COOPERATIVE INTERACTIONS IN CONVERGED HETEROGENEOUS COMMUNICATION NETWORKS

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LIST OF ACRONYMS, SYMBOLS & ABBREVIATIONS

$\neq$	Not Equal
$>,\ \geq,\ <,\ \leq$	Greater, Greater or Equal, Less Than, Less Than or Equal
$\in,\ \ni$	Belongs In (for elements on the right or on the left)
$\nexists$, $\emptyset$	Does Not Exist In, Empty Set
$\cup,\ \bigcap$	Union, Intersection
$\forall$	For All
$\sum,\ \prod$	Sum, Product
$\subseteq,\ \supseteq$	Subset or Equal, Superset or Equal
$\lvert x\rvert,\ \lceil x\rceil$	Absolute Value of x, Value of x Rounded to the Next Higher Integer
$x!$	Value of x Factorial
iff	If and Only If
Ad-Hoc	Network formed with little or no planning
BPI	Banzhaf Power Index
CDMA, W-CDMA	Code Division Multiple Access, Wideband-CDMA
ETSI	European Telecommunications Standards Institute
GSM	Global System for Mobile communications
HPI	Holler-Packel Index
IETF	Internet Engineering Task Force
IMS	IP Multimedia Subsystem
IP	Internet Protocol
ITU-T	International Telecommunication Union - Telecommunication Standardisation Sector
LAN	Local Area Network
MNO	Mobile Network Operator
MVNO	Mobile Virtual Network Operator
PPI	Popularity Power Index
PSTN	Public Switched Telephone Network
QoS	Quality of Service
RSVP	Resource ReserVation Protocol
RTP	Real-time Transport Protocol
SDP	Session Description Protocol
SIP	Session Initiation Protocol
SSPI	Shapley-Shubik Power Index
TIPHON	Telecommunications and Internet Protocol Harmonization Over Networks
WiMax	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network

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Next Generation Communication Networks employ the idea of convergence, where heterogeneous access technologies may co-exist. Among other features, this new network model enables a user (or a set of users) to be served by any (one or many) of the multiple, available access networks. These access networks carry differing characteristics and capabilities encouraging the decoupling of carriage and content, i.e. the infrastucture operators and the service or content providers can be different entities in this new system. Furthermore, the common thread that links all this heterogeneity of Next Generation Communication Networks is the support for a user-centric paradigm of communication, converging all activities to the system's key function, i.e. to satisfy its customers. Next Generation Communication Networks plan to take advantage of these varying characteristics, exploiting them in complementary manners in order to achieve to surpass any limits imposed by any one of these networks on its own, through appropriate network synergies.

Synergies, i.e. coperation between participating entities in Next Generation Communication Networks, promote the useful co-existence of heterogeneous entities, aiming at enhancing the overall network, since the support of demanding multimedia services, such as interactive and multiparty multimedia services, becomes a challenging task due to the heterogeneity of the entities involved, the user(s) and the access network(s). This heterogeneity results in different and often conflicting interests for these entities. Since cooperation between these entities, if achieved, is expected to be beneficial, we pose the following question: Can cooperation be motivated in

interactive situations arising in Next Generation Communication Networks, and if yes, is it beneficial for the interacting entities? In pursue of answering this question, this thesis isolates and studies three different interactive situations between user(s) and network(s) in such heterogeneous environments, and proposes appropriate modes of behaviour that allow the interacting entities to achieve own satisfaction, despite their conflicting interests.

Interactions between entities with conflicting interests follow action plans designed, by each entity, in such a way as to achieve a particular selfish goal; such interactions are known as strategic interactions. Strategic interactions are studied by Game Theory, a field which develops models that prescribe actions for entities interacting in a strategic manner, such that they achieve satisfactory gains from the situation. To target the question of how to behave in interactive situations between heterogeneous entities in Next Generation Communication Networks, the thesis utilizes game theoretical models to analyze the selected strategic situations and investigates profitable behaviours of the participating entities. The study shows that cooperation can be motivated in each of the selected interactive situations and, furthermore, that such cooperative behaviour is beneficial for the interacting entities. Cooperation is motivated by characteristics of the selected situations such as repeatability of interaction, need for sharing between entities and need for participation in groups.

More specifically, the thesis seeks to find the most profitable behaviour for the entities participating in the following situations:

a. The first situation, which is studied deals with the interaction between a user and an access network when the two interact in an attempt to participate successfully in a User Generated Content service, a multimedia service. The two entities have conflicting interests since the user seeks satisfaction at the minimum price, whereas the network wants to offer the minimum satisfaction to the user (less resources - less own cost) at the highest possible price.

Profitable strategies for both the user entity and the network entity are investigated, which consider the repeated nature of their interactive relationship and in turn, new strategies are proposed that adopt the idea of punishing non-cooperative behaviour in an adaptive manner, by considering behaviour history to lessen the impact of strategies involving harsher punishments. Cooperation in this case is motivated by the repetitive nature of the interaction, and it is a beneficial mode of behaviour for the involved entities since the payoffs received by each entity from cooperation are shown to be satisfying.

b. The second situation explores the need for synergy between two networks (in particular two Mobile Virtual Network Operators participating in the heterogeneous system) to serve a premium service user request, in order to be able to provide some additional quality guarantees. Such cooperation between two selected networks is transparent to the user, i.e. the user offers some payment (e.g. for the premium service) without the knowledge that this payment will be partitioned between two networks. The thesis investigates the optimal way to partition the payment so that the two networks are motivated to cooperate. An additional issue arises in this cooperation, which is whether the cooperating networks are motivated to be truthful and how the optimal solution is affected by non-truthful behaviour. We show that being truthful to support cooperation is the best mode of behaviour for the participating networks in such a situation.

c. The third situation involves multiple access networks cooperating to support a particular anticipated service demand for a certain period (e.g. supporting a multiparty multimedia service), which none of the participating networks is prepared to handle on its own. Towards this goal, we study coalition formation between the participating networks according to their available resources, given that the payment for a particular anticipated traffic demand is paid to the coalition, considering scenarios of both transferrable and non-transferrable payoff. Furthermore, we seek a fair payoff allocation rule for the networks participating in the winning coalition. We show that the coalition most likely to be formed may be identified and based on the identified coalition the payoff allocation is fair. To achieve the corresponding payoff allocation, we propose a newly defined power index (a way to allocate weights to the players according to certain conditions) and compare it to existing power indices to show the improved performance for the particular cooperative situation.

In view of the above theoretical findings, the thesis offers additional evaluations of the proposed modes of behaviour, or strategies, that the participating entities may adopt. The evaluation is done numerically through simulations of the proposed strategies. The obtained numerical results further reinforce the theoretical findings, i.e. that cooperation may efficiently and satisfactorily be motivated to resolve conflicting interests in the selected interactive situations.

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Chapter 1

Introduction

1.1 Interactions in Next Generation Converged Communication Networks

Mobile and wireless communication networks comprise a mature industry with increasing user penetration, which has been globally available for some time and is usually deployed as one or another technology, often in competition with each other. Next Generation communication networks are envisioned to be based upon a common, flexible and scalable convergence platform, where different access networks, terminals and services can coexist [81, 89]. Furthermore, network access is being decoupled from service provision, resulting in an increasing collection of new services offered by the newly introduced service providers. Decoupling of network access has favoured the idea of convergence [97, 102], i.e. the co-existence and integration of the various access technologies in order to act as a unified platform combining their resources to best serve the increasing user requirements.

Access networks may employ different wireless and mobile technologies, such as WLAN, WiMax, Ad-Hoc/Sensor as well as GSM and CDMA/W-CDMA technologies and will be interconnected by an IP packet-switched core network [62]. This IP core network deals with all network functionality and coordinates the participating access networks, in order for the system to behave as a unified platform. The IP Multimedia Subsystem (IMS) is an architectural subsystem for the control and provisioning of IP multimedia services over a packet-based core. The IMS was first standardized by the 3rd Generation Partnership Project but it has since been adopted and contributed to by other standardization bodies, including ITU-T and ETSI. The IMS promises a scalable, integrated platform that enables the creation of new services and facilitates the convergence of telecommunications and Internet services. The IMS also promises to achieve fixed mobile convergence by enabling the seamless distribution of services over fixed and mobile broadband networks. However, this requires that IMS services need to be able to cater for heterogeneous access networks and varying user end terminal capabilities. This adaptation ability presents a significant challenge for multimedia services as such adaptation is no easy task.

Moreover, the co-existence of different access networks, terminals and services brings forth a new communication paradigm, which is *user-centric* [48], i.e. the user is no longer bound to only one access network but may indirectly *select* the *best* available access network(s) to support a service session [15]. Upon a new service request or a particular traffic demand, as well as any dynamic change affecting the session, e.g. mobility, one (or a group) of the participating access networks needs to be selected in order to support the session. Therefore, converged communication networks need to be equipped with a Network Selection mechanism to assign the *best* access network(s) to handle service activation, or any dynamic session change. Such decision may result in the selection of a single access network or even a group of networks.

A converged network, as considered in this thesis, is a multi-entity system, i.e. decisions are taken by different system entities. The decisions serve to provide the means to efficiently support a requested service to the appropriate user. At least, two entities of decision-making are necessary; one representing what the user needs and another representing what the network can provide. Thus, the entities responsible for these decisions are: (i) the user (requesting services) and (ii) the network operator (responsible to support the user requested services). Both decision-making entities can be driven by satisfaction-maximization functions, which are based on the individual entity's criteria [35]. On the one hand, the user of a communication network may decide whether or not to participate in a network and offer value to that network, selecting it to provide a requested service, its criterion being *user satisfaction* [57] in terms of, for example, experience (e.g. service quality) and cost; user experience can be improved by the consideration of context information, i.e. location, device capabilities, environment, preferences, etc. On the other hand, the network operator may decide which of the users to admit, how to allocate available resources to the participating users and how to design certain resource management mechanisms in order to maximize its capacity. All these decisions are driven mainly by only one criterion: the network's revenue maximization [103]. Therefore, on the one hand, the network operator sets the *price per user* for using network resources based on its own revenue-maximization criterion and, on the other hand, the user, given the price set by the network as well as additional parameters that comprise its own satisfaction function, makes the decision whether or not to participate in the particular network, always subject to the network's own admission policy [36, 40, 25].

Moreover, we recognize that in a converged network there exists the need to consider the *interaction between each user and each one of the available access networks* as well as any interactions between the participating networks themselves, in order to improve decision-making. 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 thesis, we utilise Game Theory in order to model, analyze and finally propose solutions (in terms of strategies for the involved entities) for three representative types of interactions in Next Generation converged communication networks. The interacting entities are the *access networks* participating in the Next Generation Communication System, on the one hand, and the actual *wireless/mobile users*, on the other hand. Well-designed user and network strategies can enhance capacity planning on a dynamic basis (for example, on a day-to-day), by allowing the constituent access networks and consequently the whole converged network to make the best use of the available capacity, at any given horizon.

For the first cooperative model, i.e. to model the interaction between the user and the access network, we consider the framework of a two-player infinitely repeated cooperation game model to be appropriate for exploring what appears to be a conflicting relationship between the user and the network participating in a converged system, in order to reach a decision that will be both user-satisfying and network-satisfying. For the second cooperative model, i.e. when two networks must cooperate, we focus on the case of partitioning the service payment in a satisfying manner between the two players. Thus, we employ from game theory, popular cooperative bargaining frameworks and corresponding solution concepts that the two cooperating networks may follow in an attempt to efficiently partition the service payment. Finally, in the case that increased service demand, which none of the access networks is capable or willing to support on its own, requires the participating access networks to cooperate in order to form appropriate coalitions that can serve the particular demand. In this case, an appropriate coalition formation game theoretic framework is developed to direct the selection of the most appropriate coalition.

Furthermore, in an attempt to improve the selection process according to the knowledge acquired during the history of the interactions under study, we proceed to enhance some of the game theoretic models developed in this thesis, with a notion of adaptivity, hence providing a more practical strategy; adaptivity may improve defined strategies in the game models motivating rational cooperative behaviours.

Overall, the proposed strategies studied throughout the thesis for the various situations considered, are evaluated through simulations that explore their numerical behaviour. The numerical results show that in addition to the motivation, which is illustrated by the theoretical analysis presented in this thesis, the players are also motivated by the numerical payoffs resulting from the proposed cooperative solutions.

1.2 Contributions

This thesis provides contributions that may be organized in three different categories according to the interaction under study: (a) the interaction of a user and a network, when a network is to be selected and the two entities must cooperate, (b) the interaction of two networks when these networks must cooperate to serve a session, and (c) the interaction between multiple networks when they must cooperate to serve a large service demand that is best served by more than one networks (for example, if none of those networks can serve the demand on its own). The contributions are organized in three corresponding subsesctions.

1.2.1 Contributions relevant to the user-network interaction

- The interaction between a user and a network participating in a converged, heterogeneous network has been modelled using game theoretic tools, in such a way as to motivate cooperation.

- It has been shown that there exists equivalence of a one-shot game model of user-network interaction to the one-shot *Prisoner's Dilemma Game*.

- It has been shown that motivation of cooperation between the two entities is achieved through a *repeated game* model of the user network interaction.

- It has been shown that when the strategies used by the players of the repeated user-network interaction model involve punishment to motivate cooperation, then harsher punishments motivate cooperation more easily.

- A new user strategy for the repeated user-network interaction game, has been proposed that uses an *adaptive* punishment method in the repeated user-network interaction game. Despite the fact that it doesnot involve as harsh punishments as the grim, this strategy also motivates cooperation and achieves such satisfying results in terms of motivation and payoffs, to become the strategy of choice for a user when compared to the other strategies examined in this thesis.

- It has been shown that a profile of the repeated user-network interaction game where the user employs the adaptive punishment method and the network employs the well-known *tit-for-tat* strategy, generates at least as high payoffs as any other strategy combination for both players.

- A network selection model is proposed, which assumes that the user is an adaptive entity with *knowledge* about the networks that changes over time, according to the networks' behaviour.

- An internal state for the user as an adaptive entity is defined and used in the proposed network selection scheme.

1.2.2 Contributions relevant to the network-network interaction

- The interaction between two networks, when cooperating to support a service session, has been modelled using game theoretic tools, in such a way as to motivate cooperation in terms of partitioning the available compensation for the particular service session.

- It has been shown that there exists equivalence between the payment-partition game and the *Rubinstein Bargaining Game*, if the agreement in the Rubinstein Bargaining Game is reached from the first negotiation period.

- It has been shown that there exists equivalence between the payment-partition game and the *Nash Bargaining Game*, due to the equivalence of the Nash bargaining game to the Rubinstein Bargaining Game, if the agreement in the Rubinstein Bargaining Game is reached from the first negotiation period.

- It has been shown that an optimal solution for the payment partition game exists and is based on the *Nash Bargaining Solution*, resulting in a partition determined by the cost each of the two networks has for supporting the service session.

- It has been shown that if a constant probability of demonstrating quality degradation is included as weight in the networks' payoff functions for the payment-partition game, this does not affect the optimal partition proposed by the Nash Bargaining Solution. However, the payoff values of the two networks are affected such that the networks receive less than the optimal payment partition.

- The payment-partition game is modelled as a one-shot *Bayesian* game, to investigate truthfulness on behalf of the participating networks regarding their own costs.

- It has been shown that no matter whether a network believes that its opponent has declared lower or higher cost than its own cost, it is still motivated to lie about its real costs.

- To motivate truthfulness, a *pricing mechanism* has been used in the payoffs of the users, which has been shown to work very effectively towards motivating the networks to be truthful.

1.2.3 Contributions relevant to the interaction between multiple networks

- The coalition formation process between multiple networks has been modelled as the *Network Synthesis* game, in which individual networks with insufficient resources form coalitions in order to satisfy service demands.

- It has been shown that the network synthesis game is equivalent to the well-known *Weighted Voting Game*.

- A comparative study of well-known *power indices* representing payoff schemes, is provided for the network synthesis game.

- A new power index, the *Popularity Power Index* (PPI), is proposed based on conclusions from the study of well-known power indices, which associates the popularity of each network to the number of stable coalitions it participates in.

- It has been shown that the newly proposed power index, PPI, achieves fairness, in the sense that it only considers the possible coalitions that would be formed if payoffs were assigned proportionally to the networks' contributions.

- An analysis of the coalition formation is provided for both transferable and non-transferable payoffs, in order to determine stable coalitions using the core and inner core concepts.

- It has been shown that from the well-known power indices we have studied, the most appropriate for the network synthesis game is a power index that provides stability under the core concept, known as the *Holler-Packel Index (HPI)* [44].

- It has been shown that coalitions that would be formed using the newly proposed PPI to assign payoffs, are only coalitions that would be stable under the inner core concept. Therefore, the PPI provides a simple payoff allocation method that is equivalent to an cooperative equilibrium solution of the Network Synthesis Game.

1.2.4 Acknowledgements of Contributions to this Thesis

Several people took part in realizing the abovementioned scientific contributions, to whom I am grateful for their cooperation and guidance. Beyond my thesis advisor, Dr. Andreas Pitsillides, Professor at the University of Cyprus, these are in alphabetical order: Dr. Chris Christodoulou, Assistant Professor at the University of Cyprus; Ms. Eva Jaho, Ph.D. Candidate at the National & Kapodistrian University of Athens; Dr. Ioannis Koukoutsidis, Lecturer at the University of Pelloponese; Dr. Loizos Michael, Lecturer at the Open University of Cyprus; Dr. Vicky Papadopoulou, Assistant Professor at the European University Cyprus; Dr. Anna Philippou, Assistant Professor at the University of Cyprus; Dr. Ioannis Stavrakakis, Professor at the National & Kapodistrian University of Cyprus; Dr. Vasos Vassiliou, Lecturer at the University of Cyprus.

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The use of adaptivity as an enhancement to the game theoretical framework has been motivated by Andreas Pitsillides, Vasos Vassiliou and Chris Christodoulou, specifically to enhance the user-network interaction study (section 3.5).

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The study of cooperation between multiple networks (sections 5.3 and 5.4) would not have been possible without the help and cooperation of Ioannis Stavrakakis, Ioannis Koukoutsidis and Eva Jaho, having contributed extensively in the theoretical analysis of coalition formation possibilities.

Finally, for the organization of numerical results in sections 3.8, 4.6 and 5.5, I acknowledge Andreas Pitsillides, Ioannis Koukoutsidis and Eva Jaho.

1.2.5 Publications

In this section, we initially provide a complete list of publications and submissions stemming from the work in this thesis and then follow with other publications related to the ideas of convergence and heterogeneity. The references to the thesis bibliography are given at the end of each publication.

- J. Antoniou, I. Koukoutsidis, E. Jaho, A. Pitsillides, I. Stavrakakis, *Access Network Synthesis in Next Generation Networks*, Elsevier Computer Networks Journal Elsevier Computer Networks Journal, vol. 53, no. 15, pp. 2716-2726, Oct. 2009 [3].

- J. Antoniou, V. Papadopoulou, V. Vassiliou, A. Pitsillides, *Cooperative User Network Interactions in Next Generation Communication Networks*, Submitted to Elsevier Computer Networks Journal, May 2009 (Under 2nd Review) [5].

- J. Antoniou, V. Papadopoulou, V. Vassiliou, A. Pitsillides, *Network Selection and Handoff in Wireless Networks: A Game Theoretical Approach*, Submitted as Book Chapter in ”Game Theory for Wireless Communications and Networking”, Aurebach Publications, CRC Press, Taylor & Francis Group, in March 2009 (Under 2nd Review) [6].

- J. Antoniou, E. Jaho, A. Pitsillides, I. Stavrakakis. *Collaborative Ph.D. Research: Access Network Synthesis Game in Next Generation Networks*, CONTENT Newsletter, December 2008. FP6-IST-0384239 CONTENT: Excellence in Content Distribution Network Research, FP6 Network of Excellence (NoE) [2].

- J. Antoniou, V. Papadopoulou, and A. Pitsillides. *Report TR-08-5: A game theoretic approach for network selection*, Technical Report, University of Cyprus, December 2008 [4].

- J. Antoniou, M. Stylianou, A. Pitsillides, *RAN Selection for Converged Networks Supporting IMS Signalling and MBMS Service*, in Proceedings of the 18th IEEE Annual International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC 2007), Athens, Greece, September 2007 [9].

- J. Antoniou, A. Pitsillides, *4G Converged Environment: Modeling Network Selection as a Game*, in Proceedings of IST Mobile Summit 2007, Budapest, Hungary, July 2007 [8].

- J. Antoniou, A. Pitsillides, *Radio Access Network Selection Scheme in Next Generation Heterogeneous Environments*, in Proceedings of IST Mobile Summit 2006, Mykonos, Greece, June 2006 [7].

Other own contributions related to the idea of convergence and heterogeneity in Next Generation Communication Networks, but focussing on more practical aspects of enhancing entity interactions, are the following:

- J. Antoniou, C. Christophorou, J. Simoes, A. Pitsillides, *Adaptive Network-Aided Session Support in Context-Aware Converged Mobile Networks*. International Journal of Autonomous and Adaptive Communication Systems, *to appear*.

- J. Antoniou, C. Christophorou, A. Neto, S. Sargento, F. C. Pinto, N. F. Carapeto, T. Mota, J. Simoes and A. Pitsillides, *Session and Network Support for Autonomous Context-Aware Multiparty Communications in Heterogeneous Mobile Systems*, International Journal of Handheld Computing Research, *to appear*.

- J. Antoniou, F. C. Pinto, J. Simoes, A. Pitsillides, *Supporting Context-Aware Multiparty Sessions in Heterogeneous Mobile Networks*. Elsevier Mobile Networks and Applications Journal, February 2010 (*invited, based on the presentation in Mobilware '09*), *to appear*.

- J. Antoniou, C. Christophorou, C. Jannetau, M. Kelil, S. Sargento, A. Neto, F. C. Pinto, N. F. Carapeto, J. Simoes, *Architecture for Context-Aware Multiparty Delivery in Mobile Heterogeneous Networks*. In Proceedings of International Conference on Ultra Modern Telecommunications (ICUMT '09), St. Petersburg, Russia, October 2009.

- J. Antoniou, C. Christophorou, A. Neto, S. Sargento, F. C. Pinto, N. F. Carapeto, T. Mota, J. Simoes, A. Pitsillides, *Context-Aware Self-Optimization in Multiparty Converged Mobile Environments*. In Proceedings of 3rd International Conference on Autonomic Computing and Communication Systems (Autonomics '09), Limassol, Cyprus, September 2009.

- J. Simoes, S. Sargento, J. Antoniou, C. Christophorou, C. Janneteau, N. Carapeto, A. Neto, *Context-Aware Control For Personalized Multiparty Sessions in Mobile Multihomed Systems*. In Proceedings of 5th International Mobile Multimedia Communications Conference (MobiMedia '09), London, UK, September 2009.

- A. Neto, S. Sargento, E. Logota, J. Antoniou, F. Pinto, *Multiparty Session and Network Resource Control in the Context Casting (C-CAST) project*. In Proceedings of 2nd International Workshop on Future Multimedia Networking (FMN '09), Coimbra, Portugal, June 2009.

- C. Jannetau, J. Simoes, J. Antoniou, C. Christophorou, M. Kelil, A. Klein, A. Neto, F. C. Pinto, P. Roux, S. Sargento, H. D. Schotten, J. Schneider, *Context-Aware Multiparty Networking*. In Proceedings of ICT Mobile Summit 2009, Santander, Spain, June 2009.

- J. Antoniou, C. Riede, F. C. Pinto, A. Pitsillides, *Context Aware Multiparty Session Support for Adaptive Multicasting in Heterogeneous Mobile Networks*, in Proceedings of the 2nd International Conference on MOBILe Wireless MiddleWARE, Operating Systems and Applications (MOBILWARE 2009), Berlin, Germany, April 2009.

- E. Alexandri, J. Antoniou, T. Clessienne, A. Correia, R. Dinis, E. Hepsaydir, R. Hockmann, H. Schotten, C. Sgraja, R. T?njes, N. Souto, S. Wendt, *RAN Enhancements for Advanced Multimedia Broadcasting and Multicasting Services*, in Proceedings of the Wireless World Research Forum 2006 (WWRF17), Heidelberg, Germany, Nov. 2006.

1.3 Thesis Overview

The current thesis is organized in the following manner: Chapter 2 introduces the concepts of convergence and game theory, focussing on game models that are subsequently applied to aspects of cooperative interactions in this thesis, and the mechanism of network selection. Chapter 3 formulates the user-network interaction and resolves it, specifically exploring the possibilities of cooperation in user-network interaction relationships. Similarly, Chapter 4 formulates the network-network interaction and resolves it in a cooperative fashion. Then, Chapter 5 formulates the multiple networks interaction case and also explores possibilities of cooperation. All three chapters provide the theoretical resolutions of the formulations presented, proposing and proving where necessary several relevant propositions and theorems, and drawing conclusions from these theoretical results on all three of the cooperation cases examined. Furthermore, they evaluate the numerical behaviour of important aspects of the theoretical results and in particular, the proposed solutions and strategies. Finally, Chapter 6 summarizes the conclusions from both the theoretical studies as well as the numerical evaluations presented in this thesis and identifies opportunities for future work.

Chapter 2

Background and Related Works

2.1 Convergence: The promising future in Mobile Communications

Traditionally, communication networks provide one of two different types of network services: circuit-switched service and datagram. The typical model for a circuit-switched network is the Public Swtched Telephony Network (PSTN). Once a call is established through the various switching centres, the path from source to destination is also established like a circuit. The transport characteristics in a circuit-switched path may be predetermined and the connection is said to be predictable in terms of the QoS it can deliver. On the other hand, the typical model for a datagram type network is the Internet, where data is broken into small units, called packets, for transmission through the network using only source and destination addresses and trusting that existing routing technologies will deliver each packet to the correct destination; this type of connection is referred to as packet-switched and it is not easy to predict the QoS it can deliver.

Voice communication networks have hitherto embraced the circuit-switched approach because of the strict delay constraints of the voice service, while data networks have been successful in using the datagram or packet-switched approach since delay bounds are more relaxed. However, the rapid deployment of emerging information technologies, including mobile communications and

Internet-related technologies in general, plus the widespread acceptance of the Internet Protocol (IP), have been some of the driving factors towards integrating voice and data networks of different technologies into a unified infrastructure, introducing the idea of convergence, i.e combining voice, data and other media such as video, audio and fax, into what appears to be a single network interface but may comprise the integration of heterogeneous wired and wireless networks.

Despite the inability of IP to offer guaranteed QoS, IP-based networks upon deployment became a very popular and cost-efficient communication solution. Even though, there were no QoS guarantees from the IP itself, additional QoS mechanisms improved QoS-provisioning so that a multitude of services could be successfully deployed over IP. The IP trend evolved to the all-IP paradigm, i.e. the IP supporting next generation communication networks, which are characterized by the convergence of heterogeneous access technologies, by deploying an IP-based core where the participating heterogeneous access technologies converge. Consequently, we may define convergence to be the creation of an environment that can ultimately provide seamless and high-quality broadband mobile communication service and ubiquitous service through wired and wireless integrated networks without spatial and temporal constraints by means of connectivity for anybody and anything, anytime and anywhere.

A converged network is a datagram type network in principle, combining traditionally circuit-switched and datagram networking into a single packet-based network. However, it needs to address reliability in order to be successfull. The IP, which was designed to support datagram type networks is not sufficient in itself to transmit real-time traffic such as voice and video. Additional protocols are needed. Many organizations are addressing this challenge, such as ETSI with TIPHON (Telecommunications and Internet Protocol Harmonization Over Network) [37], ITU-T with H.225 [53], and H.245 [54] standards for multimedia communication, and IETF with SIP (Session Initiation Protocol) [52], SDP (Session Description Protocol) [51], RTP (Real Time

Protocol) [50], RSVP (Resource Reservation Protocol [49]) and others that facilitate real-time communications over IP-based networks.

A user participating in a converged network enjoys several advantages. Although there is a multitude of underlying technologies, only one interface is perceived by the user, which means the user does not need to know how to manage multiple systems and in terms of support the user contacts only one organization, the converged platform administrator, for an increased number of available services. The access networks themselves enjoy increased user participation and economic benefits through possible cooperations with other participating networks to better support the converged network services. In addition, network performance becomes more efficient since the platform administrator can enforce certain policies to all the participating networks and due to access network synergies, the participating networks are expected to become more competitive.

In terms of challenges to overcome, the ones that a converged infrastructure needs to deal with, are three-fold: management challenges, architectural challenges, and quality challenges (i.e. service quality perceived by the user). In terms of management, the appropriate mechanisms must consider the heterogeneity of the network and perhaps the different ownership, and in turn satisfy several challenging demands, as for example, high throughput, authorization and billing, security, fairness, deployment costs and interoperability issues, ensuring that (a) environment heterogeneity is transparent to the users who simultaneously have maximum choice in their selection of and access to a network with suitable QoS and information services and (b) that information providers can reach all users. In terms of architecture, the functionalities and interactions of additional components that will enable the convergence is necessary to ensure the efficient operation of the system and allow for the management mechanisms to resolve the issues mentioned above. Management and architecture issues have various common areas in terms of design and implementation. Quality, and particularly improving user experience, touches upon network and resource management and moves on to areas such as modifications to user devices, improvements to applications and services, enhancing user capabilities (e.g. exploring context-awareness), etc..

Since network access is being decoupled from service provision, the result is an increasing collection of new services offered by the newly introduced service providers. The user-centric view evolving from this advancement, introduces a setting where the user can choose, or take active part in the selection of the best available network to serve a requested service, and no longer has to subscribe to one particular access provider. Hence, Network Selection mechanism is a newly introduced resource management mechanism in a converged network, which handles the selection of the best network to satisfy a service request, aiming to improve both user experience and network motivation to offer its resources (through increased revenues). Earlier works on Network Selection have explored varying approaches of accurately describing and analyzing the application and effects of this new resource management mechanism. Such approaches included fuzzy logic [60, 105], adaptive techniques [94, 48], utility-based and game-theoretic models [24, 78, 7], technology-specific solutions, especially focussing on the inter-operation of cellular systems with Wireless LANs [95, 41], as well as architectural models focussing on a more comprehensive architectural view [15]. Decision making in these works is either user-controlled [105, 78, 41] or network-controlled [94, 95, 15]; the interaction between them is not often taken into consideration and the selection decision mainly involves one entity, in some cases involving the other entity indirectly, e.g. decision is taken by the network but considers some user preferences [48, 7], or the decision is taken by the user but considers some network-specific rankings [60, 24].

More recent research continues to explore the above ideas indicating a popular trend towards both dynamic/automated solutions that either are based on the user as a decision-making entity [21, 16], or are network-controlled solutions proposing improvements to the user-perceived quality during netwok selection [65, 26, 55]. Other than the general solutions for network selection, specific solutions handling particular services such as multicast have been recently proposed [9, 61]; these focus on the effect of Network Selection on the particular service (e.g. multicast) in addition to user and network satisfaction aspects.

2.2 Game Theory as an Analytical Tool

2.2.1 Introduction to Game Theory

This thesis considers the interactions in a converged heterogeneous network, in particular the interactions between the user and the access networks available to the user, or the interactions between the access networks themselves. Describing and analysing entity interactions is a situation that makes a good candidate to be modeled using the theoretical framework of Game Theory. Game Theory provides appropriate models and tools to handle multiple, interacting entities attempting to make a decision, and seeking a solution state that maximizes each entity's utility. Game Theory has been extensively used in networking research as a theoretical decision-making framework, e.g. for routing [98, 77], congestion control [33, 64], resource sharing [82, 104] etc.. These interactions may benefit from such a theoretical framework that considers decision-making, interacting entities.

Game Theory[1] appeared formally in the 1940s in a text by John von Neumann and Oskar Morgenstern [99], although the ideas of games and equilibria are found as early as 500 AD in the Babylonian Talmud, which is the compilation of ancient law and tradition for the Jewish Religion [12], as well as in the 1800s in Darwin's *The Descent of Man, and Selection in Relation to Sex* [31]. Game Theory grew more popular in the 1950s and the 1960s with important contributors such as John F. Nash [69, 70, 71], Thomas Schelling [90], Robert John Aumann [10, 11] and John Harsanyi [45, 46], as well as in the 1970s with Reinhard Selten [91], giving all the above scientists Nobel Prize awards in Economics in 1994 (John F. Nash, John Harsanyi and Reinhard Selten) and in 2005 Robert John Aumann and Thomas Schelling. It is worth mentioning some more recent,

[1] the text in Section 2.2 is mainly based on [68, 42, 34, 66, 79]

important contributors of Game Theory such as Ariel Rubinstein who contributed in the theory of bargaining [86] and Vincent P. Crawford for his work with redefinition of equilibria [30].

Game theory is a theoretical framework that attempts to mathematically capture both human and non-human (computer, animal, plant) behaviour during a strategic situation. A strategic situation is a situation that involves the interaction of two or more entities in which the individual's success depends on the choices of others attempting to find equilibria between the entities (called the *players*), i.e. sets of strategies (action sequences) that players will unlikely want to change. Therefore, game theory can be used to model situations of interaction and offer solutions so that mutually agreeable results can be reached; game theoretic models make the assumption that the entities make rational choices, i.e. choices that are profitable according to each entity's own interpretation of profit.

In order for a strategic situation to become a *game* between two or more players, there must be a mutual awareness of the participants regarding the cross-effect of their actions. A strategic situation, where the actions of a participant may alter another's outcome, is primarily characterized by the players' strategies. In addition, a strategic situation contains other elements that must be taken into consideration when modelling such a situation as a game, e.g. chance and skill, (elements that are not easily controlled or modified). Game models, i.e. models of specific strategic situations, may be categorized in various ways due to the several elements that they contain. A usual categorization is made by looking at the players' movements; if they are sequential we have an extensive game form (a.k.a. sequential-moves game form), whereas if they are simultaneous the game form is referred to as normal. Furthermore, an interaction may happen only once or repeatedly; in the first situation we are faced with one-shot game models, while the second situation requires repeated game models. An additional dichotomy is whether the players are in complete conflict, where the model employed is a non-cooperative one, or they have some commonality, where a more cooperative game model may be more appropriate. Finally, another important categorization is whether we are dealing with a game where the players have complete information about all actions taken or only partial information. When characterizing a game it is important to keep in mind the various possible categorizations of game models in order to better describe the required strategic situation as completely as possible.

Moreover, regarding sequential-moves games in particular, an easy way to visualize them is by illustrating the game using tree diagrams made from nodes and branches (a.k.a. game trees); they are joined decision trees for all of the players in the game, illustrating all of the possible actions that can be taken by all of the players and indicating all of the possible outcomes of the game. This thesis employs the notion of game trees.

It has been mentioned that game models employ the element of rationality, however, one may argue that rationality implies that the players are perfect calculators and flawless followers of their best strategies, which is not always a correct replicate of a particular situation, thus we may assert that this is not the case. Therefore, rationality may be better described to be the players' knowledge of their own interests based on each player's own value system. Based on this element of rationality the players calculate their possible strategies. Depending on whether the game is normal or extensive, strategies may consist of single actions or sequences of actions and each strategy gives a complete plan of action, considering also reactions to actions that may be taken by the opponent. Strategies may be pure, i.e provide complete definitions of how a player will play in the game (his moves), or mixed, i.e. assignments of a probability to each pure strategy.

Games are motivated by *profitable* outcomes that await the players once the actions are taken. These outcomes are referred to as payoffs. Payoffs for a particular player capture everything in the outcomes that the particular player cares about. If a player faces a random prospect of outcomes, then the number associated with this prospect is the average of the payoffs associated with each component outcome, weighted by their probabilities.

The solution to a strategic game is derived by establishing equilibria. Equilibria may be reached during the interaction of players' strategies when each player is using the strategy that is the best response to the strategies of the other players (i.e. given the strategies of the other players, the selected strategy results in the highest payoffs for each player paticipating in the game). The idea of equilibrium is a useful descriptive tool and furthermore, an effective organizing concept for analyzing a game theoretic model. For normal form games the Nash Equilibrium is used as a solution concept, where every player's action is the best response to the actions of all the others. For sequential-moves games, e.g. repeated games used in this thesis, the equilibrium used is known as the subgame perfect equilibrium or the rollback equilibrium (for finite repeated games). In such games the players must use a particular type of interactive thinking; players plan their current moves based on future consequences considering also opponents' moves. Therefore, the equilibrium in such a game must satisfy this kind of interactive thinking and subgame perfect equilibrium does exactly that, by planning the best responses for every possible subgame or interaction.

The following subsections elaborate on certain game theoretic aspects that are used in this thesis. Subsection 2.2.2 presents and discusses the single-shot as well as the iterated *Prisoner's Dilemma* game, which is the most well-known game model between two interacting entities. Subsection 2.2.3 provides an overview of bargaining games and focuses on two well-known two-player models, the *Nash Bargaining game* and the *Rubinstein Bargaining game*. In subsection 2.2.4 we focus on games of incomplete information wheras subsection 2.2.5 presents the repeated game, which models iterative interactions. Finally, subsection 2.2.6 describes the interaction of coalitions of players instead of single players. Note that all these models, which we further exploit in this thesis, employ the element of cooperation to provide solutions to the various situations. This is appropriate in our study, where we aim to motivate cooperation of the various heterogeneous entities participating in the network selection mechanism, so as to achieve satisfactory outcomes for all entities involved.

2.2.2 A glance at the Prisoner's Dilemma

The *Prisoner's Dilemma* and *Iterated Prisoner's Dilemma*[2] have been a rich source of research material since the 1950s. However, the publication of Axelrod's book in 1984 [13] was the main driver that this research was brought to the attention of other areas outside of game theory, as a model for promoting cooperation.

The Prisoner's Dilemma is basically a model of a game, where two players must decide whether to cooperate with their opponent or whether to defect from cooperation. Both players make a decision without knowing the decision of their opponent, and only after the individual decisions are made, these are revealed. The story behind this model is the following: *Two suspects are arrested by the police. Since the policemen have insufficient evidence for their conviction, they separate the two suspects and offer them a deal. If one testifies (i.e. defects from the other) against the other and the other remains silent (i.e. cooperates with the other), the betrayer goes free and the silent goes to jail for* 10 *years. If both remain silent, then they both go to jail for only* 6 *months with a minor charge. If both testify, each gets a* 5*-year sentence.* Each suspect must choose whether to testify or to remain silent, given that neither learns about the decision of the other until the end of the investigation. What should they do?

Mutual cooperation has a reward for both of receiving the punishment which is the least harsh. However, such decision entails the risk that in case the other player defects, then the cooperative

[2]The text in subsection 2.2.2 is based on [59].

player will receive the harshest punishment of 10 years. Given the risk of cooperation, it is very tempting to defect because if the opponent cooperates, then defecting will result in the best payoff, which is to go free, although, if the other opponent also defects then an average punishment will be received by both (i.e. 5 years). The decision of what to do comes from the following reasoning: *If a player believes that his opponent will cooperate, then the best option is certainly to defect since the payoff will be to go free. If a player believes that his opponent will defect, then by cooperating he takes the risk of receiving the harshest punishment, i.e.* 10 *years, thus the best option is again to defect and share the average punishment of 5 years with his opponent.* Therefore, based on this reasoning, each player will defect because it is the best option no matter what the opponent chooses. However, this is not the best possible outcome of the game. The best solution would be for both players to cooperate and receive the least harsh punishment of 6 months.

The desirable cooperative behaviour must be somehow motivated so that the players' selfish but rational reasoning results in the cooperative decision. In fact, what we have described is a *one-shot* Prisoner's Dilemma, i.e. the players have to decide only once – no previous or future interaction of the two players affects this decision. Cooperation may evolve, however, from playing the game repeatedly, against the same opponent. This is referred to as Iterated Prisoner's Dilemma, which is based on a repeated game model with an unknown or infinite number of repetitions. The decisions at such games, which are taken at each repetition of the game are affected by past actions and future expectations, resulting in strategies that motivate cooperation. The way motivation may be encouraged in such games will be analyzed within the work presented in this thesis. The repeated game model is briefly overviewed in subsection 2.2.5.

2.2.3 Overview of Bargaining Games

With the exception of the groundbreaking contributions of John F. Nash [69, 71], bargaining theory[3] basically evolved from the seminal paper by Ariel Rubinstein [86], which made the procedure of bargaining quite attractive, mainly due to the proposed model's simplicity and ease of understanding.

A bargaining situation is an exchange situation, in which two individuals have a common interest to *trade* but simultaneously have conflicting interests about the *price* at which to trade, because the seller would like to trade at a higher price while the buyer would like to trade at a lower price. Therefore, in a bargaining situation, the two players have a common interest to cooperate but have conflicting interests about exactly how to cooperate. On the one hand, each player would like to reach an agreement rather than disagree; on the other hand, each player wants to reach an agreement that is as favourable to that player as possible.

Therefore, a bargaining situation may be easily seen as a game situation since the outcome of bargaining depends on both players' bargaining strategies, i.e. whether or not an agreement is reached and the terms of that agreement (if one is reached) depend on both players' actions during the bargaining process. Next we provide brief descriptions of the two well-known game models of a bargaining situation between two players, the Nash bargaining game model and the Rubinstein bargaining game model, since we will make use of these models in particular formulations presented in this thesis.

The Nash bargaining game model defines a solution (known as the Nash Bargaining Solution) by a fairly simple formula and it is applicable to a large class of bargaining situations. The Nash bargaining example is the situation where two individuals bargain over the partition of a cake of fixed size. Since the cake will be partitioned to the two players, the addition of their partitions

[3]The text in subsection 2.2.3 is based on [66].

should equal the total cake, therefore the set of non-zero partitions, which sum to the total amount is the set of possible agreements in the bargaining situation. In the case of disagreement, each player receives a penalty, which is defined according to the bargaining situation under consideration; the definition of a penalty comes from the fact that in bargaining situations the desirable outcome is agreement, thus disagreement results in a non-satisfactory payoff for the two players. The penalties of the two players are defined as the *disagreement point* of the game. Thus, the *useful payoff* for each player may be defined to be the player's payoff received from the received partition in case of agreement, minus the penalty that would be received in case of disagreement as defined in the *disagreement point*. The unique solution of the cake partition is therefore, the unique pair of partitions that maximizes the product of the players' *useful payoffs* and is referred to as the *Nash product* or the *Nash Bargaining Solution*.

The Rubinstein bargaining game is modelled as a sequential-moves game, in which the players take turns to make offers to each other until agreement is secured. This model has much intuitive appeal, because a lot of real-life negotiations are based on the idea of making offers and counter-offers. From the sequential-moves model of the bargaining process, it is easy to see that if the two negotiating players do not incur any costs or penalties for delaying the agreement decision, the solution to the bargaining game may be indeterminate, because the two players could continue to negotiate forever. Given that there is a cost to each player for delaying, then each player's bargaining power is determined by the magnitude of this cost. Consider for the Rubinstein model that, similarly to the Nash bargaining game model described above, the two players bargain over the partition of a cake of fixed size. The first player proposes a partition; if the second player accepts, agreement is reached and the game is over; otherwise, the second player proposes a different partition, and the process of alternating offers continues until an offer is accepted. However, for each additional negotiation round there is a cost to each player, i.e. the size of the cake becomes smaller.

The factor by which the cake gets smaller may be different for each player and it is referred to as the player's discount factor. The Rubinstein bargaining game model has a unique subgame perfect equilibrium, which makes use of the fact that any offer made now by a player should be equal or greater to the discounted best value that the opponent can get in the next period.

Another element that must be considered in bargaining situations, is truthfulness of the players. In order to motivate the two bargaining players to be truthful about own information that may affect the bargaining process, there must exist a mechanism that can penalize a player who turns out to lie on its real cost, assuming that it is detectable whether a player has lied or not. Such mechanisms exist and are called *pricing mechanisms* [72], constituting an interesting and very promising way to guarantee truthfulness of the participating networks. In the worldwide literature there is a whole research field that is focused on the development, limitations and capabilities of such pricing mechanisms; the Algorithmic Mechanism Design [72]. Successful paradigms in this context include (combinatorial) auctions [29] and task scheduling [100, 101] using techniques such as the Revelation Principle [72, 32, 80], Incentive-Compatibility [72, 32, 80], Direct-Revelation [72, 32, 80] and Vickrey-Clarke-Groves Mechanisms [43]. The algorithmic tools and theoretical knowledge that have already developed in the field of Algorithmic Mechanism Design constitute a fruitful pool for extracting algorithmic tools for enforcing players to truthfulness, through pricing mechanisms, once these tools are customized and further developed for handling the needs of any specific scenario.

2.2.4 The Bayesian Game Model

In several situations where interactions occur, the interacting entities may not have complete information about each other's characteristics. The model of a Bayesian game [4] is designed to

[4] The text in subsections 2.2.4, 2.2.5, 2.2.6 is based on [79].

model such situations. A player's uncertainty about the opponent's characteristics, is modelled by introducing a set of possible states, i.e. probable sets of characteristics that a player may have, also known as a player's *types*. Each player assigns a probability of occurence to each of the opponent's possible *types*. Therefore, a definition of a Bayesian game is similar to the definition of a normal form game, with the additional elements of the *types* for each player and the corresponding probability of occurence, as believed by the player's opponent(s).

A Bayesian game can be modelled by introducing Nature as a player in the game[5] . Nature assigns a random variable to each player, which could take values of types for each player and associate probabilities with these types. In the course of the game, Nature randomly chooses a type for each player according to the probability distribution across each player's type space. The type of a player determines the player's payoff and the fact that a Bayesian game is one of incomplete information means that at least one player is unsure of the type and thus the payoff of another player.

In any given play of a Bayesian game, each player knows his type and does not need to plan what to do in the hypothetical event that he is of some other type. However, when determining a player's best action, he must consider what the other player(s) would do if any of the other possible types were to occur, since any player may be imperfectly informed about the current state of the game. Therefore, a Nash Equilibrium of a Bayesian game is the Nash equilibrium of the normal form game in which the set of players includes all possible types for each player, and consequently the set of actions includes all possible actions for each such state of every player considered. In brief, to reach a Nash equilibrium in a Bayesian game, each player must choose the best action available to him, given his belief about the occurence of his opponent's types, the state of the game and the possible actions of his opponent.

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[5]This approach was proposed by John C. Harsanyi in [46]

2.2.5 The Repeated Game Model

The model of a repeated game is designed to examine the logic of long-term interaction. It captures the idea that a player will take into account the effect of his current behaviour on the other player's future behaviour. Repeated game models aim to explain phenomena like cooperation, threats and punishment.

The repeated game models offer insight into the structure of behaviour when individuals interact repeatedly, a structure that may be interpreted in terms of social norm. The results show that the social norm needed to sustain mutually desirable outcomes involves each player threatening to *punish* any other player whose behaviour is undesirable. Each player uses *threats* to warn the opponent that such punishment may follow if the threats are credible and if there is sufficient incentive for the player to carry out his threat. Thus, punishment depends on how players value their future payoffs and it may be as harsh as lasting forever, or as mild as lasting for only one iteration.

The model of a repeated game has two kinds: the horizon may be *finite*, i.e. it is known in how many periods the game ends, or *infinite*, i.e. the number of game periods is unknown. The results in the two kinds of games are different, for instance, analyzing a finite version of the Prisoner's Dilemma ends in the conclusion that the players are motivated to cheat as in the one-shot Prisoner's Dilemma, whereas an infinite version of the Prisoner's Dilemma results in a motivation for both players to cooperate.

The Iterated Prisoner's Dilemma is a quite popular repeated game model which demonstrates how cooperation can be motivated by repetition (in the case the number of periods is unknown), whereas in the one-shot Prisoner's Dilemma as well as in the finite version of the Iterated Prisoner's Dilemma, the two players are motivated to cheat. The main idea is that if the game is played repeatedly, then the mutually desirable cooperative outcome is stable because any deviation will end the cooperation, resulting in a subsequent loss for the deviating players that outweighs the payoff from the finite horizon game (horizon of one or more periods). This emerging stability is used in [76] to explain how in finite populations natural selection (occuring over an unknown number of iterations, thus modelled as an infinite horizon game) favours cooperation when starting from an individual using that strategy and further, the analysis of this phenomenon leads to natural conditions for evolutionary stability in finite populations. Thus, when applying the model of a repeated game to a specific situation or problem, e.g. natural selection, we must first determine whether a finite or infinite horizon is appropriate, based on the characteristics of the realistic situation.

2.2.6 Games of Coalitions

Coalitional Games deal with the situation, in which interactions occur between groups of players (coalitions) and thus actions are assigned to coalitions even though individual entities may consider their own preferences, especially when selecting a particular coalition in which to participate. Therefore, a coalitional model is characterized by its focus on what groups of players can achieve rather than on what individual players can achieve.

Furthermore, in coalitional games, the way a coalition operates internally, i.e. among its members, is not considered as important for a coalitional game so that the outcome does not depend on such details. A solution concept for coalitional games assigns to each game a set of outcomes, capturing consequences for the participating coalitions. The solution defines a set of arrangements that are stable in some sense, i.e. that the outcomes are immune to deviations of any sort by groups of players.

In order to determine the solution to a coalitional game, we must first define the way payoffs are assigned to the various coalitions; such assignment can occur per group as a whole, or per group using a particular division arrangement within the group for its members. When payoffs are assigned per group, the players that participate in the same group are associated with the group's payoff and it is not defined how this payoff may be further partitioned among its members. This case of payoff assignment is referred to as transferrable payoff coalitional game. The alternative is known as non-transferrable payoff coalitional game, and in such model there exists a rule on how group payoffs are divided among participating players.

A well-known solution concept for a coalitional game model is the *core*. The core is a solution concept that requires that no set of players be able to break away and take a joint action that makes all of them better off. Overall, the idea of the *core* is analogous to that behind a Nash equilibrium of a non-cooperative game, i.e. an outcome is stable if no deviation is profitable. In the case of the *core*, an outcome is stable if no coalition can deviate and obtain an outcome better off for all its members.

2.3 Cooperation in Networking

Next Generation mobile communication networks will consist of a multiplicity of wireless and mobile networks, each possessing different characteristics and capabilities. Next Generation networks plan to take advantage of these varying characteristics, exploiting them in complementary manners in order to surpass any limits imposed by any one of these networks on its own, through appropriate network synergies.

Synergies, i.e. cooperation between entities have been popular at the level of nodes in ad-hoc, peer-to-peer as well as sensor networks, where communication is in fact based on cooperation between the participating nodes. In [19] cooperation with a neighbouring node takes place if the reputation of the neighbouring node is satisfactory. Reputations are maintained in a distributed manner in such networks, i.e. a node's reputation and trust is the collection of relevant ratings maintained by other nodes. Each node is thus, its own authority and needs appropriate incentives in order to cooperate with its neighbours and facilitate communication by e.g. forwarding packets [20]. In [63] sensor nodes are encouraged to collect and carry information not only in their own interest but also in the interest of other mobile nodes. Appropriate incentives could include rewards for cooperation, i.e. the mobile nodes could be rewarded with their own ability to send traffic [87]. Mobile nodes could also be motivated to cheat because of their own selfish nature, and this kind of behaviour can be predicted and prevented, through appropriate incentives [88].

Next Generation mobile communication networks have motivated cooperation at the level of networks, since they promote the co-existence of different networks on a convergence platform such that the actual network serving a particular request is transparent to the mobile user. Network Selection is the mechanism responsible to select the network(s) to serve a particular request out of the set of available networks. Selecting the network(s) to serve a user demand that both satisfies the user preferences and the network constraints may become a challenging task. Since Network Selection is a mechanism involving important decision making, it must take into consideration some strategical planning on behalf of the entities involved in this decision. Given that Game Theory is a theoretical framework for strategical decision-making, it has been a very popular approach amongst many of the recently presented research works. In addition to the most commonly seen non-cooperative games [23, 22, 27, 8], several cooperation schemes have emerged to propose solutions in situations where limited resources or need for quality guarantees exist [74, 3].

Furthermore, interconnection of networks results in various forms of infrastructure cooperation, which, although socially desirable may not always be beneficial for the participating networks. Therefore, to avoid defection from cooperation, this is sometimes made mandatory for the cooperating networks, since higher data rates, better coverage, improved energy consumption as well as more accurate location estimation could result from infrastructure cooperation [75]. Underlying principles of cooperative techniques as well as several applications demonstrating the use of such techniqus in practical systems, are demonstrated in [38]. Given such cooperative environments, enhanced services can be designed to take advantage of the existing cooperation between networks and network components [39]. Moreover, the development of wireless and mobile communications industry and technology in the near future depends largely upon the merging of the Internet with the mobile world, requiring the cooperation of the involved heterogeneous network entities, to achieve attractive scenarios for the future mobile user [58].

The current thesis contributes to the cooperation paradigm at the level of networks and explores Game Theory as an interaction modeling framework in order to achieve some decision-making such that all decision-making entities in each interactive situation are satisfied.

Chapter 3

Cooperation in User-Network Interaction

3.1 Introduction

The user-centric paradigm employed in Next Generation converged mobile networks has brought about the decoupling of content and carriage, with the mobile network operators taking the role of the content carrier, whilst the task of content provisioning is being handled by independent content providers. Therefore, mobile networks participating in Next Generation mobile network environmnents are called upon to handle, on the one hand, the grand speed at which technology develops and, on the other hand, the ever-changing content pools.

Next, we investigate the cooperative aspects of the relationship between the user and the mobile network when they interact, considering an illustrative example scenario where the user participates in a User Generated Content (UGC) service [93] supported by the mobile network.

3.2 Illustrative User-Network Interaction Scenario

As mobile Internet services grow rapidly, new interactive services invite users to participate actively in the network, changing the mobile subscriber role from a passive customer into an active participant. UGC services, which depend on user contribution, become more and more popular in the fixed Internet (Facebook, Flickr, YouTube), and are expected to dominate the mobile market as well. Through such services, the user acting as a content provider uses the mobile network infrastructure to distribute audio and video content to the community of mobile subscribers. A mobile network operator supporting UGC services, attracts users by allowing them to become producers of their own content and distribute this content to other mobile subscribers in a relatively inexpensive way. Thus, mobile operators are in a position to benefit from the increasing interest in UGC services, by attracting more customers, who are offered a quick and easy way to socialize audio and video content, often generated by the mobile phone itself, that would otherwise just reside in the phone itself. Hence, given that both the user and the network have incentives to participate in UGC services, cooperation between the user and the network is desirable.

Consequently, this model creates a new user-network relationship from which both entities have something to give and something to receive, i.e. an exchange relationship. The user offers a compensation to participate in the UGC service hosted by the network, and the network distributes the user generated content.

The scenario considered for illustrating the user-network interaction employs the idea of UGC services in Next Generation converged mobile networks, where the user wants to participate in such a service supported by the mobile network. Allowing the user to become a content provider, results in the network having no control over the *quality* of the uploaded content, with the issue becoming more serious in the case of infringing content. The user could upload infringing content, which may cost in terms of reputation and fines (from possible copyright sues) to the network. Thus, the network is motivated to prevent such situation.

Recognizing infringing content could be achieved through the setup and maintainance of a secure framework aiming to thwart infringement by employing content identification technology [84], in order to match newly uploaded content against existing copyrighted content. A broker entity could undertake this task and provide networks the option of checking the *originality* of contents uploaded by their users, through the use of this content identification framework, for a certain fee per request.

The interaction is the following:

The user wants to participate in the UGC service and upload some own audio or video content. To participate in the service, the user must make a UGC service request to the network. For simply participating in the service, the request is referred to as a *basic* service request. In addition to this, the user may request *content identification* of the uploaded audio or video content, i.e. request that the content is checked and identified as *non-infringing*, content. This may be referred to as an *enhanced* service request. Note that for the *basic* service case, the user is expected to *assure* the network that the content is not copyright-infringing. In this case the user may or may not be truthful.

The payment of the user for participating in the *basic* service is less than the payment to participate in the *enhanced* service, because content identification entails additional cost for the network, which needs to request such identification from a *copyright broker* entity[1] . We assume that, for content identification, the network entails a certain cost per request by the copyright broker.

[1]A copyright broker is an entity, which maintains a list of contents identified as *new* and uses effective content identification technology to locate possible infringing user-uploaded audio and video content

Let the user's payment to the network be referred as compensation, which is either given for a *basic* UGC service request or for an *enhanced* UGC service request. The user has an incentive to request the *basic* service in order to save money, but simultaneously he takes the risk that if the content is checked and identified as infringing, he will be liable (with probably higher costs in terms of fines). On the other hand, if the user requests an *enhanced* service, he will pay more but at the same time he minimizes the risk that he will be held liable if the content is identified as infringing.

The decision dilemma on the user side is not the only one in this interaction. There exists a decision dilemma on the network side as well. The network has to decide whether or not to check the uploaded content, knowing that checking entails an additional cost for the network, but at the same time minimizes the risk for liability of the network in case the content is identified as infringing. The network has an incentive not to check the content in order to avoid the additional cost, but at the same time it risks to be held liable for infringing content, which may in turn lead to even greater costs in terms of sues and fines.

Next, we summarize the possible actions, gains and costs, of both the user acting as a content provider and the mobile network, which hosts the user generated content.

1. The user faces the dilemma of either to incur the cost of requesting content identification (*enhanced* service), in addition to the payment to the network for participating in the UGC service (*basic* service), or not. The user that does not request content identification, takes the risk that such content may be identified as infringing, in which case the user may be held liable, incurring possible fines. Let the user's total cost be referred to as the compensation to the network, κ, if it encompasses the cost for content identification, or κ', if it does not, where $\kappa' < \kappa$.

2. The network will receive compensation κ or κ'. In either case, it may subsequently request to the copyright broker that the uploaded content is checked through the broker's content identification technology framework, which is able to detect in most cases whether a content is infringing. Thus to check content quality q, the network undertakes an additional cost. If it decides not to check quality of content (refer to unchecked quality as q'), it saves money but it risks that the content may be infringing and thus may result in even greater costs in terms of fines. Thus the network's total cost for hosting this request is $c(q)$, which includes the content identification costs if it checks content quality. Otherwise, the network's total cost for unchecked content quality is $c(q')$, and $c(q') < c(q)$.

3. The user experience could be quantified in terms of satisfaction, where a content identified as non-infringing, i.e. of quality q, results in satisfaction $\pi(q)$. On the other hand, a content identified as infringing, i.e. of quality q', results in satisfaction $\pi(q')$, where $\pi(q') < \pi(q)$, since a non-infringing content is distributed but an identified infringing content may not, and furthermore it may result in sues and fines if the user is held liable for this infringment.

The possible actions of the user and the network, as well as their corresponding payoffs are summarized in Table 1.

Table 1: User-Network Interaction Scenario for a UGC service

	Network Checks Content	Network Does Not Check Content
User Requests Content Identification	$\pi(q) - \kappa, \kappa - c(q)$	$\pi(q') - \kappa, \kappa - c(q')$
User Does Not Request Content Identification	$\pi(q) - \kappa', \kappa' - c(q)$	$\pi(q') - \kappa', \kappa' - c(q')$

3.3 Incentives & General Assumptions

Investigating the interaction between the user and the network, we seek to identify 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 the above-mentioned scenario of user-network interaction, 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 a function of content *quality*, i.e. infringing or non-infringing, and the *compensation* offered by the user to the network, which includes the payment to participate in either *basic* UGC service or *enhanced*.

- The payoff of the network is basically the profit of the mobile network, represented as the difference between the compensation received from the user for the *basic* or *enhanced* service, and the total cost for hosting this request, which may or may not include the cost to check whether content is infringing.

Both payoffs are based on the fact that the compensation offered by the user to the network and the satisfaction in the user payoff, as well as the total cost for hosting the request by the network are comparable. In the user payoff, 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 network payoff, both the cost for identifying and distributing content and the compensation received may be expressed in terms of monetary ammounts. 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 cost, the less the *units of satisfaction* for the network.

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 *assumptions*:

Assumption 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.

Assumption 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.

Assumption 3. 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 motivate a cooperative interaction.

Assumption 4. Both the user and the network have non-negative payoff functions (same reasoning as Assumption 3).

Assumption 4 results in the following requirements:

Req. 1 For the user to participate in the interaction, the satisfaction $\pi(q)$ expected to be received should be greater than the compensation κ offered to the network. This holds also for minimum satisfaction $\pi(q')$, i.e. when the user is not satisfied. The difference, however, between $\pi(q')$ and compensation for *basic* service κ', is minimum, whereas the difference between $\pi(q)$ and κ can be much higher, since the user wants to pay less and receive more. Given that perceived satisfaction and compensation are measurable in comparable units, the user *plays* the game without risking to have a negative payoff, satisfying Assumption 4.

Req. 2 For the network to participate in the interaction, we require that the network's cost $c(q)$ from hosting the UGC service is less than the compensation κ offered by the user by an amount $\epsilon > 0$, such that the network may gain at least marginal profit from this interaction. This holds for both kinds of services, i.e. when the user chooses to give a compensation κ' for *basic service* and when the user chooses to give a compensation κ for *enhanaced* service. The difference, however, between compensation and cost, $c(q)$ or $c(q')$, when the user pays for *basic* service, is minimum, whereas the difference is much higher when the user pays for *enhanced* service, since the network wants to make more profit compared to the experienced cost. Thus, given that the compensation and cost of supporting a requested quality are measurable in comparable units, the network *plays* the game without risking to have a negative payoff, satisfying Assumption 4.

Req. 3 Given $\epsilon > 0$, it is better for a network not to reject the user's content, but accept it and decide whether to cooperate, i.e., check the content, or defect, i.e., not check the content. On the other hand, we also allow the user to be able to defect from cooperation, by not requesting to identify the content uploaded, thus ending up giving a lower amount of compensation to the network.

Initially, in our study, we treat this interaction as a *one-shot* interaction in order to derive some fundamental properties of the interaction, although unrealistic since users and networks may interact multiple times through a UGC service. In particular, as expected the theoretical analysis of the one-shot model of the game reveals that cooperation between the entities is not achieved. This result motivated us to investigate the circumstances under which the knowledge of previous outcomes of the repeated interaction, which is a more realistic assumption can result in cooperative behaviour, from which both the user and the network can be satisfied.

3.4 One-Shot User-Network Interaction Game

In this section, 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.

Consider a game between 2 heterogeneous players, the user and the network, interacting as follows.

Definition 1 (User-Network Interaction game)**.** Let the user choose between compensations κ and κ' to offer to the network for participating in a UGC service, where κ' is the cost to participate in the *basic* service, and κ is the cost for the *enhanced* service. The network receives the compensation κ or κ', and decides whether to check for infringment, with total cost for hosting the request equal to $c(q)$, or not to check for infringment with total cost equal to $c(q')$, where $c(q') < c(q)$; q represents the content quality, i.e. quality is represented by q if checked or by q' if not checked. The user perceives a certain satisfaction from the network's action, specifically $\pi(q)$ for distribution of content identified as non-infringing, or $\pi(q')$ for content identified as infringing and not distributed, where $\pi(q') < \pi(q)$; in this case content quality is represented by q if content is treated as non-infringing, or by q' if content is treated as infringing. Given the user and network choice of actions, both players aim to maximize their payoffs.

Table 1, page 40, illustrates the payoffs corresponding to each set of actions for the user and the network in the user-network interaction game.

3.4.1 Equivalence to Prisoner's Dilemma

Considering Definition 1 for the User-Network Interaction game, we prove next that this case is equivalent to a Prisoner's Dilemma type of game (Definition 2).

Definition 2 (Prisoner's Dilemma type of game)**.** [59] Consider an 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 $B_j > \frac{A_j + D_j}{2}$.

Table 2: General payoffs for the Prisoner's Dilemma

	Player 2 Cooperates	Player 2 Defects
Player 1 Cooperates	B_1, B_2	D_1, A_2
Player 2 Defects	A_1, D_2	C_1, C_2

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

We prove next that the User-Network Interaction game is equivalent to a *Prisoner's Dilemma type of game* by making use of Table 3, which illusstrates the mapping between the user and network payoffs in a User-Network Interaction game and the payoffs in a Prisoner's Dilemma type of game.

Table 3: The mapping between the user & 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	$\pi(q') - \kappa$	$\kappa' - c(q)$

Proposition 3.4.1. *The User-Network Interaction game (Definition 1) is equivalent to a Prisoner's Dilemma game.*

Proof. By Definition 1 we immediately conclude that:

Observation 1. There are two possible actions for the user: (i) to cooperate, i.e. offer compensation for *enhanced* service, and (ii) to defect from cooperation, i.e. offer compensation that includes payment for participation in *basic* service. Similarly, there are two possible actions for the network: (i) to cooperate, i.e. check uploaded content for infringment, and (ii) to defect from cooperation, i.e. not check uploaded content for infringment.

Observation 1 combined with Definition 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 type of game. In particular, Table 3 maps each player's payoffs, of Table 1 to actions A_j, B_j, C_j, D_j, where $j \in \{1, 2\}$, as defined in Definition 2. We proceed to prove:

Lemma 3.4.1. *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 2.

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 Assumption 4 and Req. 1, then $\pi(q) - \pi(q') > \kappa - \kappa'$, and 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 (Assumption 4, Req. 2), then $\kappa - \kappa' > c(q) - c(q')$, and $B_2 > C_2$. □

We now proceed to prove that:

Lemma 3.4.2. *The User-Network Interaction game, satisfies condition* 2 *of Definition 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 $B_j > \frac{A_j+D_j}{2}$.

Remember from Assumption 4 that the payoffs of both the user and the network are nonnegative, thus $(\pi(q) - \kappa) > 0$ and $(\kappa - c(q)) > 0$. Combining, we have $\pi(q) > \kappa > c(q)$ and we consider this relation in the following:

For the user,

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

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

For the network,

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

□

Observation 1, Lemma 3.4.1, and Lemma 3.4.2 together complete the proof of Proposition 3.4.1.

□

The decision of each player in the User-Network Interaction game is based on the following reasoning [59]: 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 3.4.1. *[59] In a one-shot Prisoner's Dilemma game, a best response strategy of both players is to defect from cooperation.*

Proposition 3.4.1 combined together with Corollary 3.4.1 immediately implies:

Corollary 3.4.2. *In the one-shot User-Network Interaction game, a best response strategy of both players is to cheat.*

Corrolary 3.4.1 and Corollary 3.4.2 give rise to the question of how cooperation could be motivated, since the user and the network must cooperate in order to bring about the success of UGC services, in terms of guarding against infringing content. If both players are motivated to defect from cooperation, then the user is not motivated to undertake the cost of identifying uploaded content, i.e. participate in the *enhanced* service, and the network is not motivated to undertake the additional cost for checking content for infringment. Thus, a memoryless user-network interaction results in no cooperation between the players. We proceed to investigate the sequential modelling of the one-shot User-Network Interaction game, in order to investigate whether the change from simultaneous actions into sequential actions affects the game.

3.4.2 Sequential moves game

We now present a sequential moves game modelling the user-network interaction, in order to check whether the same conclusions hold as in the simultaneous-moves one-shot game. 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. 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. 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 Figure 1.

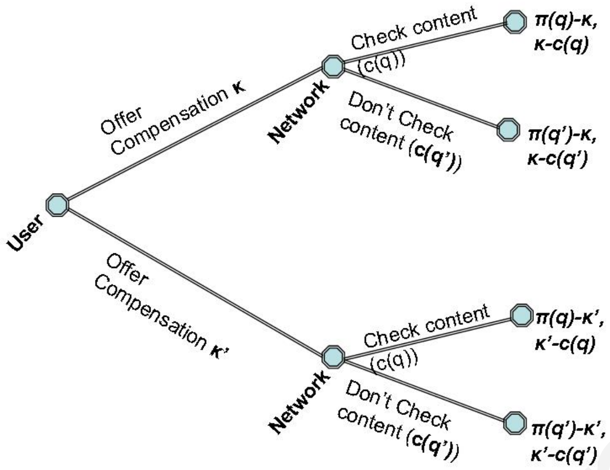

Figure 1: The one shot sequential moves game of user-network interaction in extensive form

The user has a choice of two actions, to request *enhanced* or *basic* service, offering a corresponding compensation to the network of either κ or κ'. The network then may choose to check or not to check the uploaded content, undertaking a total cost of $c(q)$ or $c(q')$. All the payoffs are illustrated at the leaves of the tree in Figure 1.

Both players want to make choices that maximize their payoff since they are *rational* players. Let's first examine the behaviour of the user. The first choice involves whether to offer payment κ' or κ. Consequently, the network decides whether to check the content or not. The network knows that the cost for not checking the content is much less than the cost for checking the content. Since, according to the payoffs, the network will not experience any *punishment* for not checking the content 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 defect from cooperation and not check the content, increasing its own payoff.

Now, since the user is a rational player and wants to maximize his own payoff, he will choose to offer a compensation for *basic* service, κ', in order to end up with the highest attainable payoff.

Using backward induction thinking, i.e., by considering which move is the best for the network is, the user may guess that the best response to the network's best behaviour of defecting is to only offer minimum compensation, expecting in return minimum satisfaction. This is done in order to maximize his own payoff as well, by making sure not to experience any extra losses due to the network's defecting behaviour. Corollary 3.4.3 summarizes these findings:

Corollary 3.4.3. *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 does not check the content, resulting in both entities defecting from cooperation.

3.4.3 Conclusions on the one-shot user-network interaction game

The above discussion on the one-shot game leads to the conclusion that cooperation between the user and the network is not supported for UGC services, when the involved entities interact only once. However, since in realistic scenarios previous outcomes of the interaction affect the behaviour of the two entities in a present interaction, we introduce in Section 3.5, a different model of the interaction, in an attempt to check whether cooperation could be reached and under what conditions. In particular, we present a repeated game model that captures the case where players have a one-unit window of the previous history of the game, i.e., they know their opponent's last action. Thus, we investigate how the behaviour of both the user and the network changes if we consider a repeated interaction between the two entities. The User-Network interaction is modelled as a repeated game with infinite horizon [34], with the payoffs for each period as indicated in Table 1.

3.5 Repeated User-Network Interaction Game

The interactions between networks and users are commonly not one-shot but re-occuring[2]. 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 game models. There are two kinds of repeated game models: the finite horizon repeated games and the infinite horizon repeated games, which are actually models of games of unknown length [34, chapter 11]. We categorize the user-network interaction model as an infinite horizon repeated game, since the users may keep requesting new UGC sessions from the networks for the particular service, 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* [42, chapter 6]. 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* [34, chapter 11], which dictates that the player participates in the relationship in a cooperative manner, 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 the user is not satisfied in one stage, i.e. the network does not provide the service promised, in the next stage the user may *punish* the network by leaving the relatiosnhip forever (e.g., stop interacting with the specific network for subsequent requests of the particular service). Given such a strategy, the network has a stronger incentive to cooperate and provide the service promised, since it faces the threat

[2] In reality we may have competition between different networks for supporting such a user request and/or some form of government intervention towards resolution

of losing its customer. The threat of non-renewal of the user's *contract* to the network, secures compliance of the network to satisfy the user request. 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* [42, chapter 6]. 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, since according to the user's strategy, if the user is not satisfied with the provided service, the user leaves the relationship, and the network loses its customer. 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 [34, chapter 11].

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. In addition, we define initially, two more possible strategies for the user and one more possible strategy for the network and provide a comparison analysis. 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 so as to allow the user to employ non-cooperative behaviour, i.e. not undertake the *enhanced* service cost. With this strategy, the user leaves after defecting from cooperation, i.e., does not continue interaction with the particular network, in order to avoid any punishment for defecting. The *Leave-and-Return* strategy is a cooperative strategy similar to the Grim strategy but we define it to capture the case where the punishment, if the network defects from cooperation, 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 defect from cooperation and not check the content, and since it cannot in reality leave the user-network relationship (if the user selects to interact with the 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. In the repeated-game it is possible to know the move of the opponent after each interaction, since the decisions are simultaneous.

3.5.1 Present Value

Examining the user-network relationship, we consider a signal that runs through the game and may stop the interaction (such a signal could represent a non-strategic event that would force either of the players to terminate the interaction e.g. a damage to the network infrastructure or a relocation of the user). 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* [34, chapter 11], 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 a player's 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 p, then the payoff a player is willing to accept today, i.e., the player's PV, would be equal to $\frac{1-p}{1+r}$. Let $\delta = \frac{1-p}{1+r}$, where $\delta \in [0, 1]$ and often referred to as the *discount factor* in repeated games [34]. 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 $1 + \delta + \delta^2 + \delta^3 + \delta^4 + \dots$, 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. At each decision node, i.e., for each period the network has the choice of two actions: either to take the risk and cooperate with the user checking the uploaded content, or to defect from cooperation and not check it. In case the network defects, and the grim trigger strategy is used by the user, the user will leave the network at the end of the session. The user on the other hand, may cooperate and offer enhanced compensation to include identification costs for the uploaded content, or defect from cooperation and offer a less compensation that does not include such costs. If the tit-for-tat strategy is used by the network, then the network will also defect in the subsequent interaction.

3.5.2 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 [68], 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* [34]. When all players play their subgame perfect strategies, then we have an equilibrium in the repeated game, known as a *subgame perfect equilibrium* [34].

Definition 3 (Cheat-and-Leave Strategy)**.** When the user cooperates and then defects from cooperation in a random period, immediately leaving in the next period to avoid punishment, the strategy is referred to as the cheat-and-leave strategy.

Definition 4 (Cheat-and-Return Strategy)**.** When the network cooperates and then defects from cooperation in a random period, immediately returning to cooperation in the next period, the strategy is referred to as the cheat-and-return strategy.

We are now ready to introduce a repeated game model of the user-network interaction when the history is taken into account in the decisions of the entities:

Definition 5 (Repeated User-Network Interaction Game)**.** Consider a game with infinite repetitions of the one shot User-Network Interaction Game with one additional action available to the user: leaving the interaction[3] . Let the payoffs from each iteration be equal to the payoffs from the one-shot User-Network Interaction game, and in the case the user leaves, let the payoff to both players be equal to zero. Then, the game is referred to as Repeated User-Network Interaction Game.

Because of the unknown number of iterations, the PV of each player is calculated after a history, i.e. record of all past actions that the players made [34, chapter 11], to be able to evaluate each available action in the remaining game. The PV makes use of the idea of a discount factor $\delta = \frac{1-p}{1+r}$, where $p \in [0, 1]$ is the probability of termination of the interaction, and r is the rate of satisfaction gain of continuing cooperation in the next period. Thus we may consider the cumulative payoffs for each player from the repeated interaction.

[3] It is logical to assume that the user can switch to a different network if dissatsfied, whereas a network cannot leave the interaction once it decides to participate in it

Let the user have a choice between the two following strategies: (i) the *grim* strategy, i.e. offer a compensation κ but if degradation is perceived, then leave the relationship forever, and (ii) the *cheat-and-leave* strategy. Let, the network have a choice between: (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 defects from cooperation, the sequence of game profiles (we will refer to this simply as profile from now on) is one of cooperation defined more formally next:

Definition 6 (Conditional-Cooperation Profile)**.** 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.

The following theorem states that the *conditional-cooperation* profile strategies provide a best response to the alternative strategies: *cheat-and-leave* for the user and *cheat-and-return* for the network.

Theorem 3.5.1. *In the repeated user-network interaction game, assume* $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$ *and* $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$*. Then, the conditional-cooperation profile strategies result in higher payoffs than the* cheat-and-leave *and* cheat-and-return *strategies.*

Proof. We assume a history of cooperative moves in the past. We compute the PVs of both the user and the network and after comparing them we conclude that the conditional-cooperation profile strategies are more motivated than the *cheat-and-leave* and *cheat-and-return* strategies.

1. Assume first that the user plays the grim strategy. Considering the network's strategies it could either play the tit-for-tat strategy, i.e. cooperate in the current period, or play the cheat-and-return strategy, where it may defect from cooperation.

If the network cooperates, then:

$$PV_{coop}^{net} = \frac{\kappa - c(q)}{1 - \delta}$$

If the network defects, then:

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

For the network to be motivated to cooperate, its PV in case of cooperation must be preferrable than its PV in case of defecting. Thus:

$$PV_{coop}^{net} > PV_{def}^{net} = \frac{\kappa - c(q)}{1-\delta} > \kappa - c(q') + \frac{\delta \cdot 0}{1-\delta}$$

If the user plays the grim strategy, the network is motivated to cooperate when $\delta > \frac{c(q)-c(q')}{\kappa - c(q')}$.

2. Assume now that the user plays the cheat-and-leave strategy. Considering the network's possible strategies, it could either cooperate or defect from cooperation in the current period.

If the network cooperates, then:

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

If the network defects, then:

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

If the user plays the cheat-and-leave strategy, the network is not motivated to cooperate since $PV_{def}^{net} > PV_{coop}^{net}$

3. Assume now that the network plays the tit-for-tat strategy. If the user plays the grim strategy, it will cooperate in the current period whereas if it plays the cheat-and-leave strategy it may defect from cooperation.

If the user cooperates, then:

$$PV_{coop}^{user} = \frac{\pi(q) - \kappa}{1-\delta}$$

If the user defects, then:

$$PV_{def}^{user} = \pi(q) - \kappa' + \frac{\delta \cdot 0}{1-\delta}$$

For the user to be motivated to cooperate, its PV in case of cooperation must be preferrable than its PV in case of defecting. Thus:

$$PV_{coop}^{user} > PV_{def}^{user} = \frac{\pi(q) - \kappa}{1 - \delta} > \pi(q) - \kappa' + \frac{\delta \cdot 0}{1 - \delta}$$

If the network cooperates, the user is motivated to cooperate when $\delta > \frac{\kappa - \kappa'}{\pi(q) - \kappa'}$.

4. Assume finally that the network plays the cheat-and-return strategy. Considering the user's possible strategies, it could either cooperate or defect in the current period.

If the user cooperates, then:

$$PV_{coop}^{user} = \pi(q') - \kappa + \frac{\delta \cdot 0}{1 - \delta}$$

If the user defects, then:

$$PV_{def}^{user} = \pi(q') - \kappa' + \frac{\delta \cdot 0}{1 - \delta}$$

If the network plays the cheat-and-return strategy, the user is not motivated to cooperate since $PV_{def}^{user} > PV_{coop}^{user}$.

It follows that the conditional-cooperation profile is motivated when $\delta > \frac{c(q) - c(q')}{\kappa - c(q')}$ and $\delta > \frac{\kappa - \kappa'}{\pi(q) - \kappa'}$. $\square$

When a strategy instructs a player to play the best response, i.e. giving the player the highest payoff, to the opponent's strategy after every history it is called a *subgame perfect strategy* [34, chapter 11]. To have a subgame perfect strategy, then we must show that for every possible iteration of the game, the current action results in the highest payoff, against all possible actions of the opponent player. In the repeated User-Network Interaction game we consider a history of cooperation from both players, and hence the best response strategy of each player against all possible actions of the opponent in the current period, is given in terms of PV and considers such a cooperative history. When both players play their *subgame perfect strategies*, then we have an equilibrium in the repeated game, known as a *subgame perfect equilibrium* [34, chapter 11].

To prove a subgame perfect equilibrium for the conditional cooperative profile, we must show that the payoff gain from defecting from cooperation now, i.e. the temptation in the current period, is less than the difference between the cooperative reward and the punishment for defecting, starting from the next period of the game and lasting forever. This technique is based on the idea of the *single-deviation principle*, i.e. at any stage allow one of the players to change his action. This technique may be applied to games where previous histories of all players are known, players move simultaneously and strategies prescribe the same behaviour and payoffs in all stages. Since our game staisfies these conditions, consider the following theorem:

Theorem 3.5.2. *In the repeated user-network interaction game, assume* $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$ *and* $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$. *Then, the conditional-cooperation profile is a subgame perfect equilibrium.*

Proof. For the user:

$$Temptation_{now} = (\pi(q) - \kappa') - (\pi(q) - \kappa) = \kappa - \kappa'$$

$$Reward_{forever} = \frac{\pi(q) - \kappa}{1 - \delta}$$

$$Punishement_{forever} = \frac{0}{1 - \delta} = 0$$

The reward and punishment are considered from the next period, therefore we discount by δ, and we have:

$$Temptation_{now} < \delta \dot{(} Reward_{forever} - Punishement_{forever})$$

$$\kappa - \kappa' < \delta \dot{(} \frac{\pi(q) - \kappa}{1 - \delta} - 0)$$

$$\delta > \frac{\kappa - \kappa'}{\pi(q) - \kappa'}$$

For the network:

$$Temptation_{now} = (\kappa - c(q')) - (\kappa - c(q)) = c(q) - c(q')$$

$$Reward_{forever} = \frac{\kappa - c(q)}{1 - \delta}$$

$$Punishement_{forever} = \frac{0}{1 - \delta} = 0$$

Similarly to the user calculations, the reward and punishment are considered from the next period, therefore we discount by δ, and we have:

$$Temptation_{now} < \delta\dot{(}Reward_{forever} - Punishement_{forever})$$

$$c(q) - c(q') < \delta\dot{(}\frac{\kappa - c(q)}{1 - \delta} - 0)$$

$$\delta > \frac{c(q) - c(q')}{\kappa - c(q')}$$

Thus, the conditional-cooperation profile is a subgame perfect equilibrium. □

Let the repeated User-Network Interaction game be modified as follows: the user may employ a strategy such that the punishment imposed to the network for defecting lasts only for one period; namely, let the user be allowed to employ the *leave-and-return* strategy as defined next:

Definition 7 (Leave-and-Return Strategy)**.** When the user cooperates as long as the network cooperates, and leaves for one period in case the network defects, 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, a new profile of the game is considered, the *one-period punishment* profile.

Definition 8 (One-Period-Punishment Profile)**.** 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 has been proven in [47], that the conditions to sustain cooperation with grim trigger strategies, which are the stricter strategies that may be employed in a repeated Prisoner's Dilemma, are necessary conditions for the possibility of any form of conditional cooperation. That is, 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 [47], we show that it is easier to impose cooperation in our game under the *conditional-cooperation* profile, than under the *one-period-punishment* profile.

Theorem 3.5.3. *Assume that $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$ and $\delta > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$ in the repeated User-Network Interaction game. Then, the conditional-cooperation profile motivates cooperation of the players. These conditions on δ are also necessary to motivate cooperation in the one-period-punishment profile.*

Proof. Given a history of cooperation, we seek the values of δ that can motivate cooperation under the *one-period-punishment* profile.

Assume first that the user cooperates in the current period. Then, the network has two options: to cooperate or to defect from cooperation.

If the network cooperates, then:

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

If the network defects, then:

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

In order for cooperation to be motivated, it must be that:

$$
\begin{aligned}
PV^{net}_{coop} > PV^{net}_{def} = \\
\kappa - c(q) + \delta \cdot (\kappa - c(q)) + \tfrac{\delta^2 \cdot (\kappa - c(q))}{1-\delta} > \\
\kappa - c(q') + \delta \cdot 0 + \tfrac{\delta^2 \cdot (\kappa - c(q))}{1-\delta}
\end{aligned}
$$

Simplifying, we get $\delta > \frac{c(q)-c(q')}{\kappa - c(q)}$.

Now, assume the network cooperates in the current period. Then, the user has two options: to cooperate or to defect from cooperation.

If the user cooperates, then:

$$PV^{user}_{coop} = \pi(q) - \kappa + \delta \cdot (\pi(q) - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}$$

If the user defects, then:

$$PV^{user}_{def} = \pi(q) - \kappa' + \delta \cdot (\pi(q') - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}$$

For cooperation to be motivated, it must be that:

$$
\begin{aligned}
PV^{user}_{coop} > PV^{user}_{def} = \\
\pi(q) - \kappa + \delta \cdot (\pi(q) - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta} > \\
\pi(q) - \kappa' + \delta \cdot (\pi(q') - \kappa) + \frac{\delta^2 \cdot (\pi(q) - \kappa)}{1-\delta}
\end{aligned}
$$

Simplifying, we get $\delta > \frac{\kappa - \kappa'}{\pi(q) - \pi(q')}$. □

The cooperation thresholds for both players are summarrized in Table 4.

Table 4: Cooperation Thresholds

	conditional cooperation	*one-period punishment*
Network Cooperates If:	$\delta^{net}_{cc} > \frac{c(q)-c(q')}{\kappa - c(q')}$	$\delta^{net}_{pun} > \frac{c(q)-c(q')}{\kappa - c(q)}$
User Cooperates If:	$\delta^{user}_{cc} > \frac{\kappa - \kappa'}{\pi(q) - \kappa'}$	$\delta^{user}_{pun} > \frac{\kappa - \kappa'}{\pi(q) - \pi(q')}$

Remark. It holds that $\delta_{cc}^{net} < \delta_{pun}^{net}$ since $c(q') < c(q)$, and also that $\delta_{cc}^{user} < \delta_{pun}^{user}$ since $\pi(q') - \kappa' > 0$, hence $\pi(q') > \kappa'$. Thus, both players are more motivated to cooperate under the conditional-cooperation profile.

3.5.3 Conclusions on Equilibria of Repeated User-Network Interaction

It appears to be easier to sustain cooperation from the user's perspective, when strategies that involve harsher punishments are used, e.g. the grim strategy. When the user employs the grim strategy, the network is motivated to cooperate, if $\delta_{cc}^{net} > \frac{c(q)-c(q')}{\kappa-c(q')}$, whereas, if the user employs the one-period punishment strategy, the network is motivated into cooperation if $\delta_{pun}^{net} > \frac{c(q)-c(q')}{\kappa-c(q)}$. The two values for δ are similar with the only difference between the two results to be the second term in the denominator, $c(q)$ instead of $c(q')$. Therefore, the second result is always greater than the first since $c(q) > c(q')$, and hence the first result (grim strategy) is easier to motivate.

For the user, cooperation is also motivated easier with the conditional cooperation profile since the two values of δ, i.e. $\delta_{cc}^{user} > \frac{\kappa-\kappa'}{\pi(q)-\kappa'}$ and $\delta_{pun}^{user} > \frac{\kappa-\kappa'}{\pi(q)-\pi(q')}$, differ only in the second term of the denominator. Given $\kappa' < \pi(q')$ according to Assumption 4 and Req. 1 of the user-network interaction, $\pi(q) - \kappa$, is greater than $\pi(q') - \kappa'$[4] , then it holds that $\delta_{cc}^{user} < \delta_{pun}^{user}$, and hence the first result (grim strategy) is easier to motivate.

Another interesting aspect is to consider the case where even if a content is identified as non-infringing and the user pays for *enhanced* service, the network due to a *quality degradation* event, which occurs at a frequency f, treats the content as infringing. Degradation frequency f is known to each network but not known to the user. Thus, when this event occurs, the user is not satisfied and may adjust his actions accordingly, whereas the network should not check the content, even if its strategy suggests to do so, so as not to undertake that additional cost. In order for the network

[4]as mentioned in the assumption presented for the one-shot user-network interaction, a user always prefers for the compensation to be kept as low as possible, whereas, on the contrary, satisfaction should be as high as possible

to handle this event it must consider its frequency f and modify its strategy accordingly, taking the degradation event into account. However, research on the occurence of such event and its consideration for generating appropriate network strategies, is left for future work.

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 repetability of the user-network interaction, and the compensation set. The architecture considered to host such model is envisioned to be a multi-entity 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, network operators, etc.) 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. An initial study of this appears in [9]. For easy reference, the relevant part in the paper discussing the adoption of IMS appears in Appendix A. However, this is beyond the scope of the thesis but its further study is highly recommended.

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 and 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.

3.6 Access Network Selection Decision

3.6.1 The user as an adaptive entity

Having examined the relationship between a user and a network, when both entities actively participate in an interactive service, through two different types of strategies for each of the players, we move on to propose a model for the mechanism of network selection in a converged environment, a mechanism through which the user selects the *best* network with which to cooperate for the service. The proposed model 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* for participating in a particular service, and *Networks* examine the compensation and make a decision concerning how many of them to accept and how many to 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 (if only one network accepts, the selection is trivial).

The evaluation of $\pi(q)_{expected}$ can be based on user measures of network context, and is normally different for each network. 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 defect from cooperation, 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 Figure 2.

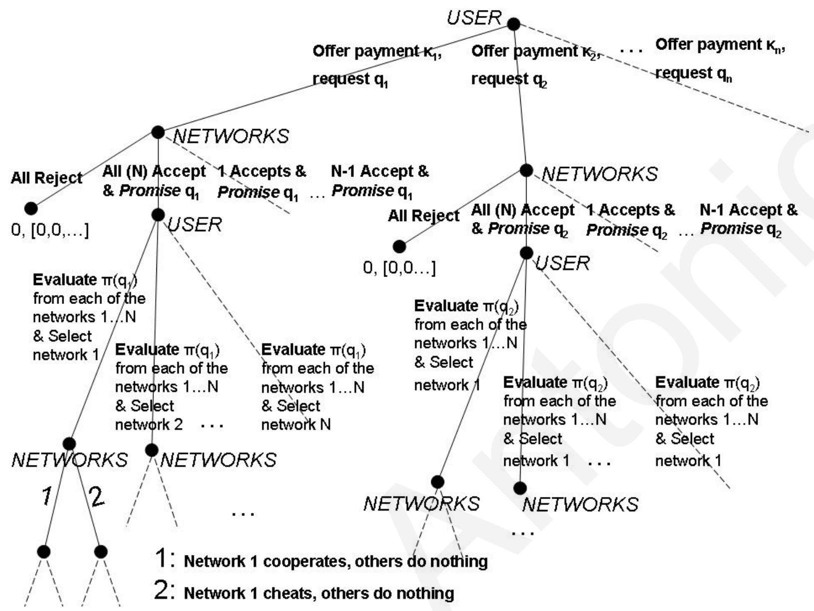

Figure 2: Network Selection model based on User-Network interactions

Within the context of network selection, the user-network interaction may be improved to reflect a user preference towards networks that do not often defect from cooperation. We employ the idea of an adaptive player, such that the user's decision of which network to select considers a network's probability to defect from cooperation based on the acquired knowledge a user gains over the course of the repeated game [47]. The probability to defect from cooperation is considered additionally to the parameters previously mentioned to comprise the $\pi(q)_{expected}$ function.

Thus, when the user must evaluate his predicted satisfaction for selecting each one of the available networks, the evaluation should consider a probability of the network defecting, calculated dynamically from observing past network behaviour. Being an adaptive player, the user makes a more informed selection decision that considers the past. This is achieved by multiplying the predicted satisfaction $\pi(q)_{expected}$ by a variable α (Definition 9), representing the estimated probability of the network cooperating. To achieve this, we assume that the user has an internal state, which modifies probability α after every interactive period with the network, and that α has a different value for each different network that interacts with the user.

Definition 9. In the network selection game, a user possesses an internal state, which, based on a network's history of behaviour, estimates a network's probability not to defect from cooperation, $\alpha \in [0, 1]$. Given that the user has an expected satisfaction for a service request, e, such that $\pi(q)_{expected} \geq e$, the value of α at the end of an interactive period is modified according to (3).

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

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 $\pi(q)_{expected} \cdot a$ instead of only $\pi(q)_{expected}$.

3.7 Proposing 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 3.5 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. 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, which is not as harsh as the grim strategy employed in the conditional-cooperation game profile, but also not as lenient as the leave-and-return strategy employed in the one-period-punishment game profile.

Let the user's strategy be the following: cooperate as long as the network cooperates; if the network defects from cooperation, 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 of 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 10. In the repeated user-network interaction game, the adaptive-return strategy for the user dictates that if the network defects from cooperation, the user 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 and is defined next:

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

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 that employs a punishment that lasts forever is the strategy that provides the strongest motivation to cooperate [47], we show that when the user employs the *adaptive-return* strategy, the network is always at least as motivated to cooperate with the user as when the user employs the one-period punishment strategy, and that further, in most cases the network is more encouraged than these minimum motivation bounds provided when the one-period punishment profile is used (in terms of δ values). Proposition 3.7.1 and Theorem 3.7.1 state and prove these claims.

Proposition 3.7.1. *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 and defect from cooperation. When the network cooperates, the PV is as follows:

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

The sum of a finite geometric progression is used to calculate the discounted value for the first $x+1$ periods, i.e. the current period and the subsequent x periods for which the punishment would hold in case of defecting. If the network defects, its PV is:

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

Consider the case that x equals to 1, i.e. the minimum number of periods that can be imposed as punishment. The conditions necessary to motivate cooperation in terms of δ when $x = 1$ are calculated next:

$$PV_{coop}^{net} > PV_{def}^{net} =$$

$$\tfrac{(\kappa-c(q))\cdot 1-\delta^{x+1}}{1-\delta} + \tfrac{\delta^{x+2}\cdot\kappa-c(q)}{1-\delta} >$$

$$\kappa - c(q') + \tfrac{1-\delta^{x}\cdot 0}{1-\delta} + \tfrac{\delta^{x+2}\cdot\kappa-c(q)}{1-\delta} \quad = \frac{1-\delta^{x=1}}{1-\delta} > \kappa - c(q')$$

For $x+1$, the above result is equal to the following:

$$\frac{1-\delta^2}{1-\delta} > \frac{\kappa - c(q')}{\kappa - c(q)}$$

Therefore,

$$\delta > \frac{c(q) - c(q')}{\kappa - c(q)}$$

□

Remark. Proposition 3.7.1 proves that, in terms of δ and when the value of x is set to 1, the motivation of the network to cooperate with the user, when the user employs the adaptive-return strategy, is equal to the motivation of the network to cooperate with the user employing the leave-and-return strategy.

Theorem 3.7.1. *When the user employs the adaptive-return strategy, the values of δ, above which the network is motivated to cooperate, decrease as the values of x, the number of punishment periods imposed by the user, increase, i.e as the punishment becomes harsher, the network is more motivated to cooperate.*

Proof. According to Proposition 3.7.1, when $x+1$, the network is motivated to cooperate for $\delta > \frac{c(q)-c(q')}{\kappa-c(q)}$.

Let $x = 2$, then:

$$\frac{1-\delta^3}{1-\delta} > \frac{\kappa - c(q')}{\kappa - c(q)}$$

Simplifying,

$$\delta + \delta^2 > \frac{c(q) - c(q')}{\kappa - c(q)}, \delta > \frac{c(q) - c(q')}{\kappa - c(q)} - \delta^2$$

Since $\delta \in (0, 1)$,

$$\frac{c(q) - c(q')}{\kappa - c(q)} - \delta^2 < \frac{c(q) - c(q')}{\kappa - c(q)}$$

Thus, the network is more motivated to cooperate when $x = 2$ than when $x = 1$.

Let $x = 3$, then:

$$\frac{1 - \delta^4}{1 - \delta} > \frac{\kappa - c(q')}{\kappa - c(q)}$$

Simplifying,

$$\delta + \delta^2 + \delta^3 > \frac{c(q) - c(q')}{\kappa - c(q)}, \delta > \frac{c(q) - c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3)$$

Since $\delta \in (0, 1)$ and $(\delta^2 + \delta^3) > \delta^2$

$$\frac{c(q) - c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3) < \frac{c(q) - c(q')}{\kappa - c(q)} - \delta^2$$

Thus, the network is more motivated to cooperate when $x = 3$ than when $x = 2$.

Let $x = n$, where $n > 3$, then:

$$\frac{1 - \delta^{n+1}}{1 - \delta} > \frac{\kappa - c(q')}{\kappa - c(q)}$$

Simplifying,

$$\delta + \delta^2 + \delta^3 + \cdots + \delta^n > \frac{c(q) - c(q')}{\kappa - c(q)}, \delta > \frac{c(q) - c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3 + \cdots + \delta^n)$$

Since $\delta \in (0, 1)$ and $(\delta^2 + \delta^3 + \cdots + \delta^n) > (\delta^2 + \delta^3)$

$$\frac{c(q) - c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3 + \cdots + \delta^n) < \frac{c(q) - c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3)$$

Thus, the network is more motivated to cooperate when $x = n$,$n > 3$, than when $x = 3$

Let $x = n+1$, where $n > 3$, then:

$$\frac{1-\delta^{n+2}}{1-\delta} > \frac{\kappa - c(q')}{\kappa - c(q)}$$

Simplifying,

$$\delta + \delta^2 + \delta^3 + \cdots + \delta^n + \delta^{n+1} > \frac{c(q)-c(q')}{\kappa - c(q)}, \delta > \frac{c(q)-c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3 + \cdots + \delta^n + \delta^{n+1})$$

Since $\delta \in (0,1)$ and $(\delta^2 + \delta^3 + \cdots + \delta^n + \delta^{n+1}) > (\delta^2 + \delta^3 + \delta^n)$

$$\frac{c(q)-c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3 + \cdots + \delta^n + \delta^{n+1}) < \frac{c(q)-c(q')}{\kappa - c(q)} - (\delta^2 + \delta^3 + \delta^n)$$

Thus, the network is more motivated to cooperate when $x = n+1$ than when $x = n$, $n > 3$, $\square$

Remark. Theorem 3.7.1 proves that, in terms of δ, for any other value of x generated by the user, when the adaptive-return strategy is employed, the network is more motivated to cooperate with the user, than when the user employs the leave-and-return strategy when the one-period-punishment profile of the game is played.

Corollary 3.7.1. *In terms of δ, the network is more motivated to cooperate when the user employs the grim strategy than when the user employs the adaptive-return strategy.*

Proof. Since $\delta > \frac{c(q)-c(q')}{\kappa-c(q')}$ when the punishment lasts forever, i.e. for an infinitely large number of periods, and since a punishment of n periods is always more lenient than the punishment forever, then we may deduce that $\frac{c(q)-c(q')}{\kappa-c(q')} < \frac{c(q)-c(q')}{\kappa-c(q)} - (\delta^2 + \delta^3 + \cdots + \delta^n)$. $\square$

Remark. The adaptive-return strategy generates a range of punishments, which can be at least as harsh as the leave-and-return strategy (as used in the one-period-punishment profile of the game), and not as harsh as the punishment generated by the grim strategy (as used in the conditional-cooperation profile of the game).

3.8 Evaluating User-Network Cooperation

This section examines the numerical behaviour of user and network strategies defined and used for the repeated user-network interaction game in Section 3.5. The evaluation is based on a Matlab 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 payoffs. The implementation of the user-network interaction game model was based on a publicly available Matlab implementation of the Iterated Prisoner's Dilemma Game [96], which has been extended to include all existing and proposed strategies examined in Section 3.5.

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 defects and one cooperates, the first gets 4 and the other gets 1, if they both defect, 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 difference between defecting 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 defects and one cooperates, the first gets 100 and the other gets 1, if they both defect, each gets 40, and if they both cooperate each gets 60. In the third set of simulations, we investigate the behaviour of the players when there is a smal difference in the payoffs between the cases of both defecting versus both cooperating. The payoffs for the third set of simulations are the following: when the user leaves, they both get 0 in the specific period, if one defects and one cooperates, the first gets 90 and the other gets 10, if they both defect, each gets 50, 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). The payoffs for the different simulation sets are summarized in Table 5.

Table 5: Payoffs for the different simulation sets

Strategies	Simulation Set 1	Simulation Set 2	Simulation Set 3
User leaves	(0,0)	(0,0)	(0,0)
One defects, one cooperates	(4,1)	(100,1)	(90,10)
Both defect	(2,2)	(40,40)	(50,50)
Both cooperate	(3,3)	(60,60)	(60,60)

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 user satisfaction and a fixed threshold of expected satisfaction are also implemented for the strategies in all simulation runs. To demonstrate the adaptivity, Figures 3 and 4 illustrate the variation of α and of $\frac{1}{\alpha}$, which is a measure of the number of periods that a punishment lasts, during its first 1000 measurements during the simulation.

The adaptivity is clearly indicated from the variation, as well from the tendency of α towards the value of 1; this shows that this user strategy motivates the network to cooperate more, increasing α towards 1.

The variation of $\frac{1}{\alpha}$ shows that the majority of the punishments are equal or close to the value of 1. For the rest of the punishments, we observe that they may be separated in three categories: (a) the ones above one but still below 25, (b) the ones between 25 and 100, and (c) the ones above 100 with occurences becoming a lot less as we move from group (a) to group (c). In fact, group (c) contains 8 out of the 1000 measurements, i.e. 0.8%.

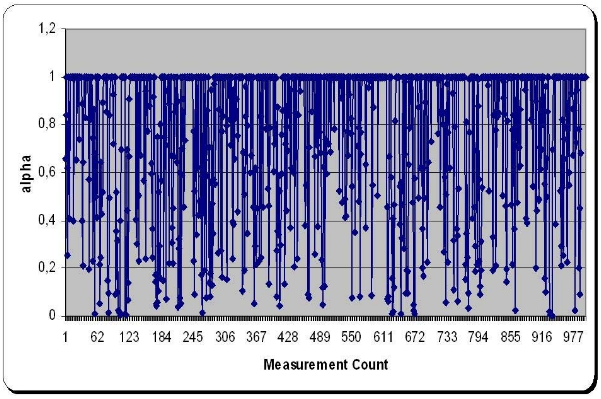

Figure 3: The variation of α (first 1000 measurements)

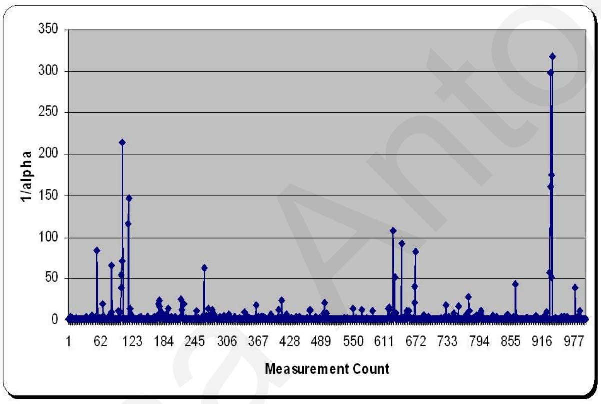

Figure 4: The variation of $\frac{1}{\alpha}$ (first 1000 measurements)

Figure 5 presents a frequency distribution of $\frac{1}{\alpha}$, in order to better visualize the overall behaviour of the punishments given during these first 1000 measurements. The frequency of occurences is measured for the following intervals of punishment periods: $1-5$, $6-25$, $26-50$, $51-100$, $101-150$, $151-200$, $201-250$, $251-300$, $301-351$. Clearly, the network is motivated to cooperate, a fact indicated by the high frequency of occurences in the first two intervals (especially in the first interval, i.e. < 5 punishment periods, where over 90% of the measurements lie).

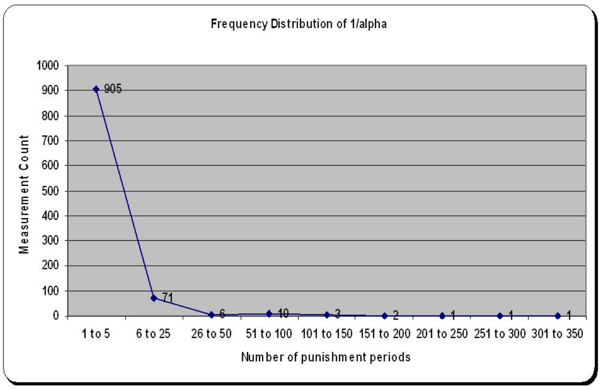

Figure 5: Frequency Distribution of $\frac{1}{\alpha}$ (first 1000 measurements)

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[5] . In both tables we see a score for each strategy combination. The score corresponds to either a user payoff (Table 6), or a network payoff (Table 7).

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 all payoffs except for the payoff received from the combination with the user's *Cheat&Leave*

[5] minimum iterations generated: 8, maximum iterations generated: 1259

Table 6: User Payoffs from all strategy combinations (1st simulation set)

	USER PAYOFFS	
	Network Strategies	
User 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 7: Network Payoffs from all strategy combinations (1st simulation set)

	NETWORK PAYOFFS	
	Network Strategies	
User 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

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. Furthermore, the combination of the two most profitable strategies in the same game profile gives the highest cumulative payoffs to both players. Based on these numerical results, we define the *Adaptive-Punishment* profile (Definition 11) for the game to consist of the *Adaptive-Return* strategy for the user and the *Tit-for-Tat* strategy for the network.

Definition 11 (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[6] . As previously, we see in both tables a score for each strategy combination. The score corresponds to either a user payoff (Table 8), or a network payoff (Table 9).

[6]minimum iterations generated: 2, maximum iterations generated: 1124

Table 8: User Payoffs from all strategy combinations (2nd simulation set)

	USER PAYOFFS	
	Network Strategies	
User 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 9: Network Payoffs from all strategy combinations (2nd simulation set)

	NETWORK PAYOFFS	
	Network Strategies	
User 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

Again, we observe that for the second set of simulations, 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[7] . The increase in the differences between cooperating and defecting 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 defecting; this result motivates the players to go ahead and cooperate.

For the third set of simulations, i.e. with the payoffs ranging from 0 to 90, the payoffs are calculated for an average of 268.6 iterations per simulation run[8] . As previously, we see in both tables a score for each strategy combination. The score corresponds to either a user payoff (Table 10), or a network payoff (Table 11).

Again, for the third set of simulations, 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, Overall, the

[7]except for the payoff in combination with the user's *Cheat&Leave* strategy, however, the preferred profile for the game is still the *Adaptive-Punishment* profile

[8]minimum iterations generated: 2, maximum iterations generated: 1342

Table 10: User Payoffs from all strategy combinations (3rd simulation set)

	USER PAYOFFS Network Strategies	
User Strategies	Tit-for-Tat	Cheat&Return
Grim	16416.6	62.7
Cheat&Leave	159.9	100.7
Leave&Return	16416.6	6423.6
Adaptive-Return	16416.6	6449.7

Table 11: Network Payoffs from all strategy combinations (3rd simulation set)

	NETWORK PAYOFFS Network Strategies	
User Strategies	Tit-for-Tat	Cheat&Return
Grim	16416.6	141.9
Cheat&Leave	80.7	76.7
Leave&Return	16416.6	13709.7
Adaptive-Return	16416.6	13710

preferred profile for the game is still the *Adaptive-Punishment* profile. The small difference between the cases of both players defecting and of both players cooperating 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 defecting; this result continues to motivate the players towards cooperation.

Furthermore, it is worth noting that, for all 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 4.4.1 that the minimum conditions for the network to cooperate when the user employs the *Adaptive-Return* strategy, are also 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 payoffs than the *Leave&Return* strategy.

An additional observation is that the *Leave&Return* strategy is weaker in the case the network decides to defect, 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 a slight improvement in the overall user payoff.

An additional factor that we should consider when interpreting the obtained payoffs, is 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.

Remark. Regading the payoff values of a repeated Prisoner's Dilemma type of game, it has been argued that pre-designed payoff functions that remain the same throughout the repeated game might not truly lead to autonomic players, since if the environment of the game changes during the repeated interaction, in such a way that it is not captured by the payoff functions, the players will not be able to cope [1]. Consequently, the issue of varying the payoff values has been targeted by several works; for instance, [56] investigates why the repeated Prisoner's Dilemma type of game is hardly seen in nature, arguing that the assumption of fixed payoff functions for each player is not a realistic assumption in nature, and [28] uses self adaptivity to evolve the payoff functions by evaluating feedback from the strategies and modifying the payoff functions accordingly. It is important to note that one of the factors examined in these works regarding the effectiveness of the payoffs, in continuing to motivate cooperation as the game evolves, is the spacing between the payoff values, a factor that we have adopted in the simulations presented in this thesis. In fact, the different simulation sets demonstrate different spacing between the players payoffs for cooperating and defecting, showing the motivation of cooperation with the selected strategies throughout the evolution of the repeated game.

Chapter 4

Cooperation in Network-Network Interaction

4.1 Introduction

In a converged network, there may exist multiple Mobile Virtual Network Operators (MVNOs), each one of them interacting with the participating users, through the use of a common IP-based mobile communications infrastructure operated by a single Mobile Network Operator (MNO), who rents out resources to the MVNOs. These MVNOs use this mobile infrastructure to motivate user participation through their offered services achieving individual revenues by offering various services to these users.

In this chapter, we consider the case where enhanced quality demands by the users for a particular service may require the cooperation of two MVNOs in advance to support a particular user. The two MVNOs are selected by the use of a prioritized list based on the estimation of the satisfaction to be received by the user, similarly to the network selection case in chapter 3 with the selection resulting in a prioritized list of mobile network operators (MVNOs and MNOs) participating in the converged communication network instead of a single MNO or a single MVNO.

Once the selection is completed the two *best* networks, in this case conider two MVNOs, are required to cooperate with their revenues coming from a payment partition of the payment for the particular service, dependant on the service they provide. The payment partition is a basically a configuration pre-calculated and adopted by the two MVNOs in order to avoid either of the two MVNOs gaining bargaining advantage by handling the partition, and furthermore to ensure that the whole process is transparent to the user, obeying the user-centric paradigm characterizing converged, next generation communication networks.

4.2 Illustrative Network-Network Interaction Scenario

Consider the case where a customer of the converged mobile communication networks makes a service request for a particular premium service with critical delay constraints for the service session. Both the preferred network and the second best network are MVNOs, both networks renting out resources from the same MNO. Further consider that it is advantageous for two MVNOs to cooperate in order to offer the user a higher guarantee of service delivery as requested. Then, to guarantee quality in terms of delay, it is beneficial for the two MVNOs to cooperate to support the particular user. The best MVNO will serve the request and simultaneously the second best MVNO will reserve resources, in order to act as a secondary network in case quality degradation is detected and/or session handoff is necessary. This cooperation enables service provision to be offered by the best MVNO and in case of need of session handoff, the session handoff is faster, enhancing service quality in terms of service continuity and handoff delay, which is a crucial aspect for real-time, critical services (e.g. medical video).

Since a network's satisfaction is represented by its revenue gain, and since two networks must cooperate for a single service, then the payment for supporting the service needs to be partitioned between them, in order for the networks to have an incentive to cooperate. Moreover, the partitioning configuration must be such that it is satisfying to both networks. This reasoning motivated this work to model the configuration as a solution to a cooperative bargaining game, which is presented next.

We present the *payment partition* as a game of bargaining between the two MVNOs, i.e. between two networks. Firstly, we define the payment partition as a game between the two MVNOs and we show that this is equivalent to the well-known Rubinstein bargaining game [66, chapter

3], when the agreement is reached in the first negotiation period. Given this equivalence, an optimal solution to the Rubinstein bargaining game, would also constitute an optimal solution to the payment partition game. The resolution of the game is presented in 4.4.

4.3 Cooperative Bargaining Model

Let $q \in Q$ be the quality level for which the two networks negotiate. Consider the payment partition scenario, where two networks want to partition a service payment $\pi_i(q)$ set by the converged platform administrator. Let $c_i(q)$ be considering the resource reservation cost of network i. Given the cost characteristics of network i, each network seeks a portion:

$$\pi_i(q) = c_i(q) + \phi_i(q), \tag{5}$$

where $\phi_i(q)$ is the actual profit of network i, such that:

$$\pi_1(q) + \pi_2(q) = \Pi(q), \tag{6}$$

where $\Pi(q)$ is the total payment announced by the converged platform administrator. The networks' goal is to find the payment partition, which will maximize the value of $\phi_i(q)$, given the values of $\Pi(q)$ and $c_i(q)$. Definition 12 defines the bargaining game between the two networks:

Definition 12 (Payment-Partition game)**.** Fix a specific quality level $q \in Q$ such that a fixed payment Π is received. Consider a one-shot strategic game with two players corresponding to the two networks. The profiles of the game, i.e. the strategy sets of the two players, are all possible pairs (π_1,π_2), where $\pi_1, \pi_2 \in [0, \Pi]$ such that $\pi_1 + \pi_2 = \Pi$. All such pairs are called agreement profiles and define set S^a. So, $S^a = \pi_1 \times \pi_2$. In addition, there exists a so called disagreement pair $\{s_1^d, s_2^d\}$, which corresponds to the case where the two players do not reach an agreement. So, the strategy set of the game is given by $\mathcal{S} = S^a \bigcup \{s_1^d, s_2^d\}$. For any agreement point $s \in S^a$ the payoff $U_i(s)$, for player $i \in [2]$, is defined as follows:

$$U_i(s) = \pi_i - c_i \tag{7}$$

Otherwise,

$$U_1(s_1^d) = U_2(s_2^d) = 0 \tag{8}$$

This game is referred to as the payment-partition game.

Fact 1. Let $s^* = (\pi_1^*, \pi_2^*)$ be an optimal solution of the payment-partition game. Then $\phi_i = \pi_i^* - c_i$, where $i \in [2]$, comprises an optimal solution of the payment partition scenario.

4.3.1 Equivalence to a Rubinstein Bargaining game

Initially, we show the equivalence between the *payment-partition* game and a Rubinstein Bargaining Game, a.k.a. the basic alternating-offers game defined next according to [66]:

Definition 13 (Rubinstein Bargaining game)**.** Assume a game of offers and counteroffers between two players, $\pi_i^r(t)$, where $i \in \{1, 2\}$ and t indicates the time of the offer, for the partition of a cake, of initial size of Π^r. The offers continue until either agreement is reached or disagreement stops the bargaining process.

At the end of each period without agreement, the cake is decreased by a factor of δ_i. If the bargaining procedure *times out*, the payoff to each player is 0. Offers can be made at time slot $t \in \mathcal{N}_0$. If the two players reach an agreement at time $t > 0$, each receives a share $\pi_i^r(t) \cdot t \cdot \delta_i$, where $\delta_i \in [0, 1]$ is a player's discount factor for each negotiation period that passes without agreement being reached. The following equation gives the payment partitions of the two players:

$$\pi_1^r(t) \cdot t \cdot \delta_1 = \Pi^r - \pi_2^r(t) \cdot t \cdot \delta_2 \tag{9}$$

So, if agreement is reached in the first negotiation period, the payment partition is as follows:

$$\pi_1^r(t) = \Pi^r - \pi_2^r(t) \tag{10}$$

The payoff U_i^r of the players $i, j \in [2]$ if the agreement is reached in iteration t is the following:

$$U_i^r(t) = \pi_i^r(t) = \Pi^r - \pi_j^r(t) \tag{11}$$

Such a game is called a Rubinstein Bargaining game.

Proposition 4.3.1. *Fix a specific quality q. Then, the payment-partition game is equivalent to the Rubinstein Bargaining game, when the agreement is reached in the first negotiation period.*

Proof. Assuming that an agreement in the Rubinstein Bargaining game is reached in the first negotiation period $t = 1$, then the game satisfies the following:

$$U_1^r(1) + U_2^r(1) = \Pi^r(1),$$

which is a constant.

In the payment partition game, assuming an agreement profile s, we have:

$$U_1(s) + U_2(s) = \pi_1 - c_1 + \pi_2 - c_2 \quad = \Pi - c_1 - c_2,$$

since $\Pi = \pi_1 + \pi_2$ and c_1, c_2 are constants for a fixed quality level. It follows that $U_1(s) + U_2(s)$ is also constant. It follows that the *Rubinstein Bargaining* game and the *Payment Partition* game are equivalent. □

We define:

Definition 14 (Optimal Payment Partition)**.** The optimal partition is when bargaining ends in an agreement profile that gives the highest possible payoff to each player given all possible actions taken by the opponent.

Proposition 4.3.1 immediately implies:

Corollary 4.3.1. *Assume that agreement in a Rubinstein Bargaining game is reached in the first negotiation period, that $\Pi^r = \Pi$, and that the corresponding profile s^*, is an optimal partition for the Rubinstein game. Then, s^* is also an optimal partition for the payment-partition game.*

4.3.2 Towards a resolution of the Payment Partition game

Since the Nash bargaining game [66, chapter 2] and the payment-partition game are equivalent, we utilize the solution of a Nash bargaining game in order to compute an optimal solution, i.e. a configuration, which is satisfactory for the two networks in terms of payoffs from the payment-partition game.

The solution of the Nash bargaining game, known as the *Nash Bargaining Solution*, captures such configuration, where the two bargaining game players are both satisfied. Therefore, since disagreement results in payoffs of 0, we are looking for an agreement profile $s = (\pi_1, \pi_2)$ such that the corresponding partition of the players is an optimal payment partition, i.e. the partition that best satisfies both players' objectives (Definition 14). Section 4.4 elaborates on resolving the Payment Partition game through the use of the Nash Bargaining solution and further addresses issues of truthfulness that arise when applying such configuration.

4.4 Payment Partition based on the Nash Bargaining Solution

In Section 4.3, we have shown how to model cooperation between the best and second best network in order to enable service continuity during a service session. Since disagreement is not a desirable strategy for either of the two cooperating players, we may conclude that the two players will reach an agreement. Consequently, the payment must be partitioned in such a way that both the participating access networks are satisfied. To reach the optimal solution we utilise the well-known *Nash Bargaining Solution* [66, chapter 2], which applies to Rubinstein bargaining games when the agreement is reached in the first negotiation period, and therefore to the payment-partition game, given the equivalence presented in Section 4.3. Since the Nash bargaining game and the payment-partition game are equivalent, we compute an optimal solution, i.e. a configuration, which is satisfactory for the two networks in terms of payoffs from the payment-partition game. The solution of the Nash bargaining game, known as the *Nash Bargaining Solution*, captures such configuration. Therefore, since disagreement results in payoffs of 0, we are looking for an agreement profile $s = (\pi_1, \pi_2)$ such that the corresponding partition of the players is an optimal payment partition, i.e. the partition that best satisfies both players' objectives.

The next Theorem proves the existence of an optimal partition of the payment between the two players, given each network's cost c_i.

Theorem 4.4.1. *There exists an optimal solution for the payment-partition game, and is given by the following:* $\pi_1 = \frac{1}{2}(\Pi + c_1 - c_2)$, $\pi_2 = \frac{1}{2}(\Pi + c_2 - c_1)$

Proof. We consider only agreement profiles and thus refer to the partition π_i assigned to player i. In any such profile it holds that $\pi_1 + \pi_2 = \Pi$. Assuming a disagreement, implies that cooperation fails between the two networks and the payoff gained by player i equals to $U_i(s^d) = 0$. Since in any such profile, it holds that $U_i(s^a) > 0$ it follows that the disagreement point is not an optimal solution. Since the payment-partition game is equivalent to the Nash bargaining game (Corollary 3.4.3), a Nash bargaining solution (NBS) of the bargaining game is an optimal solution of the payment-partition game between two players, i.e. a partition (π_1^*, π_2^*) of an amount of goods (such as the payment). According to the NBS properties it holds that:

$$NBS = (U_1(\pi_1^*) - U_1(s^d))(U_2(\pi_2^*) - U_2(s^d))$$

$$= max(U_1(\pi_1) - U_1(s^d))(U_2(\pi_2) - U_2(s^d))$$

$$0 \leq \pi_1 \leq \Pi,$$

$$\pi_2 = \Pi - \pi_1$$

Since $U_1(s^d) = 0$, $U_2(s^d) = 0$ and $\pi_2 = \Pi - \pi_1$:

$$max(\pi_1 - c_1)(\Pi - \pi_1 - c_2) =$$

$$(-2\pi_1 + \Pi - c_2 + c_1) = 0$$

Therefore,

$$\pi_1 = \frac{1}{2}(\Pi - c_2 + c_1),\ \pi_2 = \frac{1}{2}(\Pi + c_2 - c_1) \tag{12}$$

□

We proceed to investigate how the solution to the payment-partition behaves when we consider the existence of a constant set by the converged platform administrator representing the probability of degradation.

Theorem 4.4.2. *Assume that the converged platform administrator assigns a constant value p_i^f to network i representing the expected quality degradation, based on the particular service and current network conditions. Then, the value of the optimal solution is the same as in Theorem 4.4.1.*

Proof. Our game has the same strategy set as before. Concerning the utility functions of the players in case of disagreement, we have also $U_1(s^d) = 0$, $U_2(s^d) = 0$, $\pi_2 = \Pi - \pi_1$ as before. In case of agreement, we have in addition a constant probability p_i^f in the payoff function of each network:

$$U_i(s) = (1 - p_i^f)(\pi_i - c_i)$$

Therefore,

$$max(1 - p_1^f)(\pi_1 - c_1)(1 - p_2^f)(\Pi - \pi_1 - c_2) =$$

$$(1 - p_1^f)(1 - p_2^f)(-2\pi_1 + \Pi - c_2 + c_1) = 0$$

The optimization shows that if constant probabilities are considered, the optimal partition is still as previously, i.e. the networks' cost is the deciding factor for the optimal solution similarly to Equation 12:

$$\pi_1(q) = \frac{1}{2}(\Pi - c_2 + c_1),\ \pi_2 = \frac{1}{2}(\Pi + c_2 - c_1) \qquad (13)$$

□

Remark. Note that the estimated probability that the platform administrator may consider for each participating network does not affect the optimal partition, but affects each network's payoff function, therefore a network with a high estimated probability of degradation will receive much less of a payoff than the optimal payment partition calculated according to its cost.

4.5 A Bayesian form of the payment-partition game

Since the partitioning is based on each network's cost, it is required that the networks are truthful about their costs. Truthfulness is a very important consideration in cooperative situations, especially in bargaining games. The question that arises is whether it would be wise for a player to lie, considering that the player cannot be aware of who the other player is from the original set of available networks and thus cannot guess whether the other player has more or less cost, thus not being able to correctly assess the risk of such an action. Consider in our scenario that the infrastructure costs of two MVNOs renting out infrastructure from the same MNO are known, and lying over these can be easily verified, since the costs are adverrtised by the MNO. However infrastructure costs are only a part of service costs, which may additionally include content costs etc, usually different for each MVNO.

A Bayesian game [42, chapter 5] is a strategic form game with incomplete information attempting to model a player's knowledge of private information, such as privately observed costs, that the other player does not know. Therefore, in a Bayesian game, each player may have several types of behaviour (with a probability of behaving according to one of these types during the game). We use the Bayesian form for the *payment-partition* game, in order to investigate the outcomes of the game, given that each network does not know whether the cost of its opponent is lower or higher than its own.

Let each network in the *payment-partition* game have two types: the *lower-cost* type (including networks of equal cost) and the *higher-cost* type. Suppose that each of the two networks has incomplete information about the other player, i.e. does not know the other player's type. Furthermore, each of the two networks assigns a probability to each of the opponent's types according to own beliefs and evaluations. Let p_i^l be the probability according to which, network i believes that the opponent is likely to be of type *lower-cost*, and $p_i^h = (1 - p_i^l)$ be the probability according to which, network i believes that the opponent is likely to be of type *higher-cost*.

Since the two players are identical, i.e. they have the same two types and the same choice of two actions, we will only analyze network i; conclusions also hold for network j, where $i, j \in [2], i \neq j$. Therefore, network i believes that network j is of type *lower-cost* with probability p_i^l, and of type *higher-cost* with probability $1 - p_i^l$. Each network has a choice between two possible actions: to declare its own real costs (D) or to cheat (C), i.e declare higher costs $c_i' > c_i$. The possible payoffs for network 1 are given in Table 12 and in Table 13.

Table 12: Network i payoffs when opponent is of type *lower-cost*

	Network j Actions	
	D	C
Network i Actions		
D	$\frac{1}{2}(\Pi + c_i - c_j)$	$\frac{1}{2}(\Pi + c_i - c_j')$
C	$\frac{1}{2}(\Pi + c_i' - c_j)$	$\frac{1}{2}(\Pi + c_i' - c_j')$

Table 13: Network i payoffs when opponent is of type *higher-cost*

	Network j Strategies	
	D	C
Network i Strategies		
D	$\frac{1}{2}(\Pi - c_j + c_i)$	$\frac{1}{2}(\Pi - c_j' + c_i)$
C	$\frac{1}{2}(\Pi - c_j + c_i')$	$\frac{1}{2}(\Pi - c_j' + c_i')$

Lemma 4.5.1. *If network i believes that the probability p_i^l, i.e. that network j is of type* lower-cost, *is higher than the probability p_i^h, then it is more motivated to lie, where $i, j \in [2], i \neq j$.*

Proof. In Table 12, network i has higher or equal costs to network j since network j is of type *lower-cost*, thus $c_i \geq c_j$. When both players play D, i.e. they both declare their real costs, an equal or greater piece of the payment is assigned to network i, since the partition of the payment is directly proportional to the networks' costs. If network i plays C, i.e. cheats, while network j plays D, then $c_i' > c_i > c_j$, a profitable strategy for network i, since an even greater piece of the payment will be received. For the cases that network j decides to play C, then the payment partition may or may not favour network j (it depends on the actual amount of cheating, and the action of network i). If network i plays C, then it is more likely that $c'_i > c'_j$, and network i will get a greater piece, than if it plays D. □

Lemma 4.5.2. *If network i believes that the probability p_i^h, i.e. that network j is of type* higher-cost*, is higher than the probability p_i^l, then it is more motivated to lie, where $i, j \in [2], i \neq j$.*

Proof. In Table 13, network i has lower costs compared to network j, thus $c_i < c_j$. When both players play D, i.e. they both declare their real costs, an equal or greater piece of the payment is assigned to network j. If network i plays C, i.e. cheats then $c'_i > c_i$, so playing C will end up in a higher payoff for network i, and in case network j plays D, i may even get the bigger piece of the partition. If network j plays C, it is still better for network i to play C, since this will end up in network i receiving a greater piece than it would if it plays D when network j plays C, although, more likely, not the greater of the two pieces. □

4.5.1 Motivating Truthfulness

Proposition 4.5.1. *Two networks playing the Bayesian form of the* payment-partition *game, are not motivated to declare their real costs but instead they are motivated to cheat and declare higher costs, i.e $c'_i > c_i$, $i \in [2]$, in order to get greater payoffs.*

Proof. Straightforward by Lemma 4.5.1 and Lemma 4.5.2. □

In order to motivate the two networks to declare their real costs, there must exist a mechanism that can penalize a player who turns out to lie on its real cost, assuming that it is detectable whether a player has lied or not[1] ; we refer to such mechanisms as pricing mechanisms [73]. Let

[1]in fact, it is possible to estimate the costs of the two MVNOs considering that their infrastructure costs are known, content costs are usually advertized by content providers, and cost variations based on clientelle and coverage can be estimated since both MVNOs are part of the same converged communication platform

the converged platform administrator be able to detect after the service session has terminated, whether either of the participating networks has lied about its costs. In order to motivate the networks to declare their real costs we introduce a *pricing mechanism*, i.e. a new variable that tunes the resulting payoffs, in the payoff function of each player[2] . The pricing mechanism is a post-game punishment, i.e. cheating in a game does not affect the game in which a network cheats but subsequent games. Thus, a state of history of a player's behaviour in similar interactions must be kept.

We define a pricing mechanism consisting of variable $\beta_i \in [0,1]$, which represents the probability of being truthful, and it may adaptively modify the payoffs of a player. The value of β_i is adjusted at the end of a network-network interaction, according to the player's behaviour, i.e. whether the network declared its real costs or whether the network lied[3] , using a *punishment factor* $\gamma \in [0,1]$ set by the converged platform administrator[4] .

Thus, based on $\beta_i^{previous}$, i.e. the previous value of β_i for network i, is defined to be:

$$\beta_i = \begin{cases} \beta_i^{previous} - (\beta_i^{previous} \cdot \gamma), & \text{if network } i \text{ is caught lying} \\ \beta_i^{previous} - (\beta_i^{previous} \cdot \gamma) + \gamma, & \text{if network } i \text{ is truthful} \end{cases} \tag{14}$$

Equation 14 defines β_i such that on the one hand it decreases fast when cheating behaviour is observed, and on the other hand increases slowly when network i is truthful, aiming to motivate the players of the bargaining game to remain truthful since the less frequently a player cheats, the closer to 1 its β_i is. The value of $\gamma = \frac{1}{10}$ is reasonable since it allows the faster decreasing and slower increasing behaviour of β_i. Next, we plot, the general behaviour of β_i when $\gamma = \frac{1}{10}$. Thus, Figure 6 illustrates the general form of β_i as it increases from 0 to 1 and decreases back to

[2]A side effect for a network that decides to cheat, is that it risks not to be selected for supporting the service in the first place, since by declaring higher costs, the compensation received from the user might be affected, and subsequently, the user might not select the particular network

[3]We consider that a revelation of the real costs of the two access networks is always possible at a later stage of the procedure (e.g. after session termination)

[4]In our simulations (Section 4.6) we set $\gamma = \frac{1}{10}$ as a tradeoff between harsh (e.g. $\frac{1}{2}$) and light (e.g. $\frac{1}{100}$)

0. Given β_i, the administrator sets the payoff of network i to be:

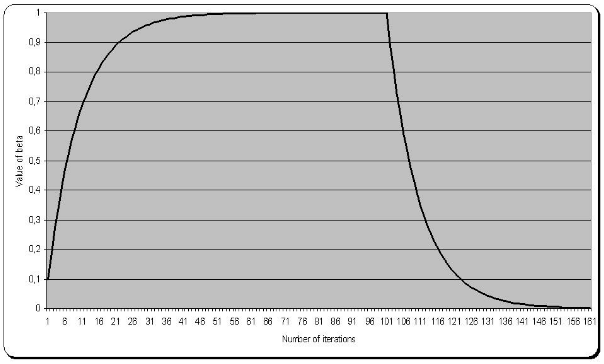

Figure 6: General form of β_i (*increasing and decreasing*)

$$\pi_i = \frac{1}{2}(\Pi + \beta_i \cdot c_i - \beta_j \cdot c_j), \tag{15}$$

where $i, j \in [2], i \neq j$. The players are motivated to declare their real costs, since any cheating, which the platform administrator is able to detect following the play of the payment-partition game, would decrease β_i, affecting any future payoffs from such procedure. An evaluation of the Bayesian form of the *payment-partition* game including β_i in the players' payoffs is given in the next section.

Remark. The bayesian form of the payment-partition game is in fact a sequential game, whereas the actual one-shot payment partition is in practice simply a configuration imposed on the two interacting networks. In the bayesian form of the game, each network has a memory of its own behaviour during past participations in interactions with other networks in payment-partition games. Thus each network keeps its own internal state information for its actions, but this does not constitute a history of the game, since the game actions are not directly affected by the internal state maintained by each player. Furthermore, the decision of the opponent player or the history of the game does not depend on this state directly. Indirectly, the action taken by each player at a given interaction, may be such as to reflect the information obtained from this internal state, but this is according to the strategy employed by each network.

4.6 Evaluating Network-Network Cooperation

In this section we evaluate the Bayesian form of the *payment-partition* game between two networks cooperating to support a service session requesting service continuity guarantees. The payoffs of the game are based on the Nash Bargaining Solution, as this has been demonstrated in Section 4.4, and further include the term β_i, described in the same section, in order to motivate the networks to cooperate. The payoff to network i, defined in Equation (15), is reproduced next:

$$\pi_i = \frac{1}{2}(\Pi + \beta_i \cdot c_i - \beta_j \cdot c_j)$$

We first run the game with the value for β_i always equal to 1, i.e. when no punishment is imposed for lying about costs. The strategies used for the evaluation of the game for Case 1 (no punishment imposed), involve three different strategies for each player, where both networks are allowed to be truthful or lie as follows:

Case 1:

Strategy 1 The player always declares the real costs.

Strategy 2 The player always lies about its real costs.

Strategy 3 The player randomly lies 50% of the time and is truthful the rest of the time.

Subsequently, we run another set of simulations but allow the value of β_i to vary, i.e. we allow punishment based on the history of the network's previous actions. Thus, for Case 2 (with punishment imposed), one more strategy is added to allow the user to monitor β_i and make a decision according to its value. This additional strategy is the following.

Case 2 (additional strategy):

Strategy 4 The player monitors its β_i and only lies if the value of β_i is high, in order to minimize the effects of cheating on its payoff.

The numerical values used for Π, c_i, c_j in case the networks are truthful or lying, obey the payoff relations given in Table 12 and in Table 13 and the overall model of the payment-partition game as described in Section 4.3 and resolved in Section 4.4.

Specifically, the payment to be partitioned is equal to 10, and the costs vary from 3 to 5, 3 and 4 for the two types of networks when they are truthful, 4 and 5 for the two types of networks when they are lying (they claim costs of one unit more than the actual cost is). Future work plans to investigate how the obtained results would be affected by different cost numbers, e.g. larger costs and unequal lying amounts.

The payoffs vary based on the type of each network as well as on whether the network has declared its real costs or has cheated. The network types are: 1 = *lower-cost* or 2 = *higher-cost* as these are explained in Section 4.5. The four strategies that each network may employ in a simulation run are denoted as follows: (1) always declare its real costs - indicated as *Only D*, (2) always cheat - indicated as *Only C*, (3) randomly declare real costs or cheat with a probablity of 0.5 for each option - indicated as *50% C/D*, and (4) only cheat if the value of β_i is high, i.e. cheat only if $\beta_i \geq 0.9$ else declare real costs - indicated as *Cheat-if-beta-high*.

First, we present the results for Case 1, when the value of β_i is equal to 1, i.e. when there is not punishment for lying. Table 14 and Table 15 show, each table corresponds to a different player, the cumulative payoffs from the payment partitions that the specific player receives for each strategy combination over 100 simulation runs.

Table 14: Payment Partition Payoffs for player 1, $\beta_1 = 1$

Network 2 Strategies	Only D	Only C	50% C/D
Network 1 Strategies			
Only D	5079.04	4578.54	4829.91
Only C	5579.04	5078.89	5329.42
50% C/D	5329.82	4829.30	5077.09

Table 15: Payment Partition Payoffs for player 2, $\beta_2 = 1$

	Network 2 Strategies	Only D	Only C	50% C/D
Network 1 Strategies				
Only D		4920.96	5421.46	5170.09
Only C		4420.96	4921.12	4670.59
50% C/D		4670.18	5170.7	4922.91

Considering the rows for Player 1, row 2 in Table 14 is the highest, showing that the best strategy for Player 1 is *Only C*. Also, for Player 2, we consider the columns in Table 15. The highest is column 2, thus for Player 2 the best strategy is also *Only C*. We observe from these results, that the highest payoffs are achieved for each player when he lies and does not declare his real costs, whilst at the same time his opponent declares the real costs. In any case, for each strategy of the opponent a player's best response is always to lie. Therefore, these results reinforce the theoretical findings of this model, i.e. that if no punishment mechanism is adopted for handling cases when player lie about their real costs, then the players are not motivated to be truthful and declare their real costs.

Next, we present the results for Case 2, when the value of β_i is allowed to vary according to player i's actions. Each player's initial value of β_i in the simulations is randomly generated and then adapted to the player's play according to the selected strategy. This initial value is indicated in the results for reasons of completion. Overall, we have run 100 simulation runs with different initial values for β_i and with a randomly generated number of iterations. The number of iterations for each simulation run is indicated in the results as *R*.

Table 16 illustrates some simulation statistics that show how many times in the simulation each network is of either type *lower-cost* or type *higher-cost* respectively, indicating that there is a uniformity in the generation of the player's types, giving us confidence in the fact that the two networks behave similarly and by examining one of them, we may draw similar conclusions for the other.

Table 16: Statistics for networks 1 and 2 regarding generation of types

Network 1 Type	Network 2 Type	Number of Times
lower-cost	*lower-cost*	27
higher-cost	*higher-cost*	26
lower-cost	*higher-cost*	21
higher-cost	*lower-cost*	26

Firstly, we show how the values of β_i evolve with time for network 1 (since corresponding values for network 2 are similar), for each of the four strategies that a network may employ. For each network i we keep its strategy fixed for each of the four plots but we allow the opponent's strategy to vary, plotting eventually the evolution of β_1. Figure 7 shows the variation of β_1 for each of the four employed strategies, indicated by a different line.

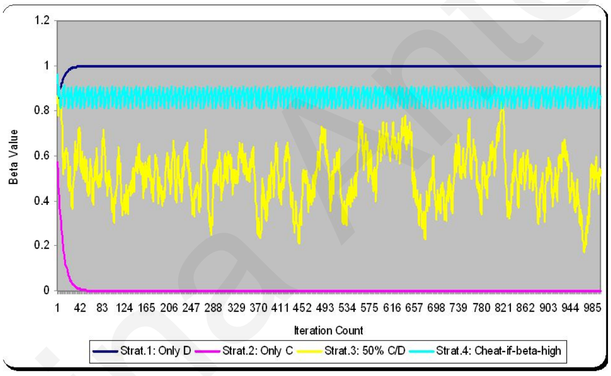

Figure 7: The variation of β_1 (first 1000 measurements)

We observe that when player 1 employs the *Only D* strategy, its β_1 achieves the values equal to 1 since the network's strategy is to always declare its real costs, causing the values of β_1 to climb up to 1 and remain there until the end of the simulation. When network i employs the *Cheat-if-beta-high* strategy, the values are also quite high, oscillating between 0.8 and 0.9 because the network only cheats if β_1 is high, and since cheating causes β_1 to immediately decrease, the network declares its real costs, the value of β_1 increases again and when it becomes high enough to allow for cheating, network 1 cheats again and so on, resulting in an oscillating behaviour for

β_1. The values for the *50% C/D* strategy are more random and vary around 0.5 ranging from around 0.2 to around 0.8, since half the times network 1 cheats and half the times it declares its real costs and this is decided in a random manner. Finally, the *Only C* strategy where we observe that the values of β_1 converge to 0. The reason for this is that the continuous cheating behaviour of network 1 causes β_1 to be decreased by the administrator after every period.

Tables 17, 18 present the averages of the cumulative payoffs from each simulation run, for all 100 simulation runs. The results are presented for the two networks (network 1 and network 2) partitioning the service payment. Tables 17, 18 illustrate through the similarity in the related payoffs that the behaviour of the two netwoks is similar. This is due to the fact that the two networks are motivated by the same incentives and use the same set of strategies. In addition, the generation of network types in the simulation runs is very similar for the two players, implying that on average the payoffs are eventually very similar for the two networks.

Table 17: Average Network 1 Payoffs from payment-partition game

Avg. R = 311.67	Min. R = 4	Max. R = 1749			
	Network 2 Strategies	Only D	Only C	50% C/D	Cheat-if-beta-high
Network 1 Strategies					
Only D		1570.83	1855.16	1879.71	1591.25
Only C		1265.66	1558.72	1405.64	1301.49
50% C/D		1454.89	1718.82	1566.51	1479.84
Cheat-if-beta-high		1548.79	1827.05	1653.01	1569.23

Table 18: Average Network 2 Payoffs from payment-partition game

Avg. R = 311.67	Min. R = 4	Max. R = 1749			
	Network 2 Strategies	Only D	Only C	50% C/D	Cheat-if-beta-high
Network 1 Strategies					
Only D		1545.84	1251.89	1436.95	1525.41
Only C		1851.01	1557.94	1711.02	1815.18
50% C/D		1661.77	1397.84	1550.16	1638.83
Cheat-if-beta-high		1567.87	1289.62	1463.66	1547.44

We observe that in all simulation runs, the second strategy, i.e. always to cheat is the least profitable strategy for both networks, regardless of their types and initial values of β_i. This is because of the presence of β_i in the payoffs, which punishes the choice of cheating, by detecting such an action after any iteration. On the other hand, the other three strategies, which include actions of declaring the real costs, i.e. being truthful are more profitable strategies. Specifically, the first strategy of always being truthful is the most profitable strategy illustrating how β_i rewards truthfulness, motivating the player to follow strategy *Only D*, i.e. always declaring the real costs. In addition, we observe that the fourth strategy of cheating only if β_i is high, generates comparable payoffs to the *Only D* strategy. This shows that even if the network decides to employ a strategy, which will allow the network to cheat a few times much less than the times it cheats when employing the 50% C/D strategy, the best option in terms of payoffs is still to be always truthful.

Furthermore, it is interesting to note that for each network, while it is more profitable to be truthful, i.e. to declare the real costs, the highest payoffs are accumulated when the opponent decides to cheat, while a network is truthful. Therefore, if a network believes that the opponent is more likely to cheat, it is very profitable to always be truthful, i.e. to only declare real costs.

In order to get a better sense of each partition, we provide for each combination of strategies, the percentage partition of the total payment given to the two networks, considering only the amount given and not the amount that would be given if they had cooperated (Table 19). We observe that the partitions when the same strategies are used by the two networks are equal or very close to 50% of the amount given, whereas, for the rest of the combinations using the strategy of always declaring the real costs, results in the greatest partition as it also seen by the corresponding payoffs.

In conclusion, using β_i as a pricing mechanism, motivates the interacting networks to declare their real costs, so as to achieve the highest possible payoffs from their interactions.

Table 19: Payment partitions for each strategy combination

Network 2 Strategies	Only D	Only C	50% C/D	Cheat-if-beta-high
Network 1 Strategies				
Only D	50.4%,49.6%	59.7%,40.3%	56.7%,43.3%	51.1%,48.9%
Only C	40.6%,59.4%	50%,50%	45.1%,54.9%	41.8%,58.2%
50% C/D	46.7%,53.3%	55.1%,44.9%	50.2%,49.8%	47.5%,52.5%
Cheat-if-beta-high	49.7%,50.3%	58.6%,41.4%	53%,47%	50.3%,49.7%

Chapter 5

Cooperation in Multiple Networks Interaction

5.1 Introduction

Access networks participating in a conveged platform may easily cooperate and share resources. Cooperation between multiple access networks might be necessary in order to meet service requirements[1] , e.g. when traffic forecast indicates that no single network alone can handle the anticipated demand over a certain period (days, months, etc.). Potentially, many different combinations of access networks can jointly provide sufficient resources to meet service demands. The access networks participating in the selected combination are expected to receive a payment by the converged platform administrator.

[1]non-cooperative proposed solutions for meeting service requirements in NGN environments exist, for example see [85]

5.2 Illustrative Multiple Networks Interaction Scenario

Consider as an example scenario of access network cooperation the need for accommodation of a multiparty service in the case that a number of collocated users (e.g. participating in a conference) have subscribed for the same live multimedia multiparty service, with its starting time and duration known in advance. Each of the subscribed users have the same interfaces to the access networks participating in the converged network in their specific location (e.g. WiFi, WiMax and WCDMA).

The particular scenario considers that we have the case that none of the participating access networks can alone support all the users subscribed to the multiparty service. Then, network cooperation can ensure a more efficient network resource planning and service support to all users, by having the networks forming coalitions and thus collectively managing to provide the total resources necessary to support the service.

A user or application will be indifferent to this cooperation, as long as its QoS requirements are satisfied. On the other hand, the networks' incentive to participate in such coalitions is the service payment, which will be paid to the *winning* coalition. Therefore, the payoff allocation to the members of the *winning* coalition is also consideration for the networks participating in the coalition formation process. Given that each network participating in a coalition is solely motivated by its need to maximize its revenues from the particular service, this chapter investigates how can such coalitions be formed that satisfy the multiparty service subscribers.

5.3 Network Synthesis Game

Consider that the different access networks are under different administration authority or ownership and therefore, the decision of whether to participate in a certain resource combination (or network coalition) or not, would be shaped by the access network's goal to maximize its revenue from the contributed resources. As a result, a coalition game would arise in this environment, with each access network aiming at participating in a "prevailing" coalition (the one that will win) and at yielding the largest possible benefit to itself. The formation of coalitions depends on the available resources of each access network, as well as on the way payoffs are allocated to the participating networks. In this section, we introduce this coalition game and refer to it as the *network synthesis* game.

The players participating in the network synthesis game aim to maximize their payoff by participating in the winning coalition. We consider for this game, a payoff allocation approach according to values of (normalized) power indices, i.e. numerical values that are used to measure the influence of a player on the formation of coalitions and thus on the game itself. Payoffs are thus determined based on the power of each access network in the game, i.e. its index. We consider well-known indices, such the *Shapley-Shubik* index [92], *Banzhaf* index [14] and the *Holler-Packel* index [44]. We proceed to propose a new index, called the *Popularity Power* index, which associates the popularity of each access network to the number of stable coalitions it participates in. This new index aims to achieve fairness, in the sense that it only considers the possible coalitions that would be formed if payoffs were assigned proportionally to the players' contributions, i.e. in a fair manner. Accordingly, we evaluate the proposed power index by introducing an analysis of the stability of coalitions according to the *core* and *inner core* concepts [67], considering both transferable and non-transferable payoffs, and we show that the coalitions that would be formed in the case of the *Popularity Power* index are only coalitions that are stable.

5.3.1 Definition of the Network Synthesis Game

Definition 15 (The Network Synthesis Game)**.** The network synthesis game is described as follows. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote the set of players (access networks) and $\mathcal{S}$ the set of all possible coalitions, i.e., the set of all non-empty subsets of $\mathcal{N}$. Let B denote the least amount of resources needed for accommodating service demands, and let b_i denote the amount of *available resources* of the ith member of a coalition (members can be ordered arbitrarily). It will be assumed that the available resources of each member are known to all members of a coalition[2] .

The characteristic function of the game is

$$v(S) = \begin{cases} 1, & \text{if } \sum_{i=1}^{|S|} b_i \geq B \\ \\ 0, & \text{otherwise .} \end{cases} \tag{16}$$

That is, a coalition has positive value only if the sum of available resources of its members is greater or equal to the resource threshold B. This definition corresponds to a simple (or 0-1) game; the game is also monotonic since $v(S_1) \leq v(S_2)$ for all $S_1 \subseteq S_2$. A coalition S is said to be *winning* if $v(S) = 1$, otherwise it is said to be *losing*. A player $i \in S$ is said to be a *null player for coalition* S if $v(S) = v(S \setminus \{i\})$. It is generally called a *null player* if this holds for every coalition S to which it may belong. To avoid trivialities, we will generally assume that $b_i < B$ $\forall i \in \mathcal{N}$, and that $\sum_{i=1}^{N} b_i \geq B$.

[2] In any wireless environment there are certain constraints such as signal interference and user mobility that make the estimation of available resources a difficult task and furthermore, the competing nature of the participating access networks may urge them to withhold or distort this information. It will be assumed that appropriate mechanisms and policies are in place that make the available resources vector $(b_1, \ldots, b_N)$ known to all operators. A formal study of this is not part of this thesis.

Candidate solutions to the game are the so-called *minimal winning coalitions*. A winning coalition is said to be minimal if it becomes a losing one upon departure of any member. A related notion is that of a *by-least winning coalition*[3] . Denoting by $W(S) = \sum_{i=1}^{|S|} b_i$ (the sum of the available resources of the members of S), a coalition S is said to be *by-least winning with* (or *for*) player i, if it is a minimal winning coalition, it contains i, and for any other minimal winning coalition S' containing i it holds that $W(S) \leq W(S')$.

5.3.2 Definitions of the Power Indices

The formation of a coalition is greatly influenced by the players themselves in terms of how much they motivate such cooperations with other players. For simple (0-1) games, a popular coalition formation method is by using power indices. A power index (or value) is commonly used to measure the influence of a player on the formation of coalitions and most importantly on the outcome of the game. The notion of power indices can be used as a naive solution concept for the game itself. One can postulate that, if no specific payoff allocation rule is specified a priori, then normalized power indices can be used to allocate payoffs. Alternatively, it can be used for payoff allocation when there is a common pool in which access networks share their resources and there is no coalition formation process by the networks themselves.

Widely used power indices are the *Shapley-Shubik Power Index* (abbreviated here as SSPI) [92], and the *Banzhaf Power Index* (abbreviated here as BPI) [14]. These are generally sums of the *marginal contributions* $(v(S)-v(S\setminus\{i\}))$ of a player i to each coalition, weighted by different probability distributions over the set of coalitions. We say that player i is *critical* to coalition S if its marginal contribution is 1, otherwise it is non-critical.

[3] In [18], the authors define a coalition S to be "least-winning" if it is minimal winning and for any other minimal winning coalition S' it holds that $W(S) \leq W(S')$. We introduce a related definition here from the point of view of each player $i \in S$.

The SSPI assumes all permutations of the order that members form a coalition are equally likely, and is defined by:

Definition 16 (SSPI)**.**

$$SSPI_i(N,v) = \sum_{\substack{S \subseteq \mathcal{N} \\ (S \ni i)}} \frac{(|S|-1)!(N-|S|)!}{N!} (v(S) - v(S \setminus \{i\})) \ . \tag{17}$$

The BPI assumes, on the other hand, that all possible coalitions that contain i are equally likely and is defined by:

Definition 17 (BPI)**.**

$$BPI_i(N,v) = \frac{1}{2^{N-1}} \sum_{\substack{S \subseteq \mathcal{N} \\ (S \ni i)}} (v(S) - v(S \setminus \{i\})) \ , \tag{18}$$

for $i = 1, \ldots, N$.

Another popular power index based on minimal winning coalitions is the *Holler-Packel Power Index* (HPI) [44]. For simple games, the HPI is defined as:

Definition 18 (HPI)**.**

$$\begin{aligned} HPI_i(N,v) &= \sum_{S \in M(N,v)} (v(S) - v(S \setminus \{i\})) \\ &= |\{S \in M(N,v) : i \in S\}| \ , \end{aligned} \tag{19}$$

for $i = 1, \ldots, N$, where $M(N,v)$ is the set of all minimal winning coalitions.

We define also the normalized *Holler-Packel value* $H\bar{P}I_i = HPI_i / \sum_{i=1}^{N} HPI_i$, which represents the proportion of minimal winning coalitions player i is in.

An important property of both the SSPI and the BPI indices in monotonic simple games is that players with greater weight (contribution) also get a greater index. This is evident here since if a player i is critical to a coalition $S \cup \{i\}$, then a player i' with $b_{i'} > b_i$ is also critical to coalition $S \cup \{i'\}$. This is also referred to as "monotonicity of the players' power indices to the weights".

5.3.3 Equivalence to the Weighted Voting Game

This section demonstrates the equivalence of the network synthesis game to the weighted voting game, a well-studied paradigm from which many useful conclusions can directly apply.

Definition 19. A weighted voting game consists of N players and a weight vector $w = (w_1, w_2, \ldots, w_N)$, where w_i reflects the "voting weight" of player i. Let $W = \sum_{i=1}^{N} w_i$. For a coalition S, the characteristic function of the game is

$$v(S) = \begin{cases} 1, & \text{if } \sum_{i=1}^{|S|} w_i > \frac{W}{2} \\ 0, & \text{otherwise .} \end{cases} \tag{20}$$

We assume $w_i \leq W/2 \; \forall i \in \mathcal{N}$.

Proposition 5.3.1. *The weighted voting game can be mapped into a network synthesis game with networks' resources $b_i = w_i$ and minimum required resources to accommodate a service equal to $B = \frac{W}{2}$.*

Proof. To prove the equivalence, it suffices to show that there exists a one-to-one mapping between vectors w and $b = (b_1, \ldots, b_N)$ so that $\sum_{i \in S} w_i > W/2$ if and only if $\sum_{i \in S} b_i \geq B$ $\forall S \subseteq \mathcal{N}$. A mapping satisfying these requirements is readily obtained by setting $w_i = b_i/2$ and W to a number B^* arbitrarily close to B such that $\sum_{i \in S} b_i \geq B$ iff $\sum_{i \in S} b_i > B^*$. (It is straightforward that such a number exists, since we have discrete b_i values.) □

Furthermore, based on the equivalence of the network synthesis game to the weighted voting game, two useful observations made in [17, 18] about the behaviour of the power indices defined in section 5.3.2 can be transferred here: First, that restricting our attention to minimal winning coalitions as with the HPI results in weaker players (in our case, players with relatively smaller available resources) getting higher power, compared to the measurement with the SSPI and the

BPI. Secondly, that with the HPI the monotonicity of the players' power indices to their weights may not be preserved: a player with smaller weight may get a higher HPI ranking than a player with greater weight.

5.3.4 Payoff Allocation

In the network synthesis game, we seek for the most possible winning coalition to support a particular traffic demand, i.e. the coalition that is most likely to be formed, so that the allocation of payoffs is more fair. Access networks participate in a coalition and offer their resources in return for some revenue (payoff). For example, the converged platform administrator may have a fixed amount of money to distribute to access networks in a coalition, as a reward for reserving their resources to handle the specific service(s). It is considered that all networks are independent and behave rationally, and that the objective of each network is to maximize its payoff.

Clearly, which coalition(s) will finally be formed depends on how payoffs are allocated. Moreover, if coalitions are formed arbitrarily and each access network could participate in more than one coalition, then the criterion for selecting which coalition to participate in, is the payoff received from each; naturally preferring the highest. This preference should be captured in the power index used to allocate payoffs, i.e the power index should be defined in a way that the most *popular* coalition, i.e. the one preferred by most players, is favoured. Let's concentrate on payoffs and consider payoff allocations for the game without the use of power indices.

Assuming that no power indices are used, and that payoffs are assigned based on coalition formation, let the total payoff allocated to the set of players be P and the payoff allocation vector be $p = (p_1, p_2, \ldots, p_N)$, such that $p_i \geq 0 \ \forall i = 1, \ldots, N$ and $\sum_{i=1}^{N} p_i = P$; an allocation satisfying the above conditions is said to be *feasible*.

We consider two cases: a) *transferable* payoffs between the access networks, and b) *non-transferable* payoffs. In the transferable payoff case, individual access networks can transfer any portion of their payoff to other members of the coalition, as long as their final payoff remains greater than zero. These transfers may be viewed as side-payments, used as a means to "attract" other players in a specific coalition. In the non-transferable case, such side payments are not allowed and we will consider that access networks attain a payoff that is proportional to their resource contribution, relative to the other members of the coalition. More specifically, if this winning coalition is $\mathcal{K}$ consisting of $K \leq N$ access networks with available resources $b_1, b_2, \ldots, b_K$, then

$$p_i = \begin{cases} \frac{b_i}{\sum_{j=1}^{K} b_j} P, & \text{if } i \in \mathcal{K} \\ 0, & \text{otherwise .} \end{cases} \tag{21}$$

(It holds that $\sum_{j=1}^{K} b_j \geq B$.)

When payoffs are transferable, this leads to trivial solutions of minimal-sized coalitions. When payoffs are non-transferable, the proportional payoff allocation case is more interesting and requires the notion of a "by-least winning" coalition. Given the defined power indices, we may relate HPI to minimal-winning coalitions, however, none of the defined power indices relates directly to the concept of by-least winning coalition; both concepts are defined in section 5.3.1. Consequently, in Section 5.4, we propose a new power index, called *Popularity Power* index (PPI), that satisfies this requirement, and further we provide a stability analysis to show that the PPI relates to coalitions that are stable.

5.4 A New Power Index

We would like to determine a *fair* way of allocating payoffs to a subset of the access networks, so that a stable coalition is formed and the desirable service(s) are provided. One could argue that every minimal winning coalition could potentially be a solution of the game. However, simple arguments show that the set of possible solutions can be further reduced, since not all minimal winning coalitions are equally likely. Rather, each player has specific preferences, i.e. to end up with higher payoff, and to be in one or more coalitions, which are by-least winning with it.

Let $M(N, v)$ denote the set of all minimal winning coalitions and let $Z_i(N, v)$ be the set of coalitions which are minimal in size for player i. A coalition S is said to be *minimal in size for* $i \in S$, iff $|S| \leq |S'|\ \forall S' \ni i$, where $S, S' \in M(N, v)$. Considering the proportional allocation rule, if a player i belongs to two minimal winning coalitions S and S', then $(b_i / \sum_{j \in S} b_j)P > (b_i / \sum_{j \in S'} b_j)P$ if $\sum_{j \in S} b_j < \sum_{j \in S'} b_j$, and hence it would get a higher payoff in the by-least winning coalition. We denote by $L_i(N, v)$ the set of all by-least winning coalitions for player i.

The new power index, is based on the popularity of all coalitions which are in $\cup_{i=1}^{N} L_i(N, v)$ (a subset of $M(N, v)$). For each minimal winning coalition $S \in M(N, v)$, we define as its *preference index* $\omega(S)$ the total number of preferences it gathers by all players:

$$\omega(S) = |\{i \in \mathcal{N} : S \in L_i(N, v)\}| \ . \tag{22}$$

We define a new index, which we will call the *Popularity Power Index* (PPI), as

$$PPI_i(N, v) = \sum_{S \in M(N,v)} \frac{\omega(S)}{\sum_{k \in M(N,v)} \omega(k)} I_{iS} \ , \tag{23}$$

where I_{iS} equals 1 if $i \in S$ and 0 otherwise. In plain words, the index PPI_i equals the probability that, if we were to pick a coalition by asking one player in $\mathcal{N}$ randomly (and further, if when this player had multiple equal preferences, he would select one of them with equal probability), then a winning coalition would be selected that contains player i. Hence, this index relates the popularity of minimal winning coalitions a player belongs in, to this player's power. As with the other indices, we can also define a normalized form of this index: $\overline{PPI}_i = PPI_i / \sum_{i=1}^{N} PPI_i$.

In Section 5.4.1, we relate PPI to the stable coalitions formed in case no power indices are used, and payoffs may be either transferrable or non-transferrable and proportionally allocated.

5.4.1 Stability Analysis

In this section, the well-known concept of the *core* (see, e.g. [67]), is used to examine the stability of coalitions formed according to the payoff allocations considered if no power index is used to allocate payoffs. Furthemore, we will show the equivalence of the proposed power index to payoff allocation for stable coalitions.

Descriptively, a payoff allocation to a set of N players is in the core of a coalitional game if there is no other coalition wherein each member can get a strictly higher payoff than dictated by the allocation. Such an allocation, as well as the coalitions that it induces, can be called stable, since there would not be a consensus to break these coalitions and form other ones.

In order to apply the core concept, we slightly modify the characteristic function of the network synthesis game, found in Equation (16) in the transferable payoff case to the following:

$$v(S) = \begin{cases} P, & \text{if } \sum_{i=1}^{|S|} b_i \geq B \\ 0, & \text{otherwise .} \end{cases} \tag{24}$$

That is, when the minimum necessary resources are available, the value of the characteristic function equals the total payoff.

For an allocation to be in the core of the transferable-payoff game – since we are not interested in how the payoff is divided among the members of the coalition – it is required that it does not have an incentive to deviate and obtain an outcome better for all its members.

Definition 20. An allocation $p = (p_1, p_2, \dots, p_N)$ is said to be in the core of the access network synthesis game with transferable payoffs iff

$$\sum_{i \in \mathcal{N}} p_i = P \text{ and } \sum_{i \in S} p_i \geq v(S),\ \forall S \subseteq \mathcal{N}\ .$$

Since $v(S)$ takes either the value 0 or P in our game, this trivially reduces to the requirement that for every winning coalition that could be formed by the networks, the sum of payoff allocations should always equal P.

For the non-transferable payoff case, we have the following definition:

Definition 21. An allocation $p = (p_1, p_2, \dots, p_N)$ is said to be in the core of the access network synthesis game with non-transferable payoffs iff $\sum_{i \in \mathcal{N}} p_i = P$ and there exists no other payoff allocation $y = (y_1, y_2, \dots, y_N)$ derived according to (21) for which $y_i > p_i,\ \forall i \in S \subseteq \mathcal{N}$, for any $S \subseteq \mathcal{N}$.

That is, the allocation must be feasible and there should exist no other allocation which gives strictly higher payoff to all members of a coalition.

A single winning coalition can be mapped to an allocation in the core. In the non-transferable payoff case, this is defined to be the coalition $\mathcal{K}$, based on which the payoff vector is derived. In the transferable payoff case, this is defined as $\{i \in \mathcal{N} : p_i > 0\}$, the set of players with positive payoff. We can then speak about "coalitions in the core", as the set of winning coalitions for which their corresponding allocations are in the core.

Not all winning coalitions are in the core. In fact, we have the following:

Theorem 5.4.1. *In both the transferable and non-transferable payoff cases defined above, only minimal winning coalitions are in the core.*

Proof. In the transferable payoff case, notice that for any non-minimal winning coalition, a corresponding minimal one can be formed by the players that are non-null (in the coalition). Then for any payoff allocation to players in the non-minimal winning coalition, the players in the minimal one can divide the excess payoff in such a way that they all get strictly higher payoff. In the non-transferable payoff case, the statement of the theorem follows directly from (21). □

Remark. This theorem is an adaptation of Riker's *size principle* [83] to this game, which was also shown for weighted voting games in [17].

Hence it is reasonable to direct our attention to minimal winning coalitions, $M(N, v)$.[4] In the case of transferable payoffs, only minimal winning coalitions which are also minimal in size for at least one of their members, denoted as $Z_i(N, v)$, will be in the core. In a sense, when we have transferable payoffs, all minimal winning coalitions of the same size must be treated as equivalent. In non-transferable payoff games, only coalitions that are by-least winning for at least one player, denoted by $L_i(N, v)$, or simply by L_i, are solutions in the core of the game.

We further proceed to study which coalitions are in the *inner core* of the game. The inner core [67] is a subset of the core that contains coalitions that are "more stable", in the sense that there exists no randomized plan that could prevent their formation.

Definition 22. A randomized plan is any pair $(\eta(S), y(S))$, $S \subseteq \mathcal{N}$, where η is a probability distribution on the set of coalitions, and y is the vector of payoff allocations for the members of coalition S, $y(S) = (y_i(S))_{i \in S}$. For non-transferable payoff games, the inner core is composed of all allocations p (or corresponding coalitions) for which $\sum_{S \supseteq \{i\}} \eta(S) y_i(S) < \sum_{S \supseteq \{i\}} \eta(S) p_i$, for some $i \in \mathcal{N}$, in all randomized plans $(\eta(S), y(S))$.

The inner core concept is used in cases where there is a mediator that invites individual players to form a coalition which is not known deterministically, but only with a certain probability

[4] Although the characteristic function v is defined usually for transferable payoff games, it is also used in this thesis in notations concerning the non-transferable payoff game such as $M(N, v)$ and $L_i(N, v)$, since, along with (21), it can be used to define the latter game.

distribution. Consider for example that in the network synthesis game, the converged platform administrator (mediator) informs the networks that, in case they don't arrive to an agreement by themselves, then a coalition of its choice will be selected, which will be S_1 with probability p_1, or S_2 with probability $p_2 = 1 - p_1$. Then, in order for a coalition to be stable, the payoff given to each network should not be smaller than the mean payoff anticipated in the coalition of the platform administrator's choice.

Theorem 5.4.2. *In the access network synthesis game with non-transferable payoffs proportional to the available resources of the participating networks, all coalitions which are by-least winning for at least one of their members are in the inner core of the game.*

Proof. In the network synthesis game, if an access network participates in several coalitions that are by-least winning with it, then in the non-transferable payoff case it would get the highest possible reward in every one of these coalitions. This reward would further be the same in every randomized plan among these coalitions, and lower for randomized plans containing coalitions other than the by-least winning.

Since, for a player i, the allocation in a by-least winning coalition is the maximum it can get, there exists no randomized plan that could block these coalitions from forming and hence the latter are in the inner core of the game. □

Remark. Of all by-least winning coalitions which are in the inner core, we may informally state that those that are by-least winning for *all* their members are "most stable". This will be made formal by defining a new concept of "stability under uncertainty of formation" in the Section 5.4.2.1.

A nice property of the game is formulated in the following:

Theorem 5.4.3. *In the access network synthesis game with non-transferable payoffs proportional to the available resources of the participating networks, there exists at least one coalition which* *is by-least winning for all its members. Further, regardless of the payoff allocation, there exists at least one coalition that is minimal in size for all its members.*

Proof. We demonstrate the theorem only for by-least winning coalitions. The proof for minimal in size coalitions is similar since the existence of a by-least winning coalition by definition implies the existence of at least a minimal winning coalition.

The proof is straightforward when there exists a coalition S, such that $\sum_{i \in S} b_i = B$, since then S is by-least winning for all its members. When $\sum_{i \in S} b_i > B$ for some $S \in \cup_{i=1}^{N} L_i$, and there exists $j \in S$ such that $S \notin L_j$, then necessarily another coalition $S_1 \neq S$ exists such that $S_1 \in L_j$ and $\sum_{i \in S_1} b_i < \sum_{i \in S} b_i$. Similarly now, if there exists $k \in S_1$, $k \neq j$, such that $S_1 \notin L_k$, then there exists another coalition $S_2 \notin \{S_1, S\}$ such that $S_2 \in L_k$ and $\sum_{i \in S_2} b_i < \sum_{i \in S_1} b_i$. Continuing this procedure, since we have a finite number of players, a finite sequence of coalitions $S, S_1, S_2, \ldots, S_m$ is produced, for which $\sum_{i \in S} b_i > \sum_{i \in S_1} b_i > \sum_{i \in S_2} b_i > \cdots > \sum_{i \in S_m} b_i > B$ and S_m is by-least winning for all its members. $\square$

Hence, in both transferable and non-transferable payoff cases studied, interests of at least some players coincide. However, it will be reasonable to assume that a player will prefer a minimal winning coalition even though it would not be by-least winning with it, if otherwise it would be excluded from the prevailing coalition and receive zero payoff.

5.4.2 The Coordination Game

We have established that each access network i would maximize its payoff and hence prefer one of the coalitions in $Z_i(N, v)$ (transferable payoff case) or $L_i(N, v)$ (proportional payoff case) to eventually be formed. Unless $\bigcap_{i=1}^{N} Z_i \neq \emptyset$ in the former, or $\bigcap_{i=1}^{N} L_i \neq \emptyset$ in the latter case, there is no mutually preferred coalition and we are led to a *coordination game* where at least one player has *conflicting preferences* with one or more of the others.

A possible resolution of such a coordination game follows, which is based on the idea of calculating the probability that these coalitions would randomly form. The analysis applies equally to the transferable and non-transferable payoff cases, and in what follows we shall use $\mathcal{G}_i(N, v)$ (or simply $\mathcal{G}_i$) to denote either $Z_i(N, v)$ or $L_i(N, v)$, depending on which case we study.

5.4.2.1 Resolution of the coordination game

The ultimate goal of the game is to find out if one or more stable coalitions can form, so that the service demands are satisfied. Further, what is more important is that, under the proportional payoff allocation rule, if an access network i can be in multiple minimal winning coalitions, then it prefers the one (or ones) which is (or are) by-least winning with it. (Clearly, if there are more than one by-least winning coalitions for a player, then they must sum to the same total resource amount.) For each player i, we denote by $L_i(N, v)$ the set of all by-least winning coalitions for i (this set will also be denoted simply by L_i).

For cases where some players have more than one by-least winning coalitions, we may examine which coalitions are more likely to be formed. For $i = 1, \dots, N$, we define the *probability of formation* $P_f^{(i)}(S)$ to be the probability that player i would anticipate coalition S to be formed, if player i participated in it and all other players $j \in S$, $j \neq i$ would independently choose to participate in one of their preferred coalitions with equal probability. That is,

$$P_f^{(i)}(S) = \begin{cases} \prod_{\substack{j \in S, \\ j \neq i}} \frac{1}{|\mathcal{G}_j|}, & \text{if } S \in \bigcap_{j \in S, j \neq i} \mathcal{G}_j \\ 0, & \text{otherwise .} \end{cases} \tag{25}$$

Then it is reasonable that a player would ultimately prefer to participate in the coalition which has the highest probability of formation, and hence, under such uncertainty, would offer it the greatest expected payoff.

To appoint a name to this concept of stability, we define a coalition S to be *stable under uncertainty of formation* if and only if there exists no other coalition S' with a common member with S that anticipates a higher probability of formation for S'.

Definition 23. In the access network synthesis game with transferable or non-transferable payoffs, a coalition S is stable under uncertainty of formation iff $P_f^{(i)}(S) > 0 \; \forall i \in S$ and[5]

$$\nexists S' \neq S \text{ s.t } P_f^{(j)}(S') > P_f^{(j)}(S) \text{ for } j \in S \cap S' .$$

This notion would help to refine solutions of the coordination game. It also creates a formal ground to confine solutions to coalitions which are minimal in size (transferable payoff case) or by-least winning (proportional payoff case) for all their members: by definition, only such coalitions are stable under uncertainty of formation (in view of (25), other coalitions have zero probability of formation for at least one member).

Remark. PPI associates a player's value to the number of stable coalitions it participates in; the higher this number, the greater the index value. In fact the preference denoted by $\omega(S)$, in the definition of PPI, refers to how many players consider coalition S, by-least winning. Clearly, the coalition with the highest ωS is *stable under uncertainty of formation*, according to Definition 23.

Thus, PPI excludes a number of coalitions which are not stable and hence would not appear if access networks formed coalitions independently. In addition, the PPI is more fair than other indices examined, in the sense that it only considers stable coalitions in the inner core that would be formed if payoffs were allocated proportionally to players' contributions, i.e. in a fair manner.

[5] s.t means "such that".

These coalitions have been shown to be the most probable to be formed, both in the transferrable and in the non-transferrable payoff cases. Section 5.5 undertakes the evaluation of the various indices and demonstrates how the PPI allocates payoffs only to the players that would participate in the minimal in size or by-least winning coalition, i.e. players that are in the inner core of the game, as we have shown that all coalitions which are by-least winning for at least one player are in the inner core.

5.5 Evaluating Cooperation between Multiple Networks

This section examines the numerical behaviour of all power indices described in the previous section.

Power index values are examined for different numbers of players and different distributions of available resources. Even though the theory extends to many players, we have selected game instances of a few players only (three, four and five players) for illustrative purposes. Individual resources for each test instance presented sum up to the same total resource amount; this is done in order to better compare results between the different cases for the same number of players. Note that collaboration between players are considered only if the sum of their resources adds up to or exceeds the amount of available resources, i.e. one (1) in the simulations.

For each set of players we consider different distributions D_i ($i = 0, \ldots, 5$) of available resources, from the case $i = 0$ where resources are uniformly distributed between access networks, i.e. each network has the same fraction of available resources, to non-uniform cases ($i = 1, \ldots, 5$), carefully selected to exhibit the varying allocations of the power indices, carefully selected to exhibit the values of the power indices when available resources are about the same, or resources are concentrated in only a few of the networks.

To avoid taking absolute values, we have considered available resources of each player i normalized with respect to the minimum resource requirement B, i.e., b_i/B. For each of the power indices BPI, SSPI, HPI and PPI, we examine both the values of the indices as well as their rankings.

The values of normalized available resources are shown in Tables 20, 22, and 24, for the cases of three, four, and five players respectively. For each one of these cases the three power indices

Table 20: Instance 1: 3 players

Distribution	$\frac{b_1}{B}$	$\frac{b_2}{B}$	$\frac{b_3}{B}$
D_0	0.4	0.4	0.4
D_1	0.8	0.2	0.2
D_2	0.8	0.3	0.1
D_3	0.9	0.2	0.1
D_4	0.6	0.35	0.25
D_5	0.55	0.45	0.25

Table 21: Instance 1 Indices

Distribution	Index	Player 1	Player 2	Player 3
D_0	BPI	0.33	0.33	0.33
	SSPI	0.33	0.33	0.33
	HPI	0.33	0.33	0.33
	PPI	0.33	0.33	0.33
D_1	BPI	0.6	0.2	0.2
	SSPI	0.67	0.17	0.17
	HPI	0.5	0.25	0.25
	PPI	0.5	0.25	0.25
D_2	BPI	0.5	0.5	0
	SSPI	0.67	0.33	0
	HPI	0.5	0.5	0
	PPI	0.5	0.5	0
D_3	BPI	0.6	0.2	0.2
	SSPI	0.67	0.17	0.17
	HPI	0.5	0.25	0.25
	PPI	0.5	0	0.5
D_4	BPI	0.33	0.33	0.33
	SSPI	0.33	0.33	0.33
	HPI	0.33	0.33	0.33
	PPI	0.33	0.33	0.33
D_5	BPI	0.5	0.5	0
	SSPI	0.67	0.33	0
	HPI	0.5	0.5	0
	PPI	0.5	0.5	0

Table 22: Instance 2: 4 players

Distribution	$\frac{b_1}{B}$	$\frac{b_2}{B}$	$\frac{b_3}{B}$	$\frac{b_4}{B}$
D_0	0.4	0.4	0.4	0.4
D_1	0.85	0.25	0.25	0.25
D_2	0.8	0.55	0.15	0.1
D_3	0.95	0.45	0.1	0.1
D_4	0.6	0.4	0.35	0.25
D_5	0.55	0.5	0.3	0.25

Table 23: Instance 2 Indices

Distribution	Index	Player 1	Player 2	Player 3	Player 4
D_0	BPI	0.25	0.25	0.25	0.25
	SSPI	0.25	0.25	0.25	0.25
	HPI	0.25	0.25	0.25	0.25
	PPI	0.25	0.25	0.25	0.25
D_1	BPI	0.7	0.1	0.1	0.1
	SSPI	0.75	0.083	0.083	0.083
	HPI	0.5	0.17	0.17	0.17
	PPI	0.5	0.17	0.17	0.17
D_2	BPI	0.5	0.3	0.1	0.1
	SSPI	0.75	0.17	0.042	0.042
	HPI	0.4	0.2	0.2	0.2
	PPI	0.33	0	0.33	0.33
D_3	BPI	0.7	0.1	0.1	0.1
	SSPI	0.75	0.083	0.083	0.083
	HPI	0.5	0.17	0.17	0.17
	PPI	0.5	0	0.25	0.25
D_4	BPI	0.33	0.33	0.17	0.17
	SSPI	0.33	0.33	0.17	0.17
	HPI	0.25	0.25	0.25	0.25
	PPI	0.2	0.4	0.2	0.2
D_5	BPI	0.33	0.33	0.17	0.17
	SSPI	0.33	0.33	0.17	0.17
	HPI	0.25	0.25	0.25	0.25
	PPI	0.2	0.4	0.2	0.2

Table 24: Instance 3: 5 players

Distribution	$\frac{b_1}{B}$	$\frac{b_2}{B}$	$\frac{b_3}{B}$	$\frac{b_4}{B}$	$\frac{b_5}{B}$
D_0	0.3	0.3	0.3	0.3	0.3
D_1	0.7	0.2	0.2	0.2	0.2
D_2	0.85	0.2	0.15	0.15	0.15
D_3	0.9	0.25	0.15	0.15	0.05
D_4	0.5	0.3	0.3	0.2	0.2
D_5	0.45	0.35	0.3	0.25	0.15

are generated also in a normalized form so that they add up to one. The values of indices for these cases are shown in Tables 21, 23, and 25.

Differences between the indices' values become more pronounced as the number of players increases (the increased number of possible coalitions allows such differences to show). In general, the SSPI and BPI give similar values, favoring the players with greater available resources. (A closer inspection reveals that SSPI systematically does that to a slightly greater extent than BPI). On the other hand, the HPI and PPI give a higher power to relatively weaker players. This is because weaker players have smaller contributions and hence are more often found in coalitions which are minimal winning, or by-least winning for some players.

The HPI and PPI are more appropriate indices for the game, since they exclude a number of coalitions which are not stable and hence would not appear if access networks formed coalitions independently. Comparing these two indices, we can argue that the PPI is more fair, in the sense that it only considers stable coalitions in the inner core that would be formed if payoffs were allocated proportionally to players' contributions, i.e. in a fair manner. In Tables 21, 23, 25, we may note that often a player is allocated zero payoff with the PPI, whereas non-zero with the HPI. These are cases where this player participates in minimal winning coalitions, but not in any of the by-least winning coalitions. For example, in Table 21, case D_3, player 2 is allocated 0.25 value with the HPI, whereas 0 with the PPI, since it does not participate in the by-least winning coalition. The monotonicity of index values to players' contributions also does not hold for the PPI in this example.

Table 25: Instance 3 Indices

Distribution	Index	Player 1	Player 2	Player 3	Player 4	Player 5
D_0	BPI	0.2	0.2	0.2	0.2	0.2
	SSPI	0.2	0.2	0.2	0.2	0.2
	HPI	0.2	0.2	0.2	0.2	0.2
	PPI	0.2	0.2	0.2	0.2	0.2
D_1	BPI	0.48	0.13	0.13	0.13	0.13
	SSPI	0.8	0.05	0.05	0.05	0.05
	HPI	0.33	0.17	0.17	0.17	0.17
	PPI	0.33	0.17	0.17	0.17	0.17
D_2	BPI	0.79	0.05	0.05	0.05	0.05
	SSPI	0.8	0.05	0.05	0.05	0.05
	HPI	0.5	0.125	0.125	0.125	0.125
	PPI	0.5	0	0.17	0.17	0.17
D_3	BPI	0.54	0.15	0.15	0.15	0
	SSPI	0.8	0.067	0.067	0.067	0
	HPI	0.5	0.17	0.17	0.17	0
	PPI	0.5	0	0.25	0.25	0
D_4	BPI	0.31	0.22	0.22	0.125	0.125
	SSPI	0.33	0.18	0.18	0.18	0.15
	HPI	0.33	0.2	0.2	0.13	0.13
	PPI	0.33	0.17	0.17	0.17	0.17
D_5	BPI	0.3	0.22	0.22	0.22	0.04
	SSPI	0.33	0.18	0.18	0.18	0.15
	HPI	0.23	0.23	0.23	0.23	0.08
	PPI	0.33	0	0.33	0.33	0

Chapter 6

Conclusions & Future Work

Interactions in Next Generation Communication Networks become a challenging task due to the heterogeneity of user(s) and the mobile network(s), resulting in different and often conflicting interests for these entities. Since cooperation between these entities, if achieved, is expected to be beneficial, we have posed the following question, at the beginning of this thesis: Can cooperation be motivated in interactive situations in converged communication networks, and if yes, is it beneficial for the interacting entities?

We have utilized, Game Theory, a theoretical framework suitable for generating profitable behaviours/strategies for interacting entities in conflicting situations and we have explored its application upon seemingly conflicting interactions occuring in converged heterogeneous communication networks. In particular, three selected interactive situations have been analyzed using existing game theoretical models, and theoretical conclusions are drawn for each interactive situation; the theoretical conclusions are further reinforced with appropriate numerical results. Overall, these conclusions show that cooperation can indeed be motivated in the selected interactive situations and furthermore, that this cooperation is beneficial for the interacting entities. Section 2.3 has listed and discussed how several networking research works have shown that cooperation is a beneficial solution both in node-to-node interactive situations (e.g. in ad-hoc and peer-to-peer networks), as well as in network-to-network interactions (e.g. in Next Generation converged communication networks). Several of these works use Game Theory as the theoretical framework through the use of which, cooperation can be motivated. Overall, Game Theory in general, and cooperation in particular have been used to solve various networking problems. In this thesis we turn our focus on interactions in Next Generation Communication Networks, however, applicable cooperation scenaria can be expected in node-to-node interactive situations.

Summarizing the work presented, we begin with the interaction between a user and a mobile network, where the cooperative nature is motivated by an infinitely repetitive game, and appropriate strategies for both the user and the network are evaluated in order to select the ones that achieve strong motivation for the two entities towards cooperating and remaining in cooperation during network selection; a new adaptive user strategy and consequently a new game profile are proposed by this thesis in Chapter 3. Next, the bargaining situation between two access networks attempting to partition a service payment optimally, is modelled and resolved using the Nash Bargaining Game model, and accordingly the Nash Bargaining Solution, which is equivalent to the immediate resolution of the widely used Rubinstein Bargaining Game. Truthfulness is an issue that must always be considered in such bargaining situations, and thus a Bayesian game model helps to propose a way to induce truthfulness from the participating players in Chapter 4. Finally, regarding the coalition formation process in the case of increased service demand, we explore the conclusions of the analytic study stemming from the assumptions presented in Chapter 5, and move on to propose an appropriate payoff scheme through the newly proposed *Popularity Power Index*. The payoffs that result from the employment of this new index reward coalitions, which are more likely to be formed (according to their popularity). Therefore, the game resolution favours a fairer payoff allocation between the participating access networks. The following paragraphs discuss in more detail the three interactive situations and deduce appropriate conclusions and future work.

The first selected interactive situation deals with the case that a user and a network interact because of a new service request. In a converged heterogeneous network, the mechanism of network selection, results in one network being assigned to each user (out of the multiple networks available to the user) to serve the particular service request, spawning the interaction between the two entities. The interaction has been modelled using game theoretic tools, in an attempt to model an interaction that motivates cooperation. Firstly, the interaction is modelled as a one-shot game, and it is shown that there exists equivalence of a one-shot game model of user-network interaction to the one-shot *Prisoner's Dilemma Game*. This is an important finding, since the *Prisoner's Dilemma* is known to have a cooperative solution under certain conditions, as for example a repeated game, motivating this thesis to explore this interaction further towards the direction of cooperation. In fact, it has been shown that motivation of cooperation between the two entities is achieved through a *repeated game* model of the user-network interaction.

Exploring existing and new strategies for the two entities, we show that when the strategies used by the players of the repeated user-network interaction model involve punishment to motivate cooperation, then harsher punishments motivate cooperation more easily. However, since practically a user wouldn't choose to employ the harshest punishment, i.e. leaving the interaction forever, we propose a new user strategy that uses an *adaptive* punishment method in the repeated user-network interaction game. The adaptive strategy, is inspired by the proposed network selection model, which assumes that the user is an adaptive entity with *knowledge* about the networks' behaviours that change over time. For that, an internal state for the user as an adaptive entity is defined and used in the proposed network selection scheme.

The adaptive strategy motivates cooperation and achieves satisfying results in terms of motivation and in terms of payoffs, becoming the strategy of choice for a user when compared to the other strategies examined in this thesis. As a consequence, it has been shown that a profile of the repeated user-network interaction game where the user employs the adaptive punishment method and the network employs the well-known *tit-for-tat* strategy, generates the most profitable payoffs for both players.

The second selected interaction involves two networks interacting to support a service with additional quality guarantees (e.g. for a premium user). Therefore, the first network supports the service and the second network reserves the appropriate resources to ensure service continuity, in the case that the first network demonstrates quality degradation so that the user is guaranteed a seamless experience, e.g. in terms of service continuity at similar QoS levels. The two networks must cooperate to partition the service payment, since the fact that two networks support the service is transparent to the user offering the service payment. This interaction between two networks has been modelled using game theoretic tools, in such a way as to motivate cooperation in terms of partitioning the available payment for the particular service.

The payment-partition model has been shown to be equivalent to the well-known *Rubinstein Bargaining Game*, if the agreement in the Rubinstein Bargaining Game is reached from the first negotiation period. In addition, the thesis has shown that there exists equivalence between the payment-partition game and the *Nash Bargaining Game*, due to the equivalence of the Nash bargaining game to the Rubinstein Bargaining Game, if the agreement in the Rubinstein Bargaining Game is reached from the first negotiation period. Thus, an optimal solution for the payment-partition game exists and is based on the *Nash Bargaining Solution*, resulting in a partition determined by the cost each of the two networks has for supporting the service. As a side result, it has been shown that if a constant probability of demonstrating quality degradation is included in the networks' payoff functions for the payment-partition game, this does not affect the optimal partition proposed by the Nash Bargaining Solution[1] . This is important since the technology employed by each network and the established quality provisioning mechanisms are always susceptible to QoS degradation due to the dynamic nature of the heterogeneous network and the mobility of the users; considering more realistic conditions for the network models, i.e. a constant degradation probability (according to the technology and quality provisioning mechanisms for each network), adds credibility to the solution.

Once the optimal partition is determined, the payment-partition game is modelled as a one-shot *Bayesian* game, to investigate truthfulness on behalf of the participating networks regarding their own costs, since the declaration of costs is very important in determining the optimal partition. It has been shown that no matter whether a network believes that the opponent network has declared lower or higher cost than its own cost, it is still motivated to lie about its real costs. To motivate truthfulness, a *pricing mechanism* has been used in the payoffs of the users, which has been shown to work very effectively towards motivating the networks to be truthful.

The third selected situation involves the interaction between multiple networks when they must cooperate to serve a large service demand that is best served by more than one networks (for example, if none of those networks can serve the demand on its own). The coalition formation process between multiple networks has been modelled as the *Network Synthesis* game, in which individual networks with insufficient resources form coalitions in order to satisfy service demands. It has been shown that the Network Synthesis game is equivalent to the well-known *Weighted Voting Game*. This equivalence encourages the use of power indices for payoff allocation, as often used to resolve the Weighted Voting Game. A comparative study of well-known *power indices* representing payoff schemes, is provided for the network synthesis game. Based on conclusions

[1]However, it affects the payoff of the individual networks

from this study, the thesis proposes a new power index, the *Popularity Power Index* (PPI), which associates the popularity of each network to the number of stable coalitions it participates in.

It is shown that the newly proposed power index achieves fairness, in the sense that it only considers the possible coalitions that would be formed if payoffs were assigned proportionally to the networks' contributions. An analysis of the coalition formation is provided for both transferable and non-transferable payoffs, in order to determine stable coalitions using the core and inner core concepts. The most appropriate power index for the network synthesis game, from the existing power indices investigated, is a power index that provides stability under the core concept, known as the *Holler-Packel Index (HPI)*. The core and inner core equilibrium concepts are further investigated to show that coalitions that would be formed using the newly proposed PPI to assign payoffs, are only coalitions that would be stable under the inner core concept. Therefore, the PPI provides a simple and fair payoff allocation method that is equivalent to a stable cooperative equilibrium solution of the Network Synthesis Game.

Future Work plans to explore further the repeated nature of the interaction between network(s) and user(s). 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. We would like to analyze further this notion but moreover, to discover other such tools that may be able to capture the characteristics of this interaction.

We plan to investigate the idea of expanding the user-network interaction model to involve more than one user and more than one network. For this enhanced game we plan to find the necessary and sufficient conditions that can enforce the players into behaviours that maximize both local (individual) and global (system) objectives. Furthemore, we plan to investigate mechanisms that will enforce the modelled interactions to converge into desired outcomes. Towards this goal, we plan to explore tools from *Mechanism Design*[72]. In particular, we will try to find suitable payoff functions for the players that the converged network will impose on the involved entities, such that trying to maximize their individual gain will end up in desired behaviours, e.g. being truthful. Moreover, the role of nature will be investigated in the context of both one-shot and repeated games.

The work on coalitional games can be extended by studying factors which may influence the coalition-formation process. Such are the order in which members are invited in a coalition (e.g., in the proportional payoff case, it is reasonable to anticipate that a player would participate in the by-least winning coalition in which it is first invited) or explicit user preferences for operators or QoS parameters. A more complete model should take into account negotiations between all interested parties, i.e. between different network operators, or different network operators and users.

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. In addition to the application of cooperation in heterogeneous converged networks, this work has closeness to peer-to-peer and mobile ad-hoc networks (e.g. enhance routing), as well as in Sensor Networks and Vehicular Networks (e.g. security), and further study is encouraged in these areas.

Appendix A

An initial study of the adoption of IMS to implement cooperative models is found in [9]. For easy reference, the relevant part in the paper appears here.

...Overall we have seen through this example that a game theoretic framework could be adopted for the selection of the best access network in 4G converged environments. Also, that it is crucial to have some consideration of user preference in the decision of which access network to serve a specific request. In such a user-centric system, the payoff needs to be a user-awarded value because, although the network selection decision is defined to be network-driven, user satisfaction is also accomplished.

B. Signalling Procedures

Once the preference is derived, there needs to be an efficient way to communicate this information to the converged system in order to consider it prior to activating a specific service. Overall, RAN Selection needs to occur once the user subscription, service announcement and primary PDP context activation (to enable exchange of control information) have been completed but prior to the completion of actual service activation. We need to define some way of pausing service activation until a RAN selection decision has been made.

Service activation is the process that registers the user in the network to enable the reception of data from a specific multicast MBMS bearer service. We incorporate RAN selection as a decision within the service activation procedure. The pausing of service activation is achieved by using preconditions in the SDP messages that are exchanged together with the SIP messages, by adding attributes on the session level of the SDP message. SDP (RFC 4566) provides a standard representation for session metadata information, irrespective of how that information is transported. In IMS, this is done via SIP messages during session procedures. When SDP is used with SIP in IMS, the offer/answer model (RFC 3264) provides a limited framework for parameter negotiation. SDP is intended to be general purpose so that it can be used in a wide range of network environments and applications and is thus appropriate to incorporate RAN selection decision.

Figure 8 illustrates the service activation signalling for MBMS service in an IMS-enabled environment. It can be seen that the MBMS signalling for joining a service is pretty much kept as defined. This is done to provide support to the MBMS service. However, this is contained within some IMS session establishment signalling to allow the MBMS service to be handled efficiently by an IMS-enabled system. Additionally we have added to the IMS signalling some additional signal exchanges in order to support RAN selection scheme, that require some negotiation prior to reaching a decision on which RAN to serve a specific request. Note that the signalling is end to end for RAN Selection, i.e. from the User Equipment (UE) to the Application Server/Session Management Enabler (AS/SME) in the Core Network.

The offer/answer model as defined for RAN selection requires an exchange of one offer and one answer between the two involved parties, the UE and the AS (SME). Once the RAN Selection mechanism is triggered from the Core Network and specifically the Session Enabler plane, the 1st SDP offer is sent with the first SIP INVITE message from the UE to the AS (SME) after service announcement and primary PDP Context Activation are completed. It comprises of a list of available RANs that the UE can connect to. The list is ordered priority-wise. The 1st SDP answer is sent back to the UE from the AS (SME) with a SIP Session Progress message (183 session progress). It

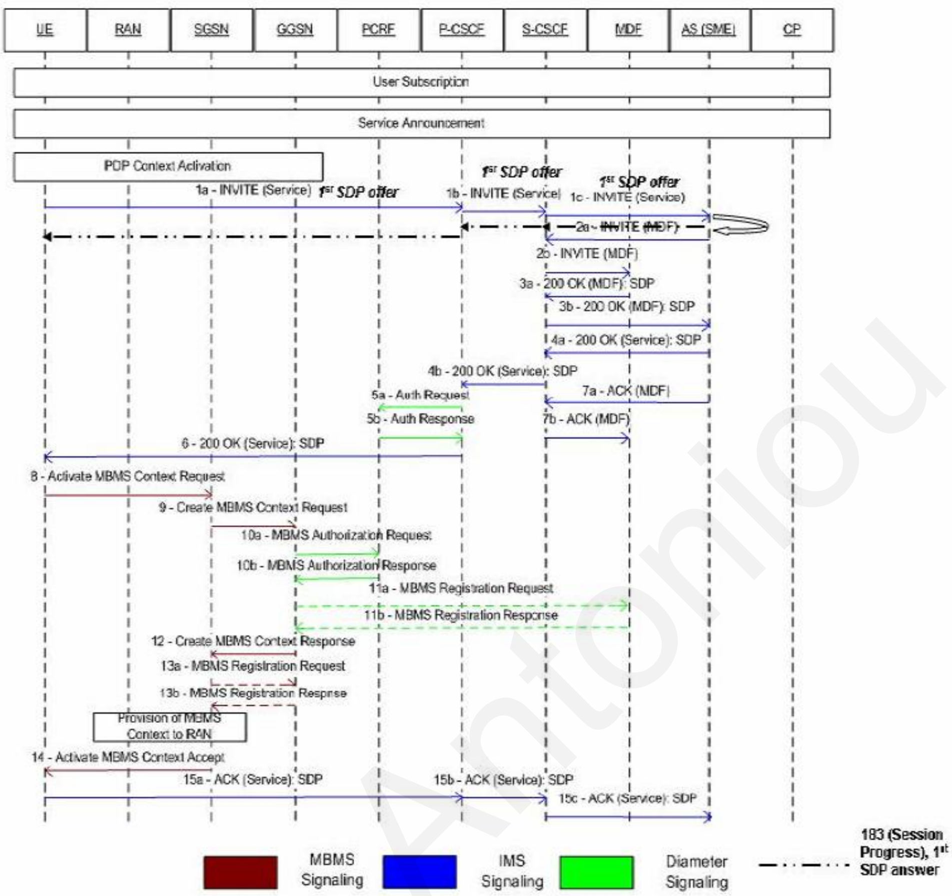

Figure 8: Service Activation with RAN Selection Signalling

provides the decision of which RAN to serve the request based on the relevant subset of RANs that can be supported by the AS (SME) for the particular service.

Once the decision is taken and communicated to the two parties, service activation may continue with media negotiations and appropriate resource reservation in the selected RAN...

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