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Markov Analysis of Students' Performance and Academic Progress in Higher Education

Alenka Brezavšček[1], Mirjana Pejić Bach[2], Alenka Baggia[1]

[1] University of Maribor, Faculty of Organizational Sciences, Kidričeva cesta 55a, 4000 Kranj, Slovenia
alenka.brezavscek@fov.uni-mb.si, alenka.baggia@fov.uni-mb.si

[2] University of Zagreb, Faculty of Economics and Business, Trg J.F. Kennedyja 6, 10000 Zagreb, Croatia
mpejic@efzg.hr

Background: The students' progression towards completing their higher education degrees possesses stochastic characteristics, and can therefore be modelled as an absorbing Markov chain. Such application would have a high practical value and offer great opportunities for implementation in practice.
Objectives: The aim of the paper is to develop a stochastic model for estimation and continuous monitoring of various quality and effectiveness indicators of a given higher education study programme.
Method: The study programme is modelled by a finite Markov chain with five transient and two absorbing states. The probability transition matrix is constructed. The quantitative characteristics of the absorbing Markov chain, like the expected time until absorption and the probabilities of absorption, are used to determine chosen indicators of the programme.
Results: The model is applied to investigate the pattern of students' enrolment and their academic performance in a Slovenian higher education institution. Based on the students' intake records, the transition matrix was developed considering eight consecutive academic seasons from 2008/09 until 2016/17. The students' progression towards the next stage of the study programme was estimated. The expected time that a student spends at a particular stage as well as the expected duration of the study is determined. The graduation and withdrawal probabilities were obtained. Besides, a prediction on the students' enrolment for the next three academic years was made. The results were interpreted and discussed.
Conclusion: The analysis presented is applicable for all higher education stakeholders. It is especially useful for a higher education institution's managers seeing that it provides useful information to plan improvements regarding the quality and effectiveness of their study programmes to achieve better position in the educational market.

Keywords: *higher education; study programme; effectiveness indicators; enrolment prediction; Markov analyses; absorbing Markov chain*

1 Introduction

Evaluation of students' progress is an essential part of any educational system. Every higher education institution can be considered as a hierarchical organization in which a student stays in a given study stage for one academic year, and then moves to the next stage or leaves the system as a graduate or dropped out. Due to continuous changing and the increasing amount of data the problem of understanding and assessing the students' progress through the educational system is very important (Mashat, Ragab & Khedra, 2012). It can help the managers of the education institution to establish an optimal educational policy, which ensures better position in the educational market. Based on the estimation of 30% drop out of first-year students and high costs of this phenomena, an attempt was made to find the strongest individual predictions of attrition (Aulck, Ve-

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lagapudi, Blumenstock & West, 2016).

Results of prior studies indicate that the students' progression towards completing their higher education degrees possess all the pertinent stochastic characteristics, and can therefore be modelled as a Markov chain (see e.g., Crippa, Mazzoleni & Zenga, 2016; Mashat et al., 2012; Rahim, Ibrahim, Kasim & Adnan, 2013; Symeonaki & Kalamatianou, 2011). Markov chains are an important family of stochastic processes, defined as a random sequence in which the dependency of the successive events goes back only one unit of time. In other words, as defined by Tijms (2003), the future probability behaviour of the process depends only on the present state of the process and is not influenced by its past history. This is called the Markovian property. Despite a very simple structure, Markov chains are extremely useful in a wide variety of practical probability problems (Tijms, 2003). The application of Markov chains can be found in various branches of natural sciences, engineering, and medical sciences (see e.g. Beichelt, 2006).

In the literature, there are many attempts to apply the Markov chain to analyse the higher education study process. For instance, Moody & DuClouy (2014) have applied the Markov chain to analyse and predict the mathematical achievement gap between African American and white American students. Furthermore, Hlavatý & Dömeová (2014) have presented the Markov chain model of students' progress throughout the particular course. To finish the course successfully, each student has to go throughout various stages of the course requirements where his success depends on the completion of the previous duties. Another approach is proposed by Symeonaki & Kalamatianou (2011) who used the theory of Non-Homogeneous Markov Systems (NHMS) with fuzzy states for describing students' educational progress in Greek Universities. Very interesting and useful are the studies which modelled the students' progression and their performance during higher education study using an absorbing Markov chain (see e.g., Adam, 2015; Adeleke, Oguntuase & Ogunsakin, 2014; Al-Awadhi & Ahmed, 2002; Al-Awadhi & Konsowa, 2010; Al-Awadhi & Konsowa, 2007; Auwalu, Mohammed & Saliu, 2013; Mashat et al., 2012; Shah & Burke, 1999). Such application provides a means for projecting the number of students' graduation and withdrawing by age, gender, and by study programme, and provides estimates of the average time a student stays in the system, the probability of completion as well as the average time to complete the study (Adeleke et al., 2014). Since the theory of the absorbing Markov chain is relatively simple, such applications indicate high practical value and therefore offer great opportunities for implementation in practice.

The aim of the paper is to develop an absorbing Markov chain model, which can be used for analysing the students' performance and their academic progress in Slovenian higher education environment. The present work represents continuation of our previous study published by Brezavšček & Baggia (2015). Comparing to the previous research, this paper adds several improvements. The time horizon used for estimating the Markov chain transition probabilities is extended from six to eight academic years that ensures a better accuracy of the obtained results. Furthermore, additional quality and effectiveness indicators of a given study programme are taking into account. Thus, the extended model enables estimation and continuous monitoring of the following indicators:

- The fraction of students that have successfully progressed toward different stages of the study programme;
- The expected time a student spends at a particular stage of a study programme and the expected duration of the study;
- The fraction of students who have finished the study successfully with graduation as well the fraction of students who have withdrawn from the study.

In addition, the model enables the prediction of future enrolment of students in a given study programme.

The paper is organized as follows: after the introduction section, we provide fundamental theoretical properties of absorbing Markov chains. Central part of the paper is dedicated to the model development. To illustrate its usefulness the model is applied to the bachelor's degree professional study programmes at the University of Maribor, Faculty of Organizational Sciences. The results obtained are interpreted and discussed. Finally, we summarize our ascertainment and open some opportunities for further research.

2 Computational background

The model for analysis of students' performance and academic progression is based on theory of *absorbing Markov chain*. This is a special Markov chain with the finite states. Since the basics of Markov chain theory are a well-known topic, they will not be described here in detail. To find more about its fundamentals see for example Beichelt (2006), Hudoklin Božič (2003) or Tijms (2003).

The general form of the probability transition matrix of an absorbing Markov chain with r absorbing and t transient states is

$$\mathbf{P} = \begin{pmatrix} \mathbf{Q} & \mathbf{R} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} \qquad (1)$$

The meaning of symbols in (1) is as follows:

- **Q** - $t \times t$ matrix expressing transitions between the transient states
- **R** - $t \times r$ matrix expressing transitions from the transient states to the absorbing states
- **0** - $r \times t$ zero matrix
- **I** - $r \times r$ identity matrix

Useful characteristics of an absorbing Markov chain are *the expected time until absorption* and *the probabilities of absorption*. In order to determine these values, we need the *fundamental matrix* **N** which can be calculated as:

$$\mathbf{N} = \left(\mathbf{I} - \mathbf{Q}\right)^{-1} \qquad (2)$$

where **I** denotes the identity matrix of size $t \times t$ (unlike the size of **I** in (1) which is $r \times r$). Elements n_{ij} of the matrix **N** express how many times (in average) a Markov chain reaches the transient state j when it started in the transient state i.

The expected time until absorption, μ_i, represents the expected number of steps before a Markov chain is absorbed into one of the absorbing states when it started in the transient state i. It can be obtained from the column vector $\boldsymbol{\mu}$ calculated from the equation:

$$\boldsymbol{\mu} = \mathbf{N1} \qquad (3)$$

where **N** is the fundamental matrix and **1** is the column identity vector. The value μ_i, is the i-th component of the column vector $\boldsymbol{\mu}$.

The probability of absorption f_{ij} can be obtained from the matrix **f**, which is calculated from the equation:

$$\mathbf{f} = \mathbf{NR} \qquad (4)$$

where **N** is the fundamental matrix and **R** is the sub-matrix from the transition matrix (1). The value f_{ij} represents the probability that a Markov chain will be absorbed into an absorbing state j when it started in the transient state i.

The distribution over states in a given time n can be written as a stochastic row vector

$$\mathbf{p}^{(n)} = \mathbf{p}^{(0)} \cdot \mathbf{P}^{n} \qquad (5)$$

where the symbol $p^{(0)}$ represents an initial vector (or initial probability distribution). The elements $p_i^{(n)}$ of $p^{(n)}$ mean the probabilities that a Markov chain is in the state i in time n.

3 The model

Generally, the duration of bachelor's degree within Slovenian higher education system is three years. After finishing the third year, a student can enrol into the so-called candidate year. During this year, the student needs to write a thesis but is not obliged to attend the lectures. Therefore, to model the student academic progress we will define the following states:

- 1 – the student is enrolled into the first year of the study programme
- 2 – the student is enrolled into the second year of the study programme
- 3 – the student is enrolled into the third year of the study programme
- *C* – the student is enrolled into the candidate year
- *I* – the student is currently inactive
- *G* – the student has graduated and successfully finished the study programme
- *W* – the student has withdrawn from the study programme

In developing the model, the following assumptions are considered:

- The student who is currently enrolled into the first or second year of the study programme can, in the following year, either progress to a higher stage or repeat a year and stay at the same stage.
- The student who is currently enrolled into the third year of the study programme can, in the following year, be either enrolled into the candidate year, or can graduate and finish the study.
- Irrespective of the stage of the study, after the end of each year, some students can become inactive.
- The student who is inactive for more than one year is classified as having withdrawn from the study programme.
- The student who has withdrawn will never finish this study programme. We have not noted whether he/she has been transferred to another study programme.
- The student who has graduated and successfully finished the study will never apply for the same study programme again. We have not noted whether he/she has applied for another study programme or continued the education at postgraduate level.

The state transition diagram for the students' progression is illustrated in Figure 1.

3.1 Construction of probability transition matrix

Considering the state transition diagram from Figure 1 the probability transition matrix can be written as follows:

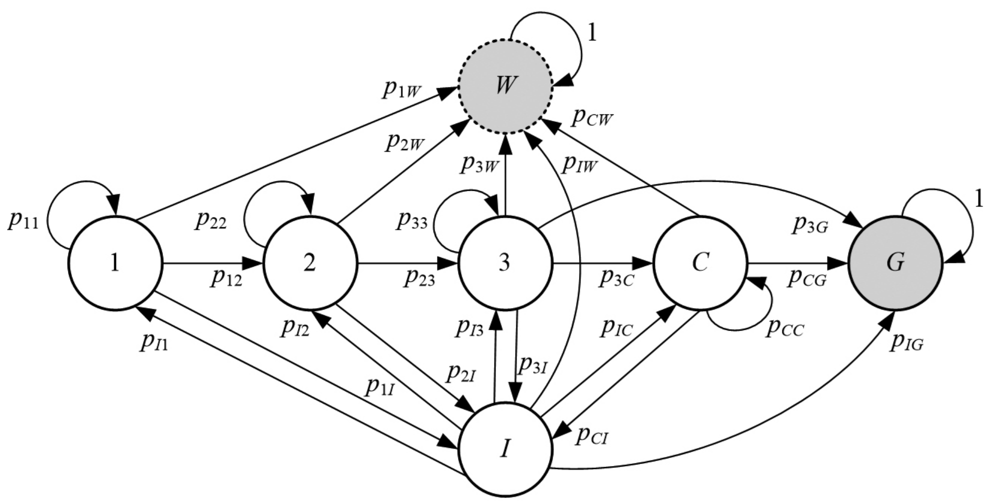

Figure 1: State transition diagram for students' academic progression

$$
\mathbf{P} = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \\ G \\ W \end{array}
\begin{array}{c}
\begin{array}{ccccccc} 1 & 2 & 3 & C & I & G & W \end{array} \\
\left[\begin{array}{ccccc:cc}
p_{11} & p_{12} & 0 & 0 & p_{1I} & 0 & p_{1W} \\
0 & p_{22} & p_{23} & 0 & p_{2I} & 0 & p_{2W} \\
0 & 0 & p_{33} & p_{3C} & p_{3I} & p_{3G} & p_{3W} \\
0 & 0 & 0 & p_{CC} & p_{CI} & p_{CG} & p_{CW} \\
p_{I1} & p_{I2} & p_{I3} & p_{IC} & 0 & p_{IG} & p_{IW} \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right]
\end{array}
\quad (\mathbf{Q}: \text{rows/columns } 1,2,3,C,I;\ \mathbf{R}: \text{rows } 1,2,3,C,I,\ \text{columns } G,W)
\tag{6}
$$

It is evident from Figure 1 and from the transition probability matrix (6) that the states $\{G,W\}$ are absorbing while the states {1,2,3,C,I} are transient. In the transition matrix **P** also the sub-matrices **Q** and **R** are marked.

The transitions probabilities *pij* in (6) can be gathered from the students' intake records. Directly from the historical data the frequency matrix can be obtained containing the absolute numbers of students' academic progress. The frequency matrix should than be transformed to the probability transition matrix, which can be done easily by normalizing each row of the frequency matrix.

3.2 Estimating students' progression between different stages

The sub-matrix **Q** contains the probabilities of students' progression from one specific stage to another during one academic year. To understand the meaning of the probability transition matrix **P**, let us consider a randomly selected student who happens to be in the inactive state at present. The probability that the student will return to active mode next year and continue the study in the second year can be gathered directly from the transition matrix **P** and is equal to p_{I2}. Similarly, the other elements of **P** can be explained.

One of the quality indicators of student performance, frequently used in evaluating study programmes, is the fraction of students who succeed to progress to a higher stage of the study programme during one academic year. The fractions of students who succeed to progress from the first, second or third year to the next stage of the study programme can be obtained directly from the transition matrix **P** as follows: p_{12}, p_{23} and p_{3c}.

3.3 The expected time a student spends at a particular stage and the expected duration of the study

The expected lifetime that a student spends at a particular stage of the study programme can be gathered from the fundamental matrix **N,** which can be calculated according to (2) using the sub-matrix **Q** from (6). We obtain the fundamental matrix in the following form:

$$
\mathbf{N} = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}
\begin{array}{c}
\begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\
\left[\begin{array}{ccccc}
n_{11} & n_{12} & n_{13} & n_{1C} & n_{1I} \\
n_{21} & n_{22} & n_{23} & n_{2C} & n_{2I} \\
n_{31} & n_{32} & n_{33} & n_{3C} & n_{3I} \\
n_{C1} & n_{C2} & n_{C3} & n_{CC} & n_{CI} \\
n_{I1} & n_{I2} & n_{I3} & n_{IC} & n_{II}
\end{array}\right]
\end{array}
\tag{7}
$$

The elements n_{ij} in **N** represent the expected time a student spends for the *j*-th study stage when he started at the *i*-th study stage.

To estimate the expected duration of the study we need to calculate the expected time until absorption according to (3). The result is the column vector **μ**:

$$\boldsymbol{\mu} = \begin{matrix} 1 \\ 2 \\ 3 \\ C \\ I \end{matrix} \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_C \\ \mu_I \end{bmatrix} \qquad (8)$$

The particular value μ_i in (8) can be interpreted as the expected duration of the study (until graduation or withdrawal) of a randomly selected student who is currently at the *i*-th stage of the study programme.

In students' performance analysis it is very useful to estimate the expected time (in academic years) a student enrolled in the first year of the study programme can expect to spend before graduating. This indicator can be calculated as the sum of the entries in the diagonal of the fundamental matrix (7):

$$E_{1G} = n_{11} + n_{22} + n_{33} + n_{CC} + n_{II} \qquad (9)$$

3.4 The graduation - withdrawal probability

The graduation or withdrawal probability can be obtained using the probability of absorption, which is calculated according to (4) using the fundamental matrix (7) and the matrix **R** from (6). The result is the matrix **f**:

$$\mathbf{f} = \begin{matrix} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{matrix} \begin{matrix} G & W \\ \left[\begin{matrix} f_{1G} \\ f_{2G} \\ f_{3G} \\ f_{CG} \\ f_{IG} \end{matrix}\right. & \left.\begin{matrix} f_{1W} \\ f_{2W} \\ f_{3W} \\ f_{CW} \\ f_{IW} \end{matrix}\right] \end{matrix} \qquad (10)$$

The values p_{iG} in the first column of (10) represent the fraction of students, currently at the *i*-th study stage, who will successfully finish the study and graduate. However, the values in the second column of (10), p_{iW}, represent the fraction of students who will withdraw from the study programme and will never finish it.

3.5 Predicting the future enrolment of students

The future enrolment of the students can be predicted using the vector $\mathbf{p}^{(n)}$, which can be calculated according to (5). The elements of the initial vector $\mathbf{p}^{(0)}$ can be estimated from the frequency data. The elements of $\mathbf{p}^{(n)}$ represent the fraction of students being at given study stage in *n*-th academic year. The probabilities $p_i^{(n)}$ from $\mathbf{p}^{(n)}$ can be than transformed into the absolute number of students at a particular stage at the beginning of the *n*-th academic year. In assessing the total enrolment of students at the beginning of the *n*-th academic year, the new enrolled students should be taken into account (Adeleke et al., 2014).

4 Numerical example

To apply the model, data were collected from the students' intake records at the University of Maribor, Faculty of Organizational Sciences. In our analysis, only the full time students of the professional study programmes were included. The frequency data during eight consecutive academic years from 2008/09 to 2016/17 are listed in Table 1.

4.1 Construction of probability transition matrix

The frequency data from Table 1 were used to estimate the transition probabilities of the transition matrix. First, we calculated "partial" transition probability matrices for a particular academic year separately. Since in Table 1 there are no data available for the state *C* in the first two years, we calculated the transition matrices for the last six academic years, e.g. from 2010/11 → 2011/12 and later. We obtained: **(next page)**

The probability transition matrix P_3 corresponds the third year (2010/11 → 2011/12), while the matrices P_4, P_5, P_6, P_7 and P_8 describe the fourth, the fifth, the sixth, the seventh and the eighth year, respectively (i.e., from 2011/12 → 2012/13 until 2015/16 → 2016/17).

We also calculated the "expected" probability transition matrix P where the expected transition probabilities were calculated as the average values considering all the eight academic years. In calculating the expected transition probabilities, we took into consideration only these entries from Table 1 where the frequency data are actually available. We obtained: **(next page)**

4.2 Estimating students' progression between different stages

The probabilities of yearly progression between successive stages of the study programme can be directly obtained from the probability transition matrices. Especially useful are probabilities of passing from the first to the second year, from the second to the third year as well as from the third year to the higher stage (the candidate year or graduation) during one academic year are. These probabilities represent the fraction of students who progressed successfully during one academic year. The results of our analysis are presented in Table 2 and Figure 2. Progres-

$$\mathbf{P}_3 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.072 & 0.38 & 0 & 0 & 0.549 & 0 & 0 \\ 2 & 0 & 0.331 & 0.521 & 0 & 0.149 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0.868 & 0 & 0.132 & 0 \\ C & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ I & 0 & 0 & 0 & 0 & 0 & 0.022 & 0.978 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \qquad \mathbf{P}_4 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.05 & 0.314 & 0 & 0 & 0.636 & 0 & 0 \\ 2 & 0 & 0.192 & 0.485 & 0 & 0.323 & 0 & 0 \\ 3 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ C & 0 & 0 & 0 & 0 & 0.034 & 0.966 & 0 \\ I & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}$$

$$\mathbf{P}_5 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.045 & 0.263 & 0 & 0 & 0.692 & 0 & 0 \\ 2 & 0 & 0.18 & 0.4 & 0 & 0.42 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0.683 & 0 & 0.317 & 0 \\ C & 0 & 0 & 0 & 0.079 & 0.175 & 0.429 & 0.317 \\ I & 0 & 0.026 & 0 & 0 & 0 & 0 & 0.974 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \qquad \mathbf{P}_6 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.023 & 0.227 & 0 & 0 & 0.75 & 0 & 0 \\ 2 & 0 & 0.195 & 0.341 & 0 & 0.463 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0.875 & 0 & 0.125 & 0 \\ C & 0 & 0 & 0 & 0 & 0.354 & 0.646 & 0 \\ I & 0.01 & 0.01 & 0.096 & 0 & 0 & 0 & 0.885 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}$$

$$\mathbf{P}_7 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.029 & 0.318 & 0 & 0 & 0.653 & 0 & 0 \\ 2 & 0 & 0.103 & 0.569 & 0 & 0.328 & 0 & 0 \\ 3 & 0 & 0 & 0.042 & 0.396 & 0 & 0.563 & 0 \\ C & 0 & 0 & 0 & 0.114 & 0 & 0.886 & 0 \\ I & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array} \qquad \mathbf{P}_8 = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.032 & 0.323 & 0 & 0 & 0.645 & 0 & 0 \\ 2 & 0 & 0.18 & 0.574 & 0 & 0.246 & 0 & 0 \\ 3 & 0 & 0 & 0.057 & 0.229 & 0 & 0.714 & 0 \\ C & 0 & 0 & 0 & 0.043 & 0 & 0.957 & 0 \\ I & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}$$

$$\mathbf{P} = \begin{array}{c|ccccccc} & 1 & 2 & 3 & C & I & G & W \\ \hline 1 & 0.057 & 0.31 & 0 & 0 & 0.603 & 0 & 0.03 \\ 2 & 0 & 0.187 & 0.528 & 0 & 0.285 & 0 & 0 \\ 3 & 0 & 0 & 0.012 & 0.563 & 0.097 & 0.328 & 0 \\ C & 0 & 0 & 0 & 0.039 & 0.094 & 0.814 & 0.053 \\ I & 0.001 & 0.036 & 0.02 & 0 & 0 & 0.003 & 0.94 \\ G & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}$$

sion probabilities were calculated from the year when the first generation of students finished this study programme (2010/11). In the last column of Table 2, we merged the students who decide to graduate immediately after the third year of study, and the students who decide to take the candidate year after the third year of study. The dashed line in Figure 2 represents the eight-year expected probability of students' progression to the next stage, which is obtained directly from **P**.

4.3 The expected time a student spends at a particular level and the expected duration of the study

Using the sub-matrices Q_3-Q_8 from the probability transitions matrices P_3-P_8 the fundamental matrices N_3-N_8 are calculated: **(page 90)**

Besides, the fundamental matrix N that correspond the expected probability transitions matrix P is obtained: **(next page)**

The elements of the fundamental matrices represent the expected number of academic years when the student is enrolled in a particular stage of the study. For example, let we assume an average student who is currently enrolled in the first year. During his enrolment in the study programme, it is expected that he will spend 1.061 academic years for the first year, 0.44 academic year for the second year, 0.252 academic year for the third year, 0.147 academic year for the candidate year, while 0.804 academic year he will be inactive. The row sum of the fundamental matrix's entries represents the expected time until absorption from a given transient state, and can be interpreted as the expected duration of the study starting at a specific study stage (i.e., the expected enrolment in the study programme until graduation or withdrawal) (see Table 3).

The sum of the diagonal elements of the fundamental matrix gives us the expected duration of the study from the first year until graduation. The results are shown in Table 4.

Table 1: Frequency matrix on students' progression through years from 2008/09 to 2016/17

2008/09 → 2009/10								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2008/09**
1	19	60	0	0	93	0	44	**216**
2	0	20	78	0	16	0	0	**114**
3	0	0	0	0	44	21	0	**65**
C	-	-	-	-	-	-	-	**-**
I	0	19	6	0	0	0	121	**146**
New	213							
Σ 2009/10	**232**	**99**	**84**	**0**	**153**	**21**	**165**	

2009/10 → 2010/11								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2009/10**
1	27	88	0	0	109	0	8	**232**
2	0	14	64	0	21	0	0	**99**
3	0	0	0	38	8	38	0	**84**
C	-	-	-	-	-	-	-	**-**
I	0	19	4	0	0	0	130	**153**
New	210							
Σ 2010/11	**237**	**121**	**68**	**38**	**138**	**38**	**138**	

2010/11 → 2011/12								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2010/11**
1	17	90	0	0	130	0	0	**237**
2	0	40	63	0	18	0	0	**121**
3	0	0	0	59	0	9	0	**68**
C	0	0	0	0	0	38	0	**38**
I	0	0	0	0	0	3	135	**138**
New	222							
Σ 2011/12	**239**	**130**	**63**	**59**	**148**	**50**	**135**	

2011/12 → 2012/13								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2011/12**
1	12	75	0	0	152	0	0	**239**
2	0	25	63	0	42	0	0	**130**
3	0	0	0	63	0	0	0	**63**
C	0	0	0	0	2	57	0	**59**
I	0	0	0	0	0	0	148	**148**
New	212							
Σ 2012/13	**224**	**100**	**63**	**63**	**196**	**57**	**148**	

2012/13 → 2013/14								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2012/13**
1	10	59	0	0	155	0	0	**224**
2	0	18	40	0	42	0	0	**100**
3	0	0	0	43	0	20	0	**63**
C	0	0	0	5	11	27	20	**63**
I	0	5	0	0	0	0	191	**196**
New	166							
Σ 2013/14	**176**	**82**	**40**	**48**	**208**	**47**	**211**	

2013/14 → 2014/15								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2013/14**
1	4	40	0	0	132	0	0	**176**
2	0	16	28	0	38	0	0	**82**
3	0	0	0	35	0	5	0	**40**
C	0	0	0	0	17	31	0	**48**
I	2	2	20	0	0	0	184	**208**
New	167							
Σ 2014/15	**173**	**58**	**48**	**35**	**187**	**36**	**184**	

2014/15 → 2015/16								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2014/15**
1	5	55	0	0	113	0	0	**173**
2	0	6	33	0	19	0	0	**58**
3	0	0	2	19	0	27	0	**48**
C	0	0	0	4	0	31	0	**35**
I	0	0	0	0	0	0	187	**187**
New	150							
Σ 2015/16	**155**	**61**	**35**	**23**	**132**	**58**	**187**	**155**

2015/16 → 2016/17								
	1	**2**	**3**	**C**	**I**	**G**	**W**	**Σ 2015/16**
1	5	50	0	0	100	0	0	**155**
2	0	11	35	0	15	0	0	**61**
3	0	0	2	8	0	25	0	**35**
C	0	0	0	1	0	22	0	**23**
I	0	0	0	0	0	0	132	**132**
New	117							
Σ 2016/17	**122**	**61**	**37**	**9**	**115**	**47**	**132**	

$$\mathbf{N}_3 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.078 & 0.612 & 0.319 & 0.277 & 0.683 \\ 0 & 1.495 & 0.779 & 0.676 & 0.223 \\ 0 & 0 & 1 & 0.868 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \quad \mathbf{N}_4 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.053 & 0.409 & 0.198 & 0.198 & 0.808 \\ 0 & 1.238 & 0.6 & 0.6 & 0.42 \\ 0 & 0 & 1 & 1 & 0.034 \\ 0 & 0 & 0 & 1 & 0.034 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

$$\mathbf{N}_5 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.047 & 0.364 & 0.146 & 0.108 & 0.897 \\ 0 & 1.238 & 0.495 & 0.367 & 0.584 \\ 0 & 0.004 & 1.002 & 0.743 & 0.132 \\ 0 & 0.006 & 0.002 & 1.088 & 0.193 \\ 0 & 0.032 & 0.013 & 0.01 & 1.015 \end{bmatrix} \end{array} \quad \mathbf{N}_6 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.034 & 0.304 & 0.197 & 0.173 & 0.977 \\ 0.008 & 1.254 & 0.499 & 0.436 & 0.741 \\ 0.003 & 0.005 & 1.033 & 0.904 & 0.325 \\ 0.004 & 0.006 & 0.038 & 1.033 & 0.371 \\ 0.011 & 0.016 & 0.106 & 0.093 & 1.048 \end{bmatrix} \end{array}$$

$$\mathbf{N}_7 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.03 & 0.365 & 0.217 & 0.097 & 0.792 \\ 0 & 1.115 & 0.662 & 0.296 & 0.366 \\ 0 & 0 & 1.044 & 0.467 & 0 \\ 0 & 0 & 0 & 1.129 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \quad \mathbf{N}_8 = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.033 & 0.407 & 0.248 & 0.059 & 0.766 \\ 0 & 1.22 & 0.742 & 0.178 & 0.3 \\ 0 & 0 & 1.06 & 0.254 & 0 \\ 0 & 0 & 0 & 1.045 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

$$\mathbf{N} = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ C \\ I \end{array}\begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & C & I \end{array} \\ \begin{bmatrix} 1.061 & 0.44 & 0.252 & 0.147 & 0.804 \\ 0 & 1.251 & 0.678 & 0.397 & 0.46 \\ 0 & 0.007 & 1.019 & 0.597 & 0.157 \\ 0 & 0.004 & 0.004 & 1.043 & 0.1 \\ 0.001 & 0.046 & 0.045 & 0.026 & 1.02 \end{bmatrix} \end{array}$$

4.4 The graduation - withdrawal probability

The graduation – withdrawal probabilities are calculated as the absorption probabilities from a given transient state. For this purpose the fundamental matrices as well as sub-matrices R gathered from the probability transition matrices were used. The results are presented in Table 5.

In Figure 3, the graduation and withdrawal probabilities considering the students in the first year of the study programme are shown. The dashed line represents the expected graduation/withdrawal probability during the last eight academic years.

4.5 Predicting the future enrolment of students

Let we assume the initial state in the academic year 2016/17. Using the frequency data from Table 1 the initial vector $\mathbf{p}^{(0)}$ is estimated:

$$\mathbf{p}^{(0)} = [{}^{122}/_{523} \;\; {}^{61}/_{523} \;\; {}^{37}/_{523} \;\; {}^{9}/_{523} \;\; {}^{115}/_{523} \;\; {}^{47}/_{523} \;\; {}^{132}/_{523}] = [0.233 \;\; 0.117 \;\; 0.071 \;\; 0.017 \;\; 0.22 \;\; 0.09 \;\; 0.252]$$

We want to predict the enrolment of students for the following three academic years. We calculated the vectors $\mathbf{p}^{(1)}$, $\mathbf{p}^{(2)}$ and $\mathbf{p}^{(3)}$ according to (5) using the expected probability transition matrix P. Calculated probabilities are than transformed into the absolute number of students. In calculations, we assumed that every academic year 120 new students are entered to the study programme. The results are given in Table 6.

Results in Table 6 show that, we can expect a quite constant number of the students in a specific stage, whereas the number of inactive students' increases.

5 Discussion

From a theoretical perspective, our study underscores the importance of using an absorbing Markov chain theory to study the pattern of students' enrolment and their academic performance within a Slovenian higher education environment. As for the study programme under consid-

Table 2: Probability of the students' progression to the next study stage during one academic year

	FRACTION OF STUDENTS WHO SUCCESSFULLY PROGRESS FROM THE FIRST TO THE SECOND YEAR p_{12}	FRACTION OF STUDENTS WHO SUCCESSFULLY PROGRESS FROM THE SECOND TO THE THIRD YEAR p_{23}	FRACTION OF STUDENTS WHO SUCCESSFULLY PROGRESS FROM THE THIRD TO THE CANDIDATE YEAR OR TO GRADUATION $p_{3C}+p_{3G}$
2010/11 → 2011/12	0.38	0.521	0.868+0.132=1
2011/12 → 2012/13	0.314	0.485	1+0=1
2012/13 → 2013/14	0.263	0.4	0.683+0.317=1
2013/14 → 2014/15	0.227	0.341	0.875+0.125=1
2014/15 → 2015/16	0.318	0.569	0.396+0.563=0.959
2015/16 → 2016/17	0.323	0.574	0.229+0.714=0.943
EXPECTED IN LAST 8 YEARS	**0.31**	**0.528**	**0.563+0.328=0.891**

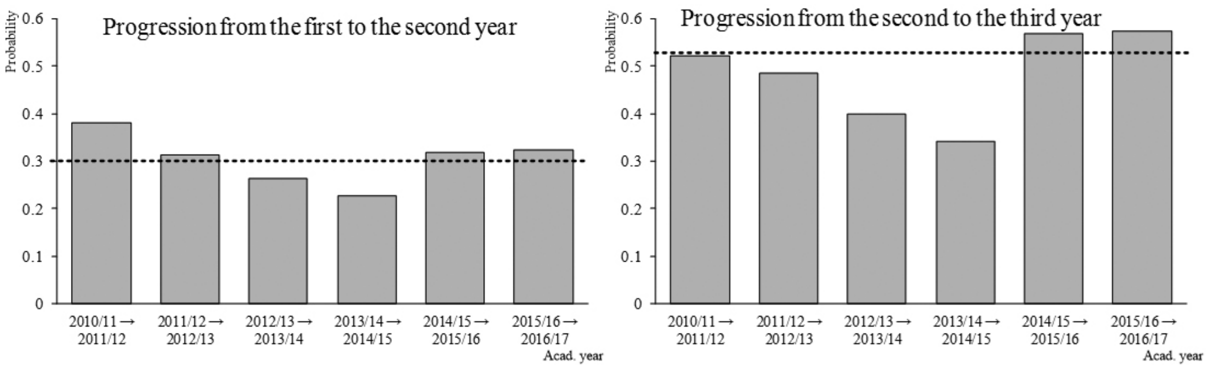

Figure 2: Probability of the students' progression to the next study level during one academic year

Table 3: The expected enrolment in the study programme (to graduation or withdrawal) from a particular study stage

STUDY STAGE	μ_3 2010/11→ 2011/12	μ_4 2011/12→ 2012/13	μ_5 2012/13→ 2013/14	μ_6 2013/14→ 2014/15	μ_7 2014/15→ 2015/16	μ_8 2015/16→ 2016/17	μ EXPECTED IN LAST 8 YEARS
1	2.97	2.67	2.56	2.68	2.5	2.51	**2.7**
2	3.17	2.86	2.68	2.94	2.44	2.44	**2.79**
3	1.87	2.03	1.88	2.27	1.51	1.31	**1.78**
C	1	1.03	1.29	1.45	1.13	1.04	**1.15**
I	1	1	1.07	1.27	1	1	**1.14**

Table 4: The expected duration of the study from the first year to graduation

	E_{1G}
2010/11→2011/12	5.572
2011/12→2012/13	5.29
2012/13→2013/14	5.39
2013/14→2014/15	5.401
2014/15→2015/16	5.317
2015/16→2016/17	5.358
EXPECTED IN LAST 8 YEARS	**5.395**

Table 5: The graduation – withdrawal probabilities from a particular study stage

t	f_3 2010/11→ 2011/12		f_4 2011/12→ 2012/13		f_5 2012/13→ 2013/14		f_6 2013/14→ 2014/15		f_7 2014/15→ 2015/16		f_8 2015/16→ 2016/17		f EXPECTED IN LAST 8 YEARS	
	G	*W*	*G*	*W*	*G*	*W*	*G*	*W*	*G*	*W*	*G*	*W*	*G*	*W*
1	0.33	0.67	0.19	0.81	0.09	0.91	0.14	0.86	0.21	0.79	0.23	0.77	**0.2**	**0.8**
2	0.78	0.22	0.58	0.42	0.31	0.69	0.34	0.66	0.63	0.37	0.7	0.3	**0.55**	**0.45**
3	1	0	0.97	0.03	0.64	0.36	0.71	0.29	1	0	1	0	**0.82**	**0.18**
C	1	0	0.97	0.03	0.47	0.53	0.67	0.33	1	0	1	0	**0.85**	**0.15**
I	0.02	0.98	0	1	0.01	0.99	0.07	0.93	0	1	0	1	**0.04**	**0.96**

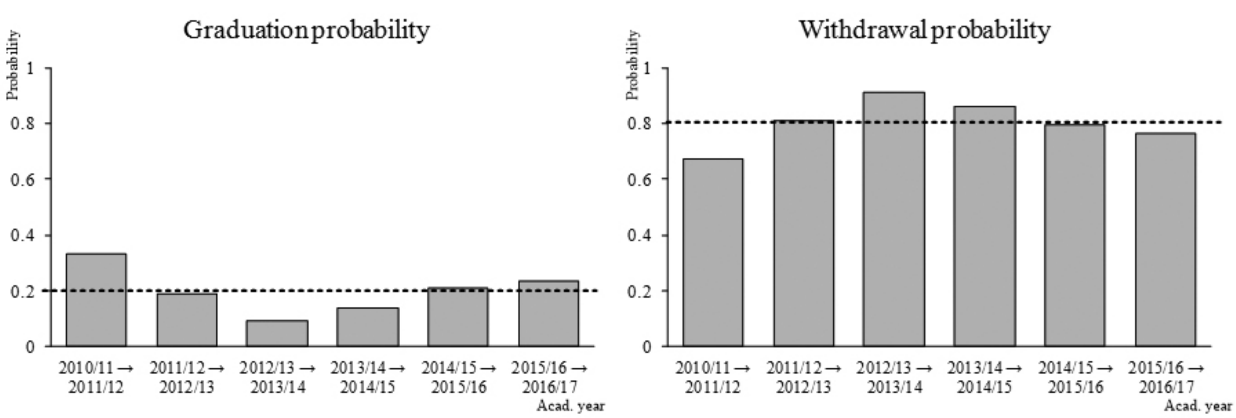

Figure 3: Graduation and withdrawal probabilities considering the students in the first year of the study programme

eration, the quantitative indicators calculated in section 4 provide some useful information the programme manager. Results in Table 2 showed that in the first four years of our analyses the fraction of students, who decide to graduate immediately after the third study year, was relatively low in comparison to the fraction of students who decided to take the candidate year. In the last two years, the situation is surprisingly opposite. This can be explained by the change of Slovenian higher education regulation in 2012, which has prevented the students who have already repeated a year or changed the study field, to take the candidate year. Nevertheless, this could also indicate that more students become mature (Borgen & Borgen, 2016) and decide to graduate as soon as possible with the intention to continue the study on the second degree study programme. In general, there were recently also positive changes in the job market (Menéndez-Valdés, 2016), which could also indicate that the students already have an opportunity for the

Table 6: Prediction of the future enrolment in the study programme

		1	2	3	*C*	*I*	*G*	*W*	Σ
2017/18	$P^{(1)}$	0.014	0.102	0.067	0.041	0.182	0.128	0.467	1
	NO. OF STUDENTS	7+120	53	35	21	95	67	244	643
2018/19	$P^{(2)}$	0.011	0.082	0.047	0.032	0.151	0.149	0.527	1
	NO. OF STUDENTS	7+120	53	31	21	97	96	339	763
2019/20	$P^{(3)}$	0.01	0.069	0.04	0.024	0.127	0.161	0.57	1
	NO. OF STU-DENTS	7+120	53	30	18	97	123	435	883

employment, and were therefore keen to finish their study as soon as possible.

Furthermore, the findings of this study (as demonstrated in Table 2) indicate that the probability of progression from the first to the second year is always lower than the probability of progression from the second to the third year. This is quite an expected result since the experiences from the class show that the students become more serious and ambitious during their progression in the study. Figure 2 shows a negative trend of both indicators from Table 2 in first four years of our analyses. Fortunately, the negative trend has changed in the last two years, when the progression probabilities exceed the eight-year expected values. This turn can be explained by several measures, which were taken at the faculty in recent years to improve the students' progression. The first measure has been introduced in 2011 when the third application period for the faculty was abolished due to the previous analysis showing the unresponsiveness of students applying in the third period. Although the trend of progression only changed in later years, we can assume that this measure had an influence on the progression from the first to the second year of study. Furthermore, in 2015 the Ministry of Higher Education, Science and Technology has successfully finished the project of information system for evidence and analyses on higher education in Slovenia. One of the advantages of the new system (the beta version has been in use since 2012) is the prevention of duplicate applications to faculties, which further results in more responsive first year students and higher level of their progression to the second year of study. In addition, to mitigate the students' progression problem, various measures have been implemented at the faculty during recent years (e.g. performance of the courses and unification of the course materials). These measures have assumingly lead to a better performance of students.

We can see from Table 3 that a student, who is currently enrolled in the first year, needs on average 2.7 years to finish the study (graduation or withdrawal). Unfortunately, the results in Table 5 show that only 20% of these students will actually graduate, while the withdrawal probability is very high (80%). The ratio of withdrawal is even higher than a constant failure rate of 60% in the first year enrolment observed in universities across OECD countries (Arias Ortiz & Dehon, 2013). One plausible explanation is that most of the first year students are rather confused due to change of educational environment and their inability to understand the tenets of academic work. According to Petty (2014), universities should escalate the process of creating a smoother transition from secondary education to the higher education. Results in Table 5 also indicate that the majority of inactive students (96%) will never graduate. On average, they leave the programme after 1.14 years (Table 3), while the expected duration of the study from the first year until graduation is 5.395 years (Table 4). Results in Table 4 also showed that the expected time to graduation is a rather constant and the values do not differ substantially during the years analysed. Nevertheless, the numbers are quite high, considering the fact that the study programme lasts three years.

However, we can see from Table 5 that the probability of graduation increases with student's progression over the study stages, and analogous, the probability of withdrawal decreases. Such result was quite expected. It may indicate that when getting older, the students become more aware of their responsibilities and therefore become more successful with their study. We can see from Figure 3 that during last three years of analyses the probability of graduation increases, while the probability of withdrawal decreases. This may indicate a positive trend, and can again be explained as a positive effect of different measures, mentioned before, that have been undertaken during past years.

Although the progression probability increased during the last two years, the relatively long expected time to graduation and increasing number of inactive students (Table 6) indicate that the study programme management would need to find some additional measures to improve these indicators. Some effort should be oriented towards increase of the graduation probability from the first study year. According to the research presented by Rodríguez-Gómez, Meneses, Gairín, Feixas & Muñoz (2016), many of students change to a different area of knowledge, showing the inefficient guidance systems and university entrance. Some successful attempts to increase the first year success are presented in the literature (Boath et al., 2016; Watterson, Browne & Carnegie, 2013; Wood, Gray-Ganter & Bailey, 2016). The increase of first year retention will result in decreasing number of inactive students and consequently in lower costs of the study.

6 Conclusion

In this paper, we have developed a Markov chain model to examine the flow of undergraduate students through the higher education system in Slovenia. The model enables estimation and continuous monitoring of different quality and effectiveness indicators of a given study programme. By introducing some additional indicators (e.g., probability of students' progression between different stages, expected time spend at a particular stage, expected duration of the study), this study represents an upgrade of the model presented in Brezavšček & Baggia (2015).

To illustrate the usefulness of the model, the model was applied to the professional study programmes at the University of Maribor, Faculty of Organizational Sciences. The results obtained proved that our research has substantial practical implications. The analysis performed provide a useful information which are valuable for managers of the educational institution to improve their processes, as well for the policy makers at government agencies (e.g., state level, competent ministry, etc.) to supervise the effectiveness of existing educational policies. Having estimated the future minimum enrolment, the school management will be able to adjust the policy when necessary (Adeleke et al., 2014). Such information are also worthwhile for students, education planners, employers and other actors in the labour market to help them make informed decisions on investment in education (Shah & Burke, 1999).

The main limitation of our study is the assumption that our Markov chain model is time-homogeneous. In other words, we have assumed temporal stability in the estimated transition probabilities. Over short to medium term this is not an unreasonable assumption because student behaviour is unlikely to change dramatically over such time span (Shah & Burke, 1999). However, when the conditions on the higher educational market would due to any reason change dramatically from year to year an inhomogeneous Markov chain should be applied. Although quite a large number of students are captured in this research, another limitation is that the research is bounded to only one educational institution.

Further analysis and research of the students' behaviour could include the simulation of students' flow in case of a successful implementation of diverse measures which the university can make to improve the success of students (Clarke, Nelson & Stoodley, 2013; Clouder, Broughan, Jewell & Steventon, 2013). Recent studies also demonstrate, that low student retention can be explained by mistaken choices (Borgen & Borgen, 2016). Therefore, Slovenian higher education system as a whole could also be investigated to establish the flow of students after their return back to the university system after their dropout.

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Alenka Brezavšček is an Assistant Professor of Stochastic Processes at the Faculty of Organizational Sciences, University of Maribor. Her main research interests are stochastic processes, system reliability and availability, and information system security.

Mirjana Pejić Bach is a Full Professor at the Department of Informatics the Faculty of Economics & Business University of Zagreb. Her main research interests are simulation, data mining, and big data.

Alenka Baggia is an Assistant Professor of Quality and Information Systems at the Faculty of Organizational Sciences University of Maribor. Her main research interests are resource scheduling, simulation and information system sustainability.