireless Communications Workshop, NRS/FWCW, 2004.
[30] C.-J. Chang, T.-L. Tsai, Y.-H. Chen, Utility and game-theory based network selection scheme in heterogeneous wireless networks, in: IEEE Wireless Communications and Networking Conference, WCNC, 2009.
[31] J. Antoniou, et al., Access network synthesis game in next generation networks, Computer Networks 53 (15) (2009) 2716–2726.
[32] M.A. Khan, et al. Cooperative game theoretic approach to integrated bandwidth sharing and allocation, in: International Conference on Game Theory for Networks, GameNets, 2009, pp. 1–9.
[33] S. Buchegger, et al., Reputation systems for self-organized networks, IEEE Technology and Society Magazine 27 (1) (2008) 41–47.
[34] J.-M. Seigneur, X. Titi, Reputation-based telecommunication network selection CoRR abs/1002.2294, 2010.
[35] N.B. Salem, J.P. Hubaux, M. Jakobsson, Reputation-based Wi-Fi deployment, ACM Mobile Computing and Communications Review 9 (3) (2005) 69–81.
[36] M. Zekri, B. Jouaber, D. Zeghlache, On the use of network QoS reputation for vertical handover decision making, in: IEEE GLOBECOM Workshops, GC Wkshps, 2010.
[37] A. Satsiou, L. Tassiulas, Reputation-based internet sharing in wireless neighborhood community networks, in: Proc. of the IEEE International Conference on Communications, 2010.
[38] H.J. Wang, R.H. Katz, J. Giese, Policy-enabled handoffs across heterogeneous wireless networks, in: Proceedings of Second IEEE Workshop on Mobile Computing Systems and Applications, WMCSA, 1999.
[39] E. Adamopoulou, Intelligent access network selection in heterogeneous networks—simulation results, in: 2nd International Symposium on Wireless Communication Systems, 2005.
[40] Q. Song, A. Jamalipour, Network selection in an integrated wireless LAN and UMTS environment using mathematical modeling and computing techniques, IEEE Wireless Communications Magazine (2005).
[41] K. Mahmud, M. Inoue, H. Murakami, M. Hasegawa, H. Morikawa, Measurement and usage of power consumption parameters of wireless interfaces in energy-aware multi-service mobile terminals, in: 15th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, vol. 2, 2004, pp. 1090–1094.
[42] R.V.V.S.V. Prasad, V. Srinivas, V.V. Kumari, K.V.S.V.N. Raju, Credibility based reputation calculation in P2P networks, in: Distributed Computing and Internet Technology, vol. 5375, 2009, pp. 188–195.



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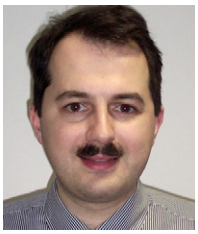

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