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Success/Leaving Rate of the Military Students

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Abstract

The military university type of education in the Czech Republic is provided by the University of Defence. As other universities, it has to deal with students prematurely leaving their studies. We have collected available data to assess students' dropout rate. Using parametric and nonparametric methods, we identified that the highest leaving rate occurs during the first study year reaching a maximum after five and a half months from the studies beginning, then it gradually slows down. We assume that our results can help the academics and commanders to make timely decision and positively encourage the students in their studies.

KEY WORDS: *military student, University of Defence, leaving rate, survival analysis, regression, kernel estimate, hazard rate.*

1. Introduction

At the beginning of the 21st century, a fundamental reform of the Czech armed forces took place. An integral part of it was the transformation of the military education system. Its aim was to eliminate extensive organizational structures and create a simpler system of military schools. It was necessary to make such changes in the military education system in order to achieve higher efficiency of the spent resources. The logical consequence was the merger of the original three separate military universities on September 1, 2004 into a single state university—the University of Defence—with its headquarters in Brno. A small but mobile and highly qualified army with university-educated professionals became the demand of the time.

The higher education of military officers is guaranteed by the University of Defence [1]. The university provides accredited education in Bachelor's, Master's and doctoral degree study programs, which are oriented to military management, engineering and medicine. The priority is to prepare military professionals working in the sphere of security and state defense based on the needs of the Army of the Czech Republic, state administration and contractual commitments with other democratic states. University graduates are prepared to work in units deployed abroad in missions and NATO operations as well.

The university consists of three faculties, two institutes and three centers. In our contribution, we focus on the Faculty of Military Leadership. Until 2013, the so-called "3+2" study program was accredited at the faculty, i.e., a three-year bachelor program followed by a subsequent two-year master program. For practical reasons, it has been replaced since 2014 by a five-year master program, with the emphasis placed on a broader focus of the graduates' professional profile, which enables their career growth in the changing military environment.

Education at the University of Defence provides students with a comprehensive range of knowledge enabling them to handle activities in the field of command and management. During the five-year course of study, students fulfill demanding requirements of theoretical and professional subjects as well as of their military training, which is implemented as a part of their studies. Not everyone successfully completes their studies.

Dropping out is a multidimensional phenomenon that might be explained through various reasons affecting students' leaving decision, which is influenced by numerous factors. In [2], there are summarized primary reasons of dropping out: school-related (e.g., poor performance, disliked school), economic (e.g., desire to work) and personal (e.g., pregnancy). Even though they are the high school dropout reasons, they can be applied to the university type of study. Several studies describing and modeling the students' dropout rate from the qualitative point of view have been conducted [3–8].

Within the military university environment, the studies and articles are less common, but we can point out at least some. Personality factors which distinguish successful recruits were studied in [9,10]. Possible predictors of

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attrition from the military medical university were identified in [11] and the attrition rate in military general surgery residency programs were studied in [12]. The impact of the distance education on military personnel and their academic persistence was studied in [13].

Dropping out is an issue, which concerns also the University of Defence, which is the only military university in the Czech Republic. This led us to the idea of evaluating the success/leaving rate of the study at one of the faculties of the university and use the results to predict the students' leaving rate.

2. Data and methods

The data are based on reading records on the dates up to which students withdraw from their studies. The collection for this assessment has been performed since September 2014, when the first students started their studies in the new five-year program. The last group of students started their studies in September 2018, and up to now, the data contains full information to describe and model the students leaving rate during the first three years of the study, which are considered to be the most critical.

The examined data are related to the students who do not finish their studies because of different reasons. Our intention is to reveal a negative turning point in their studies, to be more precise, to investigate and draw attention to critical periods of the students' dropouts. In the article, we do not deal with the reasons for the leaving (we only marginally speculate on the possible reasons), we primarily investigate the dropout rate related to the official date of the leaving (and not to the date of a submission of an application to leave, or with respect to the date when the student decided to leave).

The students are naturally divided into five groups designated by the year of the beginning of their study. In contrast to traditional labels, we denote the respective groups according to their initial year of study, e.g., the Class of 2014, etc. Enabling us to compare the Classes, which contain different number of students, we transform the data to the percentage scale and set the time axis to start on September 1 of the respective years. We are dealing with a certain type of a failure in time, therefore, we apply approaches typical for the failure rate occurrence modelling. A combination of parametric and nonparametric methods gives a local as well as a global view on the data and helps to identify critical points during the course of study.

Having, in a certain sense, the lifetime data, we start with the Kaplan-Meier estimate of a survival function. Since in the data censored observations are not present, we continue with a linear regression analysis to assess the leaving rate during the respective years of the study for all considered classes. The overall comparison is done by employing the analysis of variance and the post-hoc Tukey test. To obtain a global view on this dataset, we use the parametric regression model in the form $S = a + b \cdot f(t)$, where S denotes the percentage of the students still studying (i.e., the survivors), a, b are parameters of the regression function and f(t) is a function of time.

To describe the occurrence of student leaving and to understand its instantaneous behavior, we employ parametric and nonparametric models [14]. Typical parametric models, even though providing a powerful tool for description of a relationship between the variables, they are susceptible to an assumption of the model functional representation [15]. Therefore, we turn our attention to kernel estimates, which belong to the class of nonparametric models to estimate the true course of a function, say f, without presuming its shape in advance [16]. Concisely, the kernel estimate at point t can be written as $f_{est}(t) = \sum W(t, t_i, h, K) \cdot S_i$, where S_i are the observed values of the target variable (in our case, the percentage of survivors) and W is the weight function depending on the point t, the values of independent variable t_i, a parameter h and a kernel function K. The most important element is the parameter h, which controls the smoothness of the resulting estimate [17].

The discretely quantified data can be perceived as a sample of real-valued functions with random fluctuations around a smooth trajectory. Functional data analysis is then an appropriate tool for modeling such data [18,19]. Classic summary statistics for univariate data apply equally to functional data. The mean function is an average of all functions and the variance function is defined similarly as an average of the squared distance between the single functions and their mean function, while taking calculations pointwise for each time point [20].

3. Results and discussion

First, we applied the Kaplan-Meier estimate of the survival function, which is depicted in Figure 1 for all the classes. As we can see, the leaving rate is more or less the same for all the classes. Students' uncertainty of the right choice of the study program as well as the so called "first encounter with the university type of study" (which is completely different from the high school type of study) [21] influenced the downtrend in the first year. In the second and third year of study, the trend is still decreasing, but its slope is smaller.

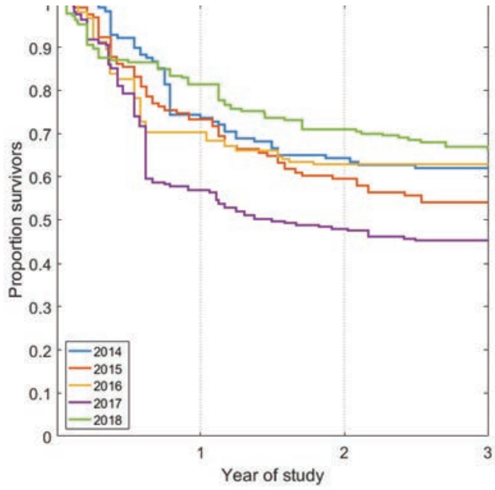


Fig. 1. Kaplan-Meier estimate of the leaving rate
(the Class of 2014 blue, 2015 orange, 2016 yellow, 2017 violet and 2018 green)

Comparing the slopes of the leaving rate within the year of the study showed that there are significant differences between the respective classes, see Table 1. During the first year, we can differ three groups, namely the Classes of 2014 and 2015 form one group, the Classes of 2016 and 2017 form another one, and the last one is represented by the Class of 2018, which can be seen in Figure 2. In the course of the second year of the study, the Class of 2015 differ from the Classes of 2016 and 2017, but the leaving rate can be considered similar for the rest of the classes pairs. Throughout the third study year, the Class of 2016 shows different behavior than the Classes of 2015, 2017 and 2018.

Table 1.

Tukey test p-values for differences between the classes in the respective years of the study

	first year				second year				third year			
Class	2015	2016	2017	2018	2015	2016	2017	*2018*	*2015*	*2016*	*2017*	*2018*
2014	0.999	0.013	0.000	0.001	0.467	0.329	0.612	0.982	0.071	0.168	0.877	0.545
2015		0.004	0.000	0.000		0.006	0.009	0.286		0.000	0.260	0.219
2016			0.986	0.000			0.935	0.782			0.014	0.000
2017				0.000				0.973				0.991

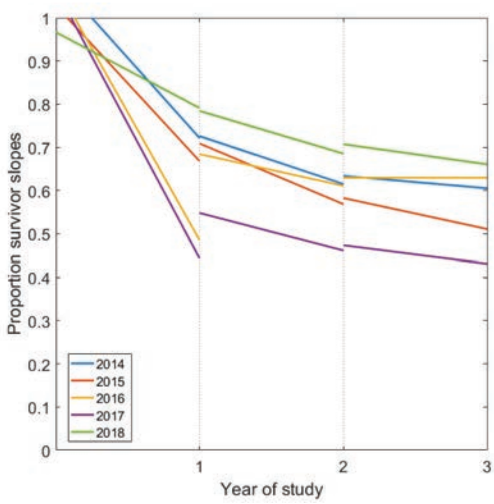
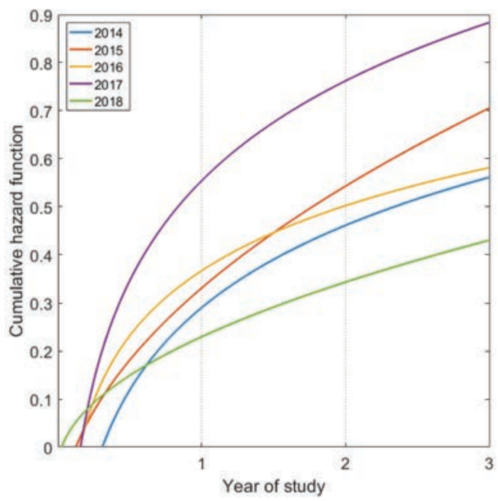


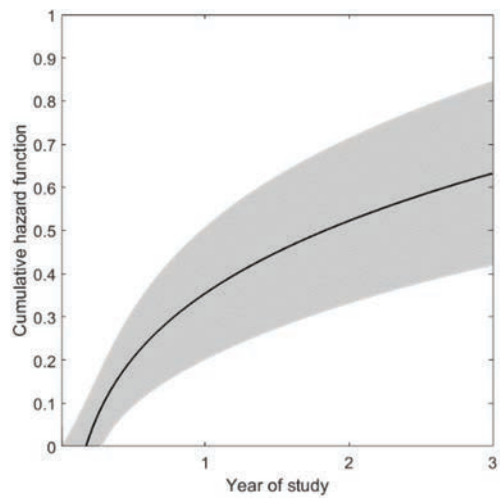
Fig. 2. Average trend of the leaving rates during the first three years of the study

The average trends given by the regression line slopes for all classes together are −1.02·10−3, −3.03·10−4, and −7.84·10−5 respectively for the individual study years. Recalculated into the percentage of survivors, it means that on average 37% of the first-year students drop out, then from those who continue to the second year of the study 11% drop out, and 3% of the rest leave before finishing their third year of the study.

As the next step, we utilized parametric regression to obtain a global view on the leaving rate. Continuing in the survival analysis, we modeled the cumulative hazard function of the single classes. The function f(t) was selected according to the basic shape of the cumulative hazard function which implied shapes of the square root function or the logarithmic function. The best model was determined according to the Akaike information criterion. The parametric models are shown in Figure 3(a).



(a) Estimated models for the single classes



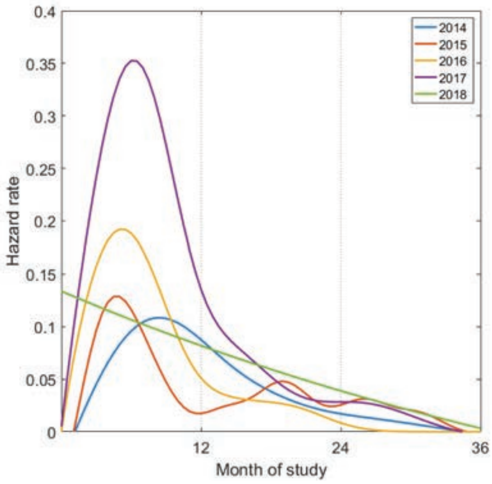
(b) Mean cumulative hazard function with 95% CI

Fig. 3 Cumulative hazard function of the students dropouts

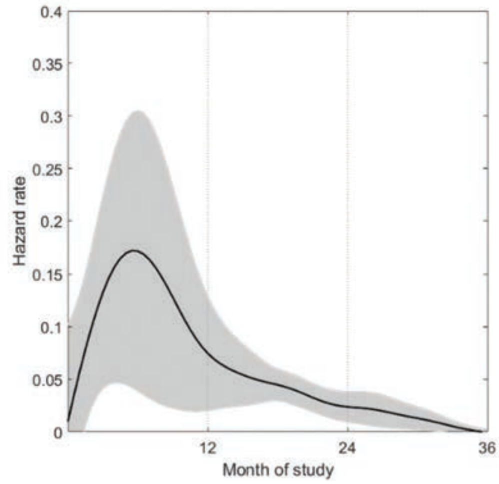
Having estimated the curves of the cumulative hazard function for the single classes, we can construct a mean cumulative hazard function using the functional data analysis approach. The resulting function is depicted in Figure 3(b) along with the 95% confidence interval (CI). The results are similar to those of previous calculations. However, the crucial piece of information is at the beginning of the mean curve, for it is here that we can identify the time point where the cumulative hazard starts its increasing course. This is the average time when students start to drop out from their study, which is two months after the beginning of an academic year.

We suppose that the reason for the early study termination may be its difficulty, as the students have to simultaneously fulfill assignments of individual (and in the first year mostly theoretical) subjects and requirements of their military training. Not everyone can adapt to such a new study system in time. Another reason could be the fact that the study field did not meet the expectations of some students.

Even though, the parametric models are easy to evaluate and interpret, they suffer from the prescribed shape of the target function to be estimated. Therefore, we applied the nonparametric estimates for reconstruction of the hazard rate, which models the students' leaving rate. Specifically, we transformed the data to the failure rates with respect to months (i.e., the number of dropouts in a month divided by the number of days in that month) and applied kernel smoothing on the discrete data. The bandwidth was calculated employing the least square cross-validation method and the hazard rate function was constructed using the local-linear estimator with the Gaussian kernel [17]. All classes results were transformed to their functional form, see Figure 4(a).



(a) Estimated hazard rate for single classes



(b) Mean hazard function with 95% CI

Fig. 4. Hazard function of the students dropouts

Similarly, as in Figures 1 and 2, we can see that the Class of 2018 behaves differently from the others, namely during the first year of the study. Nonetheless, it is obvious that the maximum of the leaving rate occurs during the first study year, especially, after the first semester, when the students fail to fulfill the first semester study requirements placed on them. Further, we constructed a mean hazard function and its corresponding 95% confidence interval (CI), see Figure 4(b). From the graphical form of the mean hazard function, we can recognize one large maximum, which take place at the time of 5.6 months from the beginning of the academic year, which coincides with the exam period. In this way, we have identified another important piece of information regarding the students' dropout rate.

The premature termination of the study is probably related to the specifics of university studies, which are in general different from the high school studies. Students receive a credit for continuous fulfilling their study tasks, but as for the successful completion of an exam, they have to respond to all topics related to the exam subject and to demonstrate knowledge of the course content for the entire semester. Some students are unable to do this and then on their own decision end their studies. Another reason for the students' leaving could be the contradiction between their idealistic ideas and reality.

4. Conclusions

In the contribution, we deal with the success/leaving rate of the military studies at the University of Defence. We primarily address the issue of students' premature termination of their studies. Using parametric and nonparametric statistical methods, we identified critical time periods during which a significant number of students end their studies. We believe that these results can help the academics and commanders to make timely decisions and select appropriate strategies leading to a reduction of the dropout rate. A positive consequence will be the attainment of higher efficiency of the funds spent on the education of military professionals, which is in line with the reform of the Czech armed forces.

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