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Prediction of student course selection in online higher education institutes using neural network

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ABSTRACT

Students are required to choose courses they are interested in for the coming semester. Due to restrictions, including lack of sufficient resources and overheads of running several courses, some universities might not offer all of a student's desirable courses. Universities must know every student's demands for every course prior to each semester for optimal course scheduling. This research examines the problems associated with course selection in the context of e-learning. This study is focused on identifying the potential factors that affect student satisfaction concerning the online courses they select, modeling student course selection behavior and fitting a function to the training data using neural network approach, and applying the obtained function to predict the final number registrations in every course after the drop and add period. The experimental sample came from 714 online graduate courses in 16 academic terms from 2005 to 2012. Findings disclosed high prediction accuracy based on the experimental data and exhibited that the proposed model outperforms three well-known machine learning techniques and two previous, naive approaches significantly. This contribution finally ends with an analysis and interpretation of results, and presentation of some suggestions and recommendations for enthusiastic educational institutes regarding how to choose the best strategy and configuration to expand and also adapt the introduced system to their specific needs.

1. Introduction

In the past decade e-learning has become increasingly popular across the higher level education spectrum. According to a recent study of more than 2500 colleges and universities in the United States, Allen and Seaman (2010) found that online education is growing quickly, with enrollment figures of roughly 1.6 million students in the fall of 2002 (or 9.6% of total enrollment) increasing dramatically to 5.6 million students in the fall of 2009 (or 29.3% of total enrollment). With increasing number of online programs and courses also comes an increase in the number of institutions providing them. This leads to competition among providers in the field of online learning (Tricker, Rangecroft, Long, & Gilroy, 2001). In this competitive environment, the most important concern for online higher education institutions is the development of high-quality online education systems. Various factors influence the overall success and quality of an e-learning system (Moore, 2002; Moore & Kearsley, 2005; Sawang, Newton, & Jamieson, 2013; Sener & Humbert, 2003). Among these factors, the student satisfaction with the online education provided is a vital indicator (Bourne & Moore, 2003; Lee, 2010; Liaw & Huang, 2013; Sawang et al., 2013; Yukselturk & Yildirim, 2008). Liegler (1997) referred to student satisfaction as the level to which student needs and expectations are met. A high degree of student satisfaction leads to lower attrition rates, an increase in student enrollment and motivation, and a more productive learning environment (Elliott & Shin, 2002; Schwitzer, Ancis, & Brown, 2001). Moreover, other research found that students who are more satisfied with their experience are more likely to enroll in future e-learning courses (Carswell & Venkatesh, 2002; Chiu, Sun, Sun, & Ju, 2007; Johnson, Hornik, & Salas, 2008; Lim, 2001; Marshall, Greenberg, & Machun, 2012).

It is reported that student satisfaction with online learning is a complex and multidimensional construct that includes a wide range of factors (Saade & Kira, 2006). One of the major factors affecting learner satisfaction is the course selection process. Prior to every academic term, students make a series of interdependent course selection decisions. The course selections they make create a chain of reactions that

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influence future course choices, skill development, and job decisions (Babad, 2001). Recently, Sun, Tsai, Finger, Chen, & Yeh (2008) conducted a survey to investigate the critical factors affecting learner satisfaction in e-learning. They extracted 13 various factors from previous literature and analyzed them statistically. The results revealed that among all these factors, course quality, which is comprised of some subfactors such as course selection and course scheduling, has the strongest association with learner satisfaction. Furthermore, it was shown that student satisfaction with a course is a key factor that influences their decisions to continue or drop-out of the course (Babad, Icekson, & Yelinek, 2008; Chiu, Hsu, Sun, Lin, & Sun, 2005; Levy, 2007). Therefore, the course selection problem is an essential area of research in the context of e-learning and needs considerable attention. This paper aims to investigate a technological learning-based method can be integrated into a system in order to predict the number of students interested in taking every course in an academic term with a high degree of reliability. This system can also learn from former student experience and current student demands.

2. Overview

A large number of universities place restrictions on which courses might run at a certain time. The restrictions are due to a lack of sufficient resources (e.g., faculty unavailability or technical constraints) and overheads involved in running too many courses. Moreover, for optimal course scheduling, prior to every semester administrators are required to know the correct number of students who are interested in taking each course. Thus, a fundamental problem in online higher education course planning is choosing the best overall set of courses to satisfy student needs considering the existing restrictions. Failing to consider this issue may lead to student dissatisfaction, inefficient scheduling, unsatisfactory registrations, and also an increase in the rates of course cancellation and selection during the drop and add period which is a few weeks into the term. Hence, the number of registrations in every course must be estimated before the scheduling. The initial approach used to make this estimation may be referencing a template of the previous semester. However, this solution often may not be effective due to differences between the following and previous terms. These differences include: changes in instructor characteristics and grading policy, student course workload, time conflicts between courses, or inappropriate class or final examination scheduling over the academic semesters. The second solution may be to allow students to vote for all courses they would like to attend. The information students use to choose their courses is obtained through a wide variety of sources. They include: academic advisors, course descriptions, course syllabi, college bulletins, past data on student ratings of instructors (Babad, Darley, & Kaplowitz, 1999), profiles of the instructors, online discussion forums, informal word of mouth, and online rating services (Davison & Price, 2009; Steffes & Burgee, 2009). The administrator would then gather the votes and eliminate those courses which have received the least number of votes. Following this process the college adjusts the courses it is offering to match student demands as much as possible. However, it should be noted that the student demands for their desirable courses are often not their actual needs and they may cancel some courses and/or select other ones during the drop and add period. This problem usually arises due to seven main reasons. First: many times students select a course without considering its prerequisites and therefore they are not allowed to take the course during the registration period. Second: large numbers of students lack an explicit and unambiguous understanding of their priorities and goals (Babad & Tayeb, 2003; Coleman & McKeachie, 1981; Warton & Cooney, 1997). Thus, the course selection process is quite ineffective and disorganized for many students. Third: frequently students ignore more valid and complete sources of information and prefer informal sources which often tend to be unreliable, distorted, and even detrimental resulting in less than optimal course selection (Babad, 2001; Dellar, 1994). Fourth: one fascinating characteristic of a course, such as a humorous instructor or an easy grade, might overshadow all other course aspects and may prevent students from considering other requirements. Fifth: during the course selection process the class time limit is not imposed. After the course selection period, the administrator using the collected votes tries to piece together a schedule that would suit instructors, students, and other university resources, requirements and facilities. Because time allocated to some of the courses might be inappropriate or cause overlapping, some students might not enroll in these classes. Sixth: some students neglect to participate in the course selection process. Seventh: through the course selection process the final examination time for each course is not imposed. Hence, the time of final examination for a course might be unsuitable for some students.

Due to the stated reasons student demands cannot reliably be used for course scheduling. Also, the courses taken by the students during the registration period may not be their final decisions due to reasons 2, 3 and 4 mentioned above (Babad et al., 2008). However, the drop and add period, which takes place a few weeks into the semester, satisfies the student actual needs as much as possible considering the university constraints. Thus, in order to find the actual student demands, the number of final registrations in every course after the drop and add period must be predicted. In other words, the process of student course selection must be modeled. Neural network techniques are powerful tools in dealing with modeling nonlinear behaviors. They enable the construction of models that efficiently describe real world systems and recently have been successfully applied to approximating nonlinear functions in many disciplines including traditional and online education (Baylari & Montazer, 2009; Guo, 2010; Lo, Chan, & Yeh, 2012; Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Moridis & Economides, 2009; Zafra, Romero, & Ventura, 2011). However, there has been no report on applying neural network to student course selection modeling. This problem is a multivariate, nonlinear one and depends on many factors (Babad, 2001; Babad et al., 2008; Babad & Tayeb, 2003; Marsh & Roche, 2000; McGoldrick & Schuhmann, 2002; Svanum & Aigner, 2011). Thus, the main focus of this study is firstly, identifying the potential factors that affect student satisfaction toward the online courses they select, secondly, modeling the student course selection problem and fitting a function to the training data through neural network approach, and lastly, using the obtained function to predict the number of final registrations in every course.

3. ELCAUT: an online graduate college

E-Learning Center of Amirkabir University of Technology (ELCAUT) was established in 2004 as the first e-learning center for higher education in Iran. ELCAUT currently offers 24 different masters programs in 9 colleges. All courses are delivered via live, synchronous online sessions through a virtual classroom tool. This technology allows an instructor to lecture and for students to ask questions, interact with other students, and even give presentations. In this research to examine the course selection problem with online distance higher education, two master's programs called "Information Technology and Management Engineering" and "Computer Networks Engineering" were considered as the case study.

ELCAUT, similar to most universities in the world, carries out online surveys at the end of each academic term to discover the degree to which students are satisfied with courses, instructors, and technical aspects of the Learning Management System (LMS). Within each of the courses taken by a student online questionnaires for course and instructor satisfaction are provided. The evaluations begin three weeks before the end of semester and end the last week of class. The data gathered through this evaluation is used by instructors as feedback for improvement of their courses. Moreover, this data is presented to the college administrators to improve student and educational affairs. Technical experts also employ some required data to improve and extend the LMS. This online survey can shorten and automate the process of analyzing data and comparing results for different courses and instructors. It can automatically calculate basic statistical data such as the mean, mode, and standard deviation. It can also generate a database for each questionnaire which can be utilized for more complex statistical operations.

4. The factors influencing student course selection

Various factors can be influential in predicting the number of students who will take a particular course in the upcoming semester. Prediction of this number helps to determine the most satisfying courses for the forthcoming academic term. This section discusses these factors in more detail.

The first three factors taken into account are associated with the level of student satisfaction with a course. The required data to calculate the values of these factors can be extracted from the online questionnaires filled by the students who took the course in the previous semester. In ELCAUT, every questionnaire consists of some questions asking the degree of agreement on a given sentence using a Likert scale of 1–5 in which 1 represents strong disagreement and 5 denotes strong agreement. The questions on the questionnaire are categorized into the three groups which appraise a course in different aspects which include course characteristics, instructor characteristics, and student workload. Since the degree of importance for each sentence in the questionnaire might differ based on student perspective for course selection, a weight is assigned to each sentence. In order to obtain these weights, an online survey was conducted and students were asked to state their opinion with regard to the influence of each factor on selecting a course. The response to each sentence was recorded on the Likert scale, ranging from 1 (not at all important) to 5 (very important). A total of 214 students participated in the survey. The mean results for each sentence were then computed and normalized between 0 and 1. The obtained weights are reflected in Tables 1–3.

4.1. Course characteristics

Typically students like to take interesting and useful courses. According to Babad (2001), one of the vital factors in selection of the first course by a student is the characteristics of the course. McGoldrick and Schuhmann (2002), over a sample of 400 undergraduate students, exposed that course selection is more of a function of relevance toward future careers and perceived interest in course topics. As mentioned earlier, an online questionnaire is formally administered to all students in all virtual classes at the end of each semester in ELCAUT. It consists of a series of statements to which the student is expected to respond to on a five-point scale, from strongly agree to strongly disagree. In addition, each sentence is associated with a weight indicating its degree of importance. Table 1 illustrates the factors related to the course characteristics extracted from the questionnaire along with their weights.

The score of each course is the arithmetic mean of the weighted average of the student responses to the questionnaire in the last semester the course was offered, computed as:

$$Course\ Score = \frac{1}{\sum_{k=1}^{L} M_k}\left(\sum_{k=1}^{L}\sum_{j=1}^{M_k}\frac{\sum_{i=1}^{N} W_i C_{kji}}{\sum_{i=1}^{N} W_i}\right)$$

where W_i is the weight of ith question in the questionnaire, C_{kji} denotes the response of jth student to ith question in the kth online class, N is the number of weights (which here equals 6), M_k is the number of students in the kth virtual class, and L implies the number of online classes offering the course. As shown, this score is used as the indicator of course characteristics without considering its instructor. Also, it should be noted that a student in the course selection process usually compares the offered courses with one another and chooses the best ones. To mimic this student behavior, a z-score for each course is computed. A z-score (also known as z-value or standard score) is a measure of the divergence of an individual experimental result from the most probable result, the mean. It indicates how many standard deviations an observation is above or below the mean. The z-score of course i in the last term it was offered is computed as:

$$z\ score(x_i) = \frac{x_i - \mu}{\delta}$$

where x_i denotes the score of course i to be standardized and μ and δ represent the mean and standard deviation of the scores of the offered courses, respectively.

Table 1
Course characteristics.

No.	Statement in questionnaire	Weight
1	The course can contribute to my personal development	0.294
2	The course helps me for present work or prepare me for future occupation	0.825
3	The course subject is interesting	0.703
4	The course is useful in giving new knowledge or skills	0.683
5	The course helps to change my attitude to life	0.316
6	The course covers modern topics in the program	0.719

Sometimes a course is going to be offered for the first time, and therefore, no corresponding student ratings from the preceding terms are available to compute its score. In this case either the experts (i.e. instructors) can vote for the course, or the mean student ratings of all the other courses offered in the previous term can be used. In this study the first approach was utilized.

4.2. Instructor's characteristics

Several studies exposed that students are drawn to the courses that have effective instructors (Babad & Tayeb, 2003; Ellis, Ginns, & Piggott, 2009; Lee, Yoon, & Lee, 2009; Paechter, Maier, & Macher, 2010). All this research disclosed that instructor characteristics contribute positively to student satisfaction with the course. Data regarding the overall satisfaction toward the instructor is taken through the online survey. The factors associated with the instructor are derived from the ELCAUT questionnaire are reported in Table 2. Note that the student ratings of an instructor for various courses may differ from one another. For instance, an instructor may be a famous expert on the topic of a particular course but not on other course topics. After extracting the required information from the questionnaires, the standardized mean of the weighted average of the instructor's characteristics in all of the online classes from the last term the course was taught by that instructor is employed as the value of this factor.

4.3. Student's workload

Entwistle and Ramsden (1983) defined student workload as the pressure placed on students in terms of demands of the syllabus and assessment tasks. Prior to every term, students might be apprehensive of those courses which are considered too difficult. According to Marsh and Roche (2000), for countless students, an important factor influencing their decisions to take a course of study is the workload they are asked or expected to do. Moreover, Centra (2003) discovered that the courses which are difficult or too elementary have low student ratings, and the courses that are considered in between or "just right" receive the highest ratings. The factors utilized in the ELCAUT questionnaire which are associated with student workload in a course are listed in Table 3. The standardized mean of the weighted average of student workload in all online classes in the last semester taught by the instructor is used as the value of this factor.

4.4. Course grade

Sometimes grades rather than learning become the primary goal of students. They might need to earn high grades for future admission into advanced programs, applying for a well-paying job, or any other personal reason. Greenwald and Gillmore (1997) found that the instructors who give higher grades were better liked. Also, Svanum and Aigner (2011) revealed that course grades have a moderately strong effect on student ratings of the course in an online university. According to Babcock (2010), students significantly tend to enroll in those courses which are taught by lenient instructors. Therefore, the mean grade of a course in the previous semester is a major criterion that students usually take into account for selecting the course. The value must be standardized by z-score transformation as well.

Sometimes an instructor teaches a particular course for the first time at the university. Since in this case the corresponding grades are not available, the mean of the grades given by the instructor in other courses taught in the preceding semester can be utilized instead. Also, if the instructor is a newcomer to the university and no information is available about him/her, the mean of the grades of all the instructors who taught the course in the previous semester could be considered to calculate the value of this factor. This technique can be applied to the two previous factors as well.

4.5. Course type

Just like in a traditional college or university, every online program has a set of required and elective course offerings. Required courses are those that must be taken to fulfill specific requirements of the program. Elective courses are those selected as supplemental to the list of

Table 2
Instructor's characteristics.

No.	Statement in questionnaire	Weight
1	The instructor starts online classes promptly	0.213
2	The instructor encourages students to participate in online class by questioning, presentation, discussion, project, etc.	0.466
3	The course materials are placed online in a timely fashion	0.529
4	The instructor has good rapport with the students	0.765
5	The instructor is easily and fast accessible outside the online classroom via communication facilities (e.g., chat, e-mail, and discussion forum)	0.657
6	The grading policy of the course is objective and impartial	0.781
7	The course materials are prepared well in an appropriate format	0.624
8	The language used for delivering instruction is clear and understandable	0.811
9	The instructor tries to use e-learning methods and techniques whenever necessary throughout the course	0.388
10	The course time is used effectively	0.387
11	The instructor helps students to develop self confidence	0.413
12	The instructor shares innovations about the course content with students	0.743
13	The instructor is a known expert on this topic	0.830
14	The provided assignments are interesting	0.551
15	The instructor motivates the students to work hard	0.378
16	The instructor respects the student personality and capabilities	0.647
17	Students are given fast and helpful feedback on the course activities such as assignments, presentation, discussion and etc.	0.735
18	The instructor fosters cooperative learning (e.g., by group activities, discussions etc.)	0.687
19	The instructor handles the e-learning environment effectively	0.711
20	The instructor is enough knowledgeable about the course	0.912

Table 3
The factors corresponding to the student's workload.

No.	Statement in questionnaire	Weight
1	The course contents are difficult to understand	0.710
2	The number of topics to be covered is large	0.735
3	The tempo of the course progress is fast	0.763
4	The frequency of quizzes is high	0.827
5	It is tough to get high grades in the exams and quizzes	0.850
6	The number of assignments is large	0.881
7	The assignments of the course are difficult	0.749
8	Attendance in the course is required	0.604

required courses on the basis of personal interest, abilities, and career goals. In most higher education institutes, required courses usually have lower degrees of freedom in selection than electives. Previous studies reported that students rate elective courses more favorably than required courses, presumably because students are participating in a course that they have an interest or focus in Darby (2006), Boland, Lehman, and Stroade (2001). Hence, course type is another major factor that needs to be considered for modeling the student course selection process.

4.6. Course time

McGoldrick and Schuhmann (2002), in a large scale study, revealed that college students' choice of courses is in large part a function of the time of day the course is offered. Those authors found that students are obviously averse to early morning and late afternoon class times, with the former least preferred. Furthermore, their study disclosed that while both late morning and early afternoon classes are statistically greatly preferred to either early morning or late afternoon class times, students place the greatest value on late morning class times. Thus, the course time is another factor and accepts 4 values including early morning, late morning, early afternoon and late afternoon.

4.7. Number of time conflicts

The online classes which are overlapping in time cannot be attended by the same students. Without taking this issue into consideration, a schedule very likely can incur time conflicts preventing lots of students from taking their intended courses. Hence, the number of time conflicts is another factor that might influence student decisions to take a course. Administrators, for better time conflict detection, can categorize all the program's courses into several groups. Each group includes those courses which cannot cause overlapping. For example, a unique course may be taught by several instructors, but every student can only choose one of them. Thus, it would be better to classify these courses under one group. Another instance is courses which require prerequisites. Obviously, selection of two different courses from distinct groups occurring in the same time interval might cause a time conflict.

4.8. Final examination time

One of the other major factors influencing a student's decision to take a course is the final examination time assigned to the course. If the time between exams is lengthened in hopes of producing more time to study and fewer conflicts, then students are able to take their desired courses. Otherwise they may avoid selecting some courses with unsuitable final examination time. To consider this factor, the weighted average of the exams happening in the past 3 days of an exam for a particular course K, called E_k is computed as:

$$E_k = \frac{1}{4}\sum_{i=1}^{4}\frac{1}{i}x_i$$

where x_i implies the number of exams occurring in the ith previous day. For example, x_1 is number of exams that take place on the exam day of course K. This score must be standardized by z-score transformation as well.

4.9. Student demands

In the course selection period, a student selects the most desirable courses among the alternatives on the basis of the available information. Although, as mentioned earlier, every decision the student makes about the alternatives during the drop and add period is more sensible than those decisions made during the initial course selection period, the first decisions are reasonably acceptable and can be applied as a feature for forecasting the final number of course registrations. Thus, for every course, the proportion of student demands to the number of eligible students in the program is obtained. Eligible students are those who are allowed into the course. For instance, students who have not previously passed the course and those who have met the prerequisites and have their advisor's permission are considered eligible.

5. Multi-layer perceptron neural networks

Several types of neural networks exist. Among them, the feed-forward neural networks are the most popular architectures due to their structural flexibility, good representational capabilities, and availability of a large number of training algorithms (Haykin, 1999). This network comprises neurons arranged in layers in which every neuron is connected to all neurons of the next layer (a fully connected network). Multilayer perceptron neural networks (MLPs) are a type of feed-forward network consisting of an input layer of nodes followed by two or more layers of neurons with the last layer being the output layer. The input layer is first layer and it accepts symptoms, signs, and experimental data. The layers between the input and output layers are referred to as hidden layers. Outputs of neurons in one layer are inputs for the next layer. There are no connections between non-adjacent layers and no connections between neurons in the same layer. Connections between layers go in only one direction, i.e. there are no feedbacks. Fig. 1 illustrates the architecture of a three-layer MLP with one hidden layer of l nodes, a p-dimensional input vector I, and a q-dimensional output vector O.

The relationship between the input and output components for this MLP can be generally expressed as:

$$O_k = \beta\left(\sum_{j=1}^{l} c_j + V_{kj}\alpha\left(\sum_{i=1}^{p} b_i + U_{ji}I_i\right)\right), \quad k = (1, 2 \ldots q)$$

where α and β are the transfer functions; b_i and c_j are the biases for neurons i and j, respectively; U_{ji} denotes the input-to-hidden layer weights at the hidden neuron j; V_{kj} is the hidden-to-output layer weights at the output unit k. As seen from Fig. 1, the neurons of each layer are connected to the neurons of the next layer by weights. In order to obtain optimal values of these connection weights, the network must be trained. During training, a set of examples N are given to the network. Each example consists of an input vector and the corresponding output vector. Then an iterative algorithm minimizes a cost function typically defined as the mean square error between its targets (desired responses) and outputs (network responses) by adjusting the network weights and neuron biases. The mean square error is defined as:

$$MSE = \frac{1}{N}\sum_{m=1}^{N}(T_m - O_m)^2$$

where T_m and O_m are the target and output of sample m, respectively. In addition to MSE, another indicator to measure the quality of a neural network is correlation coefficient (R value). It shows the relationship between the targets and outputs and is defined as:

$$R = \frac{\sum_{m=1}^{N}(T_m - \mu_T)(O_m - \mu_O)}{\sqrt{\sum_{m=1}^{N}(T_m - \mu_T)^2}\sqrt{\sum_{m=1}^{N}(O_m - \mu_O)^2}}$$

where μ_T denotes the average of targets and μ_O is the average of outputs of the network. The range of R is from -1 to 1. If the training were perfect, the targets and outputs would be exactly equal ($R = 1$) and the relationship is considered correlated, but the relationship is rarely perfect in practice. On the other hand, if R is close to -1, then there is no linear relationship between the targets and outputs and the relationship is considered anti-correlated. As the R value deviates from either of these values and approaches zero, the points are considered to become less correlated and eventually are uncorrelated.

The back-propagation algorithm is most widely used to adjust the network parameters which were established by Rumelhart, Hinton, and Williams (1986). According to this algorithm, information is passed forward from the input nodes through the hidden layers to the output nodes and the error between the desired response and the actual response of the network is computed. This error signal is then propagated backwards to the input neurons adjusting the network weights and biases. This process is repeated for each sample in the training set. As soon as the entire training set has been presented to the network, an epoch has elapsed. The training phase may comprise several epochs (Lykourentzou, Giannoukos, Mpardis, Nikolopoulos, & Loumos, 2009). A popular approach to optimizing the performance of back-propagation is the Levenberg–Marquardt algorithm (Marquardt, 1963) which has been exposed to increase the speed of convergence and effectiveness of the moderate-sized network training (Hagan, Demuth, & Beale, 1996; Hagan & Menhaj, 1994).

During the training phase, a network may end up memorizing the training data and thus lose its ability to generalize from the training samples to an unseen population. This phenomenon is called over-fitting and can be avoided by employing a separate data set called the validation set. The network parameters are estimated based only on the training set and the performance of the network is assessed by computing the MSE on the validation set. When the network performance deteriorates, it usually means that over-fitting has occurred. The

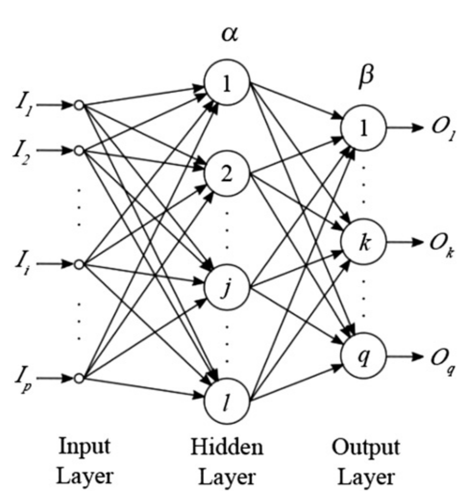

Fig. 1. Architecture of a three-layer MLP network.

training then stops and the parameters of the best previously trained network are stored. The training phase can be terminated by reaching a minimum in the cost function, by meeting the performance goal, or by detecting that the validation set produced increasing MSE. Finally, after the training is finished, the network test phase occurs. During this phase, unseen data are presented to the trained network to appraise its performance. These data comprise the test set that is disjoint to both the training and the validation data sets (Lykourentzou et al., 2009).

6. Experimental results

6.1. Data set

This study was applied on two master's programs called, "Information Technology and Management Engineering" (ITME) and "Computer Networks Engineering" (CNE), offered by ELCAUT. Each program consists of 6 required and 9 elective courses. Students are required to take and pass 4 out of 9 elective courses and also 4 out of 6 required courses during their program. The samples collected for this research included 714 courses over 16 academic terms from 2005 to 2012. The maximum capacity of each virtual class is 30 and the classes with less than 10 students enrolled are canceled in accordance with the university's guidelines. Further details about the total number of virtual classes and students enrolled in the programs from the spring 2005 to the fall 2012 semesters are reported in Table 4.

The data set used in this study was divided into three separate sets; namely the training, validation, and test set. The training set consisted of 74% of the data which corresponds to 529 courses offered in the spring 2005 to fall 2010 semesters. The validation set comprised 13% of the data which associated with 92 courses in the spring and fall 2011 semesters. The remaining 13% of the data from 93 courses offered in the spring and fall 2012 terms was used as the test set. The use of 14 semesters' data for the training phase and 2 semesters' data for the test phase was chosen to examine whether neural network are capable of predicting unseen student registration data for the next semesters.

6.2. Network architecture and training

In this study, to implement the networks, the MATLAB® R2010b platform was utilized. Previous research revealed that a three-layer MLP network is technically sufficient for achieving satisfactory approximation (Hornik, Stinchcomb, & White, 1989; White, 1989); therefore a three-layer MLP was employed. The input layer has 8 nodes equal to the input vector length or 9 nodes when the student demand factor is included. The number of nodes in the hidden layer required to make a good predictive network depends on several factors including the size of the training data set, complexity of the problem, number of nodes in both the input and output layers, network architecture, training algorithm, amount of noise in the actual output, and the required accuracy of the prediction (Sun, Peng, Chen, & Shukla, 2003). The number of nodes in the hidden layer is an important factor of a successful training because having too few hidden nodes may lead to a reduction of the learning ability of a network and too many hidden nodes may result in over-fitting or memorization of the training data set and a reduced ability of a network to generalize and predict accurately (Sun et al., 2003). No universal rule exists for finding the optimal network

Table 4
The number of online classes and students in each academic term.

No.	Semester	Program	No. of online classes	No. of registered students
1	Spring 2005	ITME	19	146
2		CNE	23	194
3	Fall 2005	ITME	21	161
4		CNE	22	180
5	Spring 2006	ITME	20	156
6		CNE	24	205
7	Fall 2006	ITME	22	177
8		CNE	23	188
9	Spring 2007	ITME	20	158
10		CNE	21	172
11	Fall 2007	ITME	23	184
12		CNE	22	186
13	Spring 2008	ITME	20	152
14		CNE	24	208
15	Fall 2008	ITME	21	160
16		CNE	23	197
17	Spring 2009	ITME	21	169
18		CNE	25	224
19	Fall 2009	ITME	22	175
20		CNE	23	196
21	Spring 2010	ITME	21	172
22		CNE	22	180
23	Fall 2010	ITME	23	191
24		CNE	24	215
25	Spring 2011	ITME	22	183
26		CNE	25	231
27	Fall 2011	ITME	22	179
28		CNE	23	194
29	Spring 2012	ITME	21	166
30		CNE	25	235
31	Fall 2012	ITME	23	180
32		CNE	24	223

Table 5
Training results of the MLP models.

	20 Neurons			30 Neurons			40 Neurons		
	MSE	*R*	Epoch	MSE	*R*	Epoch	MSE	*R*	Epoch
Without considering student demands	0.0054	0.892	83	0.0026	0.914	59	0.0025	0.927	24
With considering student demands	0.0042	0.910	74	0.0033	0.925	46	0.0014	0.946	27

parameters such as number of hidden layers, number of nodes in the hidden layers and transfer functions, even though some simple rules of thumb have been suggested (Rumelhart et al., 1986). Thus the practitioner's strategy of running a number of experiments (Curry & Morgan, 2006) is used to determine the optimal network parameters to yield the best regression results. Experimental results revealed that using two hidden layers caused over-fitting problem which led to good network training and data memorization, but an inability to generalize. Hence, the network training was conducted using a hidden layer of 20, 30, and 40 nodes. The training algorithm was selected as Levenberg–Marquardt. The transfer functions for hidden and output layers were chosen as log-sigmoid and linear, respectively. The output layer has one node and generates a value between 0 and 1. This value is a prediction of the proportion of student course registrations after the drop and add period to the number of eligible students in the program in the forthcoming semester. The networks were trained once by 8 inputs mentioned earlier and then by 9 inputs of which the ninth was student demands. During the experiments for each one of the networks, 50 training iterations took place and the best trained network was kept. The training results are summarized in Table 5.

As shown in the table, an increase in the number of neurons in the hidden layer accelerated the convergence, but only slightly improved the MSE and correlation coefficient (*R* value). However, as the number of nodes was increased to above 40, the efficiency of the network was decreased, which was likely due to overtraining of the network. The first row of Table 5 shows that the 20-neuron hidden-layer MLP with 8 inputs reached a steady MSE of 0.0054 and *R* value of 0.892 after 83 epochs. However, it only needed 24 epochs for the 40-neuron hidden-layer MLP to reach a steady MSE of 0.0025 and *R* value of 0.927, which demonstrates a quick learning. Furthermore, the best training was readily achieved by using student demands as the ninth input to MLPs (second row of Table 5). It took 27 epochs for the 40-neuron hidden-layer MLP to reach a steady MSE of 0.0014 and *R* value of 0.946. The finding implied that the student demand factor is slightly influential in modeling student course selection behavior.

6.3. Testing the trained network

The trained neural networks were presented with the test data set corresponding with 93 courses in the spring and fall 2012 semesters to examine the prediction accuracy. The quality of these networks was reflected by MSE and correlation coefficient measures. The results are tabulated in Table 6. As can be seen, both models represented good quality for forecasting. However their accuracy on the unseen data was slightly worse than on the training data. The first model (8-input network) with 20 nodes in the hidden layer returned the highest MSE of 0.0081 and the lowest correlation of 0.867 among all the others. In addition, the second model (9-input network) with 40 nodes in the hidden layer was the best performer with a MSE of 0.0029 and correlation of 0.923.

The performance of the 40-neuron hidden-layer MLP with 8 and 9 inputs during the test phase is also graphically depicted in Figs. 2 and 3, respectively. These figures show the relation between the response of the neural network (vertical axis) and the desired response (horizontal axis). It can be seen from Fig. 2 that the regression between the desired output and predicted result returns a correlation coefficient of 0.896 which indicates a good fit, in general, between them. However, the best regression is produced by considering student demands with a correlation coefficient of 0.923. As it appears in Fig. 3, only 5 out of the 93 points are drifted away from the perfect linear fit.

In order to investigate the efficiency of the proposed models, they were compared with two naive and traditional approaches. The first method was use of a template of past student registration data for the upcoming semester. Hence, for each of the two last terms (the spring and fall 2012), the number of student registrations after the drop and add period in every course was compared to the corresponding one in the previous term. The second naive alternative is collecting the student demands for the courses offered by the university and employing them as an indicator for the student enrollment in every course. The performance of the method was appraised through gathering the student demands for every course prior to the semester and comparing them with the final student enrollment in the corresponding courses after the drop and add period. Furthermore, three other machine learning techniques called "support vector regression" (SVR), "K-nearest neighborhood" (KNN) and "decision tree" (DT) were used to model the problem. In each case several experiments were conducted with different parameters and the best result was selected as the outcome of the method. All approaches utilized student demands as well. The performance of the models was measured using MSE and correlation coefficient. Table 7 reports the obtained results. For better comparison, the results of the suggested neural network model are also listed in the two last rows of the table.

Findings revealed that the neural network method with considering student demands outperformed the others. The results also show that the neural network method, without considering the student demands, is not as accurate as the model with this consideration. However, its MSE of 0.0036 and correlation coefficient of 0.896 keeps it as a useful alternative in case of lack of student demands. In this study, after neural network, DT method occupied the next position followed by KNN and SVR methods. As reported in Table 7 both of the

Table 6
Testing results of the MLP models.

	20 Neurons		30 Neurons		40 Neurons	
	MSE	*R*	MSE	*R*	MSE	*R*
Without considering student demands	0.0081	0.867	0.0045	0.880	0.0036	0.896
With considering student demands	0.0062	0.881	0.0057	0.904	0.0029	0.923

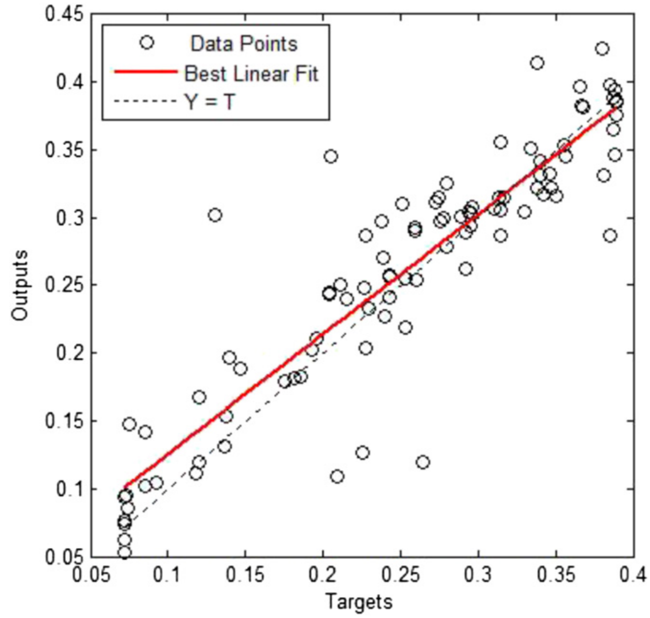

Fig. 2. Linear regression between the target and network output without considering student demands, $R = 0.896$.

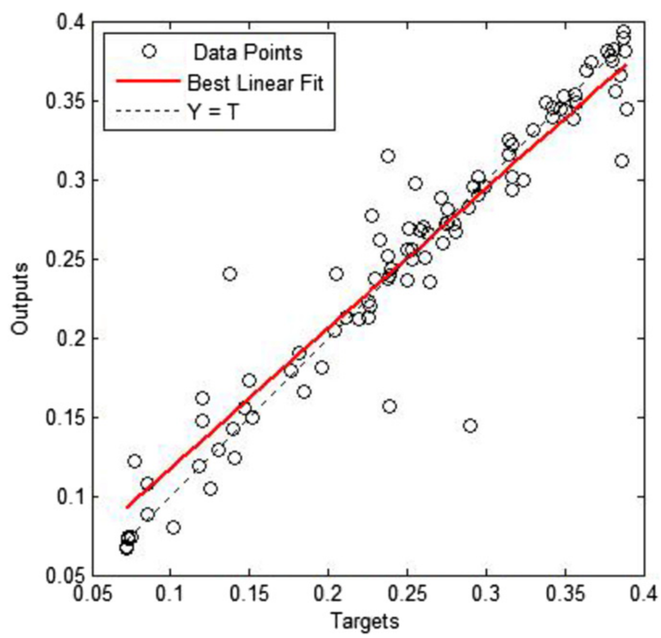

Fig. 3. Linear regression between the target and network output with considering student demands, $R = 0.923$.

Table 7
Comparison between the performance of various methods.

Method	MSE	Correlation (R value)
Past student registration data	0.0095	0.548
Student demands	0.0071	0.663
Support vector regression	0.0057	0.868
K-nearest neighborhood	0.0044	0.872
Decision tree	0.0039	0.891
NN without considering student demands	0.0036	0.896
NN with considering student demands	0.0029	0.923

naive methods gave the lowest performance. However, the latter performed better than the former. The reasons for inefficiency of the traditional approaches were also mentioned in the earlier sections and thus we avoid further discussion.

7. Conclusion and suggestions

This paper analyzed the course selection problem as a key factor of student satisfaction in online higher education institutes. A neural network-based system was suggested to imitate the student behavior in the registration and drop and add periods for selecting the offered courses in an online university. The intelligent system was then utilized to predict the satisfying courses for the following academic term. By conducting substantial investigations and thorough reviews of the relevant literature, 8 influential factors in the process were determined and used as the inputs of the model. The factors were course characteristics, instructor characteristics, course difficulty and student workload, course grade, course type in terms of required or elective, time of day of the course, number of time conflicts of the course with others, and final examination time. However, the first three included some sub-factors. It should be noted that considering each sub-factor as an individual factor may result in increasing the number of network inputs which may cause a network over-fitting problem. In total, 714 online graduate courses were used to conduct the experiments. These were broken down into training, validation, and test as follows: 529, 92 and 93. A three-layer MLP with 40 nodes in the hidden layer was trained and a MSE of 0.0036 and a correlation of 0.896 were achieved on the test data. However, the performance of the model was not perfect due to some unpredictable student personal preferences. To meet this challenge the student demands factor was provided as the ninth input for the model. It was found to be effective in the resulting prediction and by using this feature the MSE and correlation changed to 0.0029 and 0.923, respectively. This is an acceptable but not perfect prediction. The imperfection is due to some unpredictable time-dependent factors such as avoidance of taking a course because of the time conflict between the course and job. Careless and dishonest student answers to the questions on the questionnaire are also another influential factor in producing imperfect prediction results. Finally, the suggested neural network models were compared with three regression and two traditional methods. It was exposed that each proposed model is capable of producing a more accurate prediction than other methods do.

Those researchers who wish to develop the introduced prediction system for their institutes should consider three issues. First, in this implementation various experiments for finding the best configuration of the input factors to be fed into the network were examined. Although the final obtained configuration achieved a high accuracy in prediction of student enrollment for ELCAUT, this configuration may not be optimal for other institutes. For instance, considering more (or less) than four values for course time factor or an alternative formulation for final examination time may be sometimes more effective. Those discrepancies in configurations are due to the differences in cultures, educational degrees, programs and so on. Hence modifying the structure of some factors, adding new ones or eliminating some may produce effective results for an institute. Second, although neural network was experimentally detected as the best approach for this study, employing other machine learning techniques or a hybrid one may result in better prediction accuracy for other institutes. Considering this issue can particularly benefit those institutes that do not have all past student registration data required for prediction. An example would be when the data associated with student workload or demands is not available. Third, as outlined in this contribution, the developed model can only be used for prediction of student registrations for a specific course. Researchers can focus on extending the approach to automatically detect the most satisfying courses for the forthcoming term considering the existing constraints. It is an optimization problem in which its solution results in maximizing the total number of registrations and making profit for the corresponding institute. By taking these issues into account, educational institutes can effectively adapt the system to their needs.

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