SIMULATION BASED ANALYSIS AND DEVELOPMENT OF DECISION SUPPORT SYSTEM FOR VIRTUAL NETWORK BANDWIDTH MANAGEMENT

J. Asmuss [a], G. Lauks [b]

Institute of Telecommunication, Faculty of Electronics and Telecommunication,
Riga Technical University, Azenes str. 12, LV-1048, Riga, Latvia

[a] Julija.Asmuss@ rtu.lv, [b] Gunars.Lauks@ rtu.lv

ABSTRACT

We develop fuzzy logic based methodology of decision making on bandwidth allocation in a substrate network with DaVinci architecture, according to which the physical substrate network is divided into virtual networks. We show that fuzzy game theory can be effectively used as a framework of decision making tools for bandwidth allocation mechanisms. The effectiveness of this methodology is evaluated and improved within simulation experiments realized by using Coloured Petri Nets Tools.

Keywords: bandwidth allocation problem, decision making system, game theory, simulation, CPN Tools

1. INTRODUCTION

We consider the problem of resource allocation in a substrate network with DaVinci architecture (He, Zhang-Shen, Li, Lee, Rexford and Chiang 2008), according to which the substrate physical network is divided into multiple virtual networks, and we develop a fuzzy logic based methodology of its analysis. Each virtual network is logically separated and can be modified for a particular class of traffic. All resources that are offered by the substrate network are shared between virtual networks. Finding the suitable bandwidth resource allocation to virtual networks is one of the main problems for virtualization-enabled networking infrastructures (Chowdhury and Boutaba 2010; Haider, Potter and Nakao 2009; Zhang, Wang and Gao 2009; Zhou, Li, Sun, Jin, Su and Zeng 2010).

We deal with the problem, which can be considered as a maximization problem for the aggregate utility of all virtual networks. Accordingly to DaVinci principles individual virtual networks do not have the knowledge of other virtual network's conditions and cannot cooperate with each other. We suppose that at a smaller period of time each virtual network acts individually to maximize its own performance. The main question here is whether optimization of virtual networks combined with the bandwidth share adaptation scheme performed by the substrate network, which does not know the performance objectives of virtual networks, actually maximizes the aggregate utility.

Under such assumptions the resource allocation issue can be modelled as a non-cooperative game. In the context of game theory it can be modelled how virtual networks interact with each other in an effort to achieve their own goals. In the resource allocation game each virtual network is self-interested and is striving to maximize his utility function, where the utility function represents the virtual network's performance and controls the outcomes of the game. Many researchers have used game theory to model different decision processes in networks (see, e.g., Cao, Shen, Milito and Wirth 2002; Zhou, Li, Sun, Jin, Su and Zeng 2010; Han, Niyato, Saad, Basar and Hjorungnes 2012). However, classical mechanisms usually are not capable of making decisions in uncertain conditions, which are prevailing in the modern networks. In this paper for the first time we combine the concepts of game theory and fuzzy logic theory to involve the uncertainties of information in the model of network bandwidth allocation. Networks having a centralized authority that controls the entire network will give way to self-optimizing networks. We suppose that the substrate network does not know the utility functions of all virtual networks. The aim of this research is to develop an efficient decision support scheme simulated in the form of a non-cooperative game with imprecise information, using fuzzy logic concepts that can assist network management in making an effective decision on bandwidth allocation.

In this paper we develop a fuzzy approach for network bandwidth management presented at the last EUSFLAT conference (Asmuss and Lauks 2013). This methodology was suggested for two virtual networks and was based on fuzzification and defuzzification principles and the expert knowledge database of fuzzy rules. The simulation experiments were conducted for two traffic classes – delay sensitive and throughput sensitive traffic. The main aim of the present paper is to develop this approach for the case of multiple traffic classes. We show the way it will be done by extending the decision making system and simulation scheme with the game theory based module that fairly and efficiently share resources among multiple traffic classes. We apply fuzzy game theory based approach by considering fuzzy players, which use fuzzy rules to make strategic decisions.

2. BANDWIDTH ALLOCATION PROBLEM

The problem of bandwidth allocation in a substrate network is a maximization problem for the aggregate objective of multiple virtual networks with different requirements. According to the DaVinci approach (He, Zhang-Shen, Li, Lee, Rexford and Chiang 2008) each traffic class is carried on its own virtual network with customized traffic management protocols. The substrate network by assigning resources to each virtual link gives each virtual network the illusion that it runs on a dedicated physical infrastructure.

Let the topology of a substrate network be given by a graph $G_S = \{V_S, E_S\}$ with a set V_s of nodes (or vertices) and a set E_S of links (or edges). We suppose that links $l \in E_s$ are with finite capacities C_l. Correspondingly to G_S we consider DaVinci model with N virtual networks, indexed by k, where $k = 1, 2, \ldots, N$. Let the key notations be the following:

$\mathbf{y}^{(k)}$ – bandwidth of virtual network k, $k = 1, 2, \ldots, N$;

$\mathbf{z}^{(k)}$ – path rates for virtual network k, $k = 1, 2, \ldots, N$;

$\lambda^{(k)}$ – satisfaction level degree of virtual network k, $k = 1, 2, \ldots, N$;

$O^{(k)}$ – performance objective for virtual network k, $k = 1, 2, \ldots, N$.

In the case when different types of traffic coexist over the same network substrate, each virtual network could control only a subset of resources at each node and link. This means that at a smaller timescale, each virtual network runs according to a distributed protocol that maximizes its own performance objective independently. Due to the bandwidth limitation, it is important, but impossible for virtual networks to communicate and cooperate with each other, so as to optimally utilize the resources. Under such conditions in a dynamically changing virtual network environment a fundamental issue of resource allocation is the design of dynamically adaptive bandwidth allocation mechanisms.

Bandwidth values $\mathbf{y}^{(k)} = (y_l^{(k)})_{l \in E_S}$ are assigned by the substrate network, taking into account such local information as current satisfaction indicators and performance objectives. The substrate network periodically reassigns bandwidth shares for each substrate link $l \in E_S$ between its virtual links. Thus, values $\mathbf{y}^{(k)}$ and $O^{(k)}$ are periodically updated. Usually it is supposed that the objective function $O^{(k)}$ depends on both virtual link rates $\mathbf{z}^{(k)}$ and virtual link capacity $\mathbf{y}^{(k)}$.

We associate objective or utility function with each virtual network, and we refer to a resource allocation scheme as being socially optimal if it maximizes the sum of utilities of all users in the network. Each virtual network tries to maximize its individual interest, while the system strives to increase its efficiency, i.e. the overall system performance. The goal of the substrate network is to optimize the aggregate utility of all virtual networks (see, e.g., Lin and Shroff 2006; He, Zhang-Shen, Li, Lee, Rexford and Chiang 2008). So, we formulate the optimization problem for the aggregate utility:

$$
\begin{array}{ll}
\text{maximize} & \sum_{k=1}^{N} O^{(k)}(\mathbf{z}^{(k)}, \mathbf{y}^{(k)}) \\
\text{subject to} & \mathbf{H}^{(k)}\mathbf{z}^{(k)} \le \mathbf{y}^{(k)},\ k = 1, 2, \ldots, N, \\
& \sum_{k=1}^{N} \mathbf{y}^{(k)} \le \mathbf{C}, \\
& g^{(k)}(\mathbf{z}^{(k)}) \le 0,\ k = 1, 2, \ldots, N, \\
& \mathbf{z}^{(k)} \ge \mathbf{0},\ k = 1, 2, \ldots, N, \\
\text{variables} & \mathbf{z}^{(k)},\ \mathbf{y}^{(k)},\ k = 1, 2, \ldots, N.
\end{array}
$$

The maximization is subject to the capacity constraint and possibly other constraints described in terms of $g^{(k)}(\mathbf{z}^{(k)})$. The capacity constraint requires the link load $\mathbf{H}^{(k)}\mathbf{z}^{(k)}$ to be no more than the allocated bandwidth. To compute the link load we use routing indexes

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

and path rates $z_j^{(k)i}$ that determine for source i the amount of traffic directed over path j of virtual network k.

An optimization scheme follows directly from DaVinci principles. First, the substrate network determines how satisfied each virtual network is with its allocated bandwidth. Satisfaction level degree $\lambda_l^{(k)}$ is an indicator that a virtual network k may want more resources on link l. Next, the substrate network determines how much bandwidth virtual network k should have on link l: the substrate network increases or decreases value $y_l^{(k)}$ in dependence on the satisfaction level $\lambda_l^{(k)}$.

Provided that each virtual network is acting independently, the question is whether individual virtual networks without communication and cooperation with each other, together with the bandwidth share adaptation performed by the substrate network, which does not know the performance objectives of virtual networks, actually maximize the overall performance objective.

3. DECISION MAKING METHODOLOGY

Our work focuses on decision making on the substrate network level on bandwidth shares for link $l \in E_s$. We denote by t_j, where $j = 1, 2, \ldots$, moments of system adaptation, i.e. moments of decision on bandwidth shares $y_l^{(k)}(t_j)$ for $k = 1, 2, ..., N$. Such decision is based on the results of monitoring the performance of the system during interval $\left[t_{j-1}, t_j\right]$ and values $y_l^{(k)}(t_{j-1})$, $k = 1, 2, ..., N$. We suppose that values $y_l^{(k)}(t_0)$ for $k = 1, 2, ..., N$ are given and consider the behaviour of the system for $t \geq t_0$.

We consider the substrate network shared by many users, where the goal is to share the network resources in an optimal manner. Since the substrate network does not know the utility functions of all users, the network is not able to evaluate the optimal resource allocation. Networks having a centralized authority that controls the entire network will give way to self-optimizing networks.

Game theory is a tool used for modelling and analyzing conflict and cooperation between decision makers called players. Such a situation occurs when multiple decision makers with different objectives act in a system or share resources. Game theory provides a natural framework for the modelling of the bandwidth allocation mechanism in this paper. In the context of this work, we use non-cooperative games due to the competitive nature of the players (virtual networks or users in our case). Two or more virtual networks compete for a limited bandwidth of links of the substrate network.

Every virtual network attempts to maximize its utility in the game. A significant aspect of the game theory is that each virtual network's utility is based on the decision of every other virtual network and hence, each virtual network is able optimize its utility only with respect to every other virtual network's decision. In our model we consider the non-cooperative game of N players (virtual networks) with stages $S_l(t_j)$, $j = 1, 2, ...$, accordingly to decision moments t_j, $j = 1, 2, ...$. A strategy of each virtual network is a decision rule that specifies: does virtual network k want more resources or not. The result of bandwidth reallocation (i.e. bandwidth shares $y_l^{(k)}(t_j)$ for $k = 1, 2, ..., N$) depends on the strategies of all virtual networks.

A crucial aspect of the specification of a game involves the information that players have when they choose strategies. The simplest games (from the perspective of logical structure) are those in which agents have perfect information, meaning that at every point where each agent's strategy tells him to perform an action, he knows everything that has happened in the game up to that point. In contrast, we consider a game in which virtual networks do not know everything what has happened in the game up to that point when they take actions (such games are classified as games with imperfect information). Given that each virtual network is acting independently. This means that at moment t_j player k has information on behavior during interval $\left[t_{j-1}, t_j\right]$ only for virtual network k. Games with imperfect information can be modelled by using fuzzy logic based systems. We apply fuzzy game theory based approach by considering fuzzy players, which use fuzzy rules to make strategic decisions. Such generalization of business games was introduced and effectively applied in business management (Oderanti and De Wilde 2010; Oderanti and De Wilde 2011; Oderanti and De Wilde 2012).

4. GAME DECISION SUPPORT SYSTEM

We suppose that each player (virtual link) uses fuzzy rules to make strategic decisions. The procedures necessary for designing the proposed decision support system (Ross 1995; Piegat 2001) are listed below.

1. List fuzzy variables (factors) that will be considered in taking the decision.
2. Determine the strategies of virtual networks (players).
3. Develop membership functions for all variables.
4. Formulate decision rules for the rule base.
5. Describe the fuzzy inference technique.
6. Play the game.

4.1. Input fuzzy variables

The first step of fuzzy logic based decision making system design is to define fuzzy variables. We use one output variable $F_l^{(k)}(t_j)$ and three input variables for each link l and each virtual network k:

$U_l^{(k)}(t_j)$ – the average utilization of the virtual link;

$L_l^{(k)}(t_j)$ – the average length of queue;

$D_l^{(k)}(t_j)$ – the average delay of packets.

Input variables are used to describe the system state and the starting point of adaptation decision. These variables are evaluated for the period $\left[t_{j-1}, t_j\right]$ and have linguistic values according to their membership functions. We use the denotations $LU_l^{(k)}(t_j)$, $LL_l^{(k)}(t_j)$ and $LD_l^{(k)}(t_j)$ for the linguistic values of $U_l^{(k)}(t_j)$, $L_l^{(k)}(t_j)$ and $D_l^{(k)}(t_j)$ correspondingly.

4.2. Strategy variable

We introduce one fuzzy variable for each virtual network k to denote an output variable in the strategy decision process with respect to virtual link l at moment $t_j : F_l^{(k)}(t_j)$.

The strategy of virtual network k at moment t_j depends on a defuzzified output value of the fuzzy inference module. We use the denotation $LF_l^{(k)}(t_j)$ for the linguistic value of this variable.

4.3. Membership functions

For all input variables we consider three linguistic values „Low", „Medium" and „High" (we use the notation L, M and H as indexes). But for the strategy variable linguistic values are: „More" (meaning that the corresponding virtual network wants more bandwidth resources), „Constant" and „Less" (meaning that the corresponding virtual network wants less bandwidth resources).

The membership function for each linguistic value is given by a triangular or trapezoidal fuzzy number.

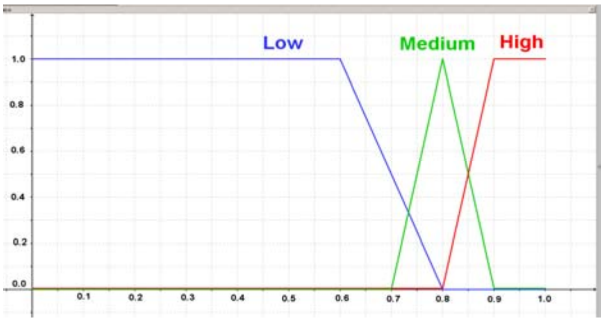

Figure 1: Membership Functions of the Linguistic Values for the Utilization Variable

For example, Fig.1 shows the graphs of the membership functions of linguistic values U_L, U_M, U_H for the utilization variables. These membership functions are considered to be independent on l, k and j. Obviously, such assumption is not true for the membership functions of other linguistic values: the membership functions for delay and queue variables depend on traffic class.

4.4. Decision rules

The knowledge base for our model is made as rule database, which is based only on the "expert knowledge", where the experts are the authors of the paper, and the rules are assumed as logical assumptions, e.g.:

if $LU_l^{(k)}(t_j) = "High"$ and $LL_l^{(k)}(t_j) = "Low"$ and $LD_l^{(k)}(t_j) = "Low"$, then $LF_l^{(k)}(t_j) = "Constant"$;

if $LU_l^{(k)}(t_j) = "High"$ and $LL_l^{(k)}(t_j) = "Low"$ and $LD_l^{(k)}(t_j) = "Medium"$, then $LF_l^{(k)}(t_j) = "More"$;

if $LU_l^{(k)}(t_j) = "Low"$ and $LL_l^{(k)}(t_j) = "Low"$ and $LD_l^{(k)}(t_j) = "Low"$, then $LF_l^{(k)}(t_j) = "Less"$;

if $LU_l^{(k)}(t_j) = "Medium"$ and $LL_l^{(k)}(t_j) = "Low"$ and $LD_l^{(k)}(t_j) = "Medium"$, then $LF_l^{(k)}(t_j) = "More"$ …

The rule database depends on the type of traffic and it can be freely modified as well as the membership function definitions. The assumed fuzzy rules and the membership functions of input and output values were used for the proposed approach performance evaluation by simulation process and the impact of their modification is considered as the field for the future research. Our future work will mainly focus on modify our approach by applying training (learning) algorithms to the decision process.

4.5. Fuzzy inference technique

We list the following parameters of decision making, which are used in our model in order to achieve the advanced goals (see, e.g., Ross 1995; Piegat 2001):

- the number of linguistic values and the membership functions of linguistic values for each input and output variable;
- the base of if-then rules;
- the method of defuzzification of output parameters;
- the type of decision making system.

In our model we apply the fuzzy inference technique, introduced by Mamdani (Mamdani 1974; Mamdani and Assilian 1975; also see Ross 1995; Piegat 2001). The COG (centre of gravity) defuzzification method was used in this decision making process.

4.6. Dynamic game

Our game is a repeated game. It is a special case of dynamic games, when players interact by playing a similar stage of the game numerous times. The next section is devoted to the description of stages of the game.

5. STAGES OF THE GAME

The game stage $S_l(t_j)$ for link $l \in E_s$ is represented as vector

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

where $y_l^{(k)}(t_j)$ represents the bandwidth value for virtual network k, obtained at moment t_j, and $P_l^{(k)}(t_j)$ gives the game payoff for virtual network k, which is evaluated for interval $\left[t_{j-1}, t_j\right]$ accordingly to virtual network's strategies at the stage $S_l(t_{j-1})$, $k = 1, 2, \ldots, N$, $j = 1, 2, \ldots$.

Initial stage of the game is

$$S_l(t_0) = (\, y_l^{(k)}(t_0),\ P_l^{(k)}(t_0) \mid\ k = 1, 2, \ldots, N\,),$$

where

$$P_l^{(k)}(t_0) = 0\ ,\quad k = 1, 2, ..., N\ ,$$

but values $y_l^{(k)}(t_0)$ are given. We can take

$$y_l^{(k)}(t_0) = C_l \,/\, N\ ,\ k = 1, 2, ..., N\ .$$

We suppose that in the starting stage all virtual networks choose the strategy „Constant" (of course, it is possible to take into account the choice of virtual network's own strategies in the initial stage, also). This means that during the first time interval $\left[t_0, t_1\right]$ the distribution of the link bandwidth will be uniform.

At moment t_1 payoffs $P_l^{(k)}(t_1)$, $k = 1, 2, ..., N$, are evaluated and all virtual links choose the strategies for time interval $\left[t_1, t_2\right]$, taking into account the behavior of the system during the first time interval $\left[t_0, t_1\right]$. It is done accordingly to the general game algorithm, which is described below for t_j, $j = 1, 2, ...$. In order to achieve the efficiency of the substrate network, our primary concern is to design the payoff functions, which will motive individual virtual networks to adopt a social behaviour and to improve the system performance by sharing the resources. In this context we apply a pricing technique (see, e.g., Zhou, Li, Sun, Jin, Su and Zeng 2010).

The payoff value $P_l^{(k)}(t_j)$ is obtained by three parts:

$$P_l^{(k)}(t_j) = U_l^{(k)}(t_j) - A_l^{(k)}(t_j) - B_l^{(k)}(t_j),$$

where $U_l^{(k)}(t_j)$ represents the utility value of virtual network k, $A_l^{(k)}(t_j)$ is the pricing part and $B_l^{(k)}(t_j)$ gives the congestion value for virtual network k for interval $\left[t_{j-1}, t_j\right]$ and link l. The payoff function has the physical meaning of utility value minus costs.

We denote by p_l the price of the bandwidth on the physical link l for one time unit. Virtual network k should pay

$$A_l^{(k)}(t_j) = p_l\, y_l^{(k)}(t_{j-1})(t_j - t_{j-1})$$

as the total price for the assigned bandwidth on link l during time interval $\left[t_{j-1}, t_j\right]$. The value $B_l^{(k)}(t_j)$ for virtual network k is the measure of the congestion cost according to the assigned bandwidth and actual link rate on the base of congestion price β_l of link *l*. If the total link rate of all virtual networks is less than the capacity of the physical link, no congestion cost will be charged. In our model we assume that the real rate is not the reason that causes the congestion, and we simplify the formula by taking β_l =0.

According to our approach all virtual networks use fuzzy rules to make strategic decisions. As it was described in the previous section each virtual network is considering as a fuzzy player, which apply the fuzzy inference technique to make strategic decisions. The suggested fuzzy solution requires one output variable for each virtual network k, which determines a fuzzy logic based decision on its strategy at moment $t_j : F_l^{(k)}(t_j)$. A defuzzified output value belongs to the interval $\left[0, 1\right]$. The value 0.5 corresponds to the strategy „Constant", the minimal value corresponds to the strategy „Less" and the maximal value corresponds to the strategy „More", accordingly.

Bandwidth shares $y_l^{(k)}(t_j)$, $k = 1, 2, ..., N$, for all virtual networks at the game stage $S_l(t_j)$ are evaluated proportionally to the requested values $b_l^{(k)}(t_j)$, $k = 1, 2, ..., N$, which are 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 should not differ from the previous one more than 20 percent. It is clear that this policy can be modified by modifying the formula.

Taking into account all requested values, new bandwidth shares $y_l^{(k)}(t_j)$, $k = 1, 2, ..., N$, now are calculated by the following way:

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

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

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

6. SIMULATIONS

For a practical realization of the proposed approach we extend the design and simulation scheme of dynamically adaptive bandwidth allocation method, which was proposed for two traffic classes (Asmuss, Zagorskis and Lauks 2012; Asmuss and Lauks 2013). The simulation experiments in our previous papers were conducted for two traffic classes - delay sensitive and throughput sensitive traffic. Now we describe the extension done by including the fuzzy game theory based module that fairly and efficiently share resources among multiple traffic classes.

Our simulation scheme is based on Coloured Petri Nets (CPN) Tools (Jensen 1992-1997; Ratzer, Wells, Larsen, Laursen, Qvortrup, Stissing, Westergaard, Christensen and Jensen 2003; Jensen, Kristensen and Wells 2007; Jensen and Kristensen 2009; Gehlo and Nigro 2010). CPN Tools is a discrete event modelling computer tool for CPN models supporting interactive and automatic simulations, state spaces and performance analysis and combining Coloured Petri Nets and the functional programming language CPN ML which is based on Standard ML. Colours can be effectively used for modelling virtual networks accordingly to the DaVinci architecture. CPN model of a substrate network describes the states of each virtual network of the system and the events (transitions) that can cause the system to change state. By making simulations of the network CPN model with CPN Tools it is possible to investigate different scenarios and explore the behaviours of the system, to use simulation-based performance analysis for decision making and adaptation processes.

To simplify the issue at the present stage of our research we simulate the adaptive bandwidth allocation on the link level. Traffic FIFO queues and virtual links are separated due to colours. The transmission time depends on the size of a packet and the bandwidth of the corresponding virtual link and is calculated for each packet transmission. Flows of packets for all virtual links are parallel controlled and analyzed. For more details we refer to our previous papers (Asmuss, Zagorskis and Lauks 2012; Asmuss and Lauks 2013).

The extended simulation scheme involves bandwidth shares adaptation module, which involves the proposed above fuzzy game theory based decision making submodule. The bandwidth allocation adaptation module is specially designed to update the virtual link resources allocation for dynamically changing traffics. Special observation functions and data collection monitors are included for monitoring the performance of the system. A monitoring mechanism is used not only to control, but also to modify simulations of the net. The decision making system is based on data collection monitors that allow calculating the system performance measures such as the delay in each queue, the length of each queue, the utilization of each link.

We experiment with two and three traffic classes. Simulation results allow us to improve adaptation mechanism by modification of fuzzy rules and membership functions. Bandwidth of substrate links in our experiment is determined as 100 Mbps and 150 Mbps, correspondingly. Packets are generated with exponentially distributed arrival time. In our experiments the initial resource allocation is uniform, i.e. we set the capacity of each virtual link as 50 Mbps. By changing traffic parameters we observe the resource allocation adaptation process (see Table 1 with simulation results for three traffic classes).

Our simulation results demonstrate that the adaptive bandwidth allocation mechanism can efficiently react to traffic changes for $k=2$ when $j=7$ and for $k=1$ when $j=12$. The simulations show that the proposed adaptation technique has good adaptation results: after three iterations we obtain bandwidth shares corresponding to virtual network's traffic.

Table 1: Bandwidth Allocation Results for Three Traffic Classes

	$b_l^{(k)}(t_j)$			$y_l^{(k)}(t_j)$			Utility
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

Of course, these results have been obtained through simulations using very strict assumptions and settings rather than real life scenarios. But they can be considered as an illustration of the proposed approach.

7. CONCLUSION

We are applying the concepts of fuzzy logic and game theory to model the decision process on bandwidth allocation. We are suggesting a model and a simulation scheme that can serve as a good tool for network bandwidth management and future investigation. Our future work will mainly focus on improving and modification of our approach by applying learning mechanisms. What we are trying to show is that the uncertainty in network bandwidth management can be suitably modelled or represented using fuzzy logic and game theory concepts.

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