VILNIUS UNIVERSITY

Irina Vinogradova

DISTANCE COURSE SELECTION OPTIMISATION

Summary of Doctoral Dissertation

Physical Sciences, Informatics (09 P)

Vilnius, 2015

The doctoral dissertation was prepared at the Institute of Mathematics and Informatics of Vilnius University in 2010-2014.

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The dissertation will be defended at the public meeting of the Council of the Scientific Field of Informatics Sciences of Vilnius University in the auditorium 203 at the Institute of Mathematics and Informatics of Vilnius University at 11 a. m. scheduled for the 23th of March 2015.

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The summary of the doctoral dissertation was sent out on 23rd of February 2015.

A copy of the doctoral dissertation is available for review at the Library of Vilnius University or on this website: www.vu.lt/lt/naujienos/ivykiu-kalendorius

VILNIAUS UNIVERSITETAS

Irina Vinogradova

NUOTOLINIŲ KURSŲ PARINKIMO OPTIMIZAVIMAS

Daktaro disertacijos santrauka

Fiziniai mokslai, informatika (09 P)

Vilnius, 2015

Disertacija rengta 2010-2014 metais Vilniaus universiteto Matematikos ir informatikos institute.

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Disertacija bus ginama viešame Vilniaus universiteto Informatikos mokslo krypties tarybos posėdyje 2015 m. kovo 23 d. 11 val. Vilniaus universiteto Matematikos ir informatikos instituto 203 auditorijoje.

Adresas: Akademijos g. 4, LT-08663 Vilnius, Lietuva.

Disertacijos santrauka išsiuntinėta 2015 m. vasario 23 d.

Disertaciją galima peržiūrėti Vilniaus universiteto bibliotekoje ir VU interneto svetainėje adresu: www.vu.lt/lt/naujienos/ivykiu-kalendorius

1. Introduction

Research area and relevance of the problem

The quality of education and science is one of the most important goals of our society. Education has always been important for cultural development, social welfare, and economic advancement. The level of education is directly associated with the quality of work. A new scientific research and innovations funding programme Horizon 2020 was prepared in the European Union in 2014, whereas one of the aims of the programme is the *advanced science*. The implication of a*dvanced science* is to induce high-level scientific researches in order to create knowledge and new technologies based long-term globally competitive European economy.

The development of information technologies (IT) has an impact on all areas of human activities, including science and education. Probably most advantages of information and communication technologies are associated with distance learning, which is rapidly gaining popularity due to its flexibility and possibility to study at the convenient time and place. However, the variety of information and communication technologies and their application does not determine the efficiency of the study process. To implement that, the ability of selecting the most appropriate means for distance learning organisation, the evaluation of their potential, knowledge of alternative measures, and possession of a clear remotely organised study plan is needed, as well as the ability to answer a number of questions related to distance learning issues. The new emerging information and communication tools allow us to improve the traditional studies making them more acceptable by changing the organisation principle of the studies so that it becomes increasingly focused on a student. The obsolete teaching and learning methods are supplemented or replaced with more flexible ones. Up to the present moment, each Lithuanian University uses a virtual learning environment to improve the quality of studies. The majority of higher schools arrange remotely operated study programmes. In this case, much attention is paid to a qualified preparation of distance courses.

The quality of the distance course depends on attributes such as the course material, presented in a distinct and interesting manner, a well-organised training process, information assets used during the process, relevance of the course material, students' motivation and teachers' qualification and professionalism. Specialists of the relevant field, i.e. experts, evaluated these attributes.

Vilnius Gediminas Technical University (VGTU) has 15-year experience in providing the training by distance. During the meetings, the Distance Learning Evaluation Committee members decide whether the course meets the quality requirements. The commended distance learning courses are equivalent to the printed educational publications. The actual work presents a complex distance course evaluation methodology, used to determine the quality of the VGTU distance courses.

The proposed methodology relies on mathematics-based methods, taking into account the uncertainty of expert data. The methodology presumes the distance course evaluation involves individuals of various activities who are interested in a high quality education: lecturers, students, the staff of the distance learning centre, and the administration of an educational institution. This kind of diversified approach reflects different interests of the course participants, gives possibility to improve the course according to grades and notes of the participants. A complex methodology was developed which joins both Bayesian and stable MCDM methods taking into account the subjectivity of experts' opinion. A Bayesian method is used for adjusting expert evaluation, in relation with both competency of experts and the experience accumulated over the years. MCDM methods are used for evaluating the course while applying criteria of quality evaluation and it's weights based on experts' evaluation. The result of evaluation is strongly influenced by the determined weight of criteria. The methods of mathematical statistics, the theory of fuzzy sets and stable multi-criteria methods have been applied in order to evaluate the uncertainty of expert data.

Aim and objectives

The aim of this work is to propose a complex quality evaluation methodology for distance learning courses, taking into consideration the subjectivity of experts' opinion and the uncertainty of their evaluation. The suggested methodology is implemented for evaluating the quality of distance learning courses of VGTU.

To achieve the aim, the following objectives are considered:

1. To make the analysis of scientific researches on a distance course, virtual learning environment and expert evaluation.
2. To distinguish evaluation stages of distance learning courses and expert evaluation groups based on Lithuania's and other countries experience of quality evaluation in the studies.
3. To apply the Bayesian approach in evaluating the quality of distance learning courses, adjusting an expert's grade with regard to one's competence and experience accumulated over the years.
4. To present MCDM methods as a component of mathematics-based optimisation methods.
5. An algorithm of fuzzy pairwise comparison matrix of the criteria of independent expert group was proposed.
6. To apply the Bayesian approach to recalculate the weights of criteria, taking into account opinions of other expert groups.
7. To propose an algorithm to determine the stability of MCDM methods, regarding the uncertainty of experts' grades and to choose the result of the most stable MCDM method to evaluate the quality of distance course learning.
8. To evaluate the distance learning courses based on the complex quality evaluation methodology proposed in the thesis.

The research methods

The systematic analysis method was applied during the preparation of the forensic part of the study. The methods stability revision by means of the statistical simulation method was performed while investigating the indeterminacy impact on the estimated MCDM methods results. The pseudo-random numbers for each imitation were generated by changing the initial decision data.

In order to establish the MCDM methods' stability and calculate MCDM evaluation results, using the weights established by Analytic Hierarchy Process (AHP) and Analytic Hierarchy Process Fuzzy (AHPF) methods, special programs were prepared using the

MATLAB (R2011a) mathematical package. In order to calculate posterior mean functions, the mathematical package *Derive* 5 was used.

The expert evaluation method was applied in practical realisation of the proposed methodology. Miscellaneous methods were applied to complete the survey of the experts: based on the expert peer-connection – loose expert method was applied; based on the evaluation of reconciliation procedure – a one-time survey method was implemented; based on the number of experts – an individual interview method was applied. To distinguish the groups' quality criteria of distance learning course, V. Belton and T. Stewart's principles were applied during the process.

After performing the expert evaluation, the statistical data analysis method was applied subsequently. Then the comprehensive assessment was initiated, and the comparative analysis method was used to summarise the results of the research.

Scientific novelty

As a result of the dissertation the following original results have been obtained:

1. An approach of quality evaluation of a course was proposed applying the Bayesian approach, taking into consideration the uncertainty of estimates.
2. A new algorithm of fuzzy pairwise comparison matrix of the criteria of independent expert group.
3. The application of the Bayesian approach to recalculate the weights of criteria, taking into account the opinion of other expert groups.
4. An approach for evaluating the quality of a course has been proposed using a stable MCDM method.
5. A complex quality evaluation methodology of distance courses is proposed, with regard to different methods.

The practical value of the study results

The suggested complex evaluation methodology has been practically implemented for evaluating the quality of VGTU distance courses. The methodology provides a possibility to evaluate distance learning course for representatives of different scholar fields who are interested in high quality courses. Lecturers, students, the staff of the distance learning centre, and the administration of the educational institution are amongst them. This type of multidisciplinary approach reflects the different interests of the course participants and provides an opportunity to develop the course, with regard to the grades and observations of the participants. The proposed complex quality evaluation methodology takes into account the uncertainty of data and subjectivity of expert opinion. The initiated comprehensive evaluation methodology of the course quality might be applied to evaluate quality of other similar tasks.

Statements presented for defence

1. The Bayesian approach applied in the expert evaluation takes into consideration the experts' qualifications and the accumulated experience of the University.
2. In order to determine the quality of a distance learning course the most stable MCDM method approach, ensuring the certainty of the evaluation result, is applied.
3. The Fuzzy set proposed to determine the weights of the criteria takes account the subjective opinion of the independent experts group.
4. The Bayesian approach can be applied to recalculate the weights of criteria, in connection with different groups of experts' opinion.
5. The complex quality evaluation methodology of the distance learning course comprehensively considers the subjectivity of expert opinion and uncertainty of the course evaluation.

Approbation of the research results

The main results of the thesis were published in 13 articles: 2 in peer-reviewed scientific publications, 3 in other scientific publications, 8 in conference publications. The main results were also presented and discussed at 16 international and national conferences.

The structure and scope of the dissertation

The thesis work consists of five units, the list of references and two appendices. The titles of the thesis units are: Introduction, Review of literature, The quality evaluation methodology of the distance learning course, The integrated assessment of the distance learning courses and Conclusions. Data sheets, illustrations and a list of used markers and abbreviations have also been provided in the thesis. The total scope of the thesis without the appendices is 145 pages. Overall 47 pictures and 24 tables, including the annexes, were presented in the thesis.

2. Quality assessment of a distance learning course

The issue of quality evaluation is relevant in various fields. Depending on the field the quality definition can be interpreted in different ways. In the quality standards document ISO 9000, the quality is defined as a degree of eligible characteristics corresponding to the requirements. The quality issues of distance learning are analysed in Lithuanian and world scientists' works. They mainly focus on selection of the quality of the teaching content and IT aids selection. A large number of works, related to the quality of distance education research and evaluation, have been done (*R. Laužackas, V. Dagienė, E. Kurilovas, D. Rutkauskienė, M. Teresevičienė, A. Volungevičienė, A. Targamadzė, R. Petrauskienė, S. Priedys, T. I. Wang, K. H. Tsai, U. D. Ehlers etc.*).

Qualified evaluation field specialists, i.e. experts, usually determine the degree of quality. The word 'expert' descended from Latin that meant 'experienced', therefore the experts are people that possess special knowledge and skills in a specific area. The experts are selected based on features related to the professional competence: work experience, tenure, scientific degrees, and scholarly activities, and the ability to solve specific problems in the field concerned. Furthermore, there are other methods of experts' competence evaluation and selection. However, even though qualified experts were selected, the evaluation might be incorrect due to some human error occurrence. For example, fusion of the evaluation with other conclusions, desire to influence the final result, reluctance to oppose the dissentients or excessive confidence might lead to incorrect or inaccurate evaluation. The data obtained on the basis of the expert evaluation are of stochastic nature: the outcome will be ambiguous if regrouping of the experts takes place, reduction or increasing the number of experts is implemented, or the repetition of evaluations is involved.

The distance learning course is defined as a study subject that is taught in a remote way, with the help of information technologies. A virtual learning environment, that ensures the availability of distance learning course for students, their tutors as well as for the course administrators, is used to organise distance learning. Vital aspects for evaluating distance learning courses are content verification, IT tools adjustment and students' opinion on the quality of a course and studies. During the distance learning module arrangement and the implementation of training, the main focus of attention is on the preparation of teaching material. It is possible to improve the quality of distance learning and to reduce learning barriers during the course preparation by targeted selection of IT tools. In order to achieve the quality of learning, it is necessary to persistently analyse the needs of learners.

A different point of view is acceptable regarding the quality evaluation of distance courses. One of the approaches proposed by the author of the thesis is adaptation of the Bayesian approach. The opinions on the Bayesian approach applied in the expert evaluation differ. B. G. Buchanan and E. H. Shortliffe claim that application of the approach inevitably prevents the possibility to obtain accurate results, since the probabilities used are subjective. Hence, it is the main argument contradicting the probability approach. Such arguments provide an objective interpretation of the concept of probability that the "right" meaning still exists, although we cannot obtain it, therefore the application of the Bayesian approach is impossible. However, according to the Bayesian approach theory, the subjective probabilities are based on a well-known precision and a clear system of axioms. Therefore, from the mathematical perspective, it is beyond any doubt, a reliable approach. The approach is widely used in various fields of science: social science, economic models, medicine (whenever a diagnosis is determined according to the tokens of the disease) (*J. O. Berner, C. Howson, P. Urbach*), in informatics (when dealing with electronic spam) (P. Graham), in image analysis (*L. Stabingiene*), classical regression (*C.M. Bishop and M.E. Tipping*), data mining (*L. Sakalauskas G. Jakimauskas*), in classification, neural network modelling (*D. J. C. MacKay*) and in the uncertainty of measurement data evaluation (*A. Possolo and C. Elster*), etc. Application of this method was investigated by such Lithuanian scientists as J. Mockus, A. Zilinskas, V. Tiešis, G. Dzemyda and others.

Another approach is based on application of the most stable MCDM methods. Most of the well-known decision-making approaches and methods of the greatest interest those which give an opportunity to take account of multicriteria and uncertainty as well as possibility of choosing various options according to the criteria with different rating scales. Over the past two centuries, MCDM methods have been applied in many areas and have been used in solving practical problems in the fields such as medicine, human resources, production management systems, technical diagnostics, market generation, environment and energy, ecology, management, economics, etc. The MCDM methods are widely applied in Lithuanian researchers' works (*E. K. Zavadskas, A. Kaklauskas, V. Podvezko, L. Ustinovičius, J. Šaparauskas, J. Antuchevičienė, etc.*).

3. The quality evaluation methodology of distance learning courses

This section presents the complex quality evaluation methodology of distance learning courses. The distance course evaluation takes place in three successive stages: Stage 1 – evaluation of the content of the course, Stage 2 – effective usage of IT tools, Stage 3 – students' evaluation of the course. The course is evaluated by three groups of experts: lecturers, IT specialists, and students. A Bayesian approach-based method is proposed in the first part of the methodology. The Bayesian approach adjusts the set of experts' grades according to their accumulated many-year experience and professional competence. A continuous case of the Bayesian equation is applied in the thesis. Various *a priori* information and the expert opinion evaluation in the cumulative density function usage are introduced in the work. The most appropriate combination of distributions was selected to evaluate a course.

The second approach is based on a stable MCDM method, i.e. while implementing the evaluation in several MCDM methods, it was suggested to choose the result of the most stable method. The method is considered to be stable, whenever an inconsistent change in the results is applicable to the minor changes of the primary expert evaluations. In order to identify the weights of MCDM method criteria, mathematically based AHP and Fuzzy AHP (AHPF) methods were applied. Generation of a new Fuzzy pairwise comparison matrix of the AHPF method is proposed in the thesis, with regards to the opinions of the group of independent experts. In view of the opinion of other expert groups, the work proposed the Bayesian approach to recalculate the criteria weights.

Applicability of the Bayesian approach in evaluating the quality

The framework of the methodology is based on the Bayesian approach, whenever the expert grade is specified by the posterior mean function $f_{mean}(X)$, which depends on the *a priori* evaluation experience of the course and expert's decision-making qualification.

For convenience, a continuous case will be examined in the thesis. The continuous approximation will be applied in the work, where the expert evaluation and real quality is described by integers.

The Bayesian formula is presented as follows:

$$f(\theta \vee X) = \frac{f(X \vee \theta) \cdot f(\theta)}{f(X)} \qquad (1)$$

θ is the real quality, the state of nature.

$f(\theta)$ is the *a priori* probability density function. Thus, it is the primary information about the quality of θ obtained from the previous evaluations.

$f(X \vee \theta)$ is X of the conditional probability density of new evaluations, where the real state of nature is θ. The function defines the expert error that depends on the qualification of the expert.

X is the grade of the expert.

$f(X)$ is the X evaluation of the probability density of all the possible θ meanings:

$$f(X) = \int_{-\infty}^{\infty} f(X \vee \theta) \cdot f(\theta) d\theta. \qquad (2)$$

$f(\theta \vee X)$ is the posterior θ probability density function, if X is known.

The expert grade X is specified by the posterior mean function:

$$f_{mean}(X) = \int_{a}^{b} \theta \cdot f(\theta \vee X) d\theta. \qquad (3)$$

The specified $f_{mean}(X)$ and X grade difference will be called the expert grade adjustment.

While there are no real data on a course evaluation, it is supposed that the 'state of nature' is equally distributed on the evaluation scale, therefore the continuous case $f(\theta)$ is used in the thesis. Since the cumulated data on the course quality is known, it will be easy to provide it in 3 numbers: the smallest, largest, and most probable μ. Since the *a priori* experience might be not sufficient enough, the standard evaluation scale interval is used to describe the smallest and largest value of the triangle [1,10]. The *a priori* triangular probability density function is as follows:

$$f(\theta) = \begin{cases} \frac{2(\theta - a)}{(\mu - a)(b - a)}, as\ a \leq \theta \leq \mu \\ \frac{2(b - \theta)}{(b - \mu)(b - a)}, as\ \mu \leq \theta \leq b \\ 0, as\ \theta \notin [a, b] \end{cases}. \qquad (4)$$

The standard (Gaussian) distribution is applied to the data analysis, whereas the data is approximately normally distributed. The medium μ and standard deviation σ of the *a priori* Gaussian distribution function might be indicated according to the data collected by the institution, i.e. university course μ and σ values:

$$f(\theta) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\theta-\mu)^2}{2\sigma^2}}. \qquad (5)$$

To determine the expert error, the conditional triangular and the Gaussian probability density function were applied. Given that the real quality θ of the course is unknown, it might appear in any position of the interval $[a, b]$, therefore the expert error function is sliding throughout the entire *a priori* distribution interval. The expert error triangular probability density function $f(X \vee \theta)$ is symmetrical in relation to a state of nature θ. The expert error *k* is identified as evaluation deviation from the true course quality θ. The error of an experienced expert usually is not more than $k = 1$. The higher qualification is involved, the smaller error, i.e. the error of a very experienced expert is $k = 0.8$. The error of a less experienced expert is $k = 1.2$.

The conditional triangular probability density function is:

$$f(X \vee \theta) = \begin{cases} \frac{X - \theta + k}{k^2}, as\ \theta - k \leq X \leq \theta \\ \frac{-X + \theta + k}{k^2}, as\ \theta \leq X \leq \theta + k \\ 0, as\ X \notin [\theta - k, \theta + k] \end{cases} \qquad (6)$$

The conditional Gaussian probability density function is:

$$f(X \vee \theta) = \frac{1}{k\sqrt{2\pi}} e^{-\frac{(X-\theta)^2}{2k^2}}. \qquad (7)$$

The pilot course evaluation is executed during the process of changing *a priori* data and expert error distribution parameter values. The results are analysed and compared to one another. The following combinations are noticed: *a priori* uniform distribution with the conditional triangular and Gaussian functions, *a priori* triangular distribution with the conditional triangular function, and *a priori* Gaussian distribution with the conditional triangular and Gaussian functions.

The combination 'Uniform+Triangle' and 'Uniform+Gauss'

If the *a priori* probability density function is expressed as a uniform distribution and $f(X \vee \theta)$ as conditional triangular or Gaussian probability density functions, the posterior mean function $f_{mean}(X)$ is equal to X.

Whenever *a priori* data is described by uniform distribution, regardless the expert qualification k, the specified expert's grade value $f_{mean}(X)$ is equal to the actual value X, i.e. specification of the expert evaluation is equal 0. Therefore, the obtained evaluation results with collected *a priori* data are easily compared with the function $f_{mean}(X) = X$, which means the lack of initial information.

The combination 'Triangle+Triangle'

The *a priori* data are described by the probability density function of the triangular distribution presented in equation (4). The expert error is given by the conditional probability density function of triangular distribution with the mode in the point θ. In the specific case, where the average value of the probability density function of the *a priori* triangular distribution is $\mu = 6$ and the expert sliding symmetrical triangular distribution ($k = 1$) the value of θ obtains grade 7 presented in the Figure 1.

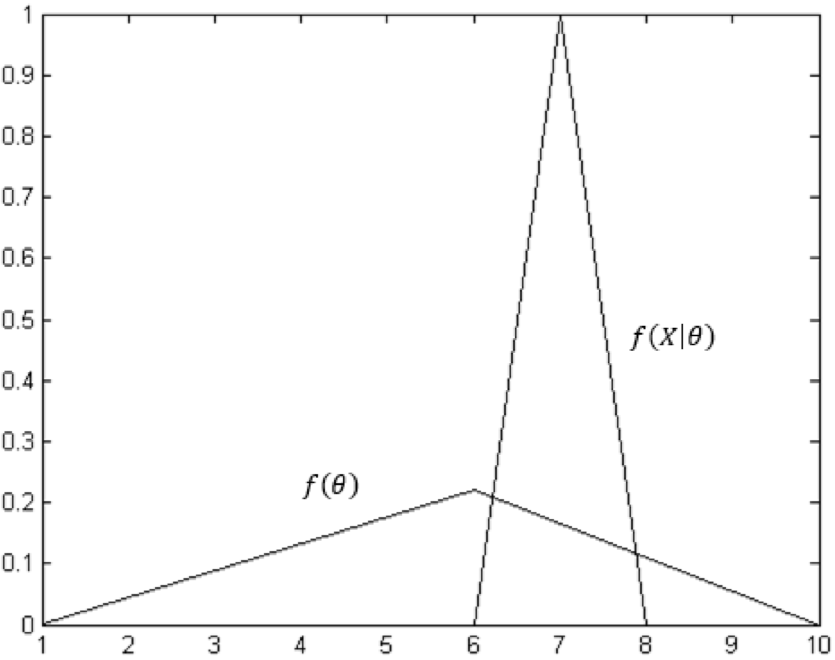

Fig. 1 *The a priori and conditional distributions presented as triangles (μ=6, k=1)*

The triangle of the expert error is sliding throughout the entire *a priori* distribution interval. The possessed function $f_{mean}(X)$ is accepted as a continuous approximation of the equivalent average expert evaluation X. The diagram function of the $f_{mean}(X)$ where the *a priori* and conditional distributions are presented as triangles *(μ=6, k=1)*, provided is illustrated in Figure 2 (no. 1).

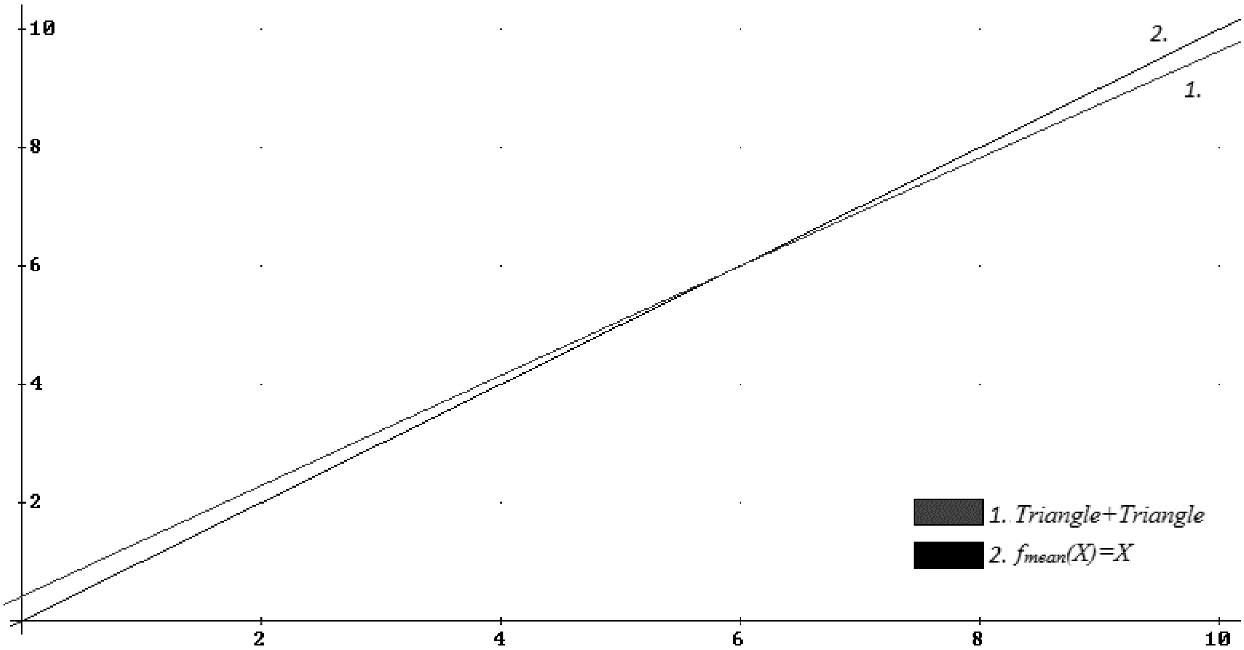

Fig. 2 *The diagram of the mean function, as a priori triangle distribution parameters are μ =6, a=1, b=10 and the conditional distribution is presented as a triangle with the error k=1*

According to the analysis of the results, the given $f(X)_{mean}$, values in Figure 2 no. 1 are larger in diagram no. 2 as $X < \mu$ and lesser as $X > \mu$. The average μ of *a priori* probability density function influences the expert's specified grade $f(X)_{mean}$: when value $X < \mu$ is increased, when $X > \mu$ – is decreased.

While analysing how big impact the expert's competence will have on the expert's grade X specification, it appeared that the higher expert's competence level is, the smaller adjustments are required.

The expert grade X is slightly adjusted for the smaller expert error ($k = 0{,}8$). In case the error k increases, the expert's X grade adjustments increase respectively.

The results have shown that if the meaning μ of the *a priori* distribution is high (or low) (see Fig. 3), the diagram of the function turns down, since the diagram of the conditional triangular probability density $f(\theta \vee X)$ gains the value θ in the final *a priori* function interval. Hence the conditional triangular probability density function falls outside the *a priori* triangular distribution interval border set. Subsequently, the significance of the $f(10)_{mean}$ function is not precise.

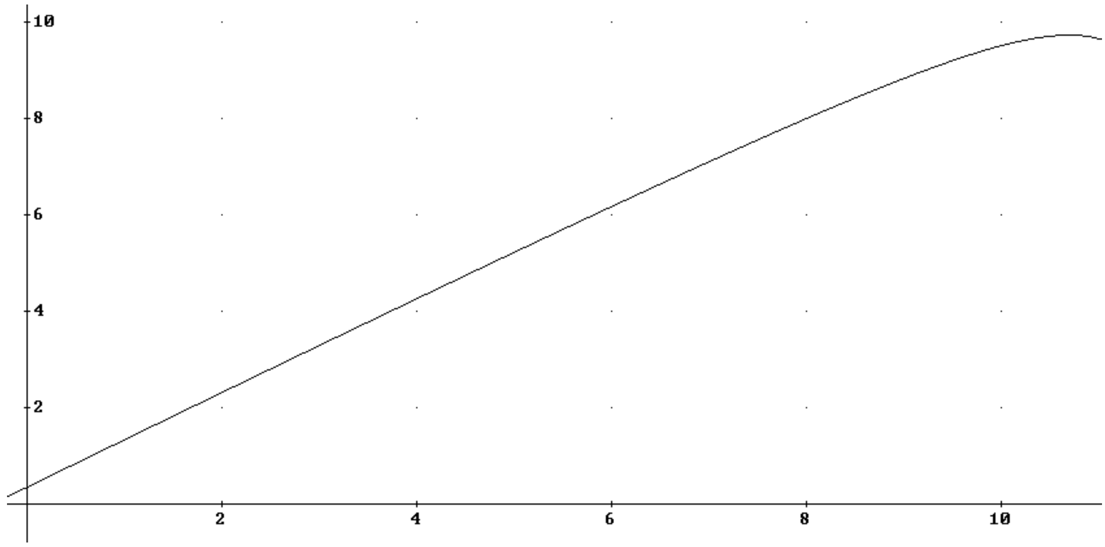

***Fig. 3** The diagram of the mean function, the value of the a priori triangular distribution are μ=8.3, a=1, b=10 and the conditional distribution is presented as a triangle with the error k=1*

In the case of *'Triangle + Triangle'* function, whenever the *a priori* μ value is high (low), the combination is not advised to be used due to the inaccuracy at the end (at the beginning) of the posterior function average.

The combination 'Gauss+Triangle'

The *a priori* Gaussian distribution (as $\mu = 5$, $\sigma = 1$) and the expert symmetrical triangle distribution (as $k = 1$) diagrams are provided in Figure 4, whereas θ of the sliding triangle is in position 7.

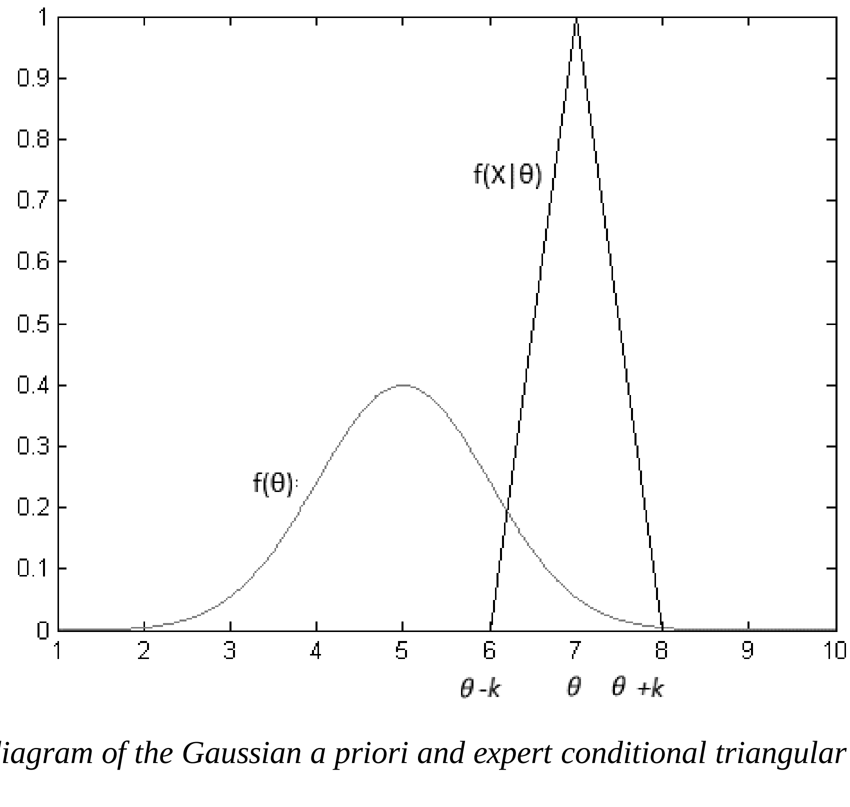

***Fig. 4** The diagram of the Gaussian a priori and expert conditional triangular distributions*

If the average of the Gaussian probability density function is large, the area (under the Gaussian function diagram) at the beginning of the interval is small. The conditional triangle falls outside the *a priori* function interval border set whenever the value of the conditional triangular θ is at the beginning of the *a priori* function interval. Discontinuity appears in the function $f(X)_{mean}$ due to a small area of the *a priori* and conditional probability density functions (see Fig. 5). In the case of the Gaussian *a priori* function value μ increases, the discontinuous interval increases at the beginning of $f(X)_{mean}$ function.

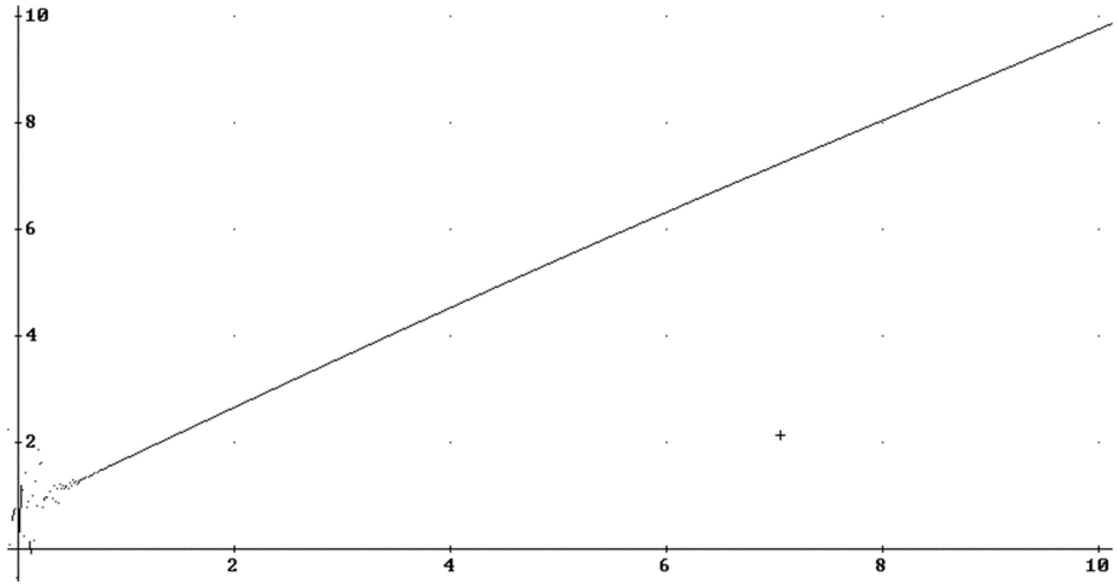

Fig. 5 *Diagram of the mean function, as Gaussian a priori distribution values are μ=8.3, σ=1 and conditional distribution is presented as a triangle with the merge of error k=1*

In the case of the 'Gauss+Triangle' where a high *a priori* value appears, the diagram of the function is not continuous at the beginning. Whenever the average of the Gaussian *a priori* function increases, the discontinuous interval of the function average also increases. In the case of a low *a priori* average, the diagram of the function average is discontinuous at the end of the function interval.

The combination 'Gauss+Gauss'

Due to the appearance of discontinuities with high values of the *a priori* distribution average in the functions of the previous combinations, a comparison of the experts with different levels of competence will be initiated, whereas the *a priori* average is very high – $\mu = 9$.

Firstly, a small standard deviation $\sigma = 1$ of *a priori* distribution will be analysed bellow (Table 1).

Table 1. *The calculation results of the $f_{mean}(X)$ for certain X*

Experts' errors / Experts' grades	X=1	X=2	X=4	X=6	X=8	X=9	X=10
$k = 0.8$	4.12	4.73	5.95	7.17	8.38	8.93	9.33
$k = 1$	5	5.5	6.5	7.50	8.47	8.89	9.21
$k = 1.2$	5.72	6.13	6.95	7.77	8.53	8.85	9.12

Despite the fact that, the *a priori* average grade is high ($\mu = 9$), $f(X)_{mean}$ function is continuous throughout the entire function interval. The adjustment of the grade increases in case the parameter k is also increasing.

With different level of experts' competence, the value $f(X)_{mean}$ was compared, when dissemination of grades $\sigma = 2$ *a priori* distribution was increased.(Table 2).

Table 2. *The calculation results of the $f_{mean}(X)$ for the certain X*

Experts' errors / Experts' grades	X=1	X=2	X=4	X=6	X=8	X=9	X=10
$k = 0.8$	2.2	2.97	4.69	6.41	8.13	8.87	9.35
$k = 1$	2.67	3.41	5	6.6	8.15	8.78	9.2
$k = 1.2$	3.17	3.86	5.32	6.79	8.16	8.69	9.08

Whenever the grade dissemination is larger, the results are less adjusted and therefore are closer to the real expert grade X. The grade adjustment of the high expert qualification ($k = 0.8$) is smaller. When the *a priori* average evaluation is high (or low) in the 'Gauss+Gauss' case, coherent results are obtained throughout the entire interval.

The above mentioned cases are compared with one other, the value of the average of the *a priori* probability density function is $\mu = 7.3$, $\sigma = 1$ and the expert error is $k = 1$.

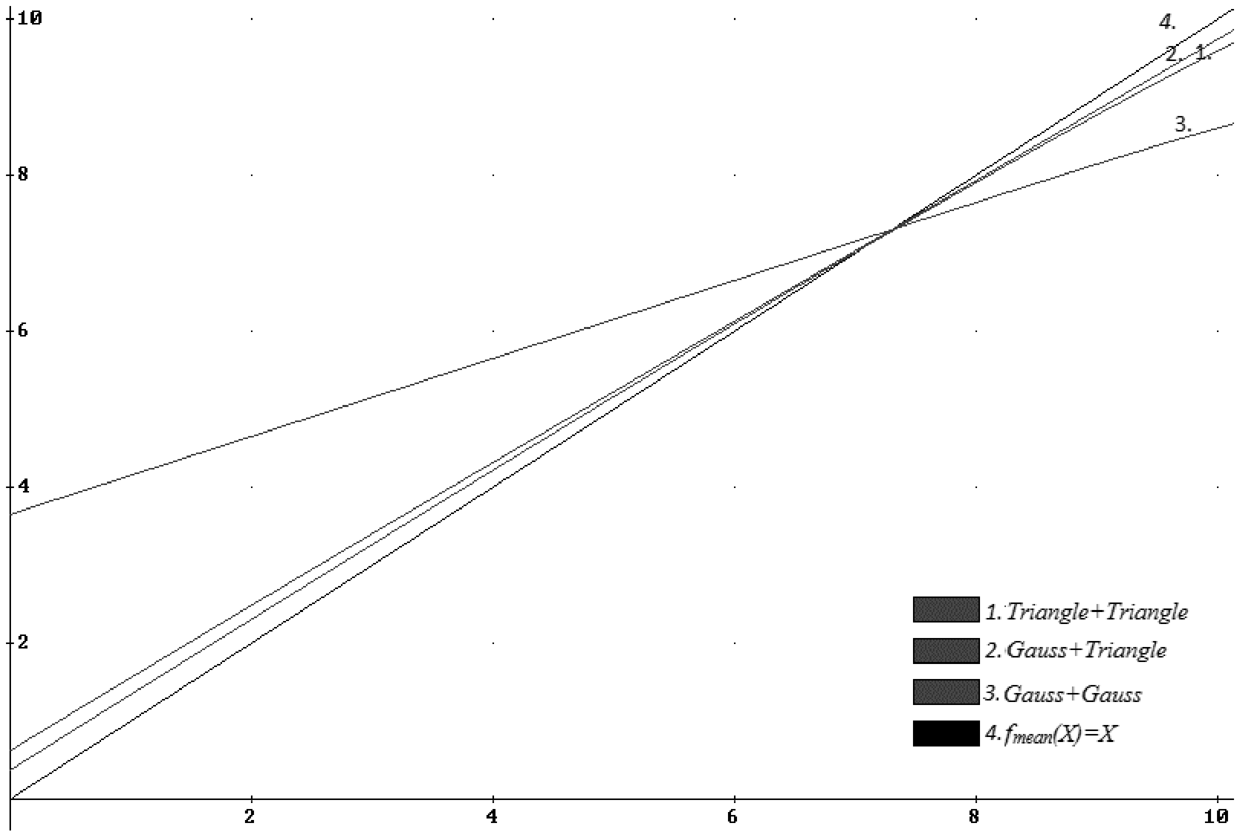

Fig. 6 *The results of the $f_{mean}(X)$ where μ=7.3, $\sigma = 1$, k=1*

Table 3. *Stipulation of the course average evaluation where the expert grade is X*

Functions/Expert's grades	X=1	X=2	X=4	X=6	X=7,3	X=8	X=10
'Triangle+Triangle'	1.34	2.30	4.22	6.09	7.28	7.91	9.59
'Gauss+Triangle'	1.65	2.60	4.44	6.19	7.3	7.89	9.63
'Gauss+Gauss'	4.15	4.65	5.65	6.65	7.3	7.65	8.6

The following conclusions can be drawn from the investigation:

- The values of the mean function $f(X)_{mean}$ coherently change depending on the *a priori* experience: they increase as $X <\mu$, and decrease as $X >\mu$.
- The adjustment of the high expert qualification (*k=0.8*) grade is minor. Whenever the merge of error k (*k=1, k=1.2*) increases, the error of the evaluation adjustment increases as well.
- The results are closer to the real expert evaluation with the increase of σ in the case of the *a priori* Gaussian distribution.
- In the 'Gauss+Gauss', case coherent results are obtained throughout the entire interval.

The assessment of distance learning courses applying a stable MCDM method

The MCDM methods calculate the course evaluation by means of the expert evaluation data. The data is the course quality grades according to the presented quality criteria and evaluation of the weights of this criteria.

There are a lot of MCDM methods and their algorithms differentiate. Due to this reason, the calculated by different MCDM methods, are located in different intervals. Typically, the MCDM methods are applied to determine the best alternative, i.e. in order to choose the optimal one from a number of possible. Due to this reason, the MCDM methods are convenient to consider in the mathematical optimisation framework.

In order to calculate the criteria weights, the AHP and AHPF mathematical methods are applied in the thesis. The compilation of algorithm of AHPF method a pairwise comparison matrix, that takes into account the opinion of an independent expert group was proposed in the thesis.

The quality of the course has been evaluated in three stages, whereas the course evaluation was performed by different expert groups at each stage, since every expert group evaluates the course according to their knowledge and experience in the field. The final course evaluation is summed up out of the three evaluation stages. The summation takes place with regard to the importance of each stage, set by administration of an university.

Altogether, it is proposed in the thesis to apply the Bayesian approach for recalculating the weights of the criteria in view of the opinion of other expert groups.

The Bayesian equation allows us to recalculate the weights established by administration and taking into consideration the opinion of another group of experts. Due to that, it is possible to find a course for each group of experts.

The methodology suggests choosing the results calculated by the most stable method, applying several MCDM methods in the quality evaluation. That is why the stability of the applied methods has been tested at each stage of the course quality evaluation applying MCDM methods.

Formulation of optimisation tasks for MCDM methods

Whenever the number of alternatives is finite in the classic multiciriteria optimisation, when changing the criteria weights, the expert observes how the order of the sequence of alternatives is changing according to the general criterion and then chooses one out of possible arrangements of the alternatives.

In the case of optimal solution, the criteria weights of distance learning courses are determined by the experts and cannot be changed. For that reason there is a necessity to use MCDM methods such as SAW, TOPSIS, COPRAS, MOORA, PROMETHEE which apply invariable expert grades in the process of calculation.

The MCDM methods are based on the decision matrix r_{ij} and the criteria weights vector ω_j, *j=1,...,m*. In general, the case of MCDM methods can be mathematically formulated as the optimization task:

$$i_{opt}(r) = \arg max_i f_i(r, \omega), i = 1, \dots, n. \tag{8}$$

The merit of alternatives *i=1,...,n* is evaluated according to the criteria *j=1,...,m*, whereas the value is defined as $r = (r_{ij})$. Since the influence of the criteria on the evaluation outcomes is different, the vector of the criteria value $\omega = (\omega_j)$, *j=1,...,m,* that determines the importance of criteria, is stipulated.

Furthermore, one of the applied methods, presented as an optimisation task, is provided in the annotation. The *Technique for Order of Preference by Similarity to Ideal Solution* (*TOPSIS*) method is expressed as follows:

$$i_{opt}(r) = \arg max_i \frac{\sqrt{\sum_{j=1}^{m}(\omega_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{-}))^2}}{\sqrt{\sum_{j=1}^{m}(\omega_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{+}))^2}+\sqrt{\sum_{j=1}^{m}(\omega_j(\tilde{r}_{ij}-\tilde{r}_{ij}^{-}))^2}}, \text{ where } \tilde{r}_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n} r_{ij}^2}}. \tag{9}$$

$\tilde{r}_{ij}^{-}(\tilde{r}_{ij}^{+})$is the normalized worst (best) value of the j^{th} criterion of the i^{th} alternative.

Structure of the AHPF method to determine the criteria weights

The AHP method is aimed at determining the significances (weights ω_i) of the evaluation criteria. The weights of criteria reflect the opinion of expert evaluators on the importance of criteria in comparison with other criteria.

The compilation method of the pairwise comparison matrix $\tilde{P}$ for determining *AHP Fuzzy* (AHPF) criteria weights is proposed in the thesis. The *AHP Fuzzy* method forms one pairwise comparison matrix of the group by applying a triangle Fuzzy set. Consequently, the method determines the weights of the criteria that takes into account the general opinion of the expert group.

The expert group AHPF pairwise comparison matrix $\tilde{P}$ is compiled from separate AHP experts matrixes $\bar{p}_{ij}^{t}$, where $t = 1,2..T$, T is the number of experts.

The pairwise comparison matrix group of the triangle Fuzzy set $\tilde{P} = \tilde{p}_{ij} = (L_{ij}, M_{ij}, U_{ij})$ is compiled as follows:

$$M_{ij} = \frac{\sum_{t=1}^{T} p_{ij}^{t}}{T}; L_{ij} = \min_t p_{ij}^{t}; U_{ij} = \max_t p_{ij}^{t}, \tag{10}$$

as $j \geq i$ the matrix is filled in as $\tilde{P} = \tilde{p}_{ij} = (L_{ij}, M_{ij}, U_{ij})$. Since the matrix is inverse symmetric, $\tilde{p}_{ij}{}^{-1} = (\frac{1}{U_{ij}}, \frac{1}{M_{ij}}, \frac{1}{L_{ij}})$, where $i = j$, and therefore $\tilde{p}_{ij} = (1,1,1)$.

The extent analysis method proposed by Chang is used for the synthetic extent value $\tilde{S}_i$ of the pairwise comparison:

$$\tilde{S}_i = \sum_{j=1}^{\mathrm{m}} \tilde{p}_{ij} \otimes \left\{\sum_{i=1}^{\mathrm{m}} \sum_{j=1}^{\mathrm{m}} \tilde{p}_{ij}\right\}^{-1} i, j = 1\ldots, m. \tag{11}$$

The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is expressed as follows:

$$\left(\tilde{S}_{i+1} \geq \tilde{S}_i\right) = 1, if \;\; M_{i+1} \geq M_i, 0{,}001, if \;\; L_i \geq U_{i+1}, \frac{L_i - U_{i+1}}{(M_{i+1} - U_{i+1}) - (M_i - L_i)}\} \tag{12}$$

The weights of the lowest probability level are indicated:

$$V\left(\tilde{S}_{i+1} \geq \tilde{S}_i | i = 1, \ldots m\right) = \min_{i \in \{1,\ldots,m\}} V\left(\tilde{S}_{i+1} \geq \tilde{S}_i\right), i = 1, .. m. \tag{13}$$

Further, the weight vector is given:

$$w_i = \frac{V\left(\tilde{S}_{i+1} \geq \tilde{S}_i | i = 1, \ldots m; i + 1 \neq i\right)}{\sum_{g=1}^{m} V\left(\tilde{S}_g \geq \tilde{S}_i | i = 1, \ldots m; i \neq g\right)}, i = 1, \ldots, m. \tag{14}$$

The use of the Bayesian equation in the recalculation of criteria weights

The recalculation of the importance of the criteria by applying the Bayesian approach is proposed in the thesis, where the experts who made a decision wish to consider the opinion of other groups. In our case, θ_j is a valuable course quality criteria. The criteria weights, are adjusted after the new information has been received. The value of the criteria ω_j (analogue of the probability $P(\theta_j)$), shows the influence degree of the j^{th} criterion on the evaluation result, $P(H_\xi) \sim \omega_j$ and $\sum P(H_\xi) = 1$. $\omega(H | \theta_j)$ is the influence degree of j^{th} criterion on the evaluation result.

The expert groups evaluate the stage in a 10-score system. X_{jt} is the evaluation matrix of experts

$$\omega(X | H_j) = \frac{\sum_{t=1}^{T} X_{jt}}{10T} \tag{15}$$

The Bayesian equation may be modified in the following way:

$$\omega(H_j | X) = \frac{\omega(X | H_j)\omega(H_j)}{\sum_{j=1}^{m} \omega(X | H_j)\omega(H_j)} \tag{16}$$

The Bayesian approach is applied to recalculate the weights of the evaluation stages, determined by the administration in the thesis, regarding the opinions of other expert groups.

The stability verification of the MCDM method

The outcomes of several MCDM methods, applied to evaluate the distance learning courses might differ. Thus, it is not clear the results of which method are more reliable. Each method has its own logic, therefore the changes, applied to the initial data (i.e. alternative grades, criteria weights), might influence the final result.

Furthermore, any mathematical model and method might be applied in practice, in case they are stable in relation to the applied parameter. The mathematical model is considered to be stable, if changes in the results correspond to minor changes in model parameters.

Whenever the stability of the MCDM methods is verified, the initial decision matrixes are balanced (or slightly modified), i.e. vector results of the expert assessments r_{ij} and weights w_i where the reoccurrence rate best alternative of the initial data is monitored. The algorithm of the MCDM method stability verification is presented in Figure 7.

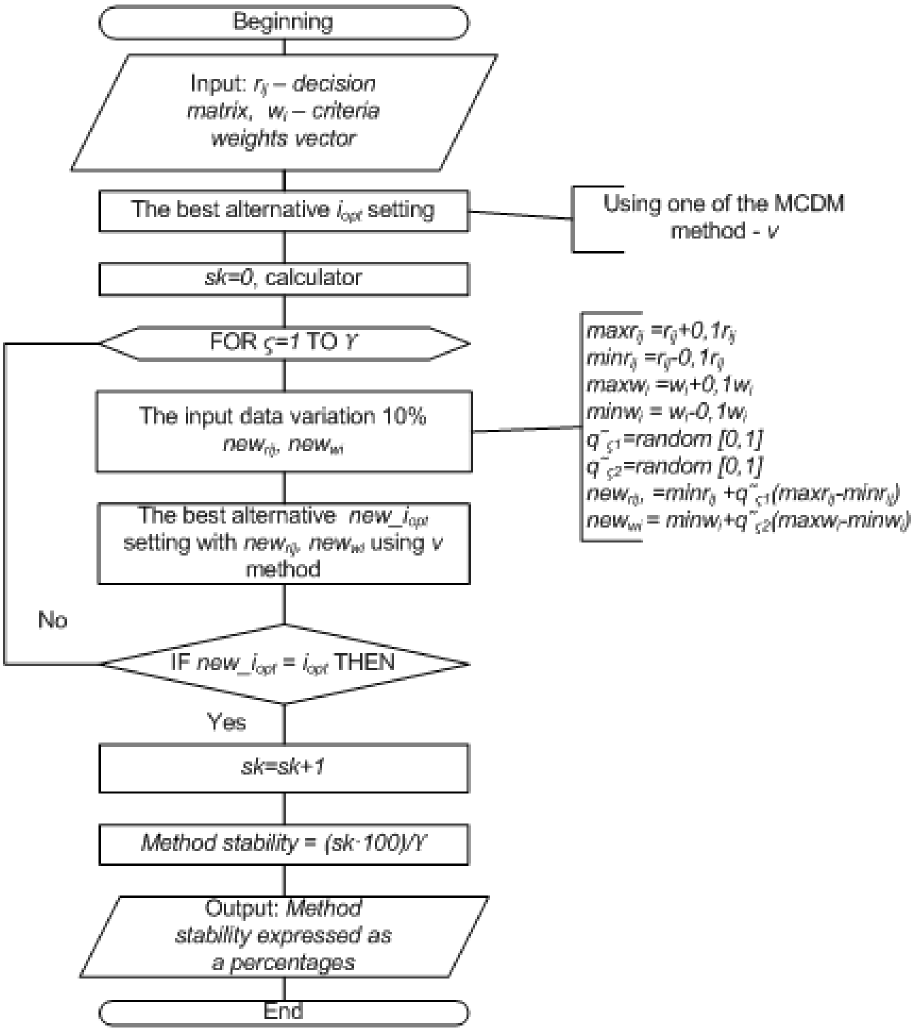

***Fig. 7** The algorithm for verifying MCDM stability*

In case the location of the MCDM method parameters is unknown, the uniform distribution has to be applied with the random $\bar{x}_\varsigma$ weights of interval $[\underline{X}, \overline{X}]$ generation:

$$\bar{x}_\varsigma = \underline{X} + \tilde{q}_\varsigma \cdot (\overline{X} - \underline{X}), \qquad (17)$$

where $\tilde{q}_\varsigma \in [0,1]$.

Applying equation (17), the random weights of the alternative grades

$$new_{r_{ij}} = \min r_{ij} + \tilde{q}_\varsigma \cdot (\max r_{ij} - \min r_{ij}) \qquad (18)$$

and the criteria weights

$$new_{w_i} = \min w_i + \tilde{q}_\varsigma \cdot (\max w_i - \min w_i) \qquad (19)$$

New data is generated by modifying the initial data r_{ij} ir w_i 10%,
where $\tilde{q}_\varsigma \in [0,1]$.

The range of variation $[\min r_{ij}, \max r_{ij}]$ of the alternative assessments r_{ij} are determined as follows:

$$\begin{aligned} \max r_{ij} &= r_{ij} + 0{,}1 \cdot r_{ij}, \\ \min r_{ij} &= r_{ij} - 0{,}1 \cdot r_{ij}. \end{aligned} \tag{20}$$

Consequently, the range of variation $[\min r_{ij}, \max r_{ij}]$ of the criteria weights w_i equals to:

$$\begin{aligned} \max w_i &= w_i + 0{,}1 \cdot w_i, \\ \min w_i &= w_i - 0{,}1 \cdot w_i. \end{aligned} \tag{21}$$

The higher the imitation number, the more accurate evaluation of the MCDM method stability is. In fact, it is enough to have 10^5 imitations to evaluate different number of imitations defining the exact outcome for evaluating the MCDM methods. If the evaluation is initiated by using several MCDM methods, it is recommended to choose the most stable result of the method. In case the stability grades of some methods are similar or slightly different, it is suggested to determine results by applying Pareto of the most stable methods.

4. A comprehensive evaluation of a distance learning course

A complex evaluation methodology of the distance learning course is accomplished in the following section, considering the characteristics of data uncertainty, applying the previously described Bayesian approach, stable MCDM methods, and the Fuzzy set.

A complex evaluation of three distance learning courses was used in the thesis: 1st Course – Discrete Mathematics, 2nd Course – Mathematics 2, 3rd Course – Integral Calculus. The courses were placed in the VGTU Moodle virtual learning environment. The evaluation was completed in three successive stages.

Stages of the course evaluation

The creation of a distance learning course is a long-term process where specialists from several fields are involved. The remote teaching has its own specifics, since it is not only the preparation of teaching material, but also it includes the course uploading to the virtual learning environment and the entire learning process organisation. An expert evaluation is implemented at the end of each course stage. In case the evaluation is negative, the course has to be improved. The learners' opinion on the course and the quality of the studies is vital for the distance learning course evaluation. The three main evaluation stages of the distance learning course evaluation and the expert groups that conduct the evaluation are emphasised in the work, respectively.

According to Belton and Stewart's principles of the identification of quality evaluation criteria, the following group of criteria was offered for each stage of the evaluation process.

The first group of criteria: evaluation of the course content.

1) The course structure: the general structure of the course, integrity of the content, and clarity. 2) Correspondence of material to the program: the content and scope of the material (purpose, tasks, number of hours) must correspond to the programme of the subject considered. 3) Relevance of material: the material has to be relevant and the data and quoted publications cannot be out-of-date. 4) Testing of knowledge: the tasks of

various types, that help master difficult material and tests with a feedback, correct answers to test one's own knowledge; tests with the view of the lecturer to evaluate the student's knowledge; a clear system of knowledge assessment. 5) Clarity of material presentation, i.e. the teaching material has to be presented in a clear and understandable mode.

The second group of criteria: effective use of tools.

6) Introduction of the course material: the course material is presented in a consistent manner. The sub-themes and a large number of files are organised in a hierarchical manner. The topic titles are listed in an accurate manner with no blank topics left. The text presented is legible. The fundamental organisational information is outlined in a brief and clear manner at the beginning of the course. The graphics of the course materials is not overwrought with colours, pictures, and animation. 7) Means of knowledge testing and calculation of the grade: are usage of tests and tools for presenting the work and checking the system's calculation of the final grade. 8) The Learners' Community: is an easy, comfortable, and fast way of communicating with the working party. Synchronic and asynchronic communication tools are envisaged. An effective videoconference tool that maintains good connection is used during the group transmission. 9) The Material legibility and availability: consist in good information transmission speed and good connection. A correct video format is chosen, the material upload is fast, the quality of the video record and sound is of a high quality. The material is available with the help of widely available aids. The material is available without additional login sessions. 10) Personalisation: the educational path is personalised according to the needs of the learners. A coercive educational path with certain regulations and/or deadlines might be implemented. 11) Some help to a student: comprehensive information and availability of instructions how to start the course and participate in a virtual lecture as well as the schedule and calendar of studies.

The third group or criteria: course teaching.

12) Professionalism of lecturers: the lecturer's ability to present the material in an interesting and clear way; 13) Organisation of teaching and help to students: an organisation of a teaching process is well implemented and the most important information is presented; the lectures are conducted smoothly and on time; a clear structure of the material. 14) The self-education: interesting and useful tasks inducing a feedback were envisaged. 15) Practical benefit of the course: acquisition of knowledge, practical skill and competences. 16) Comfortable and suitable usage of information technologies: the material is easy to open and fast to download; intuitive, simple usage, comfortable communication means, and good connections.

Application of the Bayesian approach to evaluate a distance learning course

The Bayesian approach implicates the entire experience, that is to say, the entire history information on the course evaluation and competence of the expert performing the course evaluation. The experts' competence was acknowledged considering their actual relation to the subject evaluated by them. The content of the course was rated by the experts with the basic mathematical education. The expert error were determined as follows: the highest educational degree, a professor $k = 0.8$, an associate professor $k = 1$, lecturers and assistants $k = 1.2$. The course, emplaced into the virtual learning environment and usage of the IT tools during the distance teaching were evaluated by computer specialists with university level degree and experience in distance learning course evaluation, whereas their competence was of the equal level. The third stage evaluation was accomplished by students. No attention was paid to the students' active participation in class, assessment of the subject knowledge and other factors that might evaluate the students' competence. Therefore, one general competence was assigned to the entire third group. The error $k = 1$ was assigned to the experts of the second and third stages in their evaluation groups, respectively.

The *a priori* information on the course evaluation was set by the Gaussian distribution, that is, values of the average μ and standard deviation σ. With regard to the gathered VGTU evaluation data, it is important to mention that the experts (lecturers) were evaluating the content of the course by writing an annotation on the course quality. The IT specialists evaluated the course uploaded to the virtual learning environment, by grades. They partially evaluated the factors of the first stage in the thesis, therefore the *a priori* data of the first and second evaluation stage were calculated using according to the actually gathered grades of the university courses ($\mu = 7.543$, $\sigma = 1.528$). The third stage of *a priori* Gaussian dimensions σ and μ as determined, based on the gathered grades of the university students from the courses of mathematical field ($\mu = 7.838$, $\sigma = 1.932$). The graphs of the different qualification experts' functions $f_{mean}(X)$ and $f_{mean}(X) = X$ at the first and second evaluation stages are presented in Figure 8.

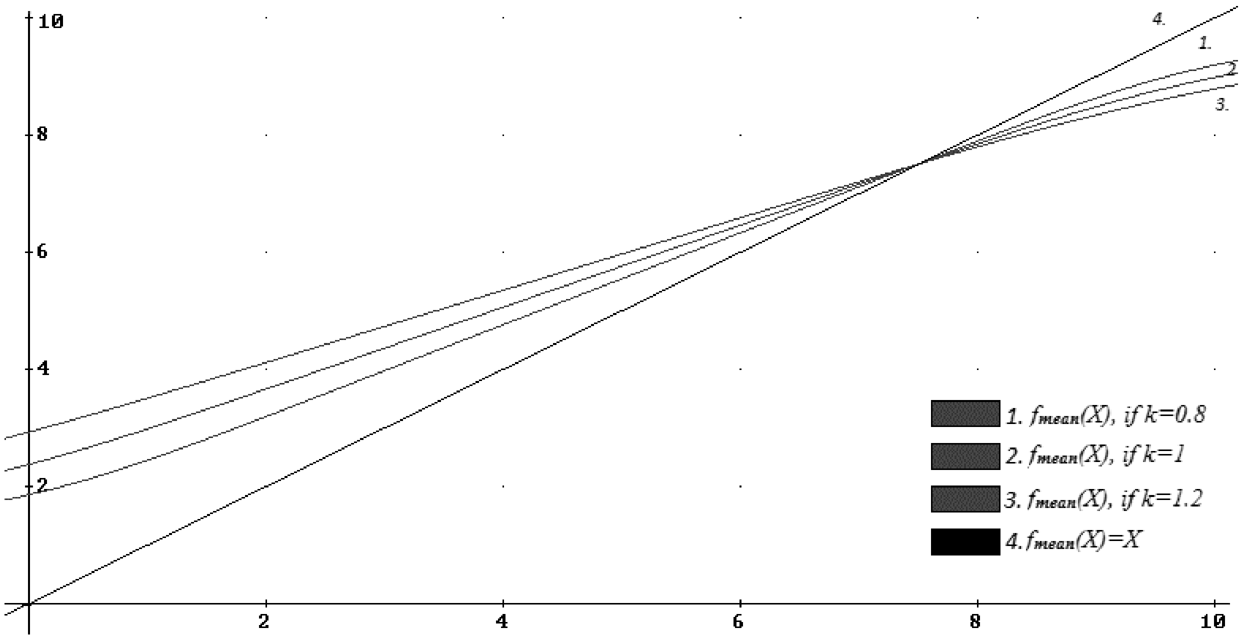

Fig. 8 *The graphs of the $f_{mean}(X)$ at the first and the second evaluation stages*

Furthermore, according to Figure 8, the graphs intersect at the same position $\{7.543; 7.543\}$, where the expert grade X is coincident with the university *a priori* average μ. If the expert grade is lower than the *a priori* average ($X < \mu$), then the function $f_{mean}(X)$ increases the grade X (graphs no. 1, 2, 3 are higher than the graph) $f_{mean}(X) = X$. If $X > \mu$ the mean function decreases the expert grade X (graphs no. 1, 2, 3 are lower than graph $f_{mean}(X) = X$). According to the different qualification graphs $f_{mean}(X)$, inexperienced experts' evaluations are more adjusted (graph no. 3, as $k = 1.2$). Proficient experts' qualification assures a lower adjustment (graph nr. 1, as $k = 0.8$), since their opinion is more trusted.

The experts distinguished the quality of the distance learning courses by accomplishing a direct ten-point scale evaluation with the grade X. The average of the initial experts' grades X is illustrated in the Figure 9.

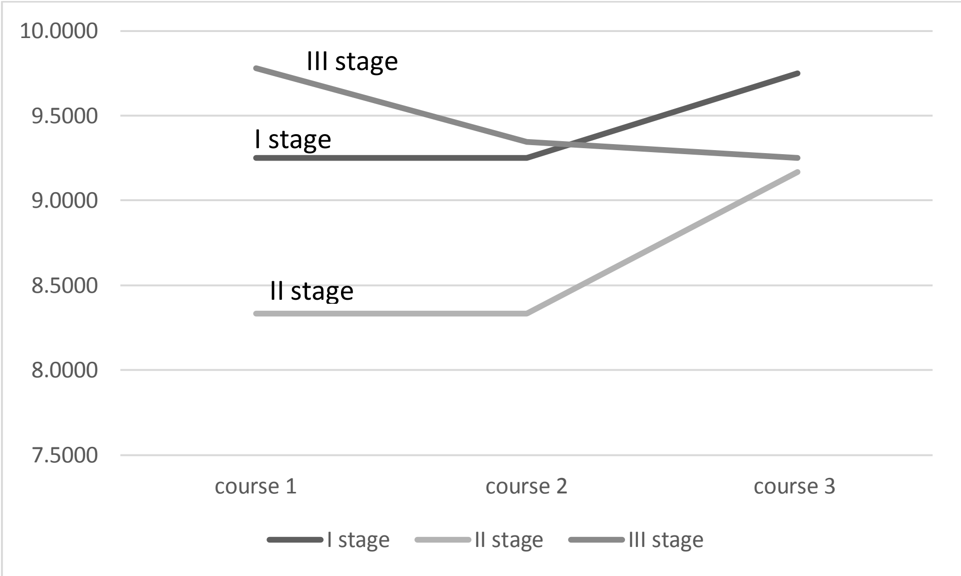

Fig. 9 *The graphs of the initial experts' grades X*

As reflected in Figure 9, the evaluation tendency of the lecturers and IT specialists is analogous. The 3rd course was identified as the best one even before it was started to be taught to students. Nonetheless, according to the students' opinion it is inferior to the other courses. The 1st and the 2nd courses were identified by the students as the best ones. Most criticism came from the IT specialists, as their evaluations were lower than that of the other expert groups. The Bayesian approach adjusts each expert grade X by applying a relevant evaluation function $f_{mean}(X)$. The three evaluation stages with the Bayesian approach applied are graphically presented in Figure 10.

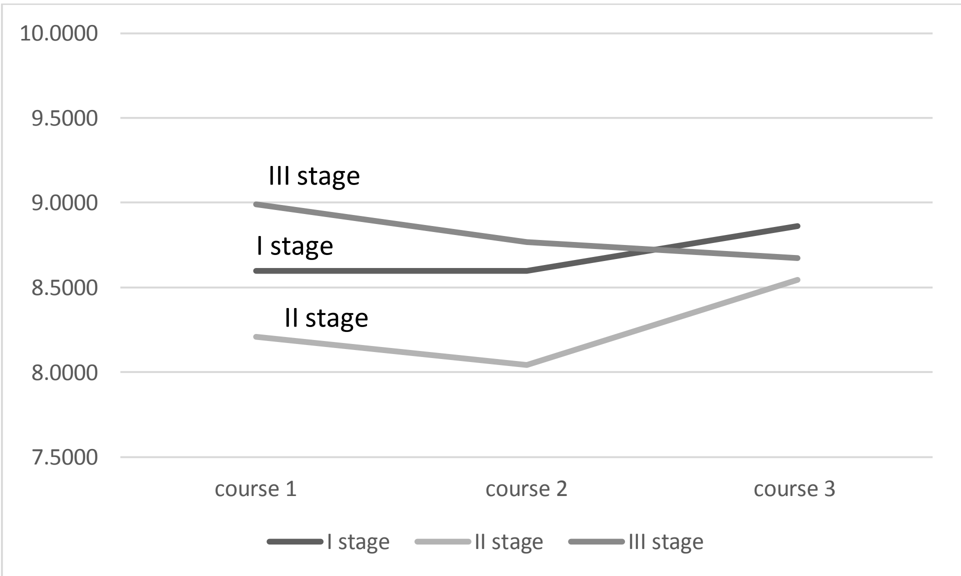

Fig. 10 *Graphs of the evaluation results applying the Bayesian approach*

As follows from Figure 10, the graphs of the three evaluation stages are situated closer to one other than in case of the initial evaluation results (Fig. 9). All of the expert evaluations were allocated in the interval from 8 to 9 points applying the Bayesian approach. Comparing these given results with the average of the initial expert X grades, all of the values of the grades have decreased considering the low *a priori* distribution average, although the evaluation tendency remained the same (Fig. 9-10).

Application of MCDM methods to evaluate distance learning courses

The importance (weights) of criteria is considered together with the course grades when applying the MCMD methods. Nonetheless, the competence of the experts involved into the evaluation is not taken into consideration.

The evaluation of the MCDM methods consists of 2 stages:

1. The course evaluation according to the criteria,
2. Determination of the criteria weights.

The experts carry out a direct course evaluation on a ten-point scale according to the quality criteria foreseen in the MCDM methods. The MCDM methods averages of the initial expert grades are presented graphically in Figure 11.

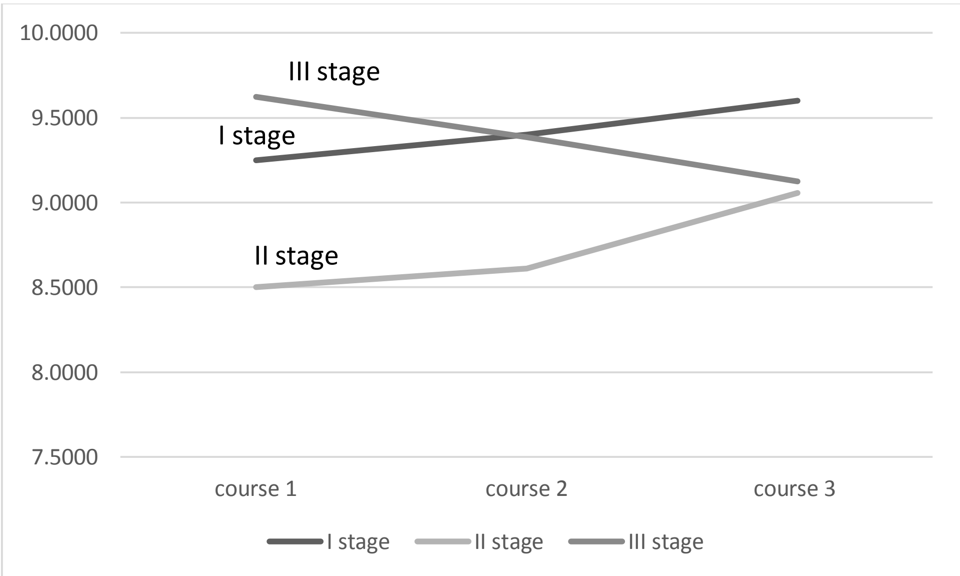

Fig. 11 *Graphs of the initial experts grades of MCDM*

As seen in Figure 11, the lecturers and IT specialists' evaluations of the course are analogous (however, the lecturers evaluated the courses with higher grades). They have determined that the best course is the 3rd one, while the 1st one is the worst. Despite that, the students' opinion drastically differs from the first two groups' opinion. They have decided the 1st course to be the best one and the 3rd to be the worst one. The quality of the course was evaluated in the narrow range of grades range between 5 and 9.7 points.

The tendency of evaluation is analogous as it appears when analysing Bayesian approach (Fig. 9) and MCDM methods (Fig. 11) grades of the initial experts evaluation average. The correlation coefficient of the average grades was calculated for higher-precision benchmarking assessment of the initial expert evaluations. In the process of comparison by evaluation stages, the correlation coefficients are as follows: Stage I – 0.904, Stage II – 0.982, Stage III – 0.93.

The AHP and AHPF methods are applied to calculate the weights of the criteria. Each expert had to fill in a pairwise comparison matrix in order to determine the criteria weights. The consistency of the matrix was examined by determining the index and the ratio of the consistency. The consistent experts' pairwise comparison matrices were selected for the further computations. Apparently, by applying the Kendall theory, it has been determined that the opinion of expert groups in three-stage evaluation is coordinated. According to the experts' opinion, distinctiveness of the learning material, understandable instructions and the structure of the course have the greatest impact on the quality of the course. The lecturers think that the correspondence of the material to the study programme is very important. IT specialists have identified that the course material, presented in a consistent, accurate and legible manner has the greatest impact on the quality of the studies. It is also important to align the importance of the material legibility, the good access to it and the usage of the knowledge examination measures. According to the learners' opinion, the greatest impact is achieved by the professionalism of the lecturer presenting the material in an interesting and understandable way. The proper organisation of a productive teaching process as well as assignment of interesting and useful tasks for the individual study is important as well.

A standard deviation was calculated to compare the two applied methods (AHP and AHPF) criteria weights in the thesis. The result has showed that the AHP method, specified standard deviation of the criteria weights is significantly higher than the AHPF method. Data scattering of the results of the AHPF method is significantly lower, since the method calculates the criteria weights taken from pairwise comparison matrix of the general group that considers the general opinion of the expert group.

Several MCDM methods are applied to establish the quality of the course after calculating the initial grades and criteria weights of the experts' course evaluation. Due to maximisation of all criteria by linear scalarisation, the calculations of the SAW and COPRAS methods coincide (hereafter, the SAW method will be mentioned in the work).

Furthermore, the stability of the methods is verified by applying several MCDM methods in the course assessment. The methods' stability results of three evaluation stages, calculated by identified AHP and AHPF weights are presented in Table 4.

Table 4. *Method stability results according to AHP and AHPF methods*

		STAGE I		**STAGE II**		**STAGE III**	
		Best Course	Method stability	Best Course	Method stability	Best Course	Method stability
SAW	AHP	Course 3	56%	Course 3	90%	Course 1	66%
	AHPF	Course 3	66%	Course 3	91%	Course 1	72%
TOPSIS	AHP	Course 3	51%	Course 3	87%	Course 1	63%
	AHPF	Course 3	67%	Course 3	86%	Course 1	71%
MOORA	AHP	Course 3	55%	Course 3	88%	Course 1	65%
	AHPF	Course 3	66%	Course 3	88-89%	Course 1	71%
PROMETHEE	AHP	Course 3	52%	Course 3	87%	Course 1	58%
	AHPF	Course 3	60%	Course 3	87%	Course 1	65%

The results given in Table 4 show that all the MCDM methods have determined the best course in an analogous manner, i.e. according to the evaluation Stage. Stage I and Stage II, the 3rd course is by far the best, the Stage III showed the 1st course is the best one.

Conspicuously, the method stability is higher if computed criteria weights established by the AHPF methods. Therefore, the criteria weights, identified by the AHPF methods will be applied in further calculations.

It is also vital to consider that the evaluation stages are not equally important in the process of recapitulating the results of three evaluation stages. The scope of the work, the timeframe needed to prepare the course and to evaluate it, and the experts' qualification are different. The high school administration department, responsible for the quality of the studies, determines the importance of evaluation. The weights of the stages determined by the administration ($\omega(X) = \{0.3649,\ 0.3261,\ 0.3090\}$).

Recalculation of criteria weights of all three stages was proposed in the thesis, considering the importance of the stages and completing a simple data transformation:

$$\widetilde{\omega}_i = \omega_i \cdot \omega_{stage}, \sum_{i=1}^{m} \widetilde{\omega}_i = 1, \tag{22}$$

where $\widetilde{\omega}_i$ are the three criteria weights of summarised evaluation equal to 1. ω_i are criteria weights of a separate evaluation stage, ω_{stage} is the importance of the evaluation stage.

Several MCDM methods were applied to estimate the overall result of the final course evaluation. The stability of the MCDM methods was verified. The summarised results of three-stage evaluation with the MCDM methods applied were presented in pie chart diagrams. (Fig. 12–15) indicate the result of each course in percentage, i.e. the overall results of the courses is presented as 100 %.

The final result of the SAW method evaluation is given in Figure 12.

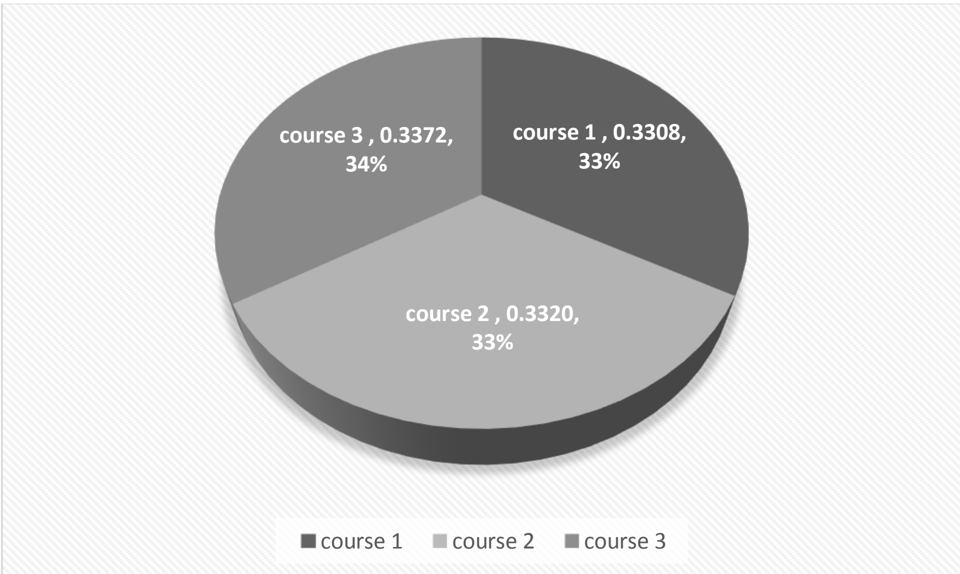

Fig. 12 *The final percentage result of the course quality evaluation using SAW method*

The results have shown that the 3rd course is by far the best. The evaluation of the other two courses is fairly identical. The defined quality of the courses is analogous since the 3rd course differs from the other two courses only by 1 %. The drawback of the SAW method is the fact that even if the smallest changes in criteria weights take place, the evaluation results might change.

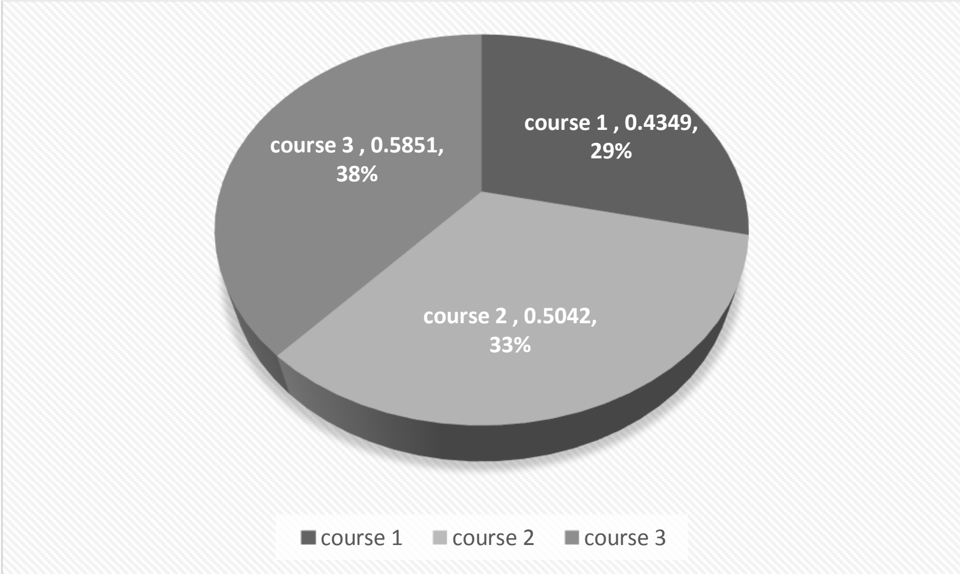

Fig. 13 *The final percentage result of the course quality evaluation using TOPSIS method*

The 3rd course was defined as the best one after completing the calculation by the TOPSIS method (Figure 13). The difference between the best course and the other courses evaluated is more noticeable when comparing the given results with that of the SAW method. The advantage of the method is that it takes account of the criteria weights and the difference between the evaluated courses is visible. The TOPSIS method evaluated the 1st course as the worst one.

After the analysis of the result, identified by the MOORA method (Figure 14), the percentage expression appears to be analogous to that of the SAW method (Figure 12). The 3rd course is the best one, the difference between the rest of the courses is insignificant, i.e. 1 %. The evaluation of the 1st and 2nd courses is equal in percentage, nonetheless the 2nd course is slightly better than the 1st one when comparing numerical indicators.

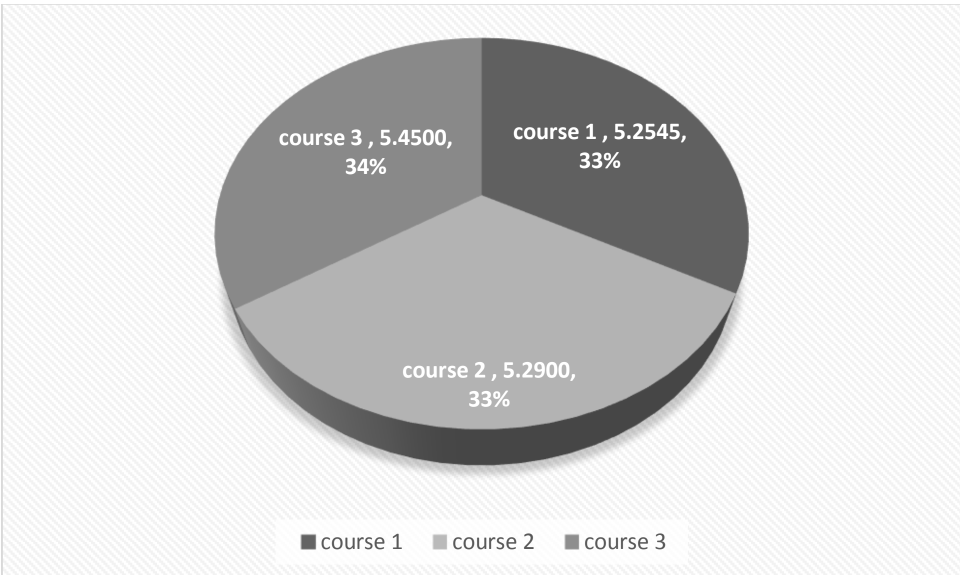

Fig. 14 *The final percentage result of the course quality evaluation using MOORA method*

The percentage result of the PROMETHEE method differs from the other methods by the evaluation results. As it is demonstrated in Figure 14, the evaluation of the 3rd course is obviously higher (47 %) than in the other methods. The worst evaluation was given to the 2nd course, whereas the other MCDM methods would rate the 1st course similarly bad. This evaluation difference appeared during the overall course evaluation calculation, i.e. with the transformed criteria weights with regard to the importance of the stages.

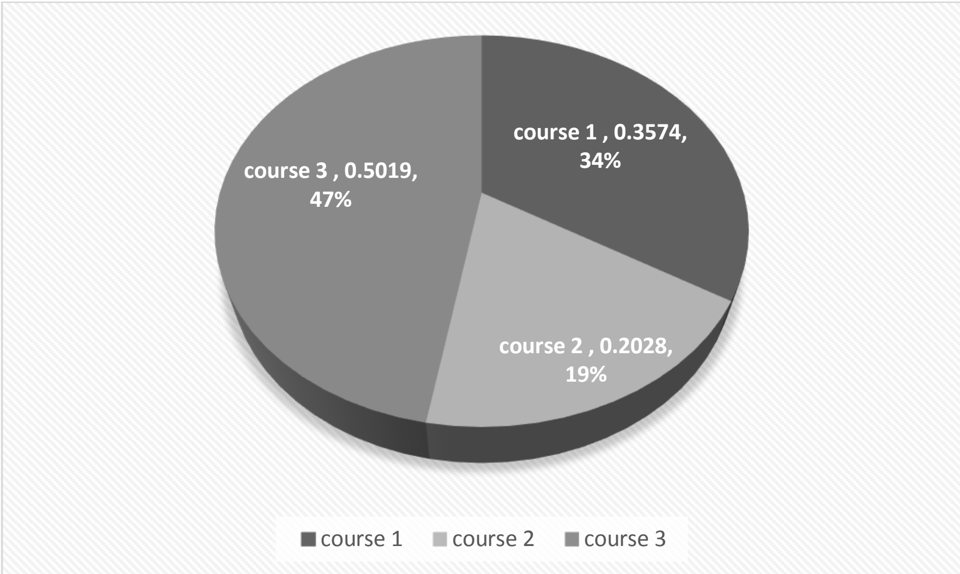

Fig. 15 *The final percentage result of the course quality evaluation using PROMETHEE method*

The stability of each method was reviewed in order to choose the most precise aggregate result of all three stages. The stability of the applied MCDMs was determined. The results are presented in Table 5.

Table 5. *The methods' stability evaluation results with aggregated weights applied*

The Method	The Method stability
SAW	68%
TOPSIS	65%
MOORA	67%
PROMETHEE	60%

The stability of all the determined methods is analogous; it varies from 60 % to 68 %. Since no high result that would tremendously stand out from the other methods was obtained, it is suggested to consider the overall methods' results by evaluating the Pareto optimum.

Table 6. *Results of the MCDM methods applying aggregate weights*

ALTERNATIVE	SAW	TOPSIS	MOORA	PROMETHEE
course 1	0.3308	0.4349	5.2545	-0.0482
course 2	0.3320	0.5042	5.2900	-0.2028
course 3	0.3372	0.5851	5.4500	0.2510

The final aggregated evaluation results of the distance course by the MCDM methods are demonstrated in Table 6. The 3rd course was determined as the Pareto optimum.

Recalculation of the criteria weights applying the Bayesian approach

Recalculation of the criteria weights is accomplished by applying the discrete Bayesian approach. The importance of the evaluation stages is defined regarding the other experts' opinion. The best course choice is individualised according to an independent expert group opinion in such cases, considering the decision maker (the administration) decision. The criteria of stages established by the administration ($\omega(X) = \{0.3649,\ 0.3261,\ 0.3090\}$) might be improved by the influence level $\omega(X|H_j)$ of the criteria, defined by independent expert groups. The weights of stage evaluation $\omega(H_j|X)$ with regards to the opinion of different expert groups are demonstrated in Table 7.

Table 7 *The weights of the stages evaluation with regard to the opinion of different expert groups*

	$\omega(X)$	Lecturers' $\omega(H_j\|X)$	IT specialists' $\omega(H_j\|X)$	Students' $\omega(H_j\|X)$
STAGE I	0.3649	0.3757	0.3757	0.3706
STAGE II	0.3261	0.2900	0.3358	0.3110
STAGE III	0.3090	0.2941	0.2893	0.3184

The weights of 3 stages were recalculated (applying the 22^{nd} equation) according to the improved weights of each expert group. The MCMD methods were applied to calculate the evaluation results. The adjustment of the criteria weights considering the opinion of all the expert groups has not changed the evaluation result in the TOPSIS and PROMETHEE methods. Nonetheless, the SAW and MOORA methods have slightly changed the result of quality evaluation of the 1^{st} and 2^{nd} courses.

Comparison of the results

The data transformation (normalisation) is accomplished in order to graphically present and compare the results of all the methods (Bayesian, SAW, TOPSIS, MOORA, PROMETHEE) applied:

$$x_{tr} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{23}$$

where x_{tr} is the result of transformed method and $x_{tr} \epsilon [0; 1]$, x is the result of the initial method, x_{min} is the lowest value of the initial results alternative, x_{max} is the highest value of the initial results alternative.

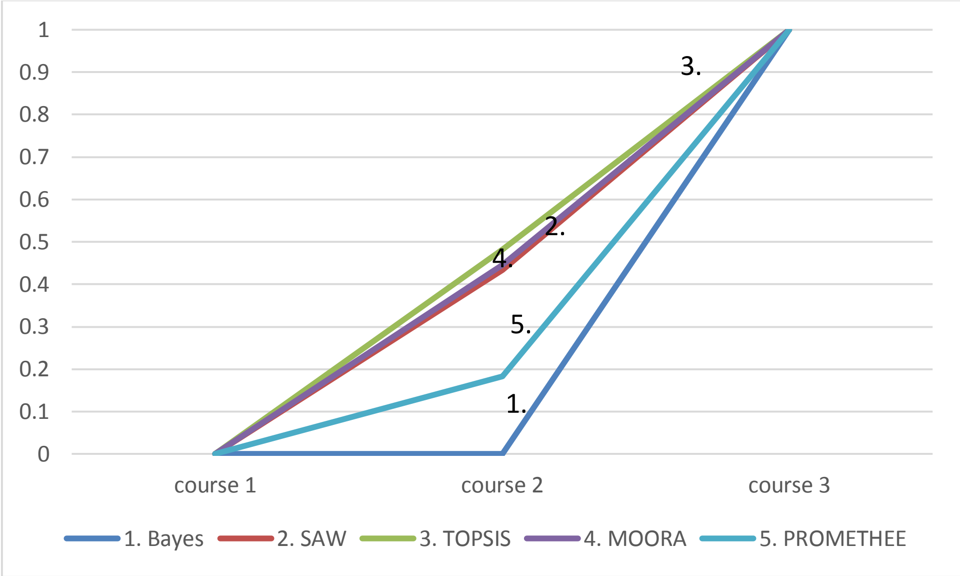

Fig. 16 *Comparison of the results of applied methods at the first evaluation stage*

The graphs of the SAW and MOORA methods are coincident. The graph of the TOPSIS method is analogous to the graphs of the SAW and MOORA methods, though the obtained grades are slightly higher. The result, determined by the PROMETHEE method, is more similar to the result, obtained by the Bayesian approach. All these methods have indicated that the 3rd course content is by far the best, while the 1st course content is the worst one.

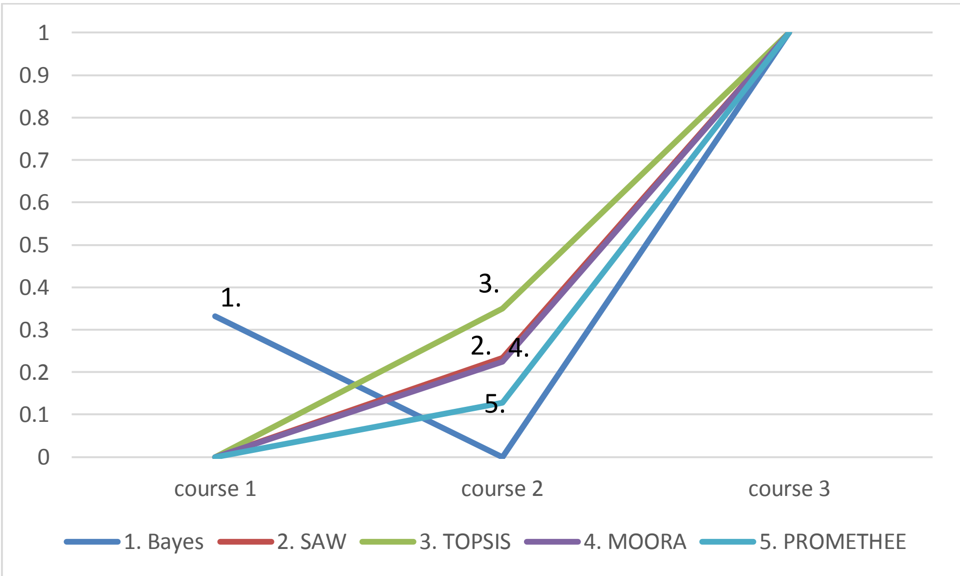

Fig. 17 *Comparison of the results of applied methods at the second evaluation stage*

The graphs of the results obtained by the SAW and MOORA methods are coincident, when the distance learning courses in virtual learning environment and IT tool usage are evaluated (Fig. 17). The TOPSIS method results are higher, whereas the PROMETHEE method results are lower than that of the mentioned above SAW and MOORA methods. All the methods defined that the IT tools were used in the most effective manner in the 3rd course. The 1st course was rated as the worst course by the MCDM methods, and the 2nd

course was rated similarly by the Bayesian approach. The distinction between the results might be explained by the different initial experts' grades of MCDM methods and the Bayesian approach; the 2nd course evaluation result is higher in the MCDM evaluation case (Fig. 9) than in the Bayesian approach case (Fig. 11).

Fig. 18 *Comparison of the results of applied methods at the third evaluation stage*

The quality of the courses was estimated by all the methods in an identical manner in the case of students'. According to the students' opinion, the best course is the 1st one, whereas the 3rd course is assumed to be the worst one (Fig. 18). The tendency of allocation of the methods' evaluation results remains the same: the graph of the SAW method is almost coincident with that of the MOORA method, the TOPSIS method evaluation result is slightly higher than that of the abovementioned methods'. The graph of the Bayesian approach is almost coincident with that of the PROMETHEE method. The result of the third stage evaluation is quite opposite to the results of the first two stages'. All these facts might influence the final result (Fig. 19).

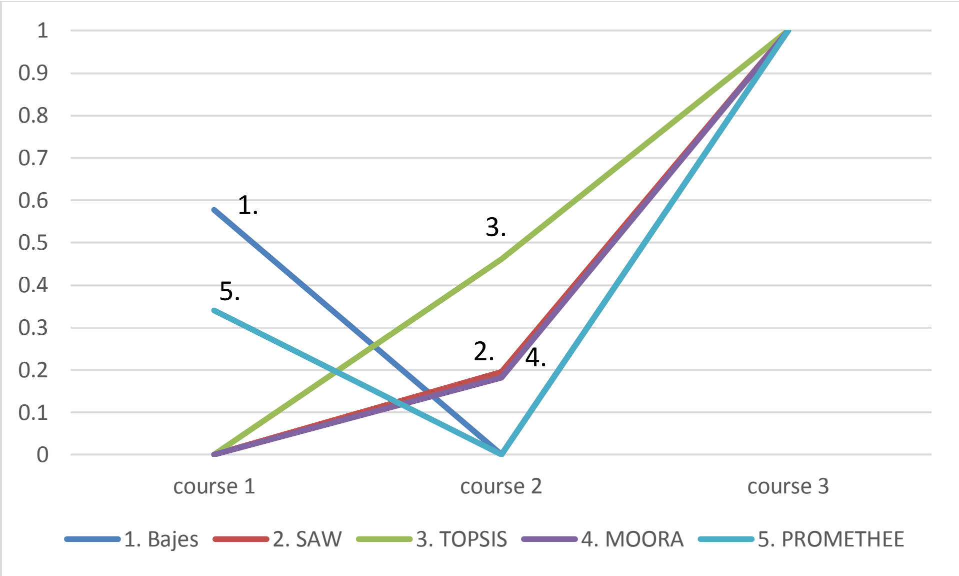

Fig. 19 *Comparison of the results of applied methods at three evaluation stages*

The aggregate result of three evaluation stages is presented in Figure 19. Consequently, after a comprehensive evaluation has been performed, it is possible to state that the 3rd course was acknowledged as the best course by all the methods applied. The results of the SAW and MOORA methods were coincident, i.e. the 2nd course was determined to be better than the 1st one. The TOPSIS method sensitively reacted to the weight recalculation, although the evaluation result was coincident with the results of the SAW and MOORA methods. The result of the PROMETHEE method was coincident with that of the Bayesian approach, though the initial expert's evaluation results are different. The results obtained differ from the other methods, applied in the evaluation of the 1st and the 2nd courses, i.e. the 1st course appeared to be better than the 2nd course. The MCDM methods' results are influenced by the criteria significance, meanwhile applying the Bayesian method – the *a priori* experience and experts' qualification.

5. General Conclusions

1. The complex evaluation methodology of distance learning courses by applying the Bayesian approach and MCDM methods, proposed in the thesis, is innovative and advantageous in practice.
2. All the methods applied consider the uncertainty of data of the expert evaluation. In this case, this fact decreases the level of subjectivity of expert evaluation.
3. The Bayesian approach adjusts the experts' grades according to their long-term experience and considers the expert competence.
4. The algorithm of pairwise comparison matrix that takes into account the data uncertainty of independent expert groups' and uses the Fuzzy set, has been proposed and applied. According to the research results, the MCDM methods are more stable when the criteria weights, identified by the AHPF but not AHP methods, are applied.
5. The Bayesian approach is suitable for recalculating the criteria weights when the opinion of the decision-making person is adjusted by other expert groups. The recalculation is fulfilled whenever the choice of the course is individualised according to separate opinions of the expert groups.
6. The result of the most stable method is selected for the task in hand by applying several MCDM methods.
7. The applied complex quality evaluation entirely allows us to tackle the problem of distance course evaluation problem considering the different logic of the methods.
8. The complex quality course evaluation methodology proposed in the thesis, could be applied in quality evaluation of the different tasks.

The list of Authors scientific publications on the dissertation thesis matter

The articles published in the peer-reviewed journals

1. Kurilovas, E., Vinogradova, I. and Serikoviene, S. (2011). Application of Multiple Criteria Decision Analysis and Optimisation Methods in Evaluation of Quality of Learning Objects. International Journal of Online Pedagogy and Course Design: 1(4), 62–76. Print: ISSN 2155-6873; Online: ISSN 2155-6881. [INSPEC] [Google Scholar].
2. Kurilovas, E. and Vinogradova, I. (2010). Improvement of Technical Quality of Virtual Learning Environments. Informacijos mokslai: 54, 63–72. Print: ISSN 1392-0561, Online: ISSN 1392-1487. [LISA] [CEEOL].

The articles in other scientific journals

1. Mockus, J. ir Vinogradova, I. (2014). Bajeso metodo taikymas nuotolinių kursų kokybei vertinti. Liet. matem. rink., LMD darbai, ser. B: 55, 90-95. Print: ISSN 0132-2818.
2. Vinogradova I. (2012). Neapibrėžtumo įtaka AHP metodo vertinimams. Liet. matem. rink., LMD darbai, ser. B:53, 243-248. Print: ISSN 0132-2818.
3. Vinogradova, I. ir Kurilovas, E. (2010). Studentų adaptuotų nuotolinių kursų kokybės vertinimas Liet. matem. rink., LMD darbai: 51, 170–175. Print: ISSN 0132-2818.

Author's background

Irina Vinogradova received her Bachelor's degree in Mathematics after graduating from the Mathematics and Informatics Faculty at Vilnius Pedagogical University in 2005. She received a master's degree in Informatics at the same faculty in 2007. The author has been working as a chief specialist at VGTU Distance Learning Centre since 2006. From 2008 to 2013, she worked as a lecturer at the VGTU Information Technology Department. The author has studied computer science for a doctoral degree at the Institute of Mathematics and Informatics in Vilnius University. Furthermore, Irina participated in projects supported by the EU Structural and Investment Funds: from 2007 to 2008, as a coordinator of the initiation issues on 'Distance learning development and its integration into the traditional teaching of the labour market teaching system'; from 2012 to 2014, as an expert in 'Lithuanian distance learning network development'.

NUOTOLINIŲ KURSŲ PARINKIMO OPTIMIZAVIMAS

Tyrimų sritis ir problemos aktualumas

Studijų ir mokslo kokybė yra vienas iš aktualiausių mūsų visuomenės uždavinių. Švietimas visada buvo svarbus visuomenės kultūriniam vystymuisi, socialinei gerovei, ekonomikos plėtrai. Išsilavinimo lygis yra tiesiogiai susijęs su darbo kokybe. Europos Sąjungoje 2014 metais parengta nauja mokslinių tyrimų ir inovacijų finansavimo programa „Horizon 2020“, kurios vienas iš siekių yra *pažangus mokslas*. Pažangaus mokslo esmė – skatinti aukšto lygio mokslinius tyrimus, siekiant sukurti žiniomis ir naujomis technologijomis pagrįstą ilgalaikę pasauliniu mastu konkurencingą Europos ekonomiką.

Informacinių technologijų plėtra daro poveikį visoms žmonių veiklos sritims, įskaitant mokslą ir studijas. Bene daugiausia informacinių ir komunikacinių technologijų privalumų siejama su nuotolinėmis studijomis, kurios sparčiai populiarėja dėl lankstumo, galimybės studijuoti patogiu laiku ir patogioje vietoje. Tačiau informacinių ir komunikacinių technologijų įvairovė, jų pritaikymas nuotolinėms studijoms savaime nesąlygoja studijų proceso efektyvumo. Tam reikia sugebėti atrinkti nuotolinių studijų organizavimui tinkamiausias priemones, įvertinti jų panaudojimo galimybes, žinoti alternatyvias priemones, turėti aiškią nuotoliniu būdu organizuojamų studijų planą, taip pat reikia atsakyti į nemažai su nuotolinėmis studijomis susijusių klausimų. Naujai atsirandančios informacinės ir komunikacinės priemonės leidžia tobulinti tradicines studijas, daro jas priimtinesnes ir keičia patį studijų organizavimo principą – studijos vis labiau orientuojamos į studentą. Šiuo metu kiekviena Lietuvos aukštoji mokykla naudoja virtualiąją mokymosi aplinką studijų kokybei pagerinti. Dauguma iš aukštųjų mokyklų rengia nuotoliniu būdu vykdomas studijų programas. Ypač didelis dėmesys skiriamas kokybiškam nuotolinių kursų rengimui.

Nuotolinio kurso kokybė priklauso nuo tokių veiksnių, kaip aiškiai pateikta ir įdomiai išdėstyta medžiaga, gerai organizuotas mokymo procesas, naudojamos tinkamos IT priemonės, kurso medžiagos aktualumas, studentų motyvacija ir dėstytojo kvalifikacija bei profesionalumas. Šiuos veiksnius vertina atitinkamos srities žinovai, t. y. ekspertai.

Vilniaus Gedimino technikos universitetas (VGTU) turi 15 metų studijų teikimo nuotoliniu būdu patirtį. Nuotolinių studijų vertinimo komisijos nariai posėdžio metu svarsto, ar kursas atitinka kokybės reikalavimus. Gerai įvertinti nuotoliniai kursai yra prilyginami spausdintiems mokymo leidiniams. Šiame darbe yra pateikta kompleksinė nuotolinių kursų vertinimo metodika. Ji buvo panaudota VGTU nuotolinių kursų kokybei nustatyti. Siūloma metodika yra pagrįsta matematiniais metodais, atsižvelgiant į ekspertinių duomenų neapibrėžtumą. Metodika numato, kad į nuotolinių kursų vertinimą įtraukiami su studijomis susiję asmenys, suinteresuoti kokybišku išsilavinimu: dėstytojai, studentai, nuotolinių studijų centro darbuotojai ir mokymo įstaigos administracija. Toks daugiapusis požiūris atspindi įvairius kurso dalyvių interesus, leidžia tobulinti kursą, atsižvelgiant į jų įverčius ir pastabas. Sudaryta kompleksinė metodika sujungia Bajeso ir stabilųjį MCDM metodus, skirtingai atsižvelgiant į ekspertų nuomonių subjektyvumą. Bajeso metodas koreguoja eksperto įvertį, atsižvelgiant į ekspertų kompetenciją ir į sukauptą ilgametę patirtį. MCDM metodais vertinamas kursas, naudojant ekspertų įverčius pagal numatytus kokybės kriterijus ir šių kriterijų svorius. Nustatytas kriterijų svoris turi didelę įtaką vertinimo rezultatui. Ekspertinių duomenų neapibrėžtumui įvertinti taikomi matematinės statistikos, neraiškiųjų skaičių teorijos ir stabilūs daugiakriteriai metodai.

Tikslas ir uždaviniai

Šio darbo tikslas – pasiūlyti kompleksinę nuotolinių studijų kursų kokybės vertinimo metodiką, atsižvelgiančią į ekspertų nuomonių subjektyvumą ir jų įverčių neapibrėžtumą. Siūloma metodika pritaikoma VGTU nuotolinių studijų kursų kokybei vertinti.
Tikslui pasiekti keliami tokie uždaviniai:

1. Atlikti nuotolinių studijų kurso, virtualiosios mokymosi aplinkos ir ekspertinio vertinimo mokslinių tyrimų analizę.
2. Išskirti nuotolinių studijų kursų vertinimo etapus ir ekspertų vertinimo grupes, remiantis Lietuvos ir kitų šalių studijų kokybės vertinimo patirtimi.
3. Nuotolinių kursų kokybei vertinti pritaikyti Bajeso metodą, koreguojantį eksperto įvertį, atsižvelgiant į ekspertų kompetenciją ir sukauptą ilgametę vertinimo patirtį.
4. Pateikti MCDM metodus kaip matematinės optimizacijos metodų sudedamąją dalį.
5. Pasiūlyti neraiškiųjų skaičių nepriklausomų ekspertų grupės kriterijų porinio palyginimo matricos kūrimo algoritmą.
6. Pritaikyti Bajeso metodą grupės kriterijų svoriams perskaičiuoti, atsižvelgiant į kitų ekspertų grupių nuomones.
7. Pasiūlyti MCDM metodų stabilumo nustatymo algoritmą, atsižvelgiant į ekspertų įverčių neapibrėžtumą ir vertinant nuotolinių kursų kokybę pasirinkti stabiliausio MCDM metodo rezultatą.
8. Remiantis pasiūlyta metodika, atlikti kompleksinį nuotolinių studijų kursų kokybės vertinimą.

Tyrimo metodika

Rengiant disertacijos analitinę dalį, buvo pritaikytas sisteminės analizės metodas. Tiriant ekspertų įverčių neapibrėžtumo įtaką MCDM rezultatams, buvo atliktas metodų stabilumo patikrinimas, taikant statistinio imitavimo metodą. Buvo generuojami pseudoatsitiktiniai skaičiai ir nežymiai keičiami pradiniai ekspertų nuotolinių kursų įverčiai ir kokybės kriterijų svoriai.

MCDM metodų stabilumui nustatyti, AHP ir AHPF metodų svoriams ir MCDM vertinimo rezultatams apskaičiuoti parašytos programos su *MATLAB (R2011a)* matematiniu paketu. Aposteriorinių vidurkio funkcijų skaičiavimams atlikti naudojamas *Derive 5* matematinis paketas.

Siūlomos metodikos praktinėje realizacijoje taikomas ekspertinio vertinimo metodas. Ekspertų apklausai atlikti buvo taikoma skirtinga metodika: pagal ekspertų tarpusavio ryšį – neakivaizdus eksperto metodas, pagal vertinimų suderinimo procedūrą – vienkartinis apklausos metodas, pagal ekspertų skaičių – individualus apklausos metodas. Nuotolinių studijų kursų kokybės kriterijų grupėms sudaryti buvo taikomi V. Beltono ir T. Stewarto principai.

Atlikus ekspertinį vertinimą duomenims apdoroti, buvo taikomas statistinės duomenų analizės metodas. Pritaikius kompleksinį vertinimą, gautiems rezultatams apibendrinti taikomas lyginamosios analizės metodas.

Darbo mokslinis naujumas

Rengiant disertaciją, buvo gauti šie nauji rezultatai:

1. Pasiūlytas kurso kokybės vertinimo būdas, atsižvelgiantis į įverčių neapibrėžtumą, taikant Bajeso metodą.
2. Pasiūlytas naujas neraiškiųjų skaičių nepriklausomų ekspertų grupės kriterijų porinio palyginimo matricos kūrimo algoritmas.
3. Pasiūlytas Bajeso metodo pritaikymas kriterijų svoriams perskaičiuoti, atsižvelgiant į kitų ekspertų grupių nuomones.
4. Pasiūlytas kurso kokybės vertinimo būdas, taikant stabilųjį MCDM metodą.
5. Pasiūlyta kompleksinė nuotolinių kursų kokybės vertinimo metodika, įvairiapusiškai atsižvelgianti į subjektyvias ekspertų nuomones.

Darbo rezultatų praktinė reikšmė

Darbe pasiūlyta kompleksinė vertinimo metodika buvo praktiškai pritaikyta VGTU nuotolinių kursų kokybei vertinti. Metodika suteikia galimybę į nuotolinių kursų vertinimą įtraukti įvairių su studijomis susijusių veiklos sričių asmenis, suinteresuotus aukšta kurso kokybe. Tai dėstytojai, studentai, nuotolinių studijų centro darbuotojai ir mokymo įstaigos administracija. Toks daugiapusis požiūris atspindi įvairius kurso dalyvių interesus, leidžia tobulinti kursą, atsižvelgiant į jų įverčius ir pastabas. Pasiūlytas kompleksinis vertinimas atsižvelgia į ekspertinių duomenų neapibrėžtumą. Kompleksinė kursų kokybės vertinimo metodika gali būti taikoma ir kitų panašių uždavinių kokybei vertinti.

Ginamieji teiginiai

1. Bajeso metodas, taikomas ekspertiniams vertinimams, atsižvelgia į eksperto kvalifikaciją ir sukauptą institucijos patirtį.
2. Nuotolinių studijų kurso kokybei nustatyti taikomas stabiliausias MCDM metodas, užtikrinantis vertinimo rezultato tikrumą.
3. Neraiškiųjų skaičių naudojimas kriterijų svoriams nustatyti atsižvelgia į nepriklausomų ekspertų grupės subjektyvias nuomones.
4. Bajeso metodas gali būti taikomas kriterijų svoriams perskaičiuoti, atsižvelgiant į skirtingas ekspertų grupių nuomones.
5. Kompleksinis nuotolinių studijų kursų kokybės vertinimas įvairiapusiškai atsižvelgia į ekspertinio vertinimo subjektyvumą ir kurso įverčių neapibrėžtumą.

Darbo rezultatų aprobavimas

Pagrindiniai disertacijos rezultatai buvo publikuoti 13 straipsnių: 2 – recenzuojamuose periodiniuose mokslo leidiniuose, 3 – kituose mokslo leidiniuose, 8 – konferencijos darbų leidiniuose. Pagrindiniai darbo rezultatai buvo pristatyti ir aptarti 16 tarptautinių ir nacionalinių konferencijų.

Darbo apimtis

Disertacija susideda iš 5 skyrių, literatūros sąrašo ir dviejų priedų. Disertacijos skyriai: Įvadas, literatūros apžvalga, Nuotolinių kursų kokybės vertinimo metodika, Nuotolinių kursų kompleksinis vertinimas, Bendrosios išvados. Disertacijoje pateikti lentelių, paveikslų bei naudotų žymėjimų ir santrumpų sąrašai. Bendra disertacijos apimtis be priedų – 145 puslapiai. Darbe, įskaitant priedus, pateikti 47 paveikslai ir 24 lentelės.

Bendrosios išvados

1. Darbe pasiūlytas kompleksinis nuotolinių studijų kursų vertinimas, taikant Bajeso ir MCDM metodus yra naujas ir naudingas praktiniu požiūriu.
2. Taikomi Bajeso ir stabilusis MCDM metodai atsižvelgia į duomenų neapibrėžtumą, tai mažina ekspertinio vertinimo subjektyvumą.
3. Bajeso metodas gali būti taikomas, koreguojant ekspertų įverčius pagal sukauptą ilgametę patirtį ir eksperto kompetenciją.
4. Pasiūlytasis neraiškiųjų skaičių porinio palyginimo matricos kūrimo algoritmas atsižvelgia į nepriklausomų ekspertų grupės duomenų neapibrėžtumą. Kaip parodė tyrimas, MCDM metodai yra stabilesni, taikant kriterijų svorius, nustatytus AHPF, o ne AHP metodu.
5. Bajeso metodas tinka kriterijų svarbumui perskaičiuoti, kai sprendimą priimančio asmens nuomonė yra koreguojama kitų ekspertų grupių.
6. Taikant vertinimams kelis MCDM metodus, pasirenkamas stabiliausias metodas, užtikrinantis vertinimo rezultato tikrumą.
7. Kompleksinis kokybės vertinimas leidžia visapusiškai ištirti sprendžiamą nuotolinių kursų vertinimo problemą, atsižvelgiant į skirtingus metodus.
8. Darbe pasiūlyta kompleksinė kursų kokybės vertinimo metodika gali būti taikoma panašiuose kokybės vertinimo uždaviniuose.

Irina Vinogradova

DISTANCE COURSE SELECTION OPTIMISATION

Doctoral Dissertation

Physical sciences,
Informatics (09 P)

Irina Vinogradova

NUOTOLINIŲ KURSŲ PARINKIMO OPTIMIZAVIMAS

Daktaro disertacija

Fiziniai mokslai,
Informatika (09 P)