JOURNAL OF E-LEARNING AND KNOWLEDGE SOCIETY
Vol. 16, No. 2 (2020), pp. 17-24

Generation of e-Learning tests with different degree of complexity by combinatorial optimization

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(submitted: 06/09/2019; accepted: 11/11/2019; published: 30/04/2020)

Abstract

The major challenge in the digital era is the management of big data. A substantial share of digitization is taken from the e-learning. In this respect, the current article deals with generation of questions for testing the acquired levels of students' knowledge. For this purpose, an algorithm for generation of questions for tests with different level of complexity is proposed. The main stage of this algorithm is using of mathematical combinatorial optimization model. Using this model makes it possible to formulate different tasks, whose solutions determine a subset of questions that correspond to different degree of test complexity. Essential part of this model is the use of binary integer variables to determine whether a question will be a part of the test or not. The advantage of the proposed approach is the flexibility to decrease or increase the number of questions used to compose the test preserving the required score in accordance to the particular level of test complexity. The conducted investigations over a year show, that the effect of testing can improve retention of knowledge and lead to improved end results. The applicability of the proposed algorithm along with the formulated mathematical model is demonstrated in a case study on the excerpt of questions from the web programming course. The proposed algorithm could be used for generation of tests with different degree of complexity for other learning contents.

KEYWORDS: Combinatorial optimization, e-learning, Mathematical model, Questions difficulties, Test generation

DOI
https://doi.org/10.20368/1971-8829/1135016

CITE AS
Borissova D., Keremedchieva D. (2020). Generation of E-learning Tests with different Degree of complexity by combinatorial optimization. *Journal of E-Learning and Knowledge Society*, *16*(2), 17-24
https://doi.org/10.20368/1971-8829/1135016

1. Introduction

The contemporary technologies of ICT along with the capabilities operations research make possible to develop new tools to support different aspects of business intelligent decisions in digital era. The new business challenges require involving the modern technology as business intelligence tools in order to improve the product quality and user satisfaction. In this respect, the latest trends in e-learning are focused not only on the e-learning content but involve the proper system to evaluate the acquired knowledge (Mustakerov & Borissova, 2017; Borissova & Keremedchiev, 2019).

In the field of digital technologies, quality gains a key role for success of the Universities that seek to be up-to-date in the modern learning technologies (Salas-Rueda, 2018). It is shown that the usage of contemporary ICT and e-learning contribute to enhancing the innovation and quality of higher education (Terzieva et al., 2020; Pavel et al., 2015). Due to the importance of evaluation of the level of acquired knowledge by the students from different learning forms variety of approaches have been proposed. Some authors investigate the effects of the

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use of different question types on the engagement and performance of programming learning for non-computer science majors (Arunoprayoch et al., 2018). The evaluation should be seen not only as describing achievements but as a powerful driver of change in the education system leading to quality improvement and higher standards of education (Borissova &. Mustakerov, 2009; Wolf et al., 1991). A test or exam can be applied on paper or on a computer and is designed to measure the knowledge of the tested student. The design of the test is complex, continuous and in some of its phases an iterative process of research that includes the stages of planning, development, confirmation and analysis of the data.

Big data contributes to the change of the e-learning process by involving new systems able for providing better user experience (Manca et al., 2016). To ensure that any single module is understood the proper monitoring system based on some kind of tests is needed to show how effectively the e-learning is. In the context of testing, a conceptual approach for development of educational web-based e-testing system is proposed (Mustakerov & Borissova, 2011). This approach allows the generation of sequential questions or shuffle, or random by predefined testing pages with questions. Another “self-testing” tool is discussed in (Mustakerov et al., 2004). This tool aims to help the trainee or student in evaluation of acquired knowledge level before official examination.

In addition, it should be noted that the peer and self-assessment in the Moodle e-learning environment could be realized by using some kind of gamification activities (Tuparov et al., 2018). In this context, the usage of friendly environment for the learning content and proper description and visualization contribute for better understanding and improving the skills in computer programming (Mustakerov & Borissova, 2017; Borissova, & Mustakerov, 2015). It should be noted that competency of problem-solving is highly correlated to the adequacy of e-learning (Kerzic et al., 2018).

The essential advantages of the web-based e-learning and online examination systems are capable to deliver the needed content to the learner irrespective of the used device with just a web browser available. This is the reason to develop online examination system suitable for distance learning compatible with mobile device (Bursalioglu et al., 2016). To improve the effectiveness of the learning process a multi-agent system with five-layer architecture is proposed (Arif et al., 2015). The e-learning supported by agents enables the users to collect different material and allows personalization and adaptation of educational content. The correct implementation of the assessment and evaluation exams is critical issue in Learning Management Systems. Therefore, a modern agent-supported academic online examination system is proposed (Tasci et al., 2014). The architecture of the proposed system provides integration between creating and updating of questions’ pool, exams created by intelligent agents in decision-making processes, managing student feedback, etc. Together with classical tools for supporting e-learning, some authors propose to create e-mentor for online learning to support the students in learning by using of email, online chat, etc. (Omar et al., 2012). The existence of dashboard in e-learning platforms allows monitoring the progress of students in real time and gets some useful information about future course designs (Dipace et al., 2019).

The inquiry-based learning model is used to explore a learning program and to test how participants’ cognitive-affective factors influence on their interest in using such model (Hong et al., 2019). Authors propose “prediction-observation-quiz-explanation” model for the purpose of green energy generation learning program. A systematic literature review concerning self-regulated learning strategies using e-learning tools for computer science is described in (Garcia et al., 2018).

Modern learning management systems (LMS) give the opportunity to create and manage learning content including different forms of exams and tests (Aldiab et al., 2019). Tests can be designed and developed with automatic grading options. Although setting up the question bank is a time consuming activity, test elements can be reused and students' exams are automatically graded. Furthermore, the immediate scoring of online exams permits students to receive rapid feedback regarding their achievements.

In contrast to the other approaches for test generation, the proposed in the current article mathematical optimization model guarantees that the selected questions for a particular test are best suited.

The rest of the article is organized as follows: Section 2 provides problem description along with the proposed algorithm for generation of questions for tests with different level of complexity. Section 3 describes the input data and formulated mathematical model for generation of e-learning tests with different degree of complexity. Section 4 describes a case study utilized to demonstrate the applicability of the proposed approach. Section 5 contains the obtained results and conclusions are given in Section 6.

2. Problem descriptions

Considering the fact that ICT is so widespread, e-learning is probably the area best suited to deploy the new technologies. The use of different mathematical methods makes possible to propose different tests using quizzes or open questions to check the level of knowledge. For the purposes of self-testing, the student could select different test complexity. This allows testing different degrees of acquired knowledge. For example, if the student passes the test with lower level of complexity he/she can do the next test where questions are more difficult. Different test levels are needed to ensure that the student will not give up if he/she first chooses the test with high complexity. In this case he/she can select the test from the previous level and check if his/her knowledge is enough to pass or he/she should select an easier test.

The process of user interaction with the system for generation of questions for tests with different level of complexity is illustrated in Fig. 1.

The algorithm starts with selection of the level of test complexity (test with highest complexity, test with middle level of complexity and test with lower level of complexity). There is no restriction on the sequence of tests and the user can choose one of them. Next the user can choose between two different cases. The first one considers generation of test questions without using the option for “restriction about the question number”, while the second one involves this restriction about the number of questions. Depending on the selected level of test complexity and the option concerning the limit of the number of questions, the proper mathematical model is needed to determine the suitable questions and their number to comply with the given restrictions.

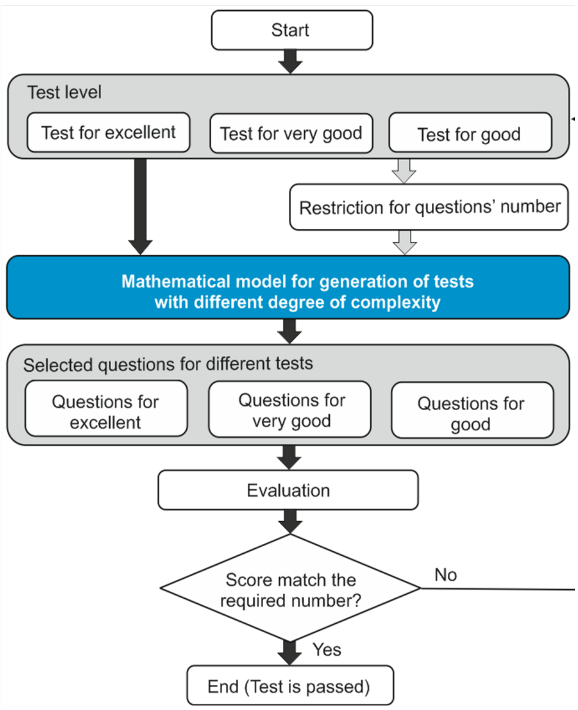

Figure 1 – Algorithm for generation of questions for tests with different level of complexity.

This model should provide the possibilities to formulate different optimization tasks whose solutions will determine the needed test questions corresponding to the selected test level. Once the needed questions for the test are known, the next evaluation step could be implemented. For the purpose of evaluation the questions' answers should be checked and the obtained scores should be checked whether they correspond to the needed scores for test level or not. In case of match with the needed score the algorithm ends. If there is no match, the user can do another test with less complexity, or do another test with the same level of difficulty where the mathematical model will guarantee that he/she will get different questions for this level of complexity.

The problem in the current article deals with the formulation of a suitable mathematical model for generation of tests with different degree of complexity that is described in the next section.

3. Mathematical model for generation of e-learning tests with different degree of complexity

Involving the big data into e-learning provides vast possibilities in making learning more effective. With customization of e-learning by the use of analytics and large data, it is possible to ensure the interactive individual learning and skills testing in accordance to the goals and expectations of each user. For this purpose, it is necessary to develop appropriate tools with the capability to process big data. The focus of this article is to provide a flexible approach for generation of tests with different degree of complexity for the purpose of e-testing. Determination of the tests with different degree of complexity requires predefined set of questions from which the selection could be done. Furthermore, each question should be evaluated toward difficulty by using of some scale in advance. To guarantee only one selection of the question within a particular test, it is needed to assign binary integer variables for all predefined sets of questions from which the selection is realized. All of these input data together with three different level of test complexity are shown in Table 1.

The set of questions is denoted by Q and is composed of M number of different questions, i.e. $Q \in \{q_1, q_2, ..., q_M\}$. For each question the degree of difficulty is determined within the range $1 \leq d_i \leq N$, where 1 means the less difficult while the value of highest difficulty is denoted by N. There is no relation between the number of questions and degrees of difficulty, but it should be noted that the sum of scores for questions' difficulties should be bigger than the required value corresponding to the excellent evaluation. Decision variables x_i are assigned to each question to realize the needed level of test complexity. Three types of complexity levels are

<table>
<tr><th>Questions</th><th>Difficulty</th><th>Decision variables</th><th colspan="3">Test complexity levels</th></tr>
<tr><td>q_1</td><td>d_1</td><td>x_1</td><td rowspan="4">L-1</td><td rowspan="4">L-2</td><td rowspan="4">L-3</td></tr>
<tr><td>q_2</td><td>d_2</td><td>x_2</td></tr>
<tr><td>…
q_i
…</td><td>…
d_i
…</td><td>…
x_i
…</td></tr>
<tr><td>q_m</td><td>d_m</td><td>x_m</td></tr>
</table>

Table 1 – Questions, difficulty and tests levels.

determined – excellent, very good and good. For these types of complexities some lower and upper boundaries are to be determined. Taking into account all of these considerations, the following optimization model for generation of e-learning tests with different complexity is proposed as follows:

$$maximize\left(L = \sum_{i=1}^{M} x_i d_i\right) \quad (1)$$

subject to

$$\sum_{i=1}^{M} d_i = D \quad (2)$$

$$L_{max} < D \quad (3)$$

$$L_{min} \leq L \quad (4)$$

$$L \leq L_{max} \quad (5)$$

The objective (1) seeks to maximize the overall scores according to the selected test and its level of complexity – test for excellent, test for very good and test for good evaluation. The questions' difficulty (D) is expressed by summing the difficulties of all questions as shown by the relation (2). The upper boundary (L_{max}) about the test for excellent evaluation is determined by the lecturer and learning content. It should be noted that the sum of questions' difficulties (D) is not the upper boundary (L_{max}) for the highest complexity of tests (test for excellent evaluation) as it is expressed by inequality (3). The restrictions (4) and (5) are used to determine some acceptable range to get the excellent evaluation. It is not needed the student always to get the full number of scores. In most cases some acceptable limit could be used to distinguish different levels of complexity and corresponding ranges for particular level. These considerations about different levels for test complexity are expressed by the restrictions (4) and (5) where the boundary values could be expressed in percentages and then converted into scores. For example, in case when assessing the acquired knowledge for excellent, the acceptable percentage range could be determined within the interval of (100-94) %. That means that all students with score in the range of 94 % to 100 % should have excellent. For the next level that match the very good performance of the knowledge another percentage limit of 9 % could be used, namely (93-85) %. Similarly, the level determining the assessment as good is expressed by the limit of other 10 % or by using the range of (84-75) %. In such way, it is possible to determine the acceptable ranges for different test complexity. The usage of binary integer variables guarantees the single selection of questions from the given list when generating the particular test.

If it is necessary to decrease the questions number the following restriction can be added to the described above model:

$$\sum_{i=1}^{M} x_i \leq K_{\max}, \; x_i \in \{0, 1\} \quad (6)$$

The restriction (6) allows setting up the upper boundary for the number of questions within the tests.

The direction of objective function (1) can be inverted and instead seeking maximal value of L could be seeking the minimal values as:

$$minimize\left(L = \sum_{i=1}^{M} x_i d_i\right) \quad (1a)$$

In this case, the next restriction (7) could be used to provide selection of more questions for a particular test complying with the upper (L_{max}) and lower (L_{min}) boundary at different test complexity:

$$\sum_{i=1}^{M} x_i \geq K_{\min}, \; x_i \in \{0, 1\} \quad (7)$$

Both boundaries for the lower (K_{min}) and upper (K_{max}) limit toward the questions' number could be used too. The restrictions (6) and (7) provide flexibility by providing the possibilities to select small number of questions, but with high difficulty and vice versa – to select more questions.

4. Numerical application

In this section, a case study is utilized to demonstrate the applicability of the proposed mathematical model for generation of e-learning tests with different degree of complexity. The numerical application of the proposed model (1) – (7) has been used over a year to generate e-learning tests with different degree of complexity using more than 200 questions for web programming course. To demonstrate the applicability in this section, a limited number of 30 questions and difficulty degree range for these questions between 1 and 10 are used. The corresponding score boundaries for different test difficulty are as follows:

- Test for excellent: L^{E}_{max} = 150 and L^{E}_{min} = 135
- Test for very good: L^{VG}_{max} = 134 and L^{VG}_{min} = 120
- Test for good: L^{G}_{max} = 119 and L^{G}_{min} = 100

The numerical testing of the proposed approach is based on usage of the described mathematical combinatorial optimization model (1) – (7) and the mention above boundaries. Two different scenarios are investigated: 1) generation of questions for tests without using restriction about the number of questions that compose the test, i.e. mathematical model (1) – (5), and 2) generation of questions by using restrictions about the questions' number, i.e. mathematical model (1) – (7). Each of these cases is tested at three different levels for the degree of complexity of the tests. The obtained results from optimization tasks solved under the both scenarios are shown in Table 2.

Set of questions	Difficulty	Scenario-1			Scenario-2		
		Values of x_i Excellent	Values of x_i Very Good	Values of x_i Good	Values of x_i Excellent $K_{max} \leq 17$	Values of x_i Very Good $K_{max} \leq 14$	Values of x_i Good $K_{max} \leq 12$
1	5	0	0	0	0	0	0
2	7	0	0	0	1	1	0
3	10	1	1	1	1	1	1
4	9	0	1	0	1	1	1
5	7	0	0	0	1	1	0
6	6	0	0	0	0	0	0
7	3	0	0	0	0	0	0
8	5	0	0	0	0	0	0
9	8	1	0	0	1	1	1
10	9	1	1	0	1	1	1
11	6	1	1	0	0	0	0
12	7	1	1	0	1	0	0
13	8	1	0	1	1	1	1
14	4	1	1	1	0	0	0
15	10	1	1	1	1	1	1
16	5	1	1	1	0	0	0
17	7	1	1	1	1	0	1
18	10	1	1	1	1	1	1
19	9	1	1	0	1	1	1
20	8	1	0	1	1	1	1
21	6	1	1	1	1	0	0
22	3	1	1	1	0	0	0
23	5	1	1	1	0	0	0
24	4	1	1	1	0	0	0
25	7	1	1	1	1	1	0
26	5	1	1	1	0	0	0
27	10	1	1	1	1	1	1
28	6	1	1	1	0	0	0
29	8	0	0	1	1	1	1
30	3	1	1	1	0	0	0

Table 2 - Questions, their difficulties, and values for binary decision variables.

The value 1 of binary decision variables indicates that the corresponding question is selected to be included in the test, while the value 0 means that the question should be omitted. Once the values of decision variables become known that means the number of questions is also known and the score for test complexity could be calculated. Therefore, the use of binary integer variables in the formulated optimization combinatorial model (1) – (7) plays an important role in forming the set of questions for the generation of tests.5. Results analysis and discussion

The proposed mathematical combinatorial optimization model makes possible to determine the number of questions taking into account the difficulty of all questions under given restrictions for the test scores and questions' number. The comparison of the obtained result for three different levels of test complexity is shown in Fig. 2.

In the case of scenario 1 and generation of test for excellent, the obtained objective function value is equal to 150 (*L-1* = 150) and the selected number of questions are 22 (*K* = 22). For the second test level corresponding to the very good evaluation the results from the optimization task solving is as follows: objective function values 134 ($L\text{-}2$ = 134) and the selected number of questions are 20 (K = 20). The results for the third test level representing the good evaluation are: objective function values 119 ($L\text{-}3$ = 119) and the selected number of questions is 18 (K = 18).

The scenario 2 expresses the situation where additional restriction for the number of questions could be added. As it could be seen from Table 3, in the formulated optimization task only one upper restriction for the questions' number is used.

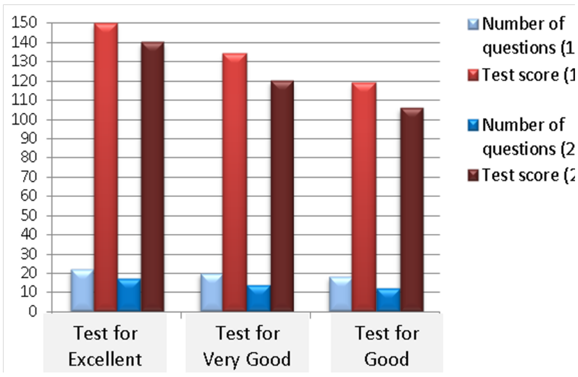

Figure 2 – Number of questions and score for different level of test complexity.

The obtained values for the tests score and selected number of questions are as follows: for test with excellent level $L\text{-}1$ = 140 and K = 17; for test with very good level $L\text{-}2$ = 120 and K = 14; for test with good level $L\text{-}3$ = 106 and K = 12.

All of these show the applicability of the proposed modelling approach to generation of tests with different levels of complexity while considering some limits about the number of questions to compose the test preserving the required score. For example, to achieve the excellent evaluation the number of questions can vary between 22 and 17. In case of very good evaluation the number of the questions is between 20 and 14, and in the case with the lowest test complexity the number is between 18 and 12. The range of variation of the relevant questions for the particular test depends on the total amount of the used questions. Also, there is a high dependence relation between the number of questions in a given test and the degree of difficulty of the questions from which the tests are generated.

Reducing the number of questions for a particular test means that the solution selects less questions but with higher difficulty and vice versa. The imposing of restriction for the minimum question number allows more questions to be selected but with less complexity to satisfy the needed score for the test. This fact could be used for future investigations where the time parameter together with the test score will determine more objective estimation.

All of the obtained results prove that the proposed algorithm for generation of questions for tests with different level of complexity along with formulated mathematical model could be used for the purposes of e-learning. There is no limit for the questions from which the selection could be done to form the test complexity.

During the development stage of the web-based system for generation of tests with different degree of complexity one group of students is involved. For the goal of validation of the proposed algorithm and mathematical model randomly selected group was chosen and all of these students periodically are passed tests corresponding to the learned material. At the end of the educational year, another random group of students was selected to compare the results obtained with the group of students who were periodically tested by tests.

The conducted testing over the last year show, that the effect of testing can improve the retention of knowledge and to encourage the users to pass periodically different online tests. The obtained results are summarized in Table 3.

	Male	Female	Results	
			Excellent evaluations	Number of fails
Using tests periodically	23	21	32 (72.72 %)	0 (0 %)
Without using tests periodically	20	21	28 (68.29 %)	2 (4.87 %)

Table 3 – Testing results

The results show, that the students using tests periodically have a little better evaluations compared with the students that are not tested periodically. For example, the excellent results from students using tests periodically exceed the excellent results from the rest with about 4.42 % (72.72 % vs. 68.29 %) and the fail results are 0 to 2 in favor of the periodically tested students (0 % vs. 4.87 %). This could be explained by the retention of knowledge due the passing of tests periodically. All of these mean that the testing effect can improve the learners' habits, thus make more efficient learners.

6. Conclusions

The article describes an algorithm for generation of tests by selection of questions with different level of difficulty for different levels of tests. A distinctive feature of the proposed algorithm is the formulation of a mathematical model for questions selection under three different level of test complexity. The formulated model is of type mixed-integer linear optimization. The selection of questions for tests relies on predefined set of questions with different degree of difficulty. The determination whether a question will be part of the test or is not is realized by using binary integer variables.

The applicability of the proposed algorithm and mathematical model is experimentally demonstrated in a case study on the excerpt of questions for web programming course and two randomly selected groups of students. Two scenarios are investigated: 1) selection of questions for tests without restriction for the questions' number, and 2) selection of questions with restrictions about questions' number. Both of these scenarios are numerically tested under three different levels about the degree of complexity of the tests. It is shown that tests with the same level of complexity could be implemented by means of different number of questions. This is due to the fact that the given set of all questions are with different degree of difficulty.

The advantage of the proposed algorithm respectively the formulated mathematical model is the flexibility to generate the tests with different degree of complexity using binary integer variables. Taking into account the vast amount of the e-learning content variety the proposed approach could applied in different learning content where some types of tests are to be generated to test the acquired knowledge and to show how effectively the learning is. The conducted testing over a year show, that the effect of testing can improve retention of knowledge and lead to improved end results. Further investigations are planned for detailed analysis concerning the influence of periodically checking by tests and final evaluation.

The proposed algorithm could be realized as web-based application for generating of questions for tests with different level of complexity. Different databases could be established and used for test generation depending on the learning contents.

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