RIGA TECHNICAL UNIVERSITY
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FUZZY LOGIC BASED METHODS FOR NGN NETWORK RESOURCE MANAGEMENT

Summary of the Doctoral Thesis

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To be granted the scientific degree of Doctor of Engineering Sciences, the present Doctoral Thesis has been submitted for the defence at the open meeting of RTU Promotional Council “RTU P-08” on May 5, 2016 at 18.00 at the Faculty of Electronics and Telecommunications of Riga Technical University, Azenes Street 12, Room 2-38.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for the review to Riga Technical University for the promotion to the scientific degree of Doctor of Engineering Sciences (Telecommunications) is my own. I confirm that this Doctoral Thesis had not been submitted to any other university for the promotion to a scientific degree.

Julija Asmuss ……………………………. (Signature)

Date …………………………

The Doctoral Thesis is written in the Latvian language, it consists of the Introduction, 4 Chapters, Conclusion, Bibliography, 5 appendices, 53 figures and illustrations, with the total number of 167 pages. The Bibliography contains 124 titles.

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GENERAL DESCRIPTION OF THE WORK

Topicality of the theme

Over the past 20–30 years, rapid development of the telecommunications industry very significantly changed telecommunication networks architecture and operating principles. If 30 years ago a telecommunication network was mostly used for voice transmission, nowadays a network is connected with a number of applications, which have recently been intensively developing and already are related not only to the voice features. For the development of multiservice network the most important idea is to combine different types of networks. The appearance of new applications with high requirements in terms of bandwidth and the ability to flexibly and efficiently process different types of traffic leads to significant changes in data transmission technology. The approach to network establishment is changing and the next-generation network is in the leading position.

Next-generation network, which development is the telecommunications industry task of the nearest future [36], is a universal and multifunctional electronic communications packet switching network that provides users with the ability to simultaneously receive voice, video and data transmission services. According to the ITU-T vision of NGN provided electronic communication services, they are independent from data transmission technology and can be offered by unrelated service providers. NGN network is characterized by the ability to guarantee the client-operator contract SLA (Service Level Agreement) certain quality of service conditions for different types of services. In modern networks, the nature of each application, the requirements for the functioning parameters and QoS (Quality of Service) should be taken into account. Now there is an active research to find the mechanisms that would be able to provide dynamic management of network resources, while providing the required QoS level for services. This quality management task is complicated and requires applying complex DSS (Decision Support Systems). There are several aspects due to which the task of network resource dynamic reallocation is considered to be very complex (see [9], [11], [30]): traffic complex structure (with multiple traffic types) and "burstable" nature; the need to guarantee QoS requirements for each type of traffic and the operational efficiency of the whole system; the need to make a decision under incomplete information; the need to ensure network resource management in a changing environment with very explicit uncertainties in the decision-making conditions.

One of the approaches that would work in a changing environment with traffic classes, focusing on differentiated services and conforming to QoS requirements for each corresponding class in the model, is network virtualization (see, for example, [2], [5], [14], [17] [32], [35], [37], [63]). One of the mechanisms to provide dynamic resource management with virtualized network structure is DaVinci (Dynamical Adaptive Virtual Network for Customized Internet) approach [13]. According to DaVinci approach, to ensure QoS classes requirements, traffic is managed by virtual networks. Considering the DaVinci concept, it is important to find an effective mechanism for network bandwidth allocation and dynamic reallocation between multiple virtual networks in a substrate network with DaVinci architecture taking into account the above mentioned on the nature of modern network traffic.

In the NGN networks context, topicality of bandwidth allocation task is explained by the fact that the ITU-T Recommendation Y.2111 (Resource and admission control functions in next-generation networks [18]) establishes only the general architecture of resource and access management RACF (Resource and Admission Control Functions) implementation and standardizes the interface, however the functional solution is the responsibility of each company. Latvian telecommunications market is characterized by a large number of small and medium-sized enterprises. Mostly, these are Internet service providers, for which large and expensive DSS systems are not available. Consequently, currently it is a very topical task on network resource management mechanisms, which can be realized using free access software.

It should be also noted that both traffic and the number of applications are constantly increasing. By 2020, the EU is planning to produce and launch the operation of up to 3 billion sensors that will be connected to a common next-generation network. Conceptually, this means that the NGN should ensure access to any device, anywhere and anytime. Such a comprehensive resource management requires intelligent resource management tools (see [14], [17], [18]). Existing technologies for such systems like MADP (Multi-Agent Decision Process) are characterized by polynomial complexity and are not used for practical topical tasks due to a large number of dimensions. Large dimension of the tasks is a serious reason that makes it necessary to find new and effective decision-making technology for network resource management. Research has shown that for effective NGN resource management a multi-agent system should be created to ensure optimum close decision-making in incomplete information conditions.

One of the most promising tools that can be used to successfully solve the problem under such conditions is the developed mathematical apparatus based on the fuzzy logic (see, for example, [49], [52]). Fuzzy logic based systems and methods were suggested [60] determining the uncertainty as an essential part of the model already at the moment of establishment. Let us also note that in the summer of 2015 two very important fuzzy logic and fuzzy system issue related international conferences took place that were devoted to the 50^{th} anniversary of the publication of the fundamental article "Fuzzy Sets" by Lotfi Zadeh [60] in 1965. At the events marking the anniversary several hundreds papers were presented in which the authors reflected the results of studies in the recent years, clearly showing that fuzzy logic based methods and technologies are developed and are efficient for many areas. In short, the experimental results in many areas prove the effectiveness of fuzzy logic rules based management solutions in complex system control and resource management.

Fuzzy logic based technique prospects for telecommunication network design in the recent years have been investigated at the Institute of Telecommunications of Riga Technical University under Professor Gunars Lauks supervision. The thesis "Fuzzy Logic Based Admission Control for MPLS-TE/GMPLS Networks" [19] defended by Jan Jelinskis in 2011 was devoted to the analysis of this problem. In his thesis J. Jelinskis rated CAC (Call Admission Control) fuzzy based application possibilities for multiprotocol switching traffic transmission and management system, as well as studied the advantages of the new method over traditional, on the threshold based methods.

This thesis is devoted to the development of the fuzzy logic based approach. The focus of the thesis is concentrated on the bandwidth allocation problem. The task is solved on the basis of virtualization principles using DaVinci architecture [13] in order to include QoS requirements appropriate for each traffic class in the model.

The aim and tasks of the research

The aim of the research is to develop bandwidth resource management algorithms for NGN networks, which provide decision making in a changing environment under uncertain conditions and incomplete information, by implementing resource allocation for traffic classes with different QoS requirements.

To achieve the aim of the thesis the following tasks were defined:

1) to formulate resource management task on bandwidth allocation for networks with DaVinci architecture accomplishing the analysis of existing research;
2) to develop decision making approximate (fuzzy) methods for bandwidth allocation between virtual networks;
3) to propose a simulation model for evaluation and improvement of the proposed decision making mechanism;
4) to develop and experimentally test new traffic representation and classification methods worked out to reduce the risk of anomalies;
5) to approbate the developed decision making mechanisms experimentally simulating resource management processes.

For effective solution of these tasks it is necessary to adapt the adequate apparatus and to develop the tools, taking into account that at this stage of telecommunication networks development the situation when the resource management related decisions should be made in imprecise and over time rapidly changing conditions in the case of large amounts of information, is becoming increasingly crucial:

1) to replace high computational complexity causing belief states with variables obtained as fuzzy transformation results, which in fuzzy clustering and classification helps reduce the dimension of a training set and consider only upper and lower bounds for cluster membership functions;
2) to apply fuzzy logic and game theory based decision making system to optimization procedure, which enables effective decision making in the incomplete and uncertain information conditions;
3) to perform a system simulation with colored Petri nets that allows reducing computational complexity for simulations.

Applied research methods

During the doctoral research the following methods implemented with Matlab software R, CPN Tools and MS Excel software were applied:

1) fuzzy logic based decision making methods for partially observable object management;
2) game theory based strategy decision methods for decision making under uncertain conditions;
3) traffic data fuzzy clustering and classification methods;
4) traffic fuzzy transformation (F-transform) method for clustering and classification purposes;
5) multi-agent system simulation methods using CPN (Coloured Petri Nets);
6) statistical methods for analysis of simulation results.

The methods applied for solving the research tasks allow using the advantages of fuzzy logic and coloured Petri nets to create decision making models and simulation tools for event condition action Fuzzy rules in telecommunications multi-agent systems, and as a result to develop the communication network resource management mechanisms.

The theses to be defended

1) The proposed decision support system for network bandwidth dynamically adaptive allocation between two virtual networks based on fuzzy logic principles can effectively adapt to the changing environment by quickly responding to changes in traffic and QoS parameters to ensure the preservation of acceptable limits.
2) By modernizing the above mentioned decision support system on the basis of game theory principles, the network bandwidth dynamically adaptive allocation between multiple virtual networks with different QoS requirements is achieved.
3) The method developed on the basis of fuzzy clustering and traffic data fuzzy transformation allows solving effectively traffic classification related tasks on anomaly detection.

The results and their scientific novelty

In this thesis, fuzzy logic and virtualization based telecommunication network bandwidth resource management method has been developed and an experimental decision support system for the evaluation of the proposed method and specification of parameters has been worked out. Traffic analysis and anomaly detection algorithm based on F-transforms and fuzzy clustering has been proposed.

The proposed methods are new. As far as it is known for the author of the thesis, in the works published by other researchers:

1) fuzzy logic based bandwidth allocation solutions in communication networks with DaVinci architecture had not previously been studied;
2) fuzzy game theory based network bandwidth allocation solutions had not previously been offered;
3) fuzzy transforms had not previously been applied solving problems arising in telecommunication.

Scientific novelty of the thesis involves:

1) integration of fuzzy logic based methods (see, for example, [49], [52]) and game theory principles ([42], [43]) with DaVinci approach [13] for the development of new methods for telecommunications network bandwidth resource management;
2) advantages of using fuzzy transforms ([46], [47]) and fuzzy clustering ([3], [25], [55], [59]) for network traffic analysis and anomaly detection.

Practical value of the research

1) Based on the theoretical and experimental results a traffic management tool including anomaly detection, decision making in a competitive environment for virtual networks, resource management and adaptive reallocation has been worked out.
2) Thesis results have been used in the research project 2013/0024/1DP/1.1.1.2.0/13/APIA/VIAA/045 "Applications of mathematical structures based on fuzzy logic principles in the development of telecommunication network design and resource control technologies" with the European Social Fund co-financing.
3) Both the developed decision support system and the proposed experimental model are used in Bachelor and Master research works.

Approbation of the results

The main results of the thesis were discussed at 18 international conferences held in Latvia and 11 foreign countries:

1) International Conference on Science, Engineering and Technology WASET 2012, Zurich, Switzerland, 5–6 July, 2012.
2) The 25th European Conference on Operational Research EURO 2012, Session on Telecommunication Networks, Vilnius, Lithuania, 8–11 July, 2012.

3) The 24th European Modeling and Simulation Symposium EMSS 2012, Vienna, Austria, 19–21 September, 2012.
4) The 6th Applied Information and Communication Technologies Conference AICT 2013, Jelgava, Latvia, 25–26 April, 2013.
5) The 26th European Conference on Operational Research EURO 2013, Session on Telecommunication Networks, Rome, Italy, 1–4 July, 2013.
6) The 8th Conference of the European Society for Fuzzy Logic and Technology EUSFLAT 2013, Milan, Italy, 11–13 September, 2013.
7) Science and Information Conference SAI 2013 (supported by the IEEE Computational Intelligence Society), London, UK, 7–9 October, 2013.
8) The 12th INFORMS Telecommunications Conference, Session on Traffic Engineering, Lisbon, Portugal, 2–4 March, 2014.
9) The 3rd International Symposium on Combinatorial Optimization ISCO 2014, Session on Network Design, Lisbon, Portugal, 5–7 March, 2014.
10) The 25th Nordic Conference in Statistics NORDSTAT 2014, Turku, Finland, 2–6 June, 2014.
11) The 12th International Symposium on Locational Decision ISOLDE 2014, Session on Network Design, Naples, Capri, Italy, 16–20 June, 2014.
12) The 26th European Modeling and Simulation Symposium EMSS 2014, Bordeaux, France, 10–12 September, 2014.
13) The 20th International Conference on Mathematical Modelling and Analysis, Sigulda, Latvia, 26–29 May, 2015.
14) The 4th International Symposium on Operational Research, Chania, Greece, 3–6 June, 2015.
15) The 27th European Conference on Operational Research EURO 2015, Glasgow, UK, 12–15 July, 2015.
16) The 4th IARIA International Conference on Data Analytics, Nice, France, 19–24 July, 2015.
17) The IEEE International Conference on Fuzzy Systems FUZZ-IEEE 2015, Istanbul, Turkey, 2–5 August, 2015.
18) The 12th International Conference on Fuzzy Systems and Knowledge Discovery FSKD 2015 (supported by the IEEE Circuits and Systems Society), Zhangjiajie, China, 15–17 August, 2015.

In total 10 scientific articles have been published in various scientific editions, as well as publications in conference books of abstracts (conference abstracts are not included in this list):

1) J. Asmuss, G. Lauks, Network Traffic Classification for Anomaly Detection: Fuzzy Clustering Based Approach, IEEE Proceedings of the 12th International Conference on Fuzzy Systems and Knowledge Discovery FSKD, Zhangjiajie, China, 2015, pp. 338–343. (in IEEE Xplore database)
2) P. Hurtik, P. Hodakova, I. Perfilieva, M. Liberts, J. Asmuss, Network Attack Detection and Classification by the F–transform, Proceedings of the IEEE International Conference on Fuzzy Systems FUZZ-IEEE, Istanbul, Turkey, 2015, ref. 15289. (in IEEE Xplore database)
3) J. Asmuss, G. Lauks, Fuzzy Clustering Based Approach to Network Traffic Classification and Anomaly Detection, Proceedings of the 4th International Conference on Data Analytics, Nice, France, 2015, pp. 78–80.
4) J. Asmuss, G. Lauks, Fuzzy Logic Based Network Bandwidth Allocation: Decision Making, Simulation and Analysis, Studies in Computational Intelligence, vol. 542, Springer, 2014, pp. 317–333. (in Scopus database)
5) J. Asmuss, G. Lauks, Simulation Based Analysis and Development of Decision Support System for Virtual Network Bandwidth Management, Proceedings of the 26th European Modeling and Simulation Symposium EMSS, Bordeaux, France, 2014, pp. 444–451. (in Scopus database)
6) J. Asmuss, G. Lauks, A Fuzzy Approach for Network Bandwidth Management, Advances in Intelligent Systems Research, vol. 32, Atlantis Press, 2013, pp. 722–727. (in Scopus and Web of Science databases)
7) J. Asmuss, G. Lauks, A Fuzzy Logic Based Approach to Bandwidth Allocation in Network Virtualization, IEEE Proceedings of Science and Information Conference, London, UK, 2013, pp. 507–513. (in IEEE Xplore and Scopus databases)
8) J. Asmuss, G. Lauks, Coloured Petri Nets Based Simulation Scheme for Adaptive Bandwidth Management, Proceedings of the 6th International Conference on Applied Information and Communication Technology, Jelgava, Latvia, 2013, pp. 98–103.
9) J. Asmuss, G. Lauks, V. Zagorskis, Simulation of Dynamically Adaptive Bandwidth Allocation Protocols Using Coloured Petri Nets, Proceedings of the 24th European Modeling and Simulation Symposium EMSS, Vienna, Austria, 2012, pp. 408–413. (in Scopus database)
10) J. Asmuss, G. Lauks, V. Zagorskis, Application of CPN Tools for Simulation and Analysis of Bandwidth Allocation, WASET Journal Engineering and Technology, vol. 67, 2012, pp. 85–89.

Thesis results were used in the research project 2013/0024/1DP/1.1.1.2.0/13/APIA/VIAA/045 "Applications of mathematical structures based on fuzzy logic principles in the development of telecommunication network design and resource control technologies".

The results were presented at seminars organized within the project and included in the project materials prepared for publication.

The structure of the thesis

The volume of the thesis is 167 pages. The thesis consists of an introduction, 4 chapters, conclusion, bibliography and appendices. The thesis contains a list of abbreviations, 53 figures and 17 tables.

Introduction validates topicality of the research, formulates the aims and objectives, lists scientific methods used in the thesis, describes the research results and scientific novelty, defended theses are listed and work approbation is characterized.

Chapter 1 provides an overview on fuzzy logic based theory on the basis of which the methods for solving resource allocation and traffic classification problems will be proposed in the following chapters. The chapter describes fuzzy sets and special types of sets (fuzzy numbers, linguistic values, basic functions of fuzzy partitions, fuzzy clusters). Fuzzy transformations (F-transforms) are defined. Fuzzification and defuzzification principles are shown and a construction of fuzzy logic based decision making systems is described. Fuzzy clustering and classification basics are given.

Chapter 2 is devoted to the problem of bandwidth allocation. It describes network virtualization principles and DaVinci architecture. Traffic classes are defined and QoS parameters for NGN networks in accordance with the ITU recommendations are considered. The DaVinci network model is descibed and bandwidth allocation task parameters are defined. Fuzzy logic and game theory based decision making system FuzDSS (Fuzzy Decision Support System) for dynamic bandwidth allocation worked out during the doctoral research is described. The chapter contains a description of the elements of the proposed system, as well as steps of the proposed decision making algorithm.

In Chapter 3 coloured Petri nets are considered as bandwidth resource management mechanism simulation tools. Simulation experiments for evaluation of the developed approach are implemented using CPN Tools by modeling a situation with two and three traffic classes. Through experiments the effectiveness the proposed methodology has been evaluated and FuzDSS mechanisms have been improved. Chapter 3 ends with conclusions and recommendations regarding the parameter choice.

Chapter 4 is devoted to traffic classification for anomaly detection methods. Traffic pre-processing algorithm based on the F-transform technique is described. This chapter contains information on the applied clustering and validation methods. It describes fuzzy classification procedure, which uses prototypes obtained as clustering results and works on the basis of discrete F-transforms. The chapter contains a comparison of the applied methods. For this merit generated traffic data with and without anomalies are used. The chapter ends with recommendations expressed with regard to the choice of methods and parameters.

The final part of the thesis presents the summarized conclusions reached for the above. Bibliography contains 124 titles. Program codes, illustrative pictures and graphs of the proposed decision support system are summarized in the appendices.

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DETAILED DESCRIPTION OF THE THESIS CHAPTERS

Chapter 1

During the current telecommunication network development phase a situation when resource management decisions have to be made based on inaccurate and rapidly alternating large size data is becoming increasingly topical. We characterize this situation as decision making within the so-called fuzzy environment. An appropriate mathematical method has to be chosen considering the condition of the environment when modeling systems and processes in a fuzzy environment and doing a quantitative and qualitative process analysis. The method used in the thesis is based on fuzzy logic. The first chapter of the thesis is essentially the introduction. The chapter contains an insight into the fuzzy logic based theory. Based on this theory further chapters describe the methods used for solving problems dealing with resource allocation and traffic classification. The notions and methods described in the chapter (fuzzy variables, linguistic values, fuzzy partitions, fuzzy transforms, fuzzification and defuzzyfication principles, fuzzy clusters) were taken from multiple literature sources (see, for example, [1], [47], [48], [49], [52], [60], [61], [62]). The definitions and denotations are adjusted to the context of Doctoral Thesis tasks.

Fuzzy logics based decision making systems use fuzzy sets and fuzzy values (a special case of fuzzy sets). The definitions of fuzzy sets and fuzzy values are based on the notion of a membership function. According to the classic approach, the sets can be defined using membership functions with 2 values: value 1 denotes that the object belongs to the set, and 0 denotes that the object does not belong. In the context of fuzzy logic membership functions take values from interval [0,1] and show the degree of membership.

Fuzzy logics based decision making systems (see, for example, [1], [31], [49], [52]) are based on variables with fuzzy linguistic values, which are efficiently used in the Doctoral Thesis models for various reasons. Let us emphasize two reasons easy to explain and understand. Firstly, working with resource allocation tasks related to ensuring QoS in uncertain conditions very often it is important to interpret the QoS conditions using the measure or degree, which satisfies or does not satisfy the condition, not using the principle "satisfies" / "does not satisfy" and comparing the strict inequality with respect to the indicator of QoS condition. If the QoS indicator has to be at least 0.9, then an incorrect decision in case of value 0.89999 could be made classifying the case as not satisfying the QoS condition. Secondly, linguistic values are a very good tool for the structure of a strategic decision making system. It is much easier to define and use decision making procedures and rules using linguistic values of input variables and the decision making indicator.

The fuzzy approach is also used for traffic classification. The classic classification task is as follows. A training set including object examples is available. Each of these examples is affiliated to one of the classes. The question is on the mechanism, which will enable us to classify new objects not belonging to the training set. In case of fuzzy classification, the object examples from the training set can be affiliated to more than one class. The affiliation to the classes is described by membership degrees. According to the fuzzy classification, the new object class is based on the membership degree to each class. This aspect plays a significant role in traffic time series classification as during classification only data on restricted time interval from the time series is used. It has to be noted that during classification the traffic profile can change exactly during the observation interval, which means that traffic can be affiliated to two classes when specifying the membership degrees.

Chapter 2

Modern telecommunication networks actually combine both calling and IP network worlds. That means the traffic in modern communication networks is heterogeneous despite the technologies (wire or wireless) that are used for data transmission. We switched from the homogeneous voice traffic model in traditional communication networks to internet and multimedia application traffic heterogeneous stream, which can be characterized as a mix of several traffic classes. As a result of the growing internet and multimedia application popularity the traffic structure gets more and more complex. Multimedia traffic has burstiness nature. Application requests are irregularly distributed during the connection period and significantly vary during different time intervals: some applications might require no or very small traffic amounts during some time intervals and during other time intervals, a huge traffic volume can lead to network overloads.

Table 1 contains network traffic data evaluation of a telecommunication company in Latvia. The bandwidth (in Mbps units) and its changes are evaluated by traffic types for twenty-four hours. It can be observed that the biggest share is browsing, internet video traffic, file sharing, voice and video calls. It includes both traffic with high transmission delay requirements (voice and video calls, Internet video) and throughput sensitive traffic

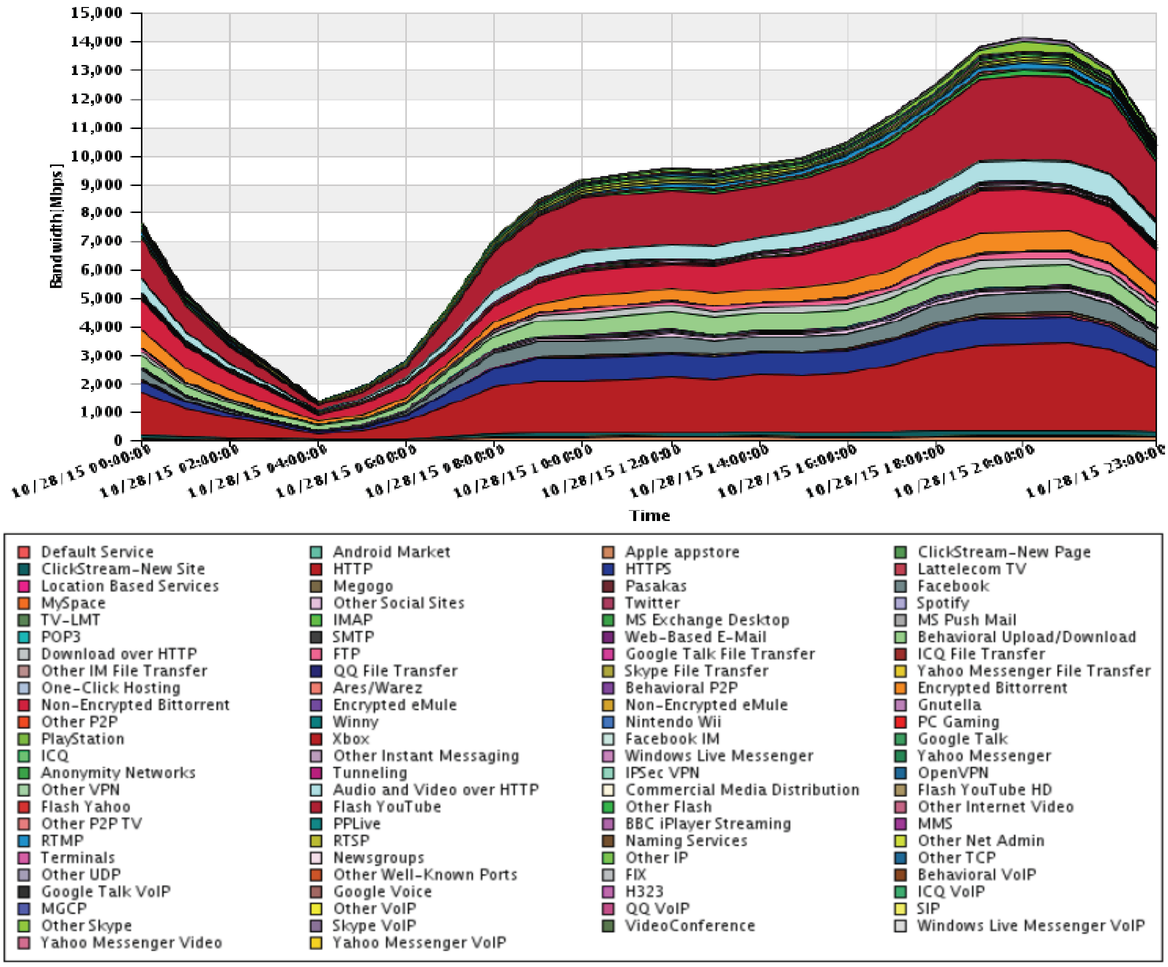


Figure 1. Traffic distribution according to data from a telecommunication company in Latvia.

Table 1.

Traffic evaluation according to data from a telecommunication company in Latvia

Traffic type	Minimal value (Mbps)	Average value (Mbps)	Maximum value (Mbps)	Changes with respect to the average value (%)
Browsing	374.00	3164.53	5315.26	12 % – 168 %
Internet video	316.29	2429.25	4277.20	13 % – 176 %
File sharing	565.67	2191.77	3468.88	26 % – 158 %
Voice and video calls	10.52	162.32	479.51	6 % – 295 %
Applications	11.40	92.42	143.39	12 % – 155 %
Private virtual networks	38.20	81.88	111.67	47 % – 136 %
Network administration	13.19	69.60	119.30	19 % – 171 %
Instant messaging	6.77	64.73	106.35	10 % – 164 %
Games	8.80	34.74	60.18	25 % – 173 %
E-mail	4.63	27.94	54.27	17 % – 194 %
Defined services	1.15	12.20	32.23	9 % – 264 %
Trading	0.03	0.52	4.31	6 % – 828 %
Other	61.52	152.14	214.28	40 % – 141 %

without specific requirements for transmission speed. In the last column of the table the change amplitude for each traffic type is calculated in percent with respect to the average value during twenty-four hours. We can see that during the observation period each type of requests significantly fluctuates. It can be 10 times lower than the average value and it also can be almost 3 times higher than the average value in the observation period. The change dynamics by hours can be seen in Figure 1, which graphically reflects each traffic data by color.

Of course, the QoS requirements for the traffic classes significantly vary depending on the application types. Based on the Cisco IOS QoS software supported ToS (Type of Service) models and traffic classification suggested by a number of researches, the thesis initially examined two traffic classes:

– DST (Delay Sensitive Traffic);
– TST (Throughput Sensitive Traffic).

The first class is comprised of traffic requiring low bandwidth throughput availability, however at the same time it requires a guaranteed secure continuous connection with no packet delays. For example, online video traffic, voice traffic and multimedia conferencing require a very low network delay level. This traffic is also called real time traffic. The second class is comprised of traffic, which in literature is called elastic traffic, for example, FTP and HTTP traffic and large size P2P file transmission. Figure 2 (which was obtained using Cisco information [6]) contains calculated shares in percentages of both traffic classes for 2014–2019 based on forecast data. As can be seen, the ratio between the shares changes significantly. In the context of our research, it is important that this ratio changes also during shorter time periods.

Table 2.

TST and DST traffic class share in 2014 – 2019 (forecast)

	DST (Delay Sensitive Traffic)		TST (Throughput Sensitive Traffic)	
	PB/month	Share (%)	PB/month	Share (%)
2014	21,651	64.45	11,943	35.55
2015	27,499	66.52	13,840	33.48
2016	36,504	70.05	15,606	29.95
2017	49,146	73.33	17,875	26.67
2018	66,288	76.61	20,233	23.39
2019	89,462	80.17	22,130	19.83

In order to ensure QoS requirements for each class in a multiservice network, traffic management solutions were actively researched. Two standardized approaches are shortly described in the thesis:

– IntServ (Integrated Services);
– DiffServ (Differentiated Services).

The integrated service model ensures service quality simultaneously guaranteeing the required bandwidth throughput and resource reserve mechanism. Considering that nowadays there are thousands of traffic streams on the Internet, the information amount supported by the routers can be too large. The model of differentiated services is introduced to ensure that the required QoS parameters are met based on the traffic classification and servicing priorities.

Regardless of the traffic transmission model it is necessary to solve a complex problem in order to ensure transmission of the different traffic classes among the network elements and guaranteeing the required QoS parameters for each class. The traffic data transmission policy has the following aims:

- to detect data transmission routes, which conform to the traffic class QoS restrictions;
- to detect transmission mechanisms, which conform to the traffic class QoS restrictions;
- to ensure efficient network resource allocation under traffic class competition conditions.

One of the QoS requirements of successful objectives assurance is to dynamically and adaptively split the network bandwidth between different traffic classes.

The Doctoral Thesis is devoted to the above mentioned task. DaVinci approach [13] is used to solve the task. The DaVinci approach is a dynamic adaptive network visualization technology to ensure different traffic classes within a single network dividing it into parallel virtual networks. The DaVinci approach greatly differs from IntServ servicing model architecture and from traditional routing protocols. It can be said that the DaVinci model is introduced as logical development of DiffServ servicing model and is the next step in comparison with the DiffServ model. The main task of the DiffServ technology is to ensure traffic data transmission based on ToS and QoS, whereas the DaVinci approach strives to solve the task of the network overall performance improvement also considering QoS particular application service quality. According to DaVinci principles, each virtual network can have its own routing policies and data transmission protocols per traffic class. In real systems there can be from two up to dozens of traffic classes.

In the context of NGN the task of bandwidth throughput split is topical and can be also explained by the fact that the ITU-T recommendation Y.2111 (Resource and admission control functions in next generation networks [18]) sets only a general architecture for realization of RACF resource and access management (see Figure 2 [18]). One of the main NGN characteristics is the separation of the service and distribution functions allowing them to be requested separately and to develop independently. RACF supports two types of resource and access management functions and accordingly contains two elements: PD-FE (Policy Decision Functional Entity) and TRC-FE (Transport

Resource Control Functional Entity). Due to such a separation of PD-FE and TRC-FE elements and functions (see Figure 3 [18]), RACF is able to support different access and substrate networks (for example, fixed and mobile access networks) using a general resource management system. The entity PD-FE has to ensure the final decision making on network resource allocation and management based on the network policy rules, client-provider SLA conditions and service information. It is considered that policy rules used in PD-FE are service based and have to be ensured by network providers.

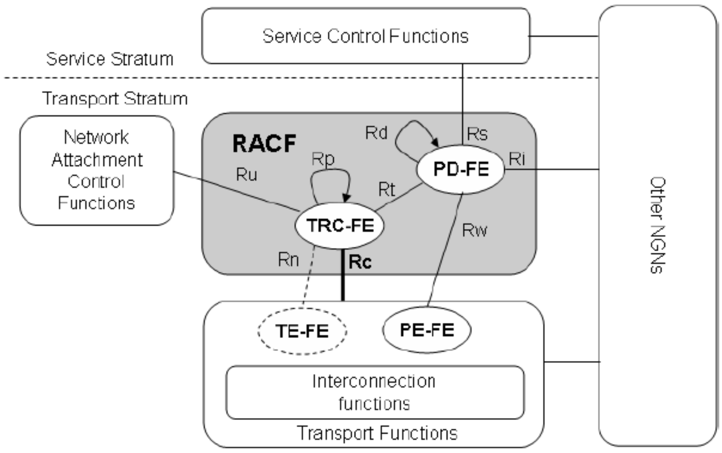


Figure 2. NGN overall architecture for resource and access management.

The main subject of the Doctoral Thesis is related to PD-FE entity, which main function is to manage network resources depending on the traffic class and QoS requirements. Let us note that the ITU-T recommendation Y.2111 [18] standardizes interfaces Rs, Rw, Rt, Rd (Figure 2), however functional solutions are left for each company to decide.

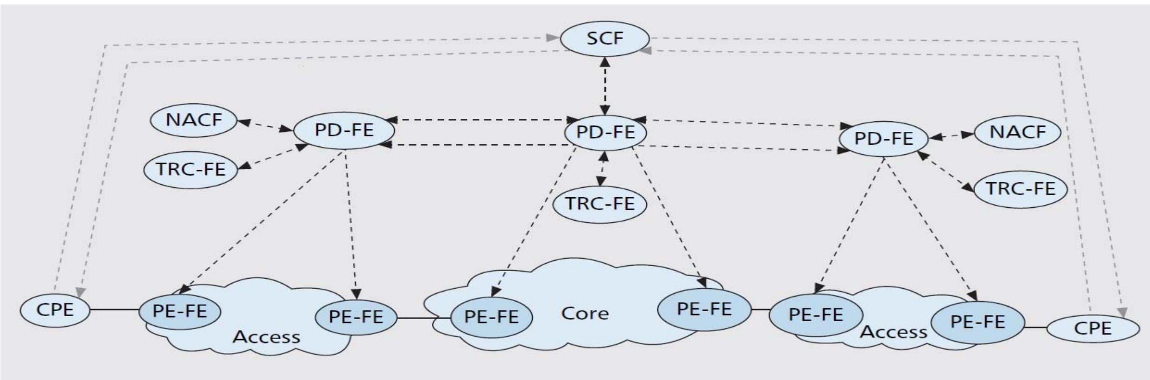


Figure 3. Functional element function division sheme in NGN network architecture.

Traffic classes. Currently QoS is considered one of the main next generation network concept elements. The ITU-T recommendation Y.1541 [16] defines NGN quality of service (QoS) classes with conditions with regard to network performance parameters, which are calculated during IP packet transmission. Each network QoS class is defined by a special performance parameter value combination. Any packet flow conforming to all QoS class performance conditions can be considered fully consistent with the recommendations of the regulatory for the appropriate class. Such QoS classes support a wide range of user applications. The classes are grouped by one-way IP packet delay, delay variation, packet loss ratio and packet error ratio with parameters defined by the ITU-T recommendation Y.1540 [15]. The Doctoral Thesis contains descriptions of the following parameters: IPTD (IP Packet Transfer Delay), IPDV (IP Packet Delay Variation), IPER (IP Packet Error Ratio), IPLR (IP Packet Loss Ratio).

The ITU-T recommendation Y.1541 [16] on IP traffic flow classification depending on the request to the particular service quality level is based on the previously mentioned parameters. Six QoS classes have been defined. The classes are defined by imposing the upper limits on one or multiple parameters. For example, class with index 0 corresponds to very interactive applications and to real time traffic flow, which are jitter sensitive. The requirements to service levels are as follows:

– IPTD average value must not exceed 100 ms;
– IPDV value must not exceed 50 ms;
– IPLR value must not exceed 0.001;
– IPER value must not exceed 0.0001.

While the class with index 5 is allocated to traffic flow packet transmission without any conditions regarding performance parameter upper values. The example for the unspecified traffic classes are traditional IP network applications. Information on other classes can be found in the Doctoral Thesis.

DaVinci virtualization model was offered in 2008 by the research published by six authors [13] as the basis for Internet network resource management. As already mentioned, the main idea is to ensure performance guarantees for separate applications with different QoS requirements by isolating the appropriate traffic for the applications and using the available resource periodical reallocation mechanisms. Network virtualization (for example, see ITU documents [14], [17]), similarly to computer virtualization, splits the bandwidth, router CPU and memory among different virtual networks. The purpose of such network design is to be able to improve the total resource usage of the substrate network and positively influence the overall performance by splitting the main elements of the physical network into virtual nodes (together with its CPU, memory and other adaptive properties) and virtual links with traffic matched bandwidth. Specialists believe that the virtualization approach will help to solve many problems connected with network functioning.

From resource allocation stand point virtual network management can be executed in two main ways: static and dynamic resource allocation. In the second case, unlike static resource allocation among simultaneously existing virtual networks during the entire virtual network existence there is a periodical resource reallocation depending on the network load and request parameters. In literature, such resource reallocation is referred to as adaptive. The aim of a periodical resource reallocation of the substrate network is to improve the overall network performance. It is considered that the isolation of the virtual networks into shorted time frames provides overall system stability and resource adaptive reallocation in longer time frames can guarantee system efficiency improvement. Dynamic allocation of resources can help achieve the desired resource utilization, as well as avoid traffic congestion, which delays packet transmission in network, adversely affects its performance and may lead to loss of transmitted information. Having analyzed the literature, let us summarize the advantages of this approach: substrate network bandwidth periodical reallocation among virtual networks; reduction of network congestions and idle; utilization increase of the substrate network optimizing the bandwidth allocation of each virtual network. It is worth mentioning that the previously mentioned advantages will apply only in case of a correct and efficient substrate network resource allocation mechanism. This research combines fuzzy logic theory and game theory concepts for the first time in order to apply information uncertainty into the bandwidth allocation model. As a result the decision making support system FuzDSS for bandwidth allocation and dynamic reallocation has been developed. Further sections are devoted to its description.

DaVinci network architecture elements. The substrate network topology is given by a graph $G_S = (V_S, E_S)$, where the set V_S contains all vertices and the set E_S contains all links. We assume that links of the set E_S are with limited capacities C_l (links are denoted with $l : l \in E_S$). According to the structure of substrate network $G_S = (V_S, E_S)$ we consider DaVinci model with N virtual networks VN indexed by k, where $k = 1, 2, ..., N$. Virtual networks will be denoted by $G_V^{(k)} = (V_V^{(k)}, E_V^{(k)})$, $k = 1, 2, ..., N$ (see Figure 4). According to DaVinci principles it holds:

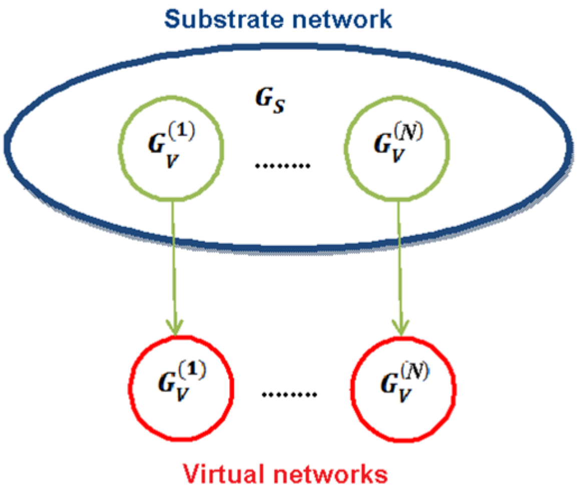


Figure 4. Substrate network SN with multiple virtual networks VN.

$$V_S = V_V^{(k)}, \; E_S = \bigcup_{k=1}^{N} E_V^{(k)} \text{ and } C_l = \sum_{k=1}^{N} C_l^{(k)} \text{ for all } l \in E_S, \; k = 1, 2, ..., N,$$

where $C_l^{(k)}$ is the bandwidth of link l in virtual network k. Let the key notations be the following: $y^{(k)}$ – bandwidth of virtual network k, $z^{(k)}$ – path rates for virtual network k, $\lambda^{(k)}$ – satisfaction level degree of virtual network k, $O^{(k)}$ – performance objective for virtual network k, $k = 1, 2, ..., N$.

The substrate network assigns bandwidth shares for each link $l \in E_s$ between virtual networks k considering such information as the current satisfaction levels and the achieved objective values of the virtual networks. The allocated values are described by vector $y^{(k)} = (y_l^{(k)})_{l \in E_s}$. The substrate network periodically reallocates the bandwidth resources of the links among the virtual networks by changing $y^{(k)}$. Hence values $O^{(k)}$ and $\lambda^{(k)} = (\lambda_l^{(k)})_{l \in E_s}$ are also periodically updated and used to calculate capacities $y^{(k)}$ for each virtual network k.

In this case when multiple traffic classes are transmitted within one substrate network, each virtual network is able to control only its allocated resource amount in each node and link. This means that within the shortest time frames each virtual network operates according to protocol which maximizes performance regardless of other virtual networks and traffic classes. Considering the limited capacity of the overall bandwidth it is important, however impossible during the short time frames, to ensure cooperation of the virtual networks to optimize the total utilization. Under such conditions, the dynamic information updating and resource allocation mechanisms play an immense role in the optimization of the substrate network.

The problem of the substrate network bandwidth allocation is a maximization problem for the overall objective with specific criteria within virtual networks and different QoS requirements (see, for example, [13], [29]). Each virtual network tries to maximize the individual objective function whereas the aim of the substrate network is to improve overall system efficiency meaning to maximize the overall performance of all virtual networks. Hence, the optimization problem [13] on the substrate network level is formulated as it is shown below. Here $w^{(k)}$ is the weight coefficient, which is assigned to virtual network k by the substrate network in order to encompass the importance of the virtual network compared to other virtual networks into the decision making model. If the substrate network considers the virtual network k having higher priority, then the weight coefficient $w^{(k)}$ will be higher than other virtual network weight coefficients. Restrictions regarding virtual link bandwidth and other possible restrictions, which are defined with $g^{(k)}(z^{(k)})$, are included into the model. Among other possible restrictions there also have to be restrictions on QoS parameter levels. In order to

$$
\begin{aligned}
\text{maximize} \quad & \sum_{k=1}^{N} w^{(k)} O^{(k)}(z^{(k)}, y^{(k)}) \\
\text{under conditions} \quad & H^{(k)} z^{(k)} \le y^{(k)},\ k = 1,2,\dots,N, \\
& \sum_{k=1}^{N} y^{(k)} \le C, \\
& g^{(k)}(z^{(k)}) \le 0,\ k = 1,2,\dots,N, \\
& z^{(k)} \ge 0,\ k = 1,2,\dots,N, \\
\text{with variables} \quad & z^{(k)},\ y^{(k)},\ k = 1,2,\dots,N.
\end{aligned}
$$

calculate the link loads $H^{(k)}z^{(k)}$ router indices defined by

$$H_{l\,j}^{(k)i}=\begin{cases}1, & \text{if virtual link } l \text{ of virtual network } k \text{ is used on path } j \text{ with source } i,\\ 0, & \text{otherwise.}\end{cases}$$

and $z_j^{(k)i}$ (describes for source i the amount of traffic transmitted over path j in virtual network k) are used.

Let us note that there are multiple reasons why the problem in such analytical form cannot be efficiently used in order to numerically solve the bandwidth resource allocation task. Virtual network objective functions cannot be defined on the substrate network level. Also it is possible that there is no information on the routing policy of each virtual network on the substrate network level. At the same time the analytical form helps to better understand the essence of the allocation problem.

The optimization scheme follows directly from DaVinci principles. Firstly, the substrate network will determine how satisfied each virtual network is with the allocated bandwidth. The satisfaction level $\lambda_l^{(k)}$ (for each link l and each virtual network k) is an indicator which defines, if the virtual network requires more resources. Secondly, the substrate network determines the desired bandwidth for the virtual network k within link l: substrate network increases or decreases value $y^{(k)}$ depending on the satisfaction level $\lambda_l^{(k)}$ within link l and the virtual network k priorities defined by $w^{(k)}$ (see Figure 5). Considering that each virtual network operates independently, the question is whether all virtual network functioning scheme with the adaptive resource reallocation ensured on the substrate network level can ensure high performance of the overall network.

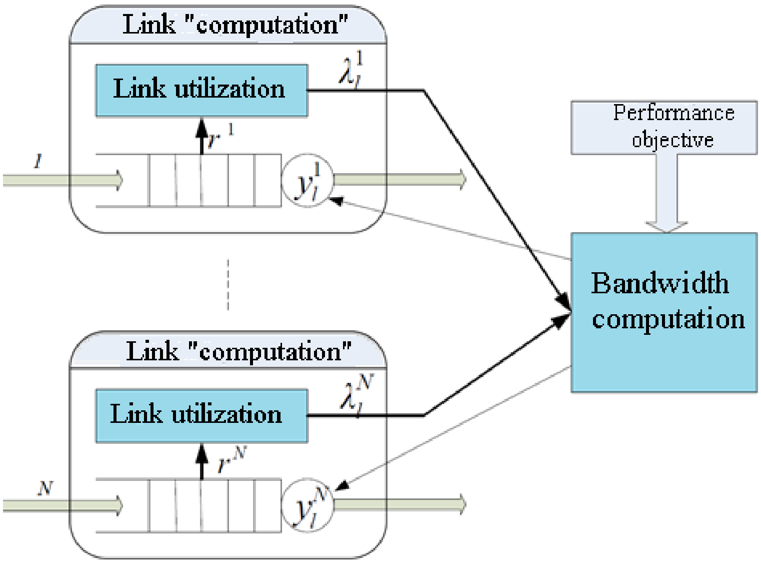


Figure 5. Bandwidth shares computation scheme.

Main elements of fuzzy logics based bandwidth reallocation method. The Doctoral Thesis is devoted to decision making on the substrate network level in order to allocate bandwidth resource of link $l \in E_s$ among virtual networks $k = 1,2,...,N$. Let us denote by t_j where $j = 1,2,...$, moments of system adaptation, i.e. moments of decision

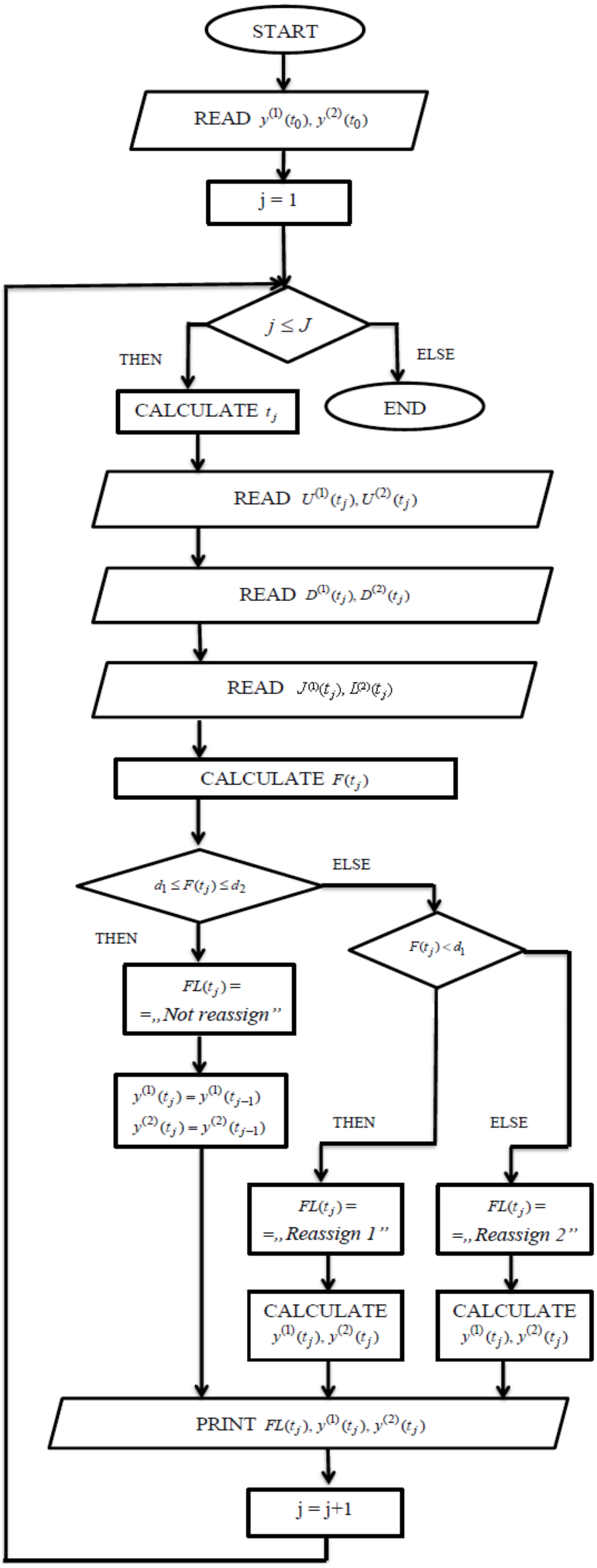


Figure 6. Bandwidth allocation decision making process flowchart.

on bandwidth shares $y_l^{(k)}(t_j)$. Such decision is based on the results of monitoring the performance of the system within time period $[t_{j-1}, t_j]$ and the assigned values $y_l^{(k)}(t_{j-1})$, $k = 1,2,...,N$. We assume that values $y_l^{(k)}(t_0)$ for $k = 1,2,...,N$ are given and consider the behaviour of the system for $t \ge t_0$.

The first step in the fuzzy logics based decision making system design is the definition of all fuzzy variables. The proposed fuzzy logics based solution requires three input variables for each link l and each traffic class k from the following list (depending on the traffic class):

$U_l^{(k)}(t_j)$ — link average utilization;

$D_l^{(k)}(t_j)$ — average delay of packets;

$J_l^{(k)}(t_j)$ — jitter in virtual link;

$L_l^{(k)}(t_j)$ — virtual link queue length.

The values of the above mentioned variables are evaluated within time period $[t_{j-1}, t_j]$ and transformed to their linguistic values according to their membership functions. The input variables describe the system state and are taken into account in adaptation decision making.

We use the denotations $LU_l^{(k)}(t_j)$, $LD_l^{(k)}(t_j)$, $LJ_l^{(k)}(t_j)$ and $LL_l^{(k)}(t_j)$ for the linguistic values of variables $U_l^{(k)}(t_j)$, $D_l^{(k)}(t_j)$, $J_l^{(k)}(t_j)$ and $L_l^{(k)}(t_j)$.

In the beginning we focus on two traffic types: delay sensitive (the aim is to reduce the average delay) and throughput sensitive (the aim is to increase the average link load). We consider that the first traffic type corresponds to the class with index 0 based on the classification of the previous section and the second traffic type corresponds to the class with index 5. According to DaVinci principles, we consider two virtual networks ($N = 2$) correspondingly to two traffic types. The suggested fuzzy logics based solution requires one output variable for each link l, which will determine the decision on resource reallocation at moment $t_j : F_l\ (t_j)$ is decision making output parameter value obtained as a result of FIS module defuzzification process. We use the denotation $FL_l\,(t_j)$ for the linguistic value of this variable.

The decision making process on link level can be described by a flowchart (see Figure 6). The decision making system can be designed using the following system elements (for example, see [49], [52]):

– the number of linguistic values;
– the membership functions for linguistic values for each input and output variable;
– the method of fuzzification of input variables;
– the method of defuzzification of an output variable;
– IF-THEN rules;
– the type of decision making system.

Center of gravity defuzzification method (COG) was used in this research. We used fuzzy logic based decision making technique [31] proposed by Mahmood Mamdani.

We assigned three linguistic values: "Low", "Medium" un "High" to all input variables (we use denotations L, M and H as indices). Three output variable linguistic values are: "Reassign 1" (meaning that the bandwidth share increases for the first traffic type and decreases for the second traffic type), "Not reassign" and "Reassign 2" (we use denotations $R1$, NR and $R2$ as indices).

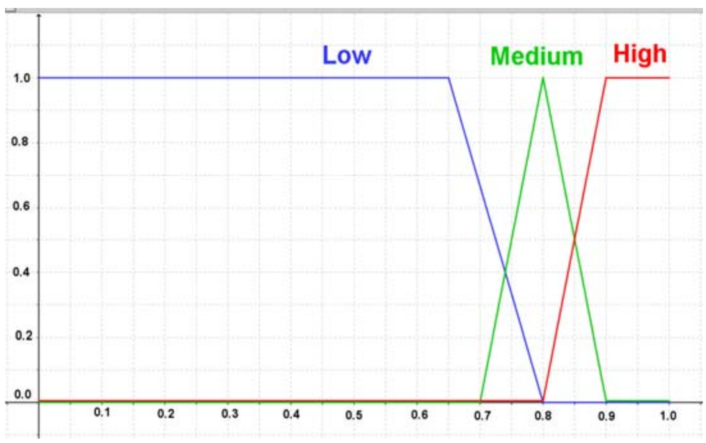


Figure 7. Membership functions for linguistic values $U_L^{(1)}, U_M^{(1)}, U_H^{(1)}$.

Mainly the IF-THEN rule number in the decision making system FIS depends on the number of linguistic values of variables. The increase of the number of the linguistic variables leads to a significant increase of the number of IF-THEN rules.

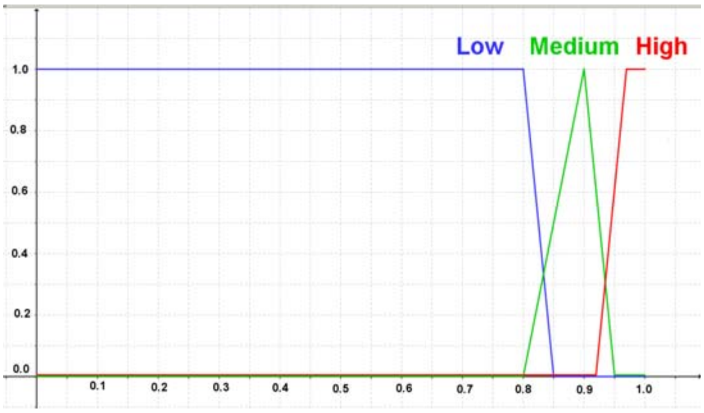


Figure 8. Membership functions for linguistic values $U_L^{(2)}, U_M^{(2)}, U_H^{(2)}$.

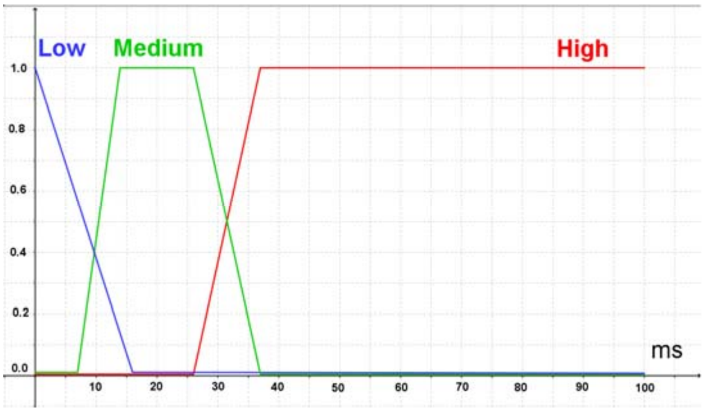


Figure 9. Membership functions for linguistic values $D_L^{(1)}, D_M^{(1)}, D_H^{(1)}$.

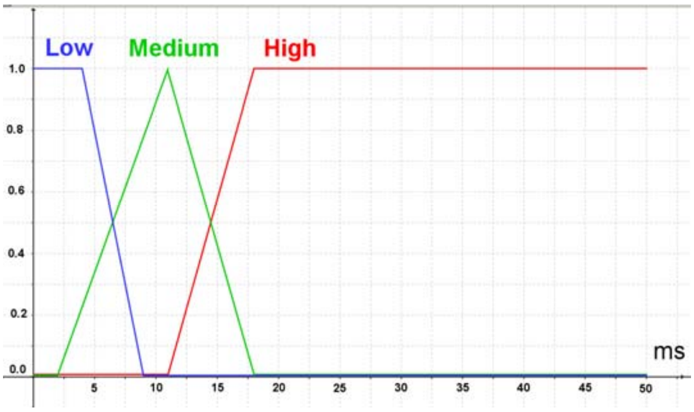


Figure 10. Membership functions for linguistic values $J_L^{(1)}, J_M^{(1)}, J_H^{(1)}$.

Value 3 is chosen considering the aforementioned and literature recommendations.

The membership function for each linguistic value is given as a triangular or trapezoidal fuzzy number. We assume that the membership functions do not depend on l and j. That is why only index k was used indexing the linguistic values of membership functions.

For example, Figure 7 shows the membership function graphs of the utilization variable $U^{(1)}$ linguistic values $U_L^{(1)}$, $U_M^{(1)}$ and $U_H^{(1)}$. Characterizing the first virtual network utilization it was considered that a very high utilization value could lead to quality level decrease with regard to jitter and delay for delay sensitive traffic. It is considered that it has to be around 80 %, characterizing such utilization as "Medium". At the same time, the increase of the second virtual network utilization is considered as the aim of the virtual network, which means that the level "High" (see Figure 8) is considered as optimal in this case. It also has to be noted that the level "High" for the second type of traffic flow transmission differs from the level "High" for the first virtual network. The considerations for the remaining membership functions (examples can also be seen in Figures 9 and 10) can be found in the Doctoral Thesis.

The knowledge base is based only on expert knowledge and the suggested model is designed using IF-THEN rule database, which consists of the following rules:

- if $UL^{(1)} = "Medium"$ and $DL^{(1)} = "Low"$ and $JL^{(1)} = "Low"$ and $UL^{(2)} = "High"$ and $LL^{(2)} = "Low"$ and $DL^{(2)} = "Low"$, then $FL = "Not\ reassign"$;
- if $UL^{(1)} = "Medium"$ and $DL^{(1)} = "Medium"$ and $JL^{(1)} = "High"$ and $UL^{(2)} = "Medium"$ and $LL^{(2)} = "Medium"$ and $DL^{(2)} = "Medium"$, then $FL = "\mathrm{Re}assign\ 1"$;
- if $UL^{(1)} = "Medium"$ and $DL^{(1)} = "Medium"$ and $JL^{(1)} = "Low"$ and $UL^{(2)} = "Medium"$ and $LL^{(2)} = "Low"$ and $DL^{(2)} = "Medium"$, then $FL = "Not\ reassign"$, … .

Fuzzy logics rule base depends on traffic types and can be modified. The modification possibilities have been analyzed during simulation experiments.

The technical realization of the above described FIS system was simplified during the research in order to reduce the used IF-THEN rule number (it can be easily calculated that before modifications the IF-THEN rule database consisted of 729 rules). The hierarchical decision making system has been proposed using the QoS indicator as an auxiliary variable: $Q_l^{(k)}(t_j)$ — QoS variable for virtual link l and traffic class k, which is evaluated for interval $\left[t_{j-1}, t_j\right]$, using linguistic values $LQ_l^{(k)}(t_j)$. We used three linguistic values for the auxiliary variable: "Yes", "Yes/No" and "No" respectively with indices Y, YN and N. All three linguistic values $Q_Y^{(1)}$, $Q_{YN}^{(1)}$, $Q_N^{(1)}$ have been used for delay sensitive traffic. However only two linguistic values $Q_Y^{(2)}$, $Q_N^{(2)}$ were used for throughput sensitive traffic, which does not have such strict restrictions. The scheme of such hierarchical decision making system can be seen in Figure 11. The system is based on 3 FIS procedures. On the first level (stage) two FIS systems are used.

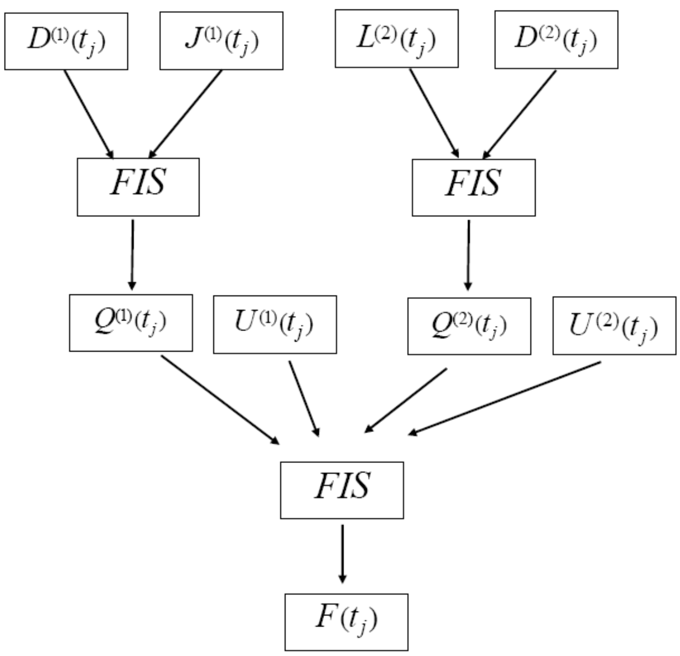


Figure 11. The hierarchical decision making FIS scheme.

Each of those is with two input and one output variable. For system functioning FAM tables (see Tables 3 and 4) have been applied. The first FIS system operation is illustrated

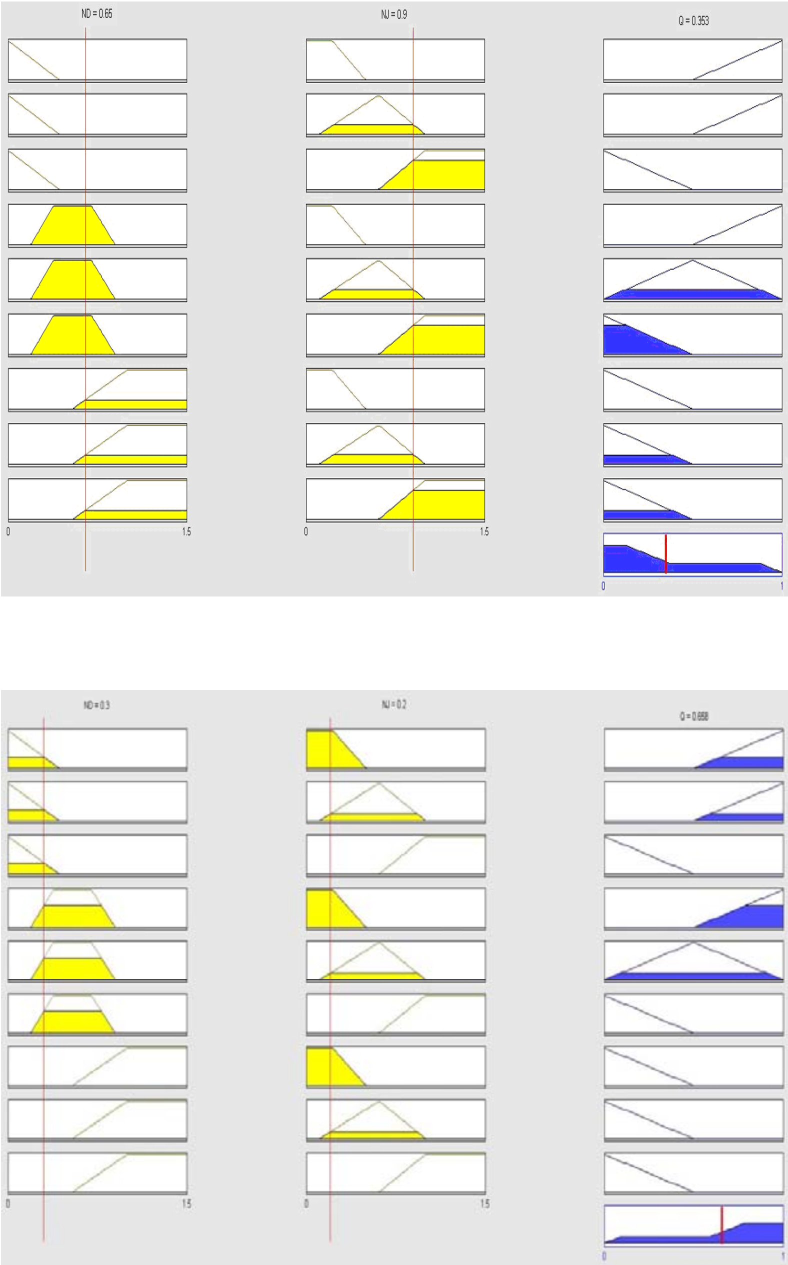


Figure 12. Output QoS parameter value calculation according to FIS rules.

in Figures 12 and 13. The first figure contains the output QoS parameter $Q^{(1)}(t_j)$ calculation scheme according to system FIS rules using fuzzification and center of gravity defuzzification procedures. The second figure contains the designed surface according to FIS rules. Let us note that the membership functions of the linguistic values of variables $D^{(1)}(t_j)$ and $J^{(1)}(t_j)$ have been normalized and replaced respectively with $ND^{(1)}(t_j)$ and $NJ^{(1)}(t_j)$.

We use the normalization procedure to achieve independency from the particular quality indicator upper values (100 ms and 50 ms) of the decision making auxiliary system and from the applied coefficient change from network to link level.

In the second stage of the decision making one FIS synthesis procedure with four input variables and one output variable is applied. IF-THEN rule base is defined with FAM table (Table 5). This time we cannot refer to the surface designed for decision making because 5 variables are used in the model. One illustrative example can be seen in Figure 14. The example corresponds to the fixed values of two variables: $U^{(1)} = U^{(2)} = 0.5$. The appendices of the thesis contain surface examples and calculation examples for the decision making parameter $F(t_j)$ evaluation.

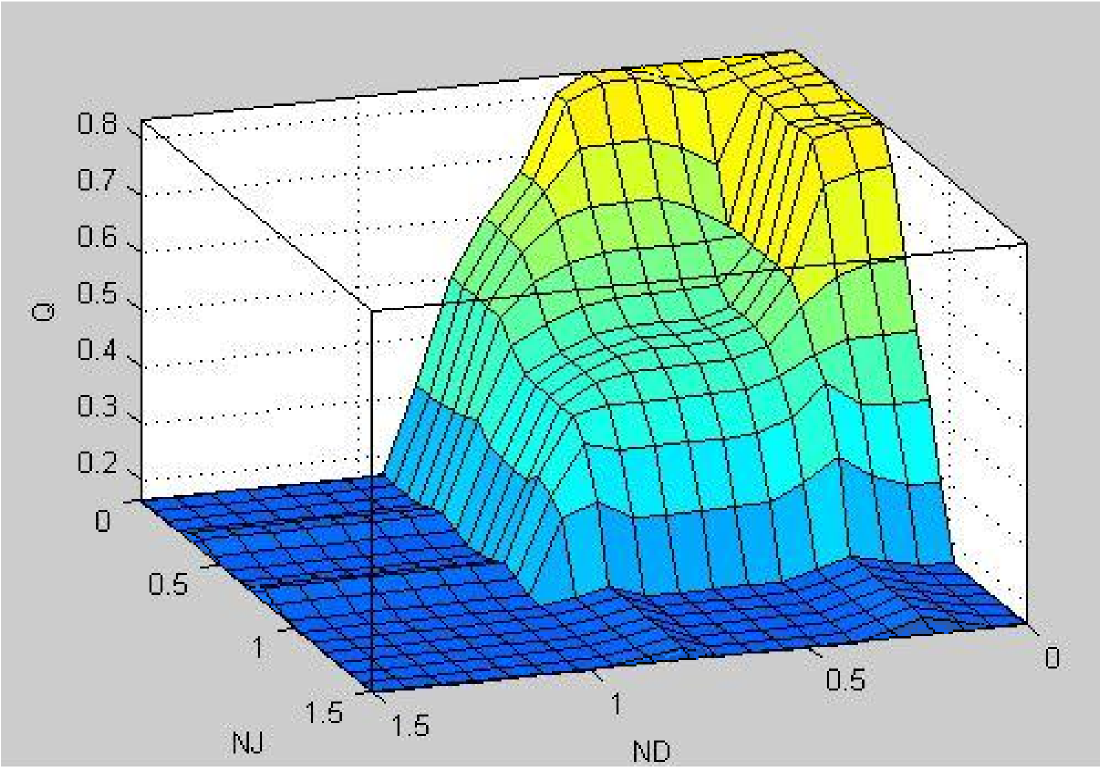


Figure 13. Surface designed for decision making in the space of variables $D^{(1)}, J^{(1)}, Q^{(1)}$.

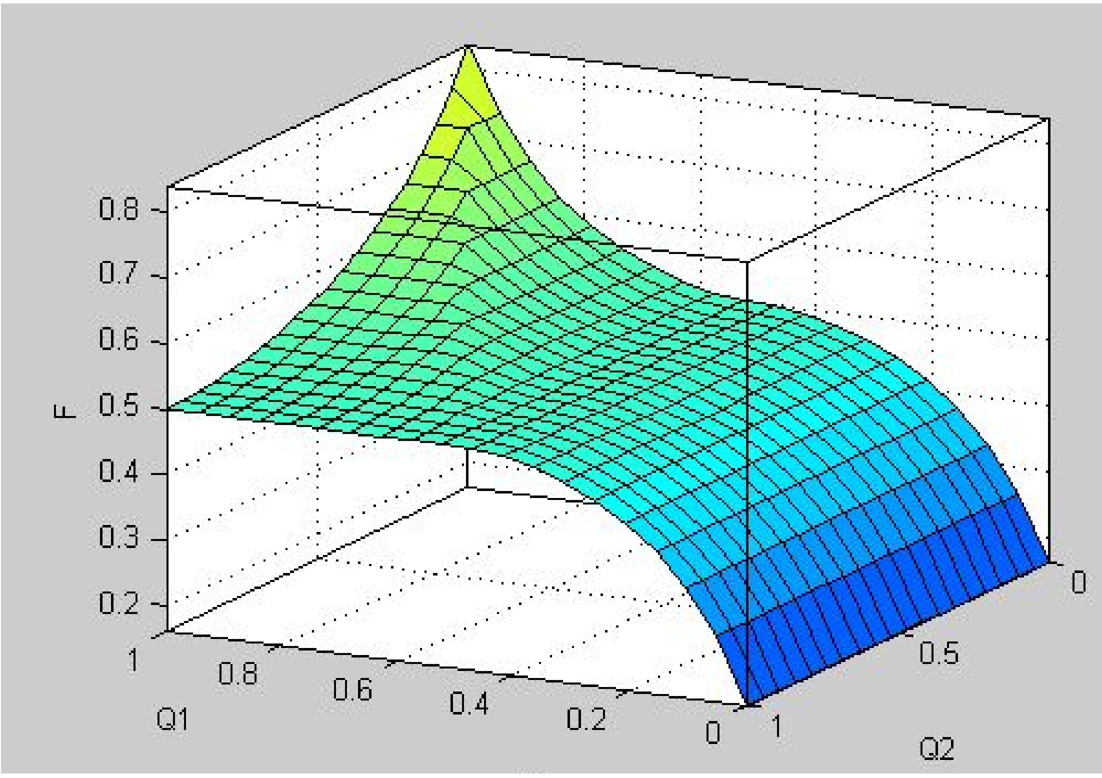


Figure 14. Surface designed for decision making in the space of variables $Q^{(1)}, Q^{(2)}, F$ with fixed values of $U^{(1)}, U^{(2)}$.

Table 3.

FAM table for QoS parameter for delay sensitive traffic

$D^{(1)}$ / $J^{(1)}$	Low	Medium	High
Low	*Y*	*Y*	*N*
Medium	*Y*	*YN*	*N*
High	*N*	*N*	*N*

Table 4.

FAM table for QoS parameter for throughput sensitive traffic

$L^{(2)}$ / $D^{(2)}$	Low	Medium	High
Low	*Y*	*Y*	*Y*
Medium	*Y*	*Y*	*N*
High	*Y*	*N*	*N*

Table 5.

FAM table for decision making system output variable

$Q^{(1)}, Q^{(2)}$ / $U^{(1)}, U^{(2)}$	*N, N*	*N, Y*	*YN, N*	*YN, Y*	*Y, N*	*Y, Y*
Low, Low	*R1*	*R1*	*NR*	*NR*	*R2*	*NR*
Low, Medium	*R1*	*R1*	*NR*	*NR*	*R2*	*NR*
Low, High	*R1*	*R1*	*NR*	*NR*	*R2*	*NR*
Medium, Low	*R1*	*R1*	*NR*	*NR*	*R2*	*NR*
Medium, Medium	*R1*	*R1*	*NR*	*NR*	*R2*	*NR*
Medium, High	*R1*	*R1*	*NR*	*NR*	*NR*	*NR*
High, Low	*R1*	*R1*	*R1*	*R1*	*R1*	*R1*
High, Medium	*R1*	*R1*	*R1*	*R1*	*R1*	*R1*
High, High	*R1*	*R1*	*NR*	*R1*	*NR*	*NR*

Game theory principles in FuzDSS for the case of multiple traffic classes. The game theory is a tool used to model and analyze player (in our case decision makers) conflict and cooperation possibilities. Such situations occur when multiple decision makers with different aims function in one system with shared resources. According to the DaVinci principles, the virtual network has no knowledge on the conditions of other virtual networks and the virtual networks can not cooperate. Each virtual network operates independently in order to optimize its functioning scheme. This fact has motivated to use the game theory approach for decision making on bandwidth resource allocation. A number of researchers have used the game theory in order to model different network related decision making processes (for example, see [12], [34], [64]). A literature analysis gives us hope that the game theory concepts will help to simplify interaction analysis among different players and to overcome the problem of network resource allocation among virtual networks. However the classical game theory approach will not provide an effective decision making under uncertain conditions that dominate in modern networks. We use a fuzzy game model introduced by F.O. Oderanti (see [42], [43]) for business process analysis.

It is possible to model player (virtual network or user) competition when using strategic games. Multiple virtual networks compete for substrate network link limited bandwidth. In our model we incorporate non-cooperative N player (in our case virtual networks) games with decision making moments t_j, $j = 1,2, \ldots$. The strategy of each virtual network k within link l in moment t_j is a decision, if virtual network k needs more link l resources in time interval $\left[t_j, t_{j+1}\right]$ or not. The bandwidth allocation $y_l^{(k)}(t_j)$ for $k = 1,2,\ldots,N$ depends on strategies of all virtual networks.

An important game classification factor is information available to players when they choose strategies. The easiest games are games where players have full information. This means that in each moment in time the players have all information on what has happened until now. However we will consider a game where virtual networks do not have all information on what has happened until now when the particular decision on players action is being taken (such games are classified as games with incomplete information). It is considered that in moment t_j player k regarding time interval $\left[t_{j-1}, t_j\right]$ has information only on virtual network k performance parameters. Games with incomplete information can be modeled using fuzzy logic based systems. We use a fuzzy logics based game theory approach incorporating fuzzy players, which use fuzzy logics rules to make strategic decisions during the game, into the model. Such generalization of business games was adopted and successfully applied in business management (see [42], [43]).

In the Doctoral Thesis a repetitive game model is used. It is a special case of a dynamic game when the players interact by playing similar game stages multiple times. The game stage $S_l(t_j)$ for link $l \in E_s$ is described by vector

$$S_l(t_j) = (\, y_l^{(k)}(t_j),\ P_l^{(k)}(t_j) \mid\ k = 1,2,\ldots,N\,),$$

where $y_l^{(k)}(t_j)$ characterizes the bandwidth value for virtual network k in time moment t_j, and $P_l^{(k)}(t_j)$ provides the game outcome value, which is evaluated for virtual network k in time interval $\left[t_{j-1}, t_j\right]$ according to all virtual network strategies on stage $S_l(t_{j-1})$, $k = 1,2,\ldots,N$, $j = 1,2,\ldots$. On the initial stage of the game: $P_l^{(k)}(t_0) = 0$, $k = 1,2,\ldots,N$, and values $y_l^{(k)}(t_0)$, $k = 1,2,\ldots,N$, correspond to the bandwidth allocation at moment t_0. We consider that all virtual networks choose the strategy "Constant" (of course, it is also possible to consider a specific strategy choice of the virtual networks) at the initial stage of the game. This means that in the first time interval $[t_0, t_1]$ the bandwidth allocation will be uniform.

It is considered that all virtual networks make the strategic decision based on the FIS system obtained decision parameter value. One FIS variable output value was used for each virtual network k and link l at moment t_j — strategy parameter $F_l^{(k)}(t_j)$ with linguistic values "More" (meaning that the virtual network needs more bandwidth resources), "Constant" and "Less" (meaning that the virtual network needs less bandwidth resources). In order to achieve efficiency of the decision making system the game rules motivating individual users to use a socially responsible strategy have to be described. For the game outcome $P_l^{(k)}(t_j)$ calculation three components are used:

$$P_l^{(k)}(t_j)=V_l^{(k)}(t_j)-E_l^{(k)}(t_j)-W_l^{(k)}(t_j),$$

where $V_l^{(k)}(t_j)$ represents the objective function for virtual network k, $E_l^{(k)}(t_j)$ is the pricing component and $W_l^{(k)}(t_j)$ gives the penalty costs based on underutilization in virtual network k and link l during interval $\left[t_{j-1},t_j\right]$. The resulting function interpretation is difference of utility value and costs.

According to our approach all virtual networks apply the decision making system to make the strategic decision on the necessity of changing the previously allocated bandwidth. As previously described, each virtual network is considered as a fuzzy player applying FIS technique for decision making (see Figure 15). The proposed solution uses for each virtual network k one output variable $F_l^{(k)}(t_j)$, which describes a fuzzy logics based decision on strategy at moment t_j. The defuzzyfied output value 0.5 conforms to the strategy "Constant", the minimal value conforms to the strategy "Less" and the maximum value conforms to the strategy "More".

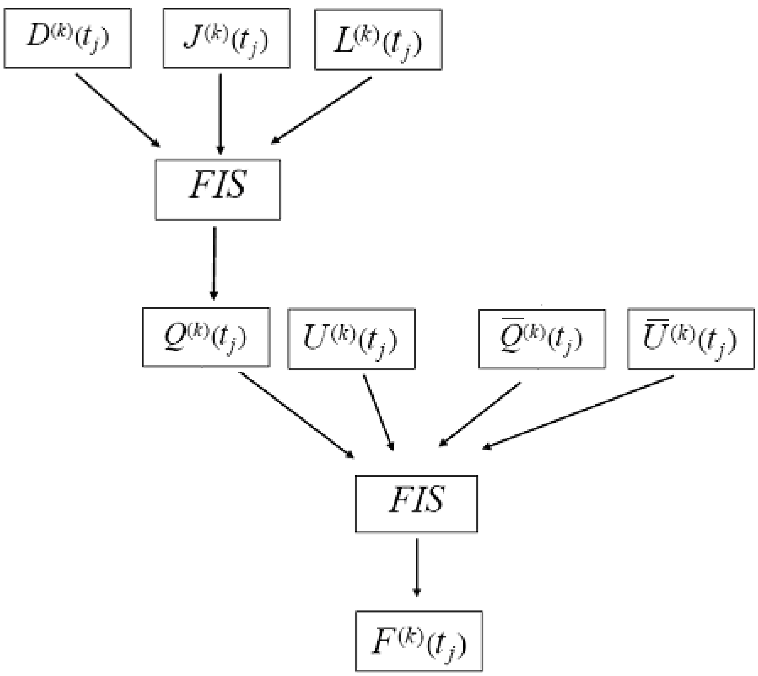


Figure 15. Strategy choice support system for player k.

The decision making support system is hierarchical. In the first stage FIS system is used for each virtual network k to evaluate the value of the QoS parameter $Q_l^{(k)}(t_j)$. Two variables from the list $D_l^{(k)}(t_j)$, $J_l^{(k)}(t_j)$, $L_l^{(k)}(t_j)$ will be used as inputs. The choice of the variables depends on the traffic class. For the first stage decision making the FAM table designed by using Table 3 will be applied for all traffic classed with numbers from 0 up to 4, and the FAM table based on Table 4 will be used for the traffic class with number 5. The player strategy choice will be realized only in the second stage. The virtual network chooses the strategy based on the assumption that all virtual networks conforming to highest priority traffic classes form a coalition and the following aggregated indicators of such virtual networks need to be taken into account in $\vec{Q}_l^{(k)}(t_j)$ and $\vec{U}_l^{(k)}(t_j)$. In the second stage of the decision making four input and one output values are used and the decision taking scheme is similar to the one described above (see Figures 11 and 15). When all decision making parameters are found and validated by condition

$$F_l^{(k)}(t_j) \le d_1 \text{ or } F_l^{(k)}(t_j) \ge d_2,$$

a decision on resource reallocation will be made. Let us note that in case none of the virtual networks satisfies the condition the resources will not be reallocated. Bandwidth shares $y_l^{(k)}(t_j),\ k = 1,2,...,N,$ for all virtual networks in game stage $S_l(t_j)$ will be evaluated proportionally to the requested values $b_l^{(k)}(t_j),\ k = 1,2,...,N,$ calculated by the formula:

$$b_l^{(k)}(t_j) = y_l^{(k)}(t_{j-1})\,(1 + 0.2(2F_l^{(k)}(t_j) - 1)).$$

This formula realizes our policy: the requested value may not vary from the previous value by more than 20 percent. Taking into account all requested values a new bandwidth allocation $y_l^{(k)}(t_j),\ k = 1,2,...,N,$ will be calculated as follows:

$$y_l^{(k)}(t_j) = b_l^{(k)}(t_j), \text{ if } \sum_{k=1}^{N} b_l^{(k)}(t_j) \le C_l;\ y_l^{(k)}(t_j) = C_l\, b_l^{(k)}(t_j) : \sum_{i=1}^{N} b_l^{(i)}(t_j), \text{ if } \sum_{k=1}^{N} b_l^{(k)}(t_j) > C_l.$$

Now all components of the game stage $S_l(t_j)$ are described. The allocated values $y_l^{(k)}(t_j),\ k = 1,2,...,N,$ will be applied within the next time interval $\left[t_j, t_{j+1}\right]$. At that moment we will start the next stage $S_l(t_{j+1})$ of the game.

Restrictions of the model. Firstly, the design of the decision making system for bandwidth allocation was based on two network performance parameters IPTD and IPDV. The traffic packet loss level indicator IPLR was not directly involved in the decision making process. The experimental model design does not foresee to drop traffic packets. In case of necessity in order to decrease the utilization within the virtual network the traffic class packets with the highest priority were transmitted via the virtual network with the lowest priority according to QoS requirements. Of course this leads to the increase of the IPTD indicator which influences the decision making process. Secondly, the experimental model scheme does not foresee errors in the process of packet transmission.

This means that the network performance indicator IPER was not used in the decision making system. The suggested method can be modified to include all four network performance indicators in the decision making process. Of course increasing the number of variables will also mean that the FIS system will be more complex because of the IF-THEN rule number increase. The number of parameters was limited in the Doctoral Thesis because of the limited computational resources at the author disposal.

Let us also note that dealing with both bandwidth resource allocation and dynamic reallocation problems we do not take into account the routing policy of each virtual network. We attempt to solve the problem on the substrate network level considering that each virtual network realized its own routing policy according to its aims. However the above mentioned restrictions do not hinder the possibility to evaluate the ability of the proposed solution to ensure the network bandwidth throughput resource dynamic reallocation among traffic classes with different QoS requirements according to traffic changes.

Chapter 3

The chapter is devoted to design of an experimental model and analysis of the obtained simulation results. We consider a practical realization of the proposed approach by means of Coloured Petri Nets (CPN) using CPN Tools software with a specially designed adaptive bandwidth allocation module, which realizes the decision support system and bandwidth allocation mechanism described above. The efficiency of the proposed network bandwidth management technique has been evaluated and improved modifying the fuzzy rules database within simulation experiments realized by CPN Tools.

CPN Tools. The concept of coloured Petri nets have been introduced as an extension of the classical Petri nets during the development of network design by Kurt Jensen in 1980-s. The construction of Petri nets $PN = (P, T, F, I)$ with places, transitions and tokens was extended (for example, see [20]) using colours, variables, expressions as well as variable and expression types: $CPN = (P, T, F, \Sigma, W, C, G, H, I)$, where the triple (P, T, F) characterizes the network structure, the pair (Σ, W) defines the types and variables, and the tuple (C, G, H, I) describes iteration processes. Thanks to this structure CPN is considered one of the most efficient mathematical modeling tools for description and analysis of discrete event systems. CPN combines a well developed mathematical theory with excellent graphical options. This combination is the main reason for the huge success of CPN in modeling and investigation of system dynamic behavior (see [10], [20]–[23]). CPN Tools (see [23], [50]) is a discrete event modeling tool combining CPN models with the functional programming language CPN ML based on Standard ML and supporting CPN model interactive and automatic simulations as well as state space and performance analysis. The CPN model colour technique can be effectively used to model DaVinci architecture virtual networks. The CPN substrate network model can consider states of each virtual network and events causing changes of the system states. Conducting simulations of the network CPN model using CPN Tools it is possible to analyze different scenarios and to understand the behavior of the system in order to use the obtained results not only for decision making and adaptation processes, but also for modifications and improvements of the decision making system.

Simulation scheme. The aim of simulations is to show that the proposed resource allocation mechanism can ensure system adaptation in a changing environment when virtual network functioning parameters will change its values due to traffic parameter changes. We simulate the adaptive bandwidth allocation mechanism on link level. A simulation scheme is described for a model with two traffic types: traffic A (delay sensitive traffic) and traffic B (throughput sensitive traffic). Colours A and B are effectively used to model and simulate this system. Firstly, the colours are assigned to token describing packets. Secondly, colors A and B are also used as respective virtual link identificators. We use the model time unit MTU as usual in timed CPN models. We assume that MTU is equal to one ms.

The CPN Tools model uses data transmission and bandwidth adaptation modules (with multiple submodules, which are designed according to the hierarchical principle and consist of other submodules functioning in one system): "Arrivals", "Link", "Link Decisions", "Link Performance Results" (Figure 16). By its nature the node "Source" is just the starting node. Both class traffic flow packets are generated by the generator module "Arrivals" and end up in the node "Buffer". The next is the packet transmission module "Link". The aim of the system is to transmit the packets through the link module till the node "Sink". The information on all transmitted packets is stored and processed in module "Link Performance Results". The module "Link Decisions" (by its nature it is an adaptation module) realizes the link bandwidth allocation and dynamic reallocation policy. For the generation of two traffic class packets within the module "Arrivals" (Figure 17) four generators are foreseen: two generators for each traffic class. The first generates the parameters for flow intensity and packet length, and the second generates flow packets. The module "Link" consists of three submodules (Figure 18): a classificator and two transmission modules "Link 1" and "Link 2". The classificator not only classifies packets (i.e. divides packets between two queues considering the marking), but also controls both queues and in case of necessity lowers the packet class for short time frames (i.e. forwards packets to the link with the lowest priority). The module of each virtual link is described separately. The packets are forwarded taking into account the virtual link FIFO queue. The transmission time depends on the packet size and the respective virtual link throughput bandwidth. The module "Link Decisions" allocates a bandwidth value to each virtual link during decision making. Initially it is assumed that both links have equal parts of the bandwidth.

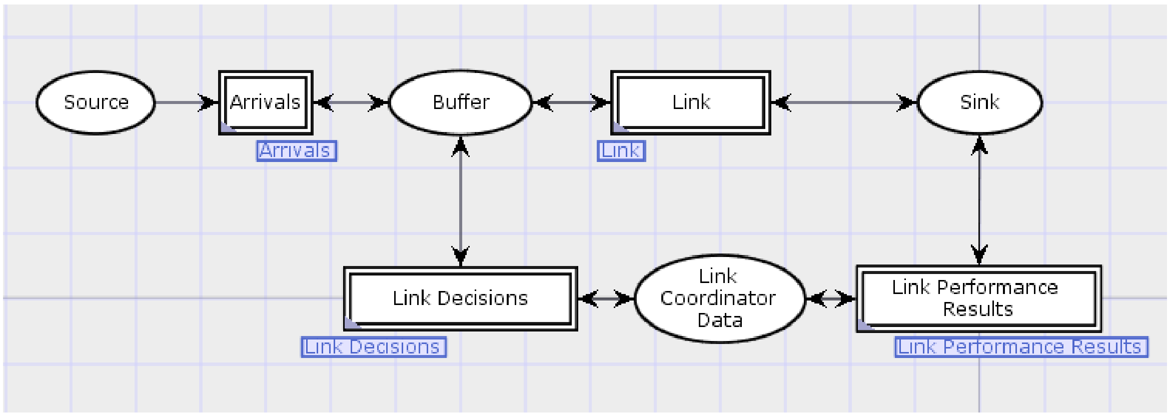


Figure 16. Bandwidth allocation process simulation experiment scheme in CPN Tools.

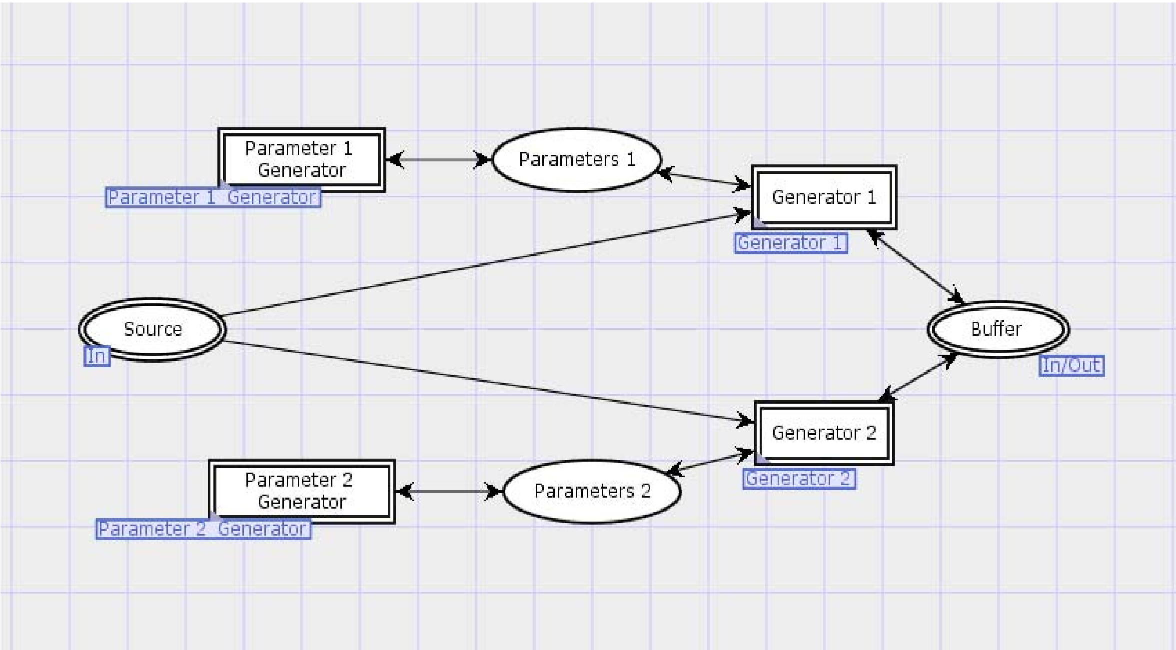


Figure 17. Traffic packet generation module in CPN Tools.

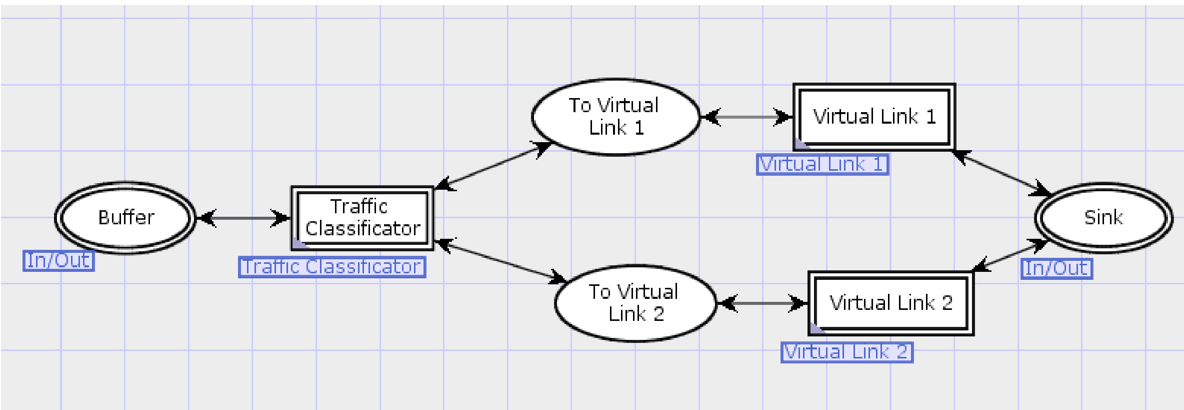


Figure 18. Traffic transmission module in CPN Tools.

The bandwidth adaptation module is designed to periodically refresh substrate link resource allocation among virtual links according to dynamically changing traffic transmission indicators. Special observation functions are used in order to observe system performance in module "Link Performance Results" (where information in the observation time interval on delays, jitter and utilization is stored) and classification module (where the queue length is controlled). The observation mechanisms are used not only to control, but also to modify the network as a result of simulations. The decision making system is based on data gathering monitor information. The decision making criteria depend on the QoS parameters in both virtual networks, therefore the information is gathered separately for each virtual network in each of the observation intervals. We consider the observation interval to be a time interval between the moments of decision making. In the moment of decision making the information is being read and processed generating a decision on resource reallocation for the virtual links. The adaptation mechanism is realized according to the proposed fuzzy logics based decision making system described in the previous chapter.

The first series of experiments was organized for two traffic classes A and B. The substrate link capacity in our experiments is 100 Mbps and initially the bandwidth allocation between virtual networks is uniform. A and B type packets are generated using a request model with Weibull distribution for intervals between the requests and uniformly distributed packet size. It is known that the Weibull distribution successfully characterizes modern traffic self-similarity and bursty characteristics. Due to the "long tail" property of the model with the Weibull distribution the probability of the time interval being long between requests increases. Thereby there might be time intervals without or with few requests and also intervals with a large number of requests leading to overload. The bandwidth resources are reallocated every 10000 MTU (considering that MTU equals to ms). We observe the model adaptation process by changing the traffic parameters.

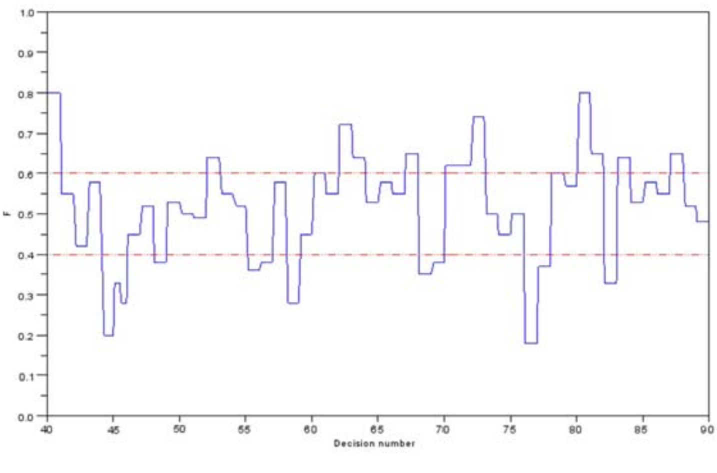


Figure 19. Results of simulation experiments: decision making indicator value.

Let us note that many authors outline that until now there is still no valid explanation on the network bandwidth allocation rate. The opinions of specialists significantly vary on the question of what the time interval needs to be like between decision making moments. In the conducted experiments the bandwidth allocation efficiency control was ensured after every 10000 MTU. At the same time, not each obtained decision has lead to reallocation of the bandwidth resources (see Figure 19). The decision making criteria depend on two parameters d_1 and d_2. Having experimented with parameter values by assigning them both symmetrically and asymmetrically with respect to the point 0.5, it was concluded in favor of the values $d_1 = 0.4$ and $d_2 = 0.6$.

A comparative result analysis is conducted for model realization for both with and without fuzzy logic based decision making system FuzDSS support. Figures 20–23 show results for 500 decision making intervals. An analysis of the average values shows that the average packet delay level for delay sensitive traffic (virtual network A) has declined from 30 ms (in case of the classical algorithm) to 23 ms using the fuzzy logics based algorithm (see Figures 20 and 22). The average load level for throughput sensitive traffic (virtual link B) stabilized at 0.96, which is a better result comparing with load level 0.92 delivered by the classical algorithm (see Figures 21 and 23). The simulations show that the

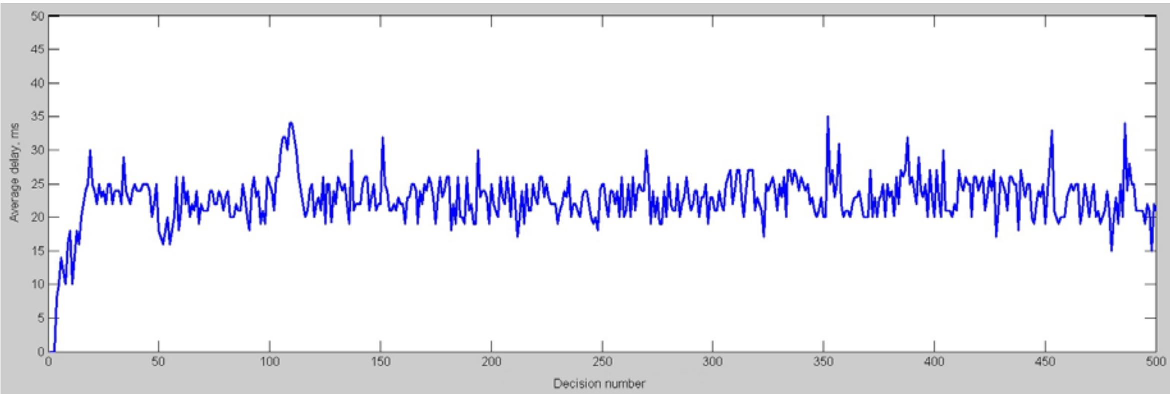


Figure 20. Simulation experiment results obtained using FuzDSS: average packet delay value for delay sensitive traffic.

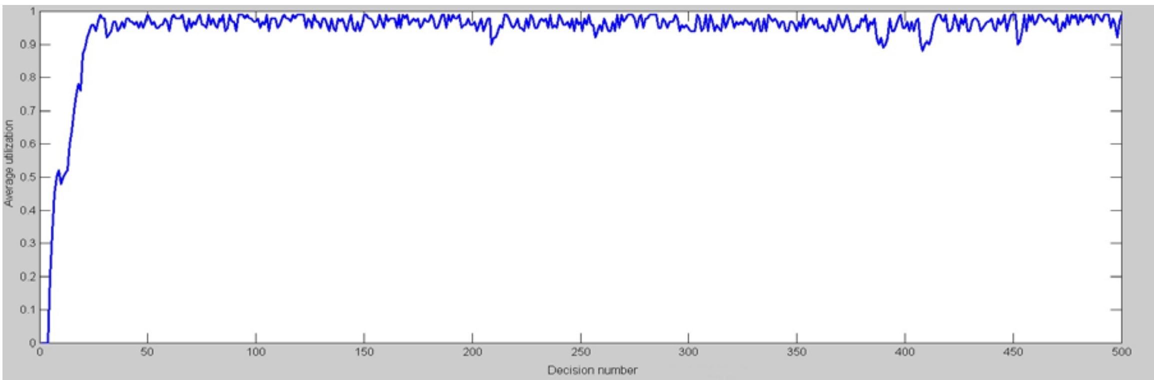


Figure 21. Simulation experiment results obtained using FuzDSS: average utilization value for throughput sensitive traffic.

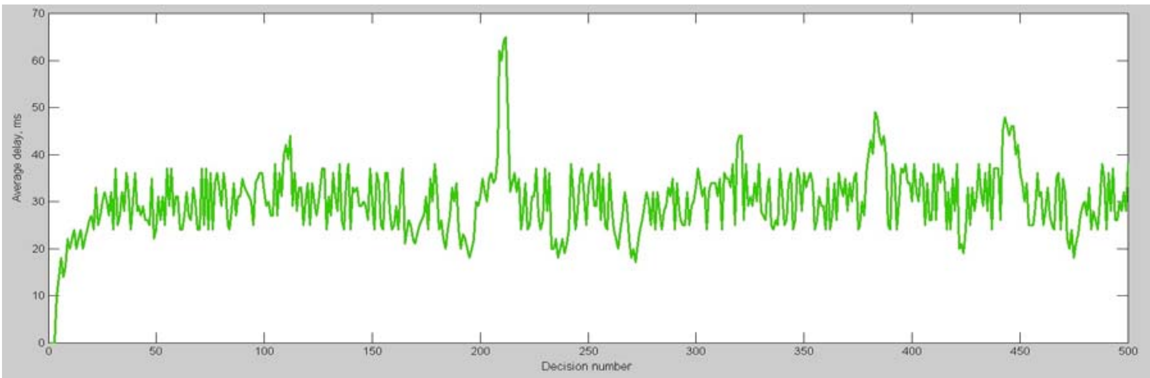


Figure 22. Simulation experiment results obtained without FuzDSS: average packet delay value for delay sensitive traffic.

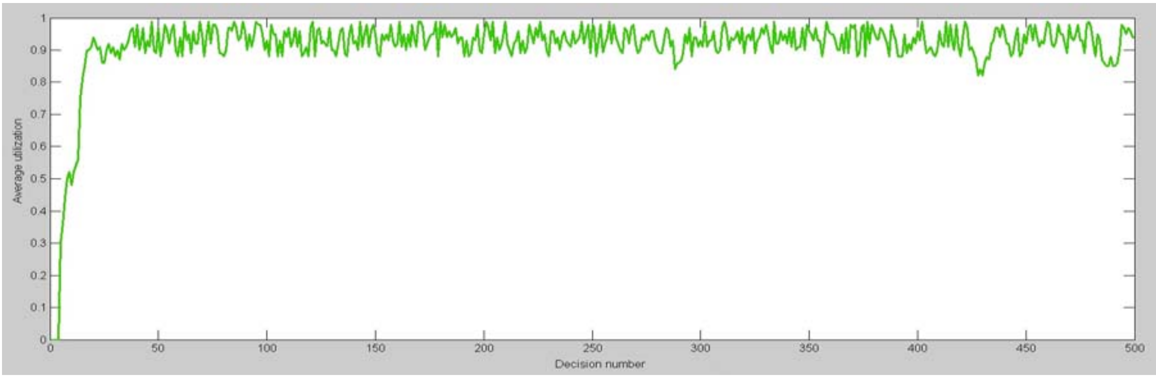


Figure 23. Simulation experiment results obtained without FuzDSS: average utilization value for throughput sensitive traffic.

fuzzy logic based decision making support system FuzDSS proposed in the Doctoral Thesis delivers good results. The adaptive bandwidth reallocation mechanism is able to dynamically and effectively react to traffic changes conforming to QoS parameter norms.

The second series of experiments was organized including in the model decision making module based on the fuzzy logic and game theory. We are experimenting with two and three traffic classes (substrate link bandwidth respectively is 100 Mbps and 150 Mbps). In the experiments it is assumed that initially substrate link bandwidth resources between the virtual links are divided uniformly, i.e. each virtual link bandwidth capacity is 50 Mbs. Changing the traffic parameters we observe the process of efficient resource reallocating at system adaptation moments. In the case of two traffic classes we obtained results that are comparable with the results obtained using previous technique. Now we describe the results of simulation experiments for three traffic classes. We start with the results from Table 6. Simulation experiments were conducted for traffic classes with indices 5, 0 and 1. Table data allows analyzing decisions made in 15 time intervals. Simulation experimental results show that the proposed bandwidth reallocation mechanism can effectively respond to changes in traffic characteristics for class $k = 2$, when $j = 7$, and for class $k = 1$, when $j = 12$.

Table 6.

Bandwidth reallocation results for three traffic classes

	$b_l^{(k)}(t_j)$			$y_l^{(k)}(t_j)$			Utilization
j \ k	1	2	3	1	2	3	
0				50	50	50	0.48
1	60	40	46	60	40	46	0.74
2	66	33	48	66	33	48	0.78
3	74	39	52	67	36	47	0.92
4	72	36	51	68	34	48	0.90
5	66	41	52	62	39	49	0.93
6	64	38	48	67	40	51	0.91
7	65	48	51	59	44	47	0.84
8	68	54	53	58	46	46	0.88
9	70	52	52	60	45	45	0.91
10	68	54	51	59	47	44	0.90
11	68	53	52	59	46	46	0.88
12	55	52	53	52	49	49	0.73
13	48	53	52	47	52	51	0.82
14	48	52	53	47	51	52	0.90
15	47	53	53	46	52	52	0.92

Simulations show that the proposed adaptive technique can give good results: after three iterations in both cases we get the bandwidth allocation which corresponds to virtual network traffic. Average performance indicators which are assessed during simulation experiments with 500 observation and decision making time intervals, with the proposed decision support system and without, are described below (Table 7).

Table 7.

Results of simulation experiments for traffic classes with indices 0, 1 and 5

Traffic class index	Performance parameter	Simulation results using FuzDSS	Simulation results without FuzDSS	Improveme nt
0	Average delay	29.5 ms	33.4 ms	12 %
0	Average jitter	11.8 ms	12.3 ms	4 %
1	Average delay	102.7 ms	119.2 ms	14 %
1	Average jitter	15.5 ms	16.7 ms	7 %
5	Average utilization	0.978	0.944	4 %

Experimental results for traffic classes with indices 0, 2 and 5 (with 500 decision making time intervals) also show improvement of performance characteristics (see Table 8).

Table 8.

Results of simulation experiments for traffic classes with indices 0, 2 and 5

Traffic class index	Performance parameter	Simulation results using FuzDSS	Simulation results without FuzDSS	Improvement
0	Average delay	26.8 ms	31.6 ms	15 %
0	Average jitter	11.1 ms	12.0 ms	7 %
2	Average delay	32.4 ms	36.2 ms	10 %
5	Average utilization	0.982	0.965	2 %

Similar results (see Table 9) were obtained in experiments for traffic classes with indices 0, 3 and 5 (with 500 decision making time intervals).

Table 9.

Results of simulation experiments for traffic classes with indices 0, 3 and 5

Traffic class index	Performance parameter	Simulation results using FuzDSS	Simulation results without FuzDSS	Improvement
0	Average delay	24.3 ms	29.9 ms	19 %
0	Average jitter	10.8 ms	11.7 ms	8 %
3	Average delay	115.3 ms	126.8 ms	9 %
5	Average utilization	0.972	0.953	2 %

Of course, these results were obtained in simulations with strict assumptions and simulation model settings, not in real scenarios. However, these assumptions do not prevent the possibility to evaluate the proposed approach. Experiments have shown that also in the case of multiple traffic classes, fuzzy approach can find a solution in the context of network bandwidth resource reallocation. We apply the concept of strategic game theory to model the decision making process of the network bandwidth allocation, where the number of traffic classes exceeds two. In the case of three traffic classes performance indicators in simulation experiments using the proposed FuzDSS system also improved: in the case of delay sensitive traffic the average value of packet delay decreased by 9–19 %; for throughput sensitive traffic the average utilization rose by 2–4 %; in the case of jitter sensitive traffic, the value of jitter decreased on average by 4–8 %.

Chapter 4

The chapter is devoted to traffic classification and anomaly detection technique. In ITU-T Recommendation Y.2111 (Resource and admission control functions in next generation networks [18]), anomaly detection is considered to be one of the most important traffic management related tasks. In this context, particular attention in the document has been paid to DDoS attacks (Distributed Denial of Service Attack). The chapter contains results obtained within the project 2013/0024/1DP/1.1.1.2.0/13/APIA/VIAA/045 in collaboration with other participants.

DDoS attacks and its detection task. The goal of DDoS attacks is to paralyze server operation. According to the CERT (Computer Emergency Response Team) classification [7], there are three categories of DDoS attacks: throughput overload attacks; protocol attacks; application layer flood attacks. This research is devoted to the third type of attacks expressed as the rapid growth of the number of requests.

Methods and approaches described in literature for DDoS attack detection (see, for example, [4], [8], [26], [57], [58]) can be divided into the following categories: statistical methods, knowledge based methods, soft computing techniques. The biggest share within such classification belongs to statistical methods. DDoS traffic detection statistical methods can be divided into three groups on the basis of applied technique: traffic self-similarity characteristics change; traffic profile deviation from the norm; traffic profile similarity to the attack profile. Despite the very large number of studies, at the moment a universal and effective tool for fighting DDoS attacks is not found. DDoS attack detection problem is still considered to be very topical ([4], [7]). Our aim is to use the advantages of the fuzzy logic based approach for analysis of network traffic dynamics and to suggest traffic classification and anomaly detection mechanisms based on fuzzy transforms, fuzzy clustering and classification with good classification success parameters and computation speed.

Traffic data representation. Let us use denotation z for network traffic function, which value $z(t)$ describes the volume of traffic at time moment $t \geq 0$. This function describes aggregated traffic (it consists of arrival packets from all connections in the input of a server). In our context, it is important to know that in a typical aggregated traffic model traffic bursts arise from a number of simultaneously active connections. In essence, we are working with traffic time series $z(t_i),\ i = 1, 2, \ldots$. Denotation z will be saved both in description of the continuous case ($z(t),\ t \geq 0$), and the discrete case ($z(t_i)$, $i = 1, 2, \ldots$). The research uses N first values of time series. We start with pre-processing of traffic time series from the training set, and as a result we obtain vectors with smaller dimension. Typically dimension is reduced using *PAA* (Piecewise Aggregate Approximation) method (see, for example, [24]) that can be defined by the formula (denotation $x = PAA[z]$ is used in the thesis):

$$x_i = \frac{k}{N} \sum_{j=1+N(i-1):k}^{Ni:k} z(t_j), \quad i = 1, 2, \ldots, k.$$

There are at least two aspects that justify the need for pre-processing of time series. The first is dimension reduction. Taking into account that without pre-processing of time series, calculations necessary for clustering and classification can be very time-consuming, task of dimension reduction is a very important task to be solved within the framework of classification problem. The second aspect (arising from the clustering and classification purposes) is connected with the aim to find similar objects. In the case of traffic time series, taking into account time series oscillating nature, application of standard similarity measures will be effective only after an averaging procedure.

Dimension reduction using fuzzy transformation. Continuous and discrete models of direct and inverse F-transforms are used in research literature (see, for example, [39]–[41] and [46]–[48]). The direct F-transform [47] converts a given function to a vector that components describe transformed function values in accordance with a fuzzy partition of the definition area. But with the direct discrete F-transform the dimension of a given vector can be reduced. We apply the uniform fuzzy partition with basic functions of triangular shape and use the discrete formula for F-transform components. The idea of using fuzzy transformation for time series analysis is not new (see [39]–[41]). The novelty of our research can be explained by the fact that we are developing the F-transform technique as a special tool for traffic data aggregation and show its role in reduction of traffic successful classification computational resources. A principal distinction between *PAA* components and the first degree F-transform [48] is that the second component of the first degree F-transform characterizes traffic change speed.

Assume that basic functions $A_1, A_2, \ldots, A_k$ form the uniform fuzzy partition of interval $[a,b]$ with respect to the classical uniform partition with parameter $\Delta\tau$: $a = \tau_0 < \tau_1 < \tau_2 < \ldots < \tau_k < \tau_{k+1} = b.$ Suppose that in interval $[a,b]$ there are fixed points $t_1, t_2, \ldots, t_N$, such that the set $P_N = \{t_1, t_2, \ldots, t_N\}$ is sufficiently dense in $[a,b]$ with respect to the given fuzzy partition, $N > k$. We consider the space V_N consisting of all functions z acting in P_N, i.e. $V_N = \{z : P_N \to \mathbb{R}\}$. If for function $z \in V_N$ introduce denotation $z_j = z(t_j)$, $j = 1,2,\ldots,N$, then the set V_N can be considered as the set of all N-dimensional vectors. If a function $z \in V_N$ and fuzzy partition $A_1, A_2, \ldots, A_k$, $N > k$, are given, then *k*-dimensional vector $(F_1^1, F_2^1, \ldots, F_k^1)$ with components-functions

$$F_i^1(t_j) = F_{i0}^1 + F_{i1}^1(t_j - \tau_i), \quad j = 1,2,\ldots,N, \; i = 1,2,\ldots,k, \text{ where}$$

$$F_{i0}^1 = \frac{\sum_{j=1}^{N} z(t_j) A_i(t_j)}{\sum_{j=1}^{N} A_i(t_j)}, \quad F_{i1}^1 = \frac{\sum_{j=1}^{N} z(t_j)(t_j - \tau_i) A_i(t_j)}{\sum_{j=1}^{N} (t_j - \tau_i)^2 A_i(t_j)}, \quad i = 1,2,\ldots,k,$$

is called the first degree discrete F-transform (F[1]–transform) for function z with respect to $A_1, A_2, \ldots, A_k$. The thesis uses denotations $F^0[z] = (F_{10}^1, F_{20}^1, \ldots, F_{k0}^1)$ and

$F^1[z]=(F^1_{11}, F^1_{21}, \dots, F^1_{k1})$. Denotation $F^0[z]$ is explained by the fact that components $F^1_{10}, F^1_{20}, \dots, F^1_{k0}$ form the discrete F–transform of degree 0 for function z. We use the uniform partition P_N with parameter h, assuming that $t_j = a+(j-1)\Delta t$, $j=1,2,\dots,N$, where $h\Delta t=\Delta\tau$.

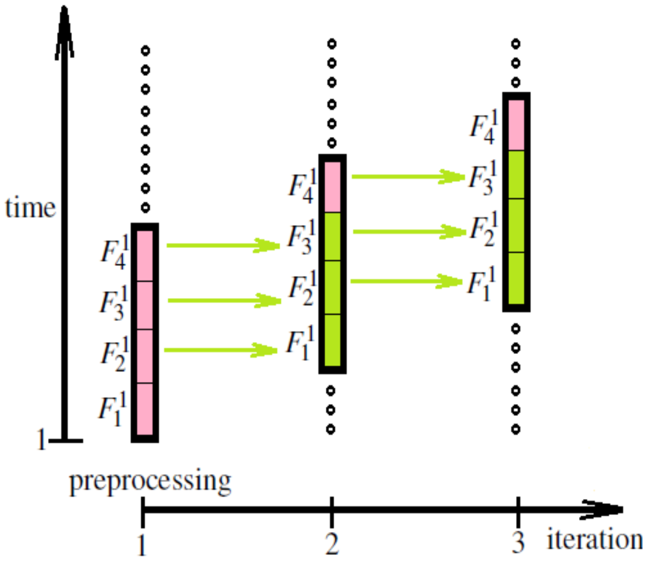


Figure 24. Traffic time series F-transform components calculation scheme.

Traffic time series pre-processing is done in the following way. We emphasize that traffic time series are infinite, but the algorithm when working with infinite time series, at each moment of time takes into account only a fixed number (we agree that this number is denoted with N) components and F-transform (or *PAA*) components. At each step, we actually calculate only one last component. Compared to last step used F-transform and the resulting vector, the first component is removed and a new component is added to the end. This iteration process is shown in Figure 24.

Applied fuzzy clustering algorithms. Fuzzy clustering methods allow that objects belong at the same time to certain clusters with different degrees of membership. In the thesis four fuzzy clustering methods with their modifications are used (eight methods in total): fuzzy C-means algorithm *FCM*, possibilistic C-means algorithm *PCM*, modified possibilistic clustering algorithm *PCA* and modified combined fuzzy possibilistic algorithm *UPFC* (see, for example, [1], [3], [25], [55], [59]).

Assume that analysed data compose a set $X=\{x^1,x^2,\dots,x^n\}$ and are k-dimensional vectors, i.e. $x^j=(x^j_1,x^j_2,\dots,x^j_k)$, $j=1,2,\dots,n$. Fuzzy clusters $X_1,X_2,\dots,X_c$ for the set X can be given with matrix $U=(u_{ij})_{c\times n}$, which elements u_{ij} contain information about the j-th object x^j affiliation to the i-th cluster X_i. In the thesis two types of matrices are used: fuzzy partition matrix U_f and possibilistic correlation matrix U_p. The set consisting of centroids $c^1,c^2,\dots,c^c$ of clusters $X_1,X_2,\dots,X_c$ is denoted by C.

FCM algorithm is based on the objective function

$$J_{FCM}(X,U_f,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^m d_{ij}^2,$$

where $m > 1$ is weight exponent, $d_{ij} = d(x^j, c^i)$, d is Euclidean distance. *PCM* algorithm with the objective function

$$J_{PCM}(X, U_p, C) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 + \sum_{i=1}^{c} \sum_{j=1}^{n} \eta_i (1 - u_{ij})^m$$

uses the following formula for η_i:

$$\eta_i = \left(\sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \right) : \left(\sum_{j=1}^{n} u_{ij}^m \right), \quad i = 1, 2, \ldots, c.$$

PCA algorithm uses the objective function

$$J_{PCA}(X, U_p, C) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 + \frac{\beta}{m^2 \sqrt{c}} \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^m \ln(u_{ij}^m) - u_{ij}^m)$$

$$\text{with } \beta = \frac{1}{n} \sum_{j=1}^{n} d(x^j, \bar{x})^2, \text{ where } \bar{x} = \frac{1}{n} \sum_{j=1}^{n} x^j .$$

UPFC algorithm is based on the function

$$J_{UFPC}(X, U_f, U_p, C) = \sum_{i=1}^{c} \sum_{j=1}^{n} (\alpha_f u_{ij}^m(f) + \alpha_p u_{ij}^r(p)) d_{ij}^2 +$$

$$+ \frac{\beta}{r^2 \sqrt{c}} \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^r(p) \ln(u_{ij}^r(p)) - u_{ij}^r(p))$$

with positive weight coefficients α_f, α_p. Here matrices U_f and U_p correspondingly consist of elements $u_{ij}(p)$ and $u_{ij}(f)$. In Gustafson-Kessel algorithm modifications *FCM.GK*, *PCM.GK*, *PCA.GK*, *UPFC.GK* (see, for example, [44]) Euclidean distance is replaced by Mahalanobis distance.

Validation process. Clustering algorithms are usually applied on the assumption that the number of clusters c is previously known. As a true value c often is not known, it should be possible to assess clustering results depending on c, and on that basis to determine the optimal number of clusters by comparing the obtained results. Such process is called validation and is implemented by clustering using all $c \in \{2, 3, \ldots, c_{\max}\}$, where $c_{\max}$ is the upper bound for optimal number of clusters. The optimum c can be evaluated by calculating validation index for the obtained result of each clustering (taking into account all clusters) and comparing the validation index values with each other. In this research four different validation indices were used (see, for example, [53]): modified partition coefficient *MPC*, Fukuyama and Sugeno validation function *FS*, Xie and Beni validation function *XB*, and separation and compactness index *SC*. Given that result, which is obtained by using one of the indices, could be interpreted as an evaluation of the optimal number of clusters done by an expert, we apply the technique of aggregation of expert opinions. For each expert (i.e. for each validation index) we introduce fuzzy preference relation with the corresponding index: R_{MPC}, R_{SC}, R_{FS}, R_{XB}. Then four preference relations are aggregated, and aggregated result R is used to determine the optimal number clusters.

Classification task is to evaluate the degree of affiliation of a new object to already existing classes on the basis of knowledge of the training set cluster structure. According to the prototype principle, classification is done using the information on the cluster prototypes obtained during clustering process. At this stage, we assume that classes for traffic time series are given by prototypes obtained from the training set. We examine normal and anomalous (or unwanted) traffic classes, and deal with the classification (new traffic series recognition) problem. The task is to identify the class for a new traffic time series or classify it as unknown. If traffic is classified as unknown, it is also considered to be anomalous.

Classification method is based on cluster centroids c^i, $i = 1, 2, \dots, c$, which are obtained during the clustering stage. For new traffic time series x the membership degrees p_i, $i = 1, 2, \dots, c$, to the relevant clusters are evaluated on the basis of all distances $d(x, c^i)$, $i = 1, 2, \dots, c$. In the thesis decision making on the risk of anomalies is done using the anomaly risk parameter

$$a(x) = \max\{1 - \max_{i \in I_n} p_i, \max_{i \in I_a} p_i\},$$

which is defined on the basis of membership degrees and information on clusters with normal and anomalous traffic. Two cluster index sets are used in the formula: I_n is the set of indices of clusters corresponding to normal traffic, and I_a is the set of indices of clusters corresponding to anomalous traffic.

Training set. By studying traffic classification techniques, it is important to use the basic information — the training set for traffic classification, which will be taken as a reference point. In general, it is a difficult task to obtain traffic datasets that describe real network traffic and contain both normal and anomalous traffic time series. Another option is to use generated traffic (obtained by generating both normal traffic and traffic with anomalies). In the thesis, the proposed classification technique is tested using the generated traffic data.

Aggregated network traffic is characterized by the following properties (see, for example, [27], [54]): the property of self-similarity and feature LRD (Long-Range Dependence), which means a high correlation in a wide time range. Experimental studies, of many authors (see, for example, [28], [38], [45]) show that the fractional Gaussian noise can be used for modelling aggregate traffic function for various types of traffic.

The fractional Gaussian noise is the increment process of the fractional Brownian motion: $G_H(t) = B_H(t+1) - B_H(t)$, where $B_H(t)$ is a fractional Brownian motion with Hurst exponent H at time moment t. The mean value and the variance of simulated traffic data are controlled using the formula $Y_H(t) = \alpha(t) + \beta(t) G_H(t)$ by two time dependent parameters $\alpha(t)$ and $\beta(t)$. Given that generated traffic function $Z_H(t)$ should be non-negative, all generated negative values of $Y_H(t)$ are cropped to zero. Traffic data are generated using the R program [51] package *fArma* [56]. A choice of parameters $\alpha(t)$ and $\beta(t)$ allows modelling different attack scenarios: rapid or slow. Let us note that it is important to identify not only the rapid attacks, but also attacks with a low speed, because the attackers are becoming smarter and trying to hide their presence in launching attacks with very low growth.

We use the data from generation experiments and create a training set using 10,000 values from each generated traffic time series. Applying a pre-processing algorithm for traffic time series from the training set, we obtain a simplified representation of time series (pre-processing parameter selection is described below). Traffic is generated on the basis of fractional Gaussian noise with mean value μ, variance σ^2 and Hurst parameter H. Fractional Gaussian noise is generated using the R program *fArma* package *fgnSim* built-in feature, for process generation Berana method is used (the program code is in the appendix). For training set creation there were generated time series, which represent fifteen kinds of traffic samples. Three traffic basic classes were generated using fractional Gaussian noise:

1) with mean value $\mu = 0$ and parameter σ, generated in accordance with the normal distribution with parameters μ_1 and σ_1;
2) generated similar to the previous sample, but with the added trend that grows linearly from 0 to u with the normal distribution with parameters μ_2 and σ_2;
3) generated similar to the previous sample, but with the added trend that is decreasing linearly from v to 0 with the normal distribution law with parameters μ_2 and σ_2.

Each basic class generating process is modified in four ways, during a time interval $[T_1, T_2]$ by adding the attack:

1) with the normally distributed intensity with parameters μ_3 and σ_3, where time moments T_1 and T_2 are uniformly distributed between t_{3000} and t_{4000}, and between t_{6000} and t_{7000};
2) with the intensity with the growing trend from 0 to the normally distributed value with parameters μ_4 and σ_4, where time moments T_1 and T_2 are uniformly distributed between t_{3000} and t_{4000}, and between t_{6000} and t_{7000};
3) with the normally distributed intensity with parameters μ_3 and σ_3, where $T_1 = 0$, but time moment T_2 is uniformly distributed between t_{2000} and t_{4000};
4) with the intensity with the growing trend from 0 to the normally distributed value with parameters μ_4 and σ_4, where $T_1 = 0$, but time moment T_2 is uniformly distributed between t_{2000} and t_{4000}.

The training set consists of 1,500 generated time series z: $z(t_i)$, $i = 1, 2, \ldots, N$. For all objects we apply one of the pre-processing procedures:

$$x = PAA[z],\ x = F^0[z] \text{ or } x = F^1[z].$$

Clustering results. The set of vectors x is divided into clusters using the above described clustering methods (the program code is in the appendix of the thesis). In order to find the number of clusters we evaluate four validation indices for each clustering method. Table 10 contains the optimal number of clusters obtained by solving optimization problems for corresponding validation functions for each of eight clustering methods (see illustrations in Figures 25 and 26). Using the described aggregation, the number of clusters for the generated training set was evaluated as 15. Next, we apply clustering techniques and determine centroids of the clusters, using all of the above mentioned methods. Cluster centroids, which have been obtained as results of clustering, are used as prototypes at the next stage.

Table 10.

Evaluation for the number of clusters obtained in validation process

Validation functions	Clustering methods							
	FCM	*FCM GK*	*PCM*	*PCM GK*	*PCA*	*PCA GK*	*UPFC*	*UPFC GK*
MPC	15	2	15	2	15	2	15	2
SC	17	19	19	15	8	15	17	15
FS	15	15	19	20	11	15	15	15
XB	15	15	7	2	15	2	15	3

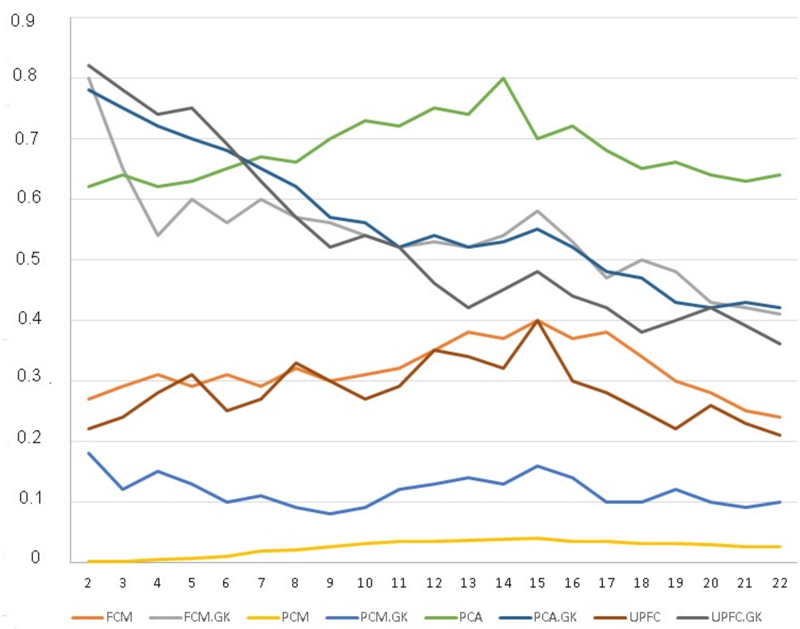


Figure 25. Validation index *MPC* values depending on the number of clusters.

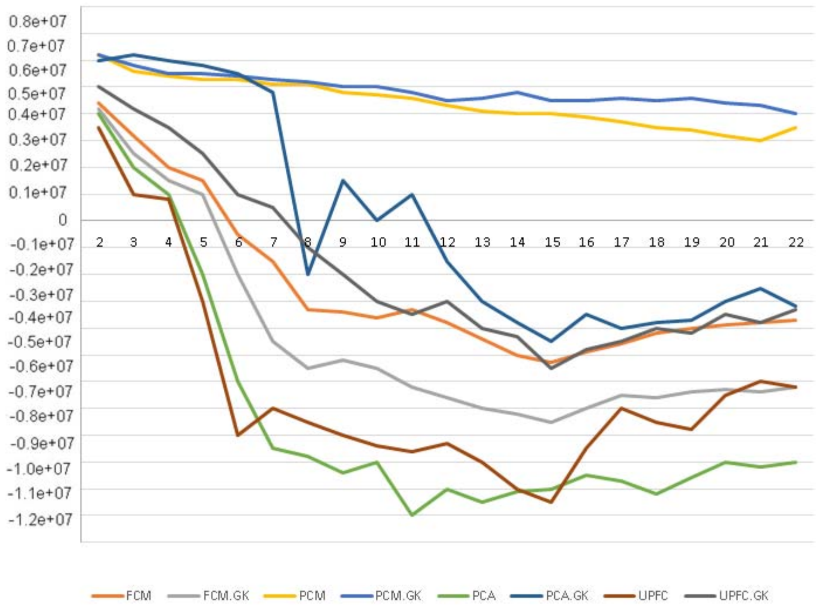
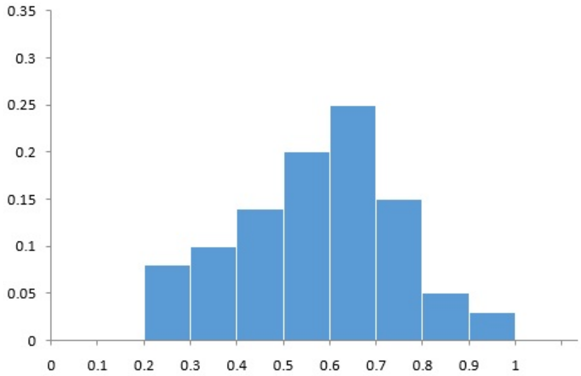


Figure 26. Validation index *FS* values depending on the number of clusters.

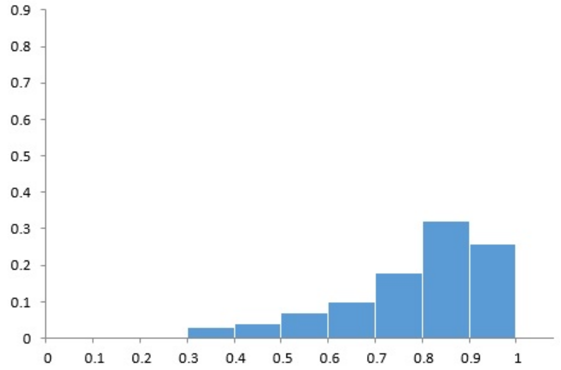
In order to evaluate the effectiveness of clustering, we also deal with the classification task (the program code is in the appendix of the thesis). We use 1,500 newly generated traffic time series with altered parameter values. Results of new time series classification are dependent on the applied traffic data transformation method and on the applied clustering algorithm. We compare the results for two methods: *FCM* (see Table 11 and Figure 27) and *UPFC.GK* (see Table 12 and Figure 28).

Taking into account that we know the real class of each generated time series, we can evaluate with what membership degree the new time series had been attributed to the right cluster. Figures 27 and 28 show the histogram for the observed membership degree (the column height is numerically equal to the proportion, which is calculated for time series with the above described membership degree belonging to the corresponding interval of the histogram). Tables 11 and 12 are formed by a similar principle. It is easy to see that in both cases, the result obtained using *PAA* method is close to the result obtained using the F-transform first component. But the result obtained using the F-transform second component is significantly better. In case, when the F-transform second component was used, the classification based on six clustering methods (*FCM*, *FCM.GK*, *PCA*, *PCA.GK*, *UPFC*, *UPFC.GK*) was successful in 100 % of cases (we consider new series classification as successful if the above described membership degree to the right cluster is grater than 0.5).

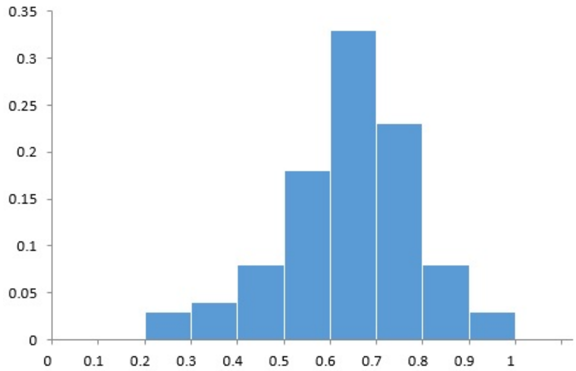
The transform parameter choice. The algorithm consists of two stages: fuzzy clustering, which can be done only once, and real-time fuzzy classification. We assess that the classification can achieve good results, by providing the classification required computation in real time in the second stage. Table 13 contains the average computing time evaluation for one classification, depending on parameter h used for F-transforms in pre-processing. In order to achieve a compromise between computing time and classification quality, we recommend using value 1000 for parameter h.



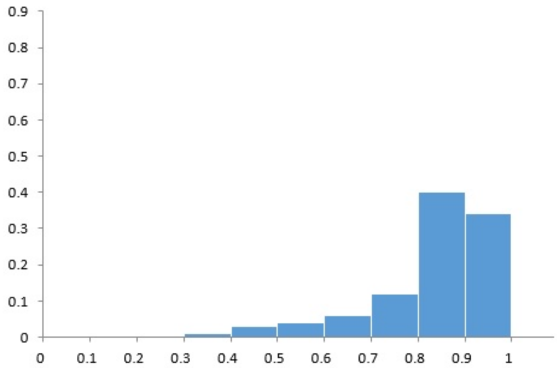
(a)



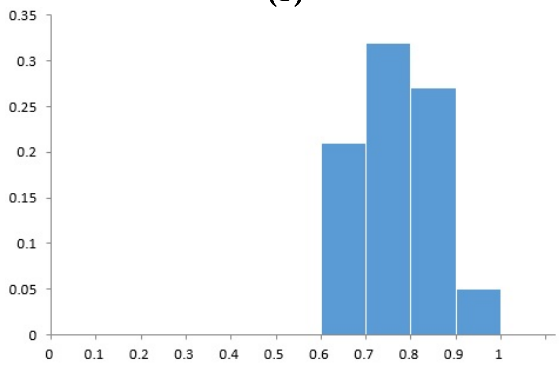
(a)



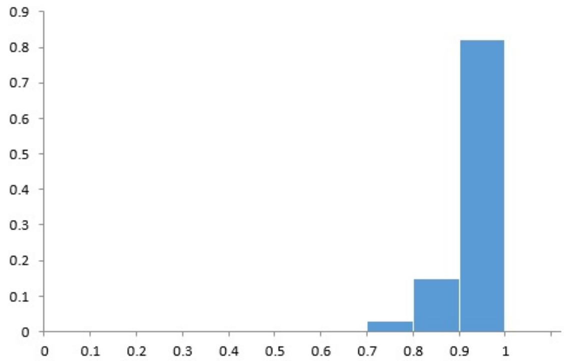
(b)



(b)



(c)



(c)

Figure 27. Classification results obtained using *FCM* clustering and the following transformation of traffic data:
(a) *PAA*;
(b) F-transform;
(c) F^1-transform.

Figure 28. Classification results obtained using *UPFC.GK* clustering and the following transformation of traffic data:
(a) *PAA*;
(b) F-transform;
(c) F^1-transform.

Table 11.

Classification results obtained using *FCM* clustering method

Level of membership to the right cluster	Transformation method		
	PAA	F-transform (the first component)	F-transform (the second component)
> 0.2	100 %	100 %	100 %
> 0.3	92 %	97 %	100 %
> 0.4	82 %	93 %	100 %
> 0.5	68 %	85 %	100 %
> 0.6	48 %	67 %	85 %
> 0.7	23 %	34 %	64 %
> 0.8	8 %	11 %	31 %
> 0.9	3 %	3 %	5 %

Table 12.

Classification results obtained using *UPFC.GK* clustering method

Level of membership to the right cluster	Transformation method		
	PAA	F-transform (the first component)	F-transform (the second component)
> 0.2	100 %	100 %	100 %
> 0.3	100 %	100 %	100 %
> 0.4	97 %	99 %	100 %
> 0.5	93 %	96 %	100 %
> 0.6	86 %	92 %	100 %
> 0.7	76 %	85 %	98 %
> 0.8	58 %	73 %	95 %
> 0.9	26 %	34 %	82 %

Table 13.

Parameter h influence on the classification process

h	Average computing time per one classification (ms)	Classification success rate (%)
100	0.052	100.0
1000	0.015	100.0
5000	0.060	24.1

Anomaly detection results. At this stage, taking into account the conclusions drawn above, six clustering methods using the second F-transform component have been applied. In order to evaluate the effectiveness of anomaly detection methods, we analyzed anomaly risk level for each of new generated traffic time series with anomalies. Anomaly risk level was evaluated using the degree of membership to all 15 clusters. Table 14 summarizes the results obtained using different clustering algorithms. Each table column corresponds to the case where the risk of anomalies is greater or equal than one of the levels (respectively, 0.5, 0.6, 0.7, 0.8 and 0.9). The value indicates what part of time series is satisfying this condition. It is easy to see that all six mentioned methods (*FCM*, *FCM.GK*, *PCA*, *PCA.GK*, *UPFC*, *UPFC.GK*) identified traffic anomaly by assigning the anomaly indicator value that is greater than 0.5 in 100 % of cases with anomalous traffic time series. However, the best results are obtained using *PCA.GK* and *UPFC.GK* methods.

Table 14.

Classification results for traffic with anomalies

Clustering methods	Risk level of anomalies				
	> 0.5	> 0.6	> 0.7	> 0.8	> 0.9
FCM	100 %	99 %	97 %	65 %	0 %
FCM.GK	100 %	100 %	94 %	57 %	0 %
PCA	100 %	100 %	99 %	98 %	96 %
PCA.GK	100 %	100 %	100 %	99 %	98 %
UPFC	100 %	100 %	99 %	98 %	96 %
UPFC.GK	100 %	100 %	100 %	99 %	98 %

These methods have identified anomalies assigning the anomaly risk indicator value that is greater than 0.7 in 100 % of cases with anomalous traffic time series. In the cases of fuzzy clustering and classification where the results are evaluated according to membership degrees, it is important to correctly assign the threshold for anomaly risk indicator, in the way that using this threshold value classification would be effective. We note that it is important that the threshold value for the anomaly risk indicator would be much greater than 0.5. Two methods *PCA.GK* and *UPFC.GK* were validated using the threshold value of 0.7 for anomaly risk. In experiments with 6,000 time series, of which 3,000 had some anomaly, an anomaly was detected in 99.2 % of all anomalous cases (detection rate — *DR*). In contrast, the risk level exceeded the threshold of 0.7 only 0.97 % of all cases without anomalies (false alarm rate — *FAR*).

For the evaluation of the proposed methods we compare the obtained results with known results for other methods (the performance characteristics are summarized in Table 15, based on publication [4] data). The third column of the table contains a reference to the possibility of providing real-time traffic classification: real-time (R) or non-real time (N).

It can be seen that the proposed method is competitive with the referred methods. In addition, if we are reasonably able to evaluate the advantage of the methods on the basis of such data, then the analysis of two indicators *DR* and *FAR* should draw conclusions on the advantages of the proposed method compared to the other methods mentioned in the table. It should be noted that such conclusion could be considered proved only in the case if the same data were used for *DR* and *FAR* indicator evaluation. However, the mentioned limitation does not eliminate the opportunity to assess the proposed method as competitive.

Table 15.

A comparison of DDoS attack detection methods

Method	The approach used	R / N	*DR*	*FAR*
DCD approach	statistical	R	98 %	< 1 %
SPUNNID model	statistical	R	94.9 %	5 %
Decision tree model	knowledge based	R	98 %	2.4 %
Clustering model	statistical	N	98.65 %	1.12 %
RBF neural net model	soft computing	R	98.2 %	0.1 %
T-test model	statistical	R	98 % – 100 %	5 % – 7 %
Perimeter based system	knowledge based	R	93 %	0.05 %
K-NN classifier approach	statistical	R	91.88 %	8.11 %
Linear prediction model	statistical	R	96.1 %	0.8 %
Ensemble of neural net model	soft computing	N	99.4 %	3.7 %

This research allows us to give priority to two clustering methods: *PCA.GK* and *UPFC.GK*. By approbating three traffic data preprocessing methods for classification merit it was shown that the first degree F-transform is better at traffic anomaly detection criteria. Conclusions on the threshold value for anomalies risk evaluation have been done. Using the first degree F-transform for data pre-processing and *PCA.GK* or *UPFC.GK* method with threshold value 0.7 for the anomaly risk indicator, it was found that during simulation experiments the anomaly detection rate *DR* is greater than 99 %; but the false alarm rate *FAR* is around 1 %.

MAIN RESULTS OF THE DOCTORAL THESIS

In accordance with ITU vision, NGN will be capable to support numerous virtual networks on a single physical infrastructure base, where each virtual network will be logically isolated from the others and is designed for specific traffic class service. The forecast says that virtualization becomes one of the most important Internet architecture solutions.

In the thesis the NGN network bandwidth resource management mechanism was developed based on fuzzy logic principles. It provides decision making solutions that can efficiently reallocate bandwidth between traffic classes with different QoS requirements in a changing virtual network environment. The proposed mechanism simulation model was implemented in CPN Tools. As a result of simulation experiments decision making system components and tools as well as decision making system parameters were improved. Initially, the network bandwidth resource management algorithm was described for the case of two virtual networks. Later it was shown that in the case of more than 2 virtual networks it is also possible to find the solution for network bandwidth resource reallocation in the context of fuzzy approach involving game theory principles.

During the doctoral research several fuzzy clustering and classification methods were validated for solving the problem of traffic classification, focusing on traffic data pre-processing task and dimension reduction. Numerical experiments have identified the most suitable methods, and recommendations for the parameter choice have been done. It is shown that the proper traffic data transformation allows improving the classification results. The advantages of fuzzy transformation are proved comparing with the classical pre-processing method with respect to traffic anomaly detection criteria.

Summary of the work done during development of the doctoral research.

1) By integrating the fuzzy logic based methods, game theory principles and DaVinci approach, NGN network bandwidth resource management mechanism that provides decision support in a changing environment was developed in the thesis.
2) Testing of the obtained model was carried out in CPN Tools using the procedures developed by the author. Tests have shown the ability of the proposed mechanism to react rapidly to changes in traffic and provide traffic classes QoS parameters preservation within acceptable limits.
3) The proposed decision support system has been implemented by Matlab using the fuzzy logic based tools.

Based on the work done during the development of the doctoral research the following main conclusions have been made.

1) Simulation experiments with traffic classes with different QoS requirements have shown that the developed bandwidth dynamic reallocation mechanism FuzDSS is able to respond quickly to changes in traffic and provide traffic classes QoS parameters preservation within acceptable limits.
2) Simulation experiments with two traffic classes DST and TST showed that the use of the proposed decision support system FuzDSS can improve QoS key parameters: for delay sensitive traffic the average value of packet delay decreased by 23 percent; at the same time, for throughput sensitive traffic the corresponding virtual link utilization on average increased by 5 percent.
3) In the case of three traffic classes performance indicators during simulation experiments using the proposed FuzDSS system also improved: in the case of delay

sensitive traffic the average value of packet delay decreased by 9–19 percent; for throughput sensitive traffic the average utilization rose by 2–4 percent; in the case of jitter sensitive traffic, the value of jitter decreased on average by 4–8 percent.

4) Recommendations are given for the proposed method parameter selection: the decision variable linguistic value parameters, FAM table values, the decision threshold parameters (it is recommended to use $d_1 = 0.4$ and $d_2 = 0.6$).
5) Taking into account several clustering and transformation algorithm comparison results, it is recommended to use traffic data classification methods based on fuzzy clustering algorithms *PCA.GK* and *UPFC.GK* and to apply the first degree F-transform second components for solving the network traffic anomaly detection task.
6) Recommendations are given for the choice of the threshold value (the threshold value of 0.7 is recommended) for anomaly risk indicator by traffic classification with anomaly detection merit. Using *PCA.GK* and *UPFC.GK* methods and data pre-processing with the first degree F-transform during the experiments it was discovered that the anomaly detection rate *DR* is greater than 99 %; but the false alarm rate *FAR* is around 1 %, which shows that the proposed method is competitive comparing with other known methods.
7) Recommendations for the parameter choice (it is recommended to use h=1000) for traffic data pre-processing with the first degree F-transform for the traffic classification purpose have been developed. It has been evaluated that one classification average computing time is 0.015 ms, which shows a good compromise between computing time and the quality of classification under such parameter choice.

In my opinion, the objective of the thesis has been achieved and the tasks of the research have been completed. To sum up the content of the thesis, I want to emphasize that the results are promising. They show that fuzzy logic based solutions of the network resource management related tasks are able to provide dynamic management and control in the changing environment under uncertain conditions, which are prevailing in modern traffic networks.

BIBLIOGRAPHY

1. L. Aleksejeva, O. Užga-Rebrovs un A. Borisovs, Klasifikācija un klasteranalīze izplūdušajā vidē, Rīgas Tehniskā universitāte, Rīga, 2012.
2. T. Anderson, L. Peterson, S. Shenker and J. Turner, Overcoming the Internet impasse through virtualization, IEEE Computer, vol. 38, no. 4, 2005, pp. 34–41.
3. J. C. Bezdek, Pattern recognition with fuzzy objective function algorithms, Plenum Press, New York, 1981.
4. M. H. Bhuyan, H. J. Kashyap, D. K. Bhattacharyya and J. K. Kalita, Detecting distributed denial of service attacks: methods, tools and future directions, Computer Journal, vol. 57, 2014, pp. 537–556.
5. N. M. Chowdhury and R. Boutaba, A survey of network virtualization, Computer Networks, vol. 54, no. 5, pp. 862–876, 2010.

6. Cisco visual networking index: forecast and methodology, 2014–2019, White paper. [Online]
Available:http://www.cisco.com/c/en/us/solutions/collateral/service-provider/ip-ngn-ip-next-generation-network/white_paper_c11-481360.html [retrieved: June, 2015]
7. Computer Emergency Response Team (CERT-EU), DDoS overview and incident response guide, 2014. [Online]
Available: http://cert.europa.eu/static/WhitePapers [retrieved: May, 2015]
8. C. Douligeris and A. Mitrokotsa, DDoS attacks and defense mechanisms: classification and state-of-the-art, Computer Networks, vol. 44, 2004, pp. 643–666.
9. M. L. Dramitinos, A bandwidth allocation mechanism for 4G, Proceedings of European Wireless Technology Conference, Rome, 2009, pp. 96–99.
10. V. Gehlo and C. Nigro, An introduction to system modeling and simulation with coloured Petri nets, Proceedings of Winter Simulation Conference, Baltimore, Maryland, USA, 2010, pp. 104–118.
11. A. Haider, R. Potter and A. Nakao, Challenges in resource allocation in network virtualization, Proceedings of the 20th ITC Specialist Seminar, Hoi An, Vietnam, 2009.
12. Z. Han, D. Niyato, W. Saad, T. Basar and A. Hjorungnes, Game theory in wireless and communication networks: theory, models, and applications, Cambridge University Press, 2012.
13. J. He, R Zhang-Shen, Y. Li, C.-Y. Lee, J. Rexford and M. Chiang, DaVinci: dynamically adaptive virtual networks for a customized Internet, ACM CoNEXT Conference, ACM, New York, 2008.
14. International Telecommunication Union, Framework of virtualization for future networks, Series Y: Global information infrastructure, internet protocol aspects and next-generation networks, Recomendation ITU-T Y.3011, 2012. [Online]
Available: http://www.itu.int/ITU-T/recommendations [retrieved: June, 2014]
15. International Telecommunication Union, Internet protocol data communication service – IP packet transfer and availability performance parameters, Series Y: Global information infrastructure, internet protocol aspects and next-generation networks, Recomendation ITU-T Y.1540, 2011. [Online]
Available: http://www.itu.int/ITU-T/recommendations [retrieved: August, 2013]
16. International Telecommunication Union, Network performance objectives for IP-based services, Series Y: Global information infrastructure, internet protocol aspects and next-generation networks, Recomendation ITU-T Y.1541, 2011. [Online]
Available: http://www.itu.int/ITU-T/recommendations [retrieved: August, 2013]
17. International Telecommunication Union, Requirements of network virtualization for future networks, Series Y: Global information infrastructure, internet protocol aspects and next-generation networks, Recomendation ITU-T Y.3012, 2014. [Online]
Available: http://www.itu.int/ITU-T/recommendations [retrieved: January, 2015]
18. International Telecommunication Union, Resource and admission control functions in next generation networks, Series Y: Global information infrastructure, internet protocol aspects and next-generation networks, Recomendation ITU-T Y.2111, 2011. [Online]
Available: http://www.itu.int/ITU-T/recommendations [retrieved: February, 2014]
19. J. Jeļinskis, Faziloģikas balstīta piekļuves vadība MPLS-TE/GMPLS tīklos, Promocijas darbs, Rīgas Tehniskā universitāte, Rīga, 2011.
20. K. Jensen, Coloured Petri nets: basic concepts, analysis methods and practical use, vol. 1, Springer-Verlag, London, 1992.
21. K. Jensen, Coloured Petri nets: basic concepts, analysis methods and practical use, vol. 2, Springer-Verlag, London, 1995.
22. K. Jensen, Coloured Petri nets: basic concepts, analysis methods and practical use, vol. 3, Springer-Verlag, London, 1997.

23. K. Jensen, L. Kristensen and L. Wells, Coloured Petri nets and CPN Tools for modelling and validation of concurrent systems, International Journal on Software Tools for Technology Transfer, vol. 9, 2007, pp. 213–254.
24. E. Keogh, K. Chakrabarti, M. Pazzani and S. Mehrotra, Dimensionality reduction for fast similarity search in large time series databases, Knowledge and Information Systems, vol. 3, 2001, pp. 263–286.
25. R. Krishnapuram and J. M. Keller, The possibilistic C-means algorithm: insights and recommendations, IEEE Fuzzy Systems, vol. 4, no. 3, 1996, pp. 385–393.
26. K. Lee, J. Kim, K. H. Kwon, J. Han and S. Kim, DDoS attack detection method using cluster analysis, Expert Systems with Applications, vol. 34, 2008, pp. 1659–1665.
27. W. E. Leland, M. S. Taqqu, W. Willinger and D. V. Wilson, On the self-similar nature of Ethernet traffic, Networking, IEEE/ACM Transactions, vol. 2, no. 1, 1994, pp. 1–15.
28. M. Li, C.-H. Chi and D. Long, Fractional Gaussian noise: a tool of characterizing traffic for detection purpose, Lecture Notes in Computer Science, vol. 3309, 2004, pp. 94–103.
29. X. Lin and N. Shroff, Utility maximization for communication networks with multi-path routing, IEEE Transactions on Automatic Control, vol. 51, 2006, pp. 766–781.
30. W. Liu, S. Li, Y. Xiang, and X. Tang, Dynamically adaptive bandwidth allocation in network virtualization environment, Advances in Information Sciences & Service Sciences, vol. 4, no. 1, 2012.
31. E. H. Mamdani and S. Assilian, An experiment in linguistic synthesis with a fuzzy logic controller, International Journal of Man-Machine Studies, vol. 7, no. 1, 1975, pp. 1–13.
32. A. Masuda, A. Isogai, T. Miyamura, and K. Shiomoto, Experiments of operating multiple virtual networks over IP-optical network, Proceedings of the 37th European Conference on Optical Communication ECOC, Geneva, Switzerland, 2011.
33. M. Mellia, A. Pescapč and L. Salgarelli, Traffic classification and its applications to modern networks, Computer Networks, vol. 53, 2009, pp. 759–760.
34. F. Meshkati, A. Goldsmith, H. Poor and S. Schwartz, A game-theoretic approach to energy-efficient modualtion in CDMA networks with dealy QoS constraints, IEEE Transactions on Communications, vol. 25, no. 6, 2007, pp. 11–14.
35. T. Miyamura, A. Masuda, and K. Shiomoto, High-performance network virtualisation for multilayer GMPLS networks, International Journal of Communication Networks and Distributed Systems, vol. 6, no. 3, pp. 283–301, 2011.
36. Nākamās paaudzes platjoslas elektronisko sakaru tīklu attīstības koncepcija 2013.–2020. gadam, apstiprināta ar LR Ministru kabineta 2012. gada 7. decembra rīkojumu Nr. 589, Rīga, 2012.
37. A. Nakao, Network virtualization as foundation for enabling new network architectures and applications, IEICE Transactions on Communications, vol. E93-B, no. 3, 2010, pp.454–457.
38. I. Norros, On the use of fractional Brownian motion in the theory of connectionless networks, Selected Areas in Communications, vol. 13, 1995, pp. 953–962.
39. V. Novák, V. Pavliska, I. Perfilieva, M. Stepnička, F-transform and fuzzy natural logic in time series analysis, Advances in Intelligent Systems Research, vol. 32, 2013, pp. 40–47.
40. V. Novák and I. Perfilieva, Time series mining by fuzzy natural logic and F-transform, Proceedings of the 48th Hawaii International Conference on System Sciences HICSS, 2015, pp. 1493–1502.
41. V. Novák, I. Perfilieva, M. Holčapek and V. Kreinovich, Filtering out high frequencies in time series using F-transform, Information Sciences, vol. 274, 2014, pp. 192–209.
42. F. O. Oderanti and P. De Wilde, Dynamics of business games with management of fuzzy rules for decision making, International Journal on Production Economics, vol. 128, 2010, pp. 96–109.
43. F. O. Oderanti and P. De Wilde, Automatic fuzzy decision making system with learning for competing and connected businesses, Expert Systems with Applications, vol. 38, 2011, pp.14574–14584.

44. J. V. De Oliveira and W. Pedrycz, Advances in fuzzy clustering and its applications, John Wiley and Sons, 2007.
45. V. Paxson, Fast approximate synthesis of fractional Gaussian noise for generating self-similar network traffic, Computer Communication Review, vol. 27, 1997, pp. 5–18.
46. I. Perfilieva, Fuzzy transforms and their applications to image compression. Fuzzy Logic and Applications, LNAI 3849, 2005, pp. 19–31.
47. I. Perfilieva, Fuzzy transforms: Theory and applications, Fuzzy Sets and Systems, vol. 157, 2006, pp. 993–1004.
48. I. Perfilieva, M. Danková and B. Bede, Towards a higher degree F-transform, Fuzzy Sets and Systems, vol. 180, 2011, pp. 3–19.
49. A. Piegat, Fuzzy modeling and control, Physica-Verlag, Heidelberg, 2001.
50. A. V. Ratzer, L. Wells, H. M. Larsen, M. Laursen, J.F. Qvortrup, M. S. Stissing, M. Westergaard, S. Christensen and K. Jensen, CPN Tools for editing, simulating and analysing coloured Petri net, Lecture Notes in Computer Science, vol. 2679, 2003, pp. 450–462.
51. R Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria, 2014. [Online]
Available: http://www.R-project.org [retrieved: May, 2014]
52. T. E. Ross, Fuzzy logic with engineering applications, McGraw-Hill, New York, 1995.
53. W. Wang and Y. Zhang, On fuzzy cluster validity indices, Fuzzy Sets and Systems, vol. 158, 2007, pp. 2095–2117.
54. W. Willinger, M. S. Taqqu, W. E. Leland and D. V. Wilson, Self-similarity in high-speed packet traffic: analysis and modeling of Ethernet traffic measurements, Statistical Science, vol. 10, 1995, pp. 67–85.
55. X. Wu, B. Wu, J. Sun and H. Fu, Unsupervised possibilistic fuzzy clustering, Journal of Information & Computational Science, vol. 7, no. 5, 2010, pp. 1075–1080.
56. D. Wuertz, fArma: ARMA Time Series Modelling, 2013. [Online]
Available: http://CRAN.R-project.org/package=fArma [retrieved: April, 2014]
57. Z. Xia, S. Lu, J. Li and J. Tang, Enhancing DDoS flood attack detection via intelligent fuzzy logic, Informatica, vol. 34, 2010, pp. 497–507.
58. Z. Xiong, Y. Wang and X. F. Wang, Distributed collaborative DDoS detection method based on traffic classification features, Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering ICCSEE, Atlantic Press, Paris, 2013, pp. 93–96.
59. M.-S. Yang and K.-L. Wu, Unsupervised possibilistic clustering, Pattern Recognition, vol. 39, 2006, pp. 5–21.
60. L. A. Zadeh, Fuzzy sets, Information and Control, vol. 8, 1965, pp. 338–353.
61. L. A. Zadeh, The role of fuzzy logic in the management of uncertainty in expert systems, Fuzzy Sets and Systems, vol. 11, 1983, pp. 199–227.
62. L. A. Zadeh, Towards a theory of fuzzy systems, Aspects of Network and System Theory, Rinehart and Winston, New York, 1971.
63. Y. Zhang, C. Wang and Y. Gao, A virtualized network architecture for improving QoS, International Journal on Information Engineering and Electronic Business, vol. 1, 2009, pp. 17–24.
64. Y. Zhou, Y. Li, G. Sun, D. Jin, L. Su and L. Zeng, Game theory based bandwidth allocation scheme for network virtualization, Proceedings of the Global Communications Conference IEEE GlobeCom 2010, Miami, Florida, USA, 2010.