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Oleksandr MELNYKOV, Veniamin GITIS
Donbas State Engineering Academy
Iryna GITIS
Kharkiv National University of Radio Electronics

FORECASTING THE SUCCESS OF EDUCATION SEEKERS FROM A SEPARATE EDUCATIONAL COMPONENT BASED ON THE RESULTS OF THE PRELIMINARY MASTERY OF SUBJECT COMPETENCIES

The paper examines the main concepts related to the quality of education in general and the assimilation of educational material by higher education seekers. The task of predicting a seeker's grade in any discipline is formulated with data on his assimilation of program learning outcomes that also correspond to this discipline. The available specialized information system of own development is described which applies a number of methods (multivariate linear regression, artificial neural networks, k-nearest neighbors) and determines which method will be the most effective for the analysis of specific data. It is noted that during the further improvement of the quality system of knowledge assessment, it is important to determine at what level the student of education possesses the acquired competences, i.e. to calculate the success of seekers in terms of general and professional competences and program learning outcomes, determined by the standards of higher education and educational programs developed on their basis. The developed algorithm for calculating the success rate of higher education applicants in terms of program learning outcomes is presented; according to this algorithm, data were prepared on the acquisition of software creation competencies by 78 seekers of the first level of higher education of the educational and professional program Intelligent Decision Support Systems specialty 124, Systems analysis, of the DSEA. To solve the problem of forecasting by the method of artificial neural networks, the programming and data analysis language R is proposed. A script for finding the optimal neural network architecture is created. It was found that the best result (correlation is 0.9599, average absolute reduced error is 0.1132, percentage of correctly predicted points on the Ukrainian scale is 79.2) provides a perceptron with two hidden layers and five neurons in each one. This network was applied to predict the success of the new academic group: correlation is 0.923, the average absolute reduced error is 0.0654, the percentage of correctly predicted points on the Ukrainian scale is 82.4. The obtained results can be used to assess the quality of the structural and logical scheme of the EPP and in the work of the department during the analysis of seekers' success, etc.

Keywords: educational and professional program, forecasting, artificial neural network, perceptron, neural network training, R-language.

Олександр МЕЛЬНИКОВ, Веніямин ГІТІС
Донбаська державна машинобудівна академія
Ірина ГІТІС
Харківський національний університет радіоелектроніки

ПРОГНОЗУВАННЯ УСПІШНОСТІ ЗДОБУВАЧІВ ОСВІТИ З ОКРЕМОЇ ОСВІТНЬОЇ КОМПОНЕНТИ НА ОСНОВІ РЕЗУЛЬТАТІВ ПОПЕРЕДНЬОГО ЗАСВОЄННЯ ПРЕДМЕТНИХ КОМПЕТЕНТНОСТЕЙ

В роботі розглянуто основні поняття, пов'язані з якістю освіти у цілому та засвоєнням здобувачами вищої освіти навчального матеріалу. Сформульовано задачу прогнозування оцінки студента з будь-якої дисципліни, маючи дані щодо засвоєння ним програмних результатів навчання, які відповідають також цій дисципліні. Описано наявну спеціалізовану інформаційну систему власної розробки, яка застосовує низку методів (багатофакторна лінійна регресія, штучні нейронні мережі, k-найближчих сусідів) та визначає такий метод, який буде максимально ефективними для аналізу конкретних даних. Зазначено, що при подальшому вдосконалюванні системи якості оцінювання знань важливо визначити, на якому рівні здобувач освіти володіє здобутими компетентностями – тобто проводити розрахунок успішності студентів у термінах загальних і фахових компетентностей та програмних результатів навчання, визначених стандартами вищої освіти та розробленими на їхній основі освітніми програмами. Наведено розроблений алгоритм розрахунку успішності здобувачів вищої освіти в термінах програмних результатів навчання; згідно з цим алгоритмом підготовлено дані щодо засвоєння 78 здобувачами першого рівня вищої освіти освітньо-професійної програми «Інтелектуальні системи прийняття рішень» спеціальності 124 «Системний аналіз» ДДМА компетентностей створення програмного забезпечення. Для розв'язання задачі прогнозування методом штучних нейронних мереж запропоновано мову програмування та аналізу даних R. Створено скрипт для пошуку оптимальної архітектури нейронної мережі. З'ясовано, що найкращий результат (кореляція – 0,9599; середня абсолютна приведена помилка – 0,1132; відсоток вірно спрогнозованих балів за українською шкалою – 79,2) забезпечує персептрон з двома прихованими шарами та п'ятьома нейронами у кожному шарі. Далі ця мережа була застосована для прогнозування успішності нової академічної групи: кореляція – 0,923; середня абсолютна приведена помилка – 0,0654; відсоток вірно спрогнозованих балів за українською шкалою – 82,4. Отримані результати можна буде застосувати для оцінки якості структурно-логічної схеми ОПП та у роботі кафедри під час аналізу успішності студентів тощо.

Ключові слова: освітньо-професійна програма, прогнозування, штучна нейронна мережа, персептрон, навчання нейромережі, мова R.

Introduction

Assessment of the material learned by students within an academic discipline, as well as the objectivity of this knowledge control, are one of the main elements of determining the quality of education [1]. It is known that the level of assimilation of new knowledge by an individual depends primarily on his diligence and the basic level of knowledge, which is almost constant during the study period, therefore a sharp deviation in the evaluation process may indicate the presence of problems, objective and subjective factors that influence on the educational process. All educational components at the corresponding level of higher education, the list of academic disciplines and the logical sequence of their study, the number of ECTS credits, as well as the expected learning outcomes and competences that must be mastered by the seeker of the corresponding level of higher education, are contained in the educational program [2]. The structural and logical scheme of training is provided in the form of a network of interdisciplinary connections and is valid throughout the entire period of implementation of the corresponding training program. So, one of the factors affecting the grade received by a higher education degree seeker from a separate discipline are grades from the disciplines that "support" it, i.e. those that precede this one.

Analysis of the subject area

In paper [3], to improve the management of the educational process at the graduation department of a higher education institution, it was proposed to develop a specialized information system which applies a number of methods (multivariate linear regression, artificial neural networks, k-nearest neighbors) and defines a method that will be the most effective for the analysis of specific data. The task was formulated as follows. A seeker's grade in any discipline needs to be predicted, using given data on grades in "supporting" disciplines:

$$y = \{x_1, x_2, ..., x_n\}, \quad (1)$$

where y is the predicted grade in the discipline;

x_i, $i=1..n$ is grade in the i-th "supporting" discipline;

n is the number of "supporting" disciplines.

The researcher sets the limit values of the parameters for each method (for example, the minimum and maximum number of hidden layers of artificial neural networks, etc.), then the software system performs the calculation for each of the methods, the results are added to the table. The researcher chooses the best, in his opinion, method (usually based on the minimum total error, but other selection criteria are also possible). The selected method is used to predict the grades of the same subject for a new group. The choice of supporting disciplines is not clearly a point of the given algorithm, since it is carried out either directly from the educational program (its structural and logical scheme), or as a result of some previous research.

The operation of the system was described using the example of data on higher education seekers majoring in System Analysis [2] and the subject of programming knowledge and skills acquisition; four input and one output factors were identified:

x_1 is a grade in the discipline Programming and Algorithmic Languages;

x_2 is a grade in the discipline Algorithms and Data Structures;

x_3 is a grade in the discipline Mathematical Logic and Theory of Algorithms;

x_4 is a grade in the discipline Optimization Methods and Operations Research;

y is a grade in the discipline Technology of Creating Software Products.

Names of groups and surnames of seekers are informative factors.

Conducted research with the help of the developed system proved that, from a number of mathematical methods (linear regression analysis, artificial neural networks, nearest neighbors), the method of artificial neural networks leads to satisfactory results of predicting the grades of higher education seekers from a separate discipline, depending on the quality of assimilation of the previous material. By conducting a series of numerical experiments, the optimal architecture of the neural network was selected, a two-hidden-layer perceptron with five neurons in each. The obtained results can be applied in the work of the department during the analysis of seekers' performance, etc.

The application of the method of artificial neural networks for solving the forecasting problem is also described in papers [4–7].

Problem formulation and input factors

However, in the further improvement of the quality system of knowledge assessment, it is important to determine at what level seeker of higher education possesses the acquired competences, i.e. to calculate the success of higher education seekers in terms of general and professional competences and program learning outcomes, determined by the standards of higher education [8] and educational programs developed on their basis [9]. A software system has been created that makes it possible to work with a list of formed competencies in subjects and program learning outcomes both within standards of higher education and EPP/ESP [10]. A feature of the developed system is the ability to analyze the success of the applicant or the entire group in terms of competencies (GC, PC) and program learning outcomes (PLO) that they have mastered. In work [11], the data analysis of the student of SA-20-mag group of the educational and professional program Intelligent Decision Support Systems of the second level of higher education, academic specialty 124, System Analysis, was carried out. Examples of calculating the success rate of the best student and the average indicator of competencies and program learning outcomes were presented.

The disadvantages of the system are the ability to work only within one academic group and the development of the curriculum in its entirety, taking into account all disciplines of free choice. And if the first drawback is overcome by downloading and storing the results of individual calculations for further processing, then taking into account the factor of "selective disciplines" has no solution since the list can change annually. In addition, a number of PLOs does not arouse interest from the point of view of the "professional image" of the graduate.

The following is suggested. First, only mandatory educational components will be considered. Secondly, an algorithm for calculating the success rate of higher education applicants in terms of program learning outcomes will be created [12].

Take the following notations:

{ОК} is a set of all mandatory components of the educational program;

$\{ОК_{select}\} \in \{ОК\}$ are mandatory components that are considered;

{PLO} is a set of program learning outcomes of an educational program;

$\{PLO_{select}\} \in \{PLO\}$ are program learning outcomes that are considered;

N is the number of mandatory components of the educational program;

M is the number of program learning outcomes of the educational program;

Cr_i is the amount of credits assigned by the educational program for the mandatory component $ОК_i$, i = 1..N;

K_i is the number of program learning outcomes, the mastery of which is provided by the mandatory component $ОК_i$, i = 1..N;

$CrK_i = Cr_i / K_i$ is the number of credits for one program learning outcome, mastery of which is provided by the mandatory component $ОК_i \in \{ОК_{select}\}$, i = 1..N, ;

Z is the number of seekers who received grades based on the results of the final control of mandatory components;

B_{ji} is the grade received by the jth higher education seeker according to the results of the final control from the mandatory component $ОК_i \in \{ОК_{select}\}$, i = 1..N, j = 1..Z;

$NB_{ji} = B_{ji} \cdot CrK_i$ is a grade recalculated per share of one program learning outcome;

NOK_k is the number of program learning outcomes, the mastery of which is provided by the mandatory component $PLO_k \in \{PLO_{select}\}$, k = 1..M.

The calculation table is filled with data according to the formula:

$$R(PLO_k) = \sum_{i=1}^{N} NB_{ji}, j = 1..Z, k = 1..M, OK_i \in \{OK_{select}\}, PLO_k \in \{PLO_{select}\}. \quad (2)$$

Next, the data is normalized, i.e. brought to the accepted 100-point scale, after which various actions are possible. For example, determining the best achievers according to individual PLOs, comparing the learning results of different academic groups, carrying out clustering, i.e. grouping the achievers depending on the level of mastery of program learning outcomes, etc.

However, the main interest of research is in predicting a seeker's grade in any discipline based on data on his/her assimilation of the "supporting" program learning outcomes:

$$y = \{PLO_1, PLO_2, ..., PLO_n\}. \quad (3)$$

Data preparation and problem solving using artificial neural networks

As in paper [3], grades of the 78 DSEA students from groups SM-13-1, SM-14-1, SM-15-1, SM-16-1 in Systems Analysis major are used (meaningful contents of the training courses and teachers have not changed in four years, the form of teaching has not changed either, there have been neither quarantines nor martial law).

According to [2], the optional discipline Technology of Creating Software Products (ВК-2.7) provides improvement of knowledge according to three program learning outcomes:

– PLO 08. To have modern methods of developing programs and software complexes and making optimal decisions regarding the composition of software, algorithms of procedures and operations;

– PLO 09. To be able to create effective algorithms for computational tasks of system analysis and decision support systems;

– PLO 13. Design, implement, test, adopt, support, operate software tools for working with data and knowledge in computer systems and networks.

Next, information on all subjects is summarized in Table 1.

Table 1

Educational components and program learning outcomes

Name	Code	PLO-K	Cr	Cr for 1 PLO	PLO-08	PLO-09	PLO-13
OK-11 Mathematical Logic and Theory of Algorithms	MLTA	2	3.5	1.75		+	
OK-16 Algorithms and Data Structures	ASD	2	3	1.5	+	+	
OK-18 Architecture of Computing Systems	AOS	3	3	1	+	+	
OK-20 Informatics	INF	5	3	0.6		+	+
OK-21 Computer Graphics	KG	1	4	4			+
OK-22 Optimization Methods and Operations Research	MODO	2	7	3.5		+	
OK-23 Methods of Artificial Intelligence	MAI	3	4	1.33		+	+
OK-25 Organization of Databases and Knowledge	OBD	3	9	3			+
OK-26 Fundamentals of System Analysis	OSA	2	6	3			
OK-28 Programming and Algorithmic Languages	PAM	4	9	2.25	+	+	+
OK-29 Information Systems Design	PIS	2	6.5	3.25			+
OK-32 Numerical Analysis	CM	2	6	3		+	
BK-2.7 Technology of Creating Software Products	TSPP		9		+	+	+

After carrying out a number of calculations according to formula (2), a new data table is obtained, some of its rows are shown in table 2 (the real names of the higher education seekers are replaced with "Seeker...").

Table 2

New data on the success of applicants

Group	Name	PRN08	PRN09	PRN13	TSPP
SM-13-1	Seeker 1	100	77.5176227	80.5758369	100
SM-13-1	Seeker 2	47.5995914	38.2170007	34.3297975	75
SM-13-1	Seeker 3	63.4320735	56.1879751	49.4558479	90
SM-14-1	Seeker 4	42.3901941	21.5480304	25.4029481	65
SM-14-1	Seeker 5	59.2441267	25.8327574	33.3103733	60
SM-14-1	Seeker 6	93.6670072	98.5348998	98.0851357	100
SM-14-1	Seeker 7	28.6006129	37.2024879	38.4350461	62
SM-14-1	Seeker 8	86.5168539	91.0352453	96.0325114	100

Next, a decision using the method of neural networks is made. The number of hidden layer neurons is related to the amount of training data and the required number of inputs and outputs of the network. The number of neurons in the hidden layers can be estimated using the inequality for estimating the number of weighting coefficients necessary for mastering a given number of examples in the training sample [13]:

$$\frac{N_y N_p}{1+\log_2 N_p} \le N_w \le N_y\left(1+\frac{N_p}{N_x}\right), \left(N_x+N_y+1\right)+N_y \qquad (4)$$

where N_w is the number of weights in the network;

N_p is the number of instances in the training set;

N_x and N_y are dimensions of the input and output signals, respectively.

Then the number of neurons *($N_н$)* in a two-layer network can be determined by the formula:

$$N_н = \frac{N_w}{N_x+N_y} \qquad (5)$$

By substituting the limit values of N_w calculated according to formula (4) into formula (5), the minimum ($N_{Н\,min}^{w}$) and maximum ($N_{Н\,max}^{w}$) number of neurons in the hidden layer of the network are obtained. All values are rounded up to the nearest whole number.

For the problem being solved, size of the input (N_x) and output (N_y) signals is equal to 3 and 1, respectively. The number of instances in the training set (N_p) is 78. Substituting these values into formulas (4) and (5), the following parameters of the neural network are obtained: $N_{min}^{w}=11$, $N_{max}^{w}=136$, $N_{Н\,min}^{w}=2$, $N_{Н\,max}^{w}=34$.

The number of neurons in the hidden layer can be specified in the process of setting up the neural network using a constructive algorithm [14]. Accordingly, the primary number of neurons is assumed to be equal to the minimum number (calculated by formula (5)). In case of unsuccessful training, one neuron is added to the hidden layer, the weight coefficients of which are assigned random values. The addition of neurons continues until the quality of the neural network reaches the required value.

The programming and data analysis language R [15] was used for calculations. This language is intended for statistical data processing and work with graphics. It is also a free and open-source programming environment developed within the framework of the GNU project. Available libraries allow to apply modern methods, including the method of artificial neural networks for solving the problem of forecasting.

A script has been created, the basic part of which is presented in the listing:

```
mydataframe <- read.table(paste(getwd(),"/StudentsC.txt",sep=""), header=TRUE, sep="\t")
w <- mydataframe[,3:6]
w <- w/100
algmas <- c("rprop+", "rprop-", "sag", "slr")
hiddens_list <- read.table("hiddens.txt", header=FALSE, stringsAsFactors=FALSE, sep="\t")
train_idx <- sample(nrow(w), 0.7 * nrow(w))
w_train <- w[train_idx, ]
w_test <- w[-train_idx, ]
net.w <- neuralnet(TSPP ~ PRN08 + PRN09 + PRN13, w_train, hidden=l_hidden, algorithm=algmas[ka], act.fct="logistic")
kk <- predict(net.w, w_test)*100
zz <- data.frame(w_test*100,res=round(kk),error=kk,ECTStspp=kk,ECTSres=kk,error2=kk,UKRtspp=kk,UKRres=kk,error3=kk)
zz$res[zz$res > 100] <- 100
zz$error <- abs(zz$res-zz$TSPP)/zz$TSPP
zz$ECTStspp[zz$TSPP < 55] <- "F"
zz$ECTStspp[(zz$TSPP >= 55) & (zz$TSPP < 65)] <- "E"
zz$ECTStspp[(zz$TSPP >= 65) & (zz$TSPP < 75)] <- "D"
zz$ECTStspp[(zz$TSPP >= 75) & (zz$TSPP < 81)] <- "C"
zz$ECTStspp[(zz$TSPP >= 81) & (zz$TSPP < 90)] <- "B"
zz$ECTStspp[zz$TSPP >= 90] <- "A"
zz$ECTSres[zz$res < 55] <- "F"
zz$ECTSres[(zz$res >= 55) & (zz$res < 65)] <- "E"
zz$ECTSres[(zz$res >= 65) & (zz$res < 75)] <- "D"
zz$ECTSres[(zz$res >= 75) & (zz$res < 81)] <- "C"
zz$ECTSres[(zz$res >= 81) & (zz$res < 90)] <- "B"
zz$ECTSres[zz$res >= 90] <- "A"
zz$error2[zz$ECTStspp == zz$ECTSres] = 1
zz$error2[zz$ECTStspp != zz$ECTSres] = 0
zz$UKRtspp[zz$TSPP < 55] <- 2
zz$UKRtspp[(zz$TSPP >= 55) & (zz$TSPP < 75)] <- 3
zz$UKRtspp[(zz$TSPP >= 75) & (zz$TSPP < 90)] <- 4
zz$UKRtspp[zz$TSPP >= 90] <- 5
zz$UKRres[zz$res < 55] <- 2
zz$UKRres[(zz$res >= 55) & (zz$res < 75)] <- 3
zz$UKRres[(zz$res >= 75) & (zz$res < 90)] <- 4
zz$UKRres[zz$res >= 90] <- 5
zz$error3[zz$UKRtspp == zz$UKRres] = 1
zz$error3[zz$UKRtspp != zz$UKRres] = 0
cor(zz$TSPP,zz$res)
sum1 <- summary(zz)
sss <- unlist(strsplit(sum1[4,lenw+2], ":"))
as.numeric(sss[2])
sss <- unlist(strsplit(sum1[4,lenw+8], ":"))
as.numeric(sss[2])*100
plot(net.w.min)
```

After numerous runs of this script for different parameters of the number of hidden layers and the number of neurons, it was found that the best result (correlation is 0.9599; average absolute reduced error equals 0.1132; percentage of correctly predicted points on the Ukrainian scale is 79.2) provides a perceptron with two hidden layers and five neurons in each one (Fig. 1, Fig. 2).

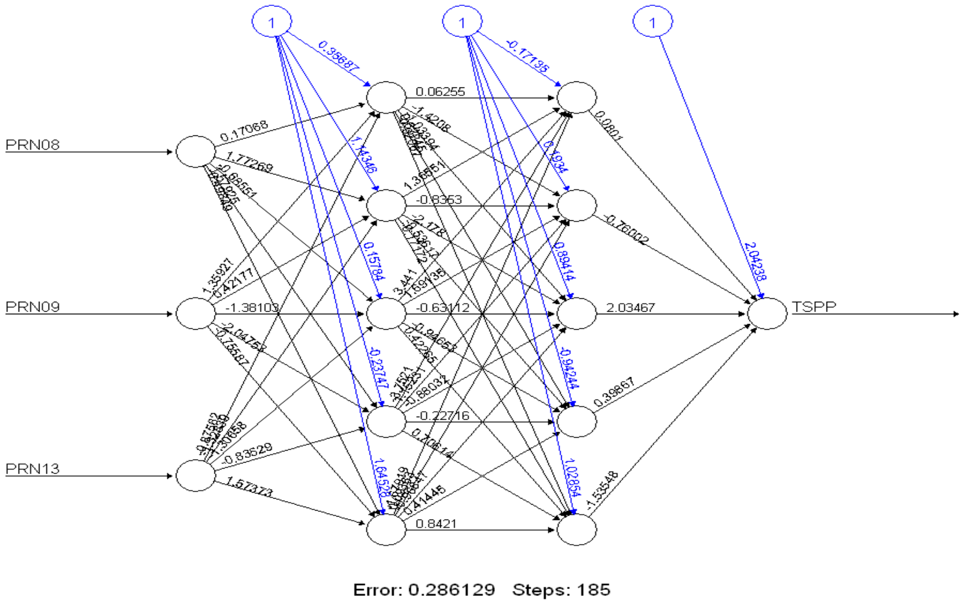

Fig. 1. Neural network graph

> zz

	PRN08	PRN09	PRN13	TSPP	res	error	ECTStspp	ECTSres	error2	UKRtspp	UKRres	error3
3	47.497	56.323	69.16	95	90	0.05263	A	A	1	5	5	1
5	47.600	38.217	34.33	75	78	0.04000	C	C	1	4	4	1
6	63.432	56.188	49.46	90	87	0.03333	A	B	0	5	4	0
19	59.244	25.833	33.31	60	70	0.16667	E	D	0	3	3	1
20	93.667	98.535	98.09	100	100	0.00000	A	A	1	5	5	1
23	76.404	65.556	57.74	81	90	0.11111	B	A	0	4	5	0
25	92.237	84.249	73.03	90	96	0.06667	A	A	1	5	5	1
26	0.000	11.113	19.75	55	66	0.20000	E	D	0	3	3	1
29	42.390	20.650	13.89	55	67	0.21818	E	D	0	3	3	1
32	90.501	89.943	82.63	98	98	0.00000	A	A	1	5	5	1
34	47.906	53.863	50.67	82	87	0.06098	B	B	1	4	4	1
36	71.604	73.155	63.76	92	94	0.02174	A	A	1	5	5	1
38	16.956	8.028	20.50	55	63	0.14545	E	E	1	3	3	1
39	94.688	91.245	94.94	99	98	0.01010	A	A	1	5	5	1
45	41.471	18.411	19.42	55	66	0.20000	E	D	0	3	3	1
53	60.776	25.935	26.56	58	69	0.18966	E	D	0	3	3	1
59	88.151	93.393	89.86	95	99	0.04211	A	A	1	5	5	1
60	69.969	83.010	80.89	97	98	0.01031	A	A	1	5	5	1
61	89.785	85.385	80.96	96	96	0.00000	A	A	1	5	5	1
63	5.516	18.245	28.27	55	71	0.29091	E	D	0	3	3	1
68	48.621	34.521	31.96	59	76	0.28814	E	C	0	3	4	0
74	74.362	69.932	76.43	77	92	0.19481	C	A	0	4	5	0
75	95.097	96.567	94.30	100	99	0.01000	A	A	1	5	5	1
78	35.546	28.459	44.81	55	75	0.36364	E	C	0	3	4	0

Fig. 2. Calculation results

Next, the network is applied to a new academic group. Result: correlation equals 0.923, the average absolute reduced error is 0.0654, the percentage of correctly predicted points on the Ukrainian scale is 82.4 (Fig. 3).

> zz

	PRN08	PRN09	PRN13	TSPP	res	error	ECTStspp	ECTSres	error2	UKRtspp	UKRres	error3
1	83.316	89.818	96.807	100	98	0.02000	A	A	1	5	5	1
2	90.074	74.133	77.633	78	92	0.17949	C	A	0	4	5	0
3	33.263	7.333	0.000	55	58	0.05455	E	E	1	3	3	1
4	94.509	93.036	93.614	95	98	0.03158	A	A	1	5	5	1
5	84.583	78.641	86.974	97	94	0.03093	A	A	1	5	5	1
6	9.504	29.541	27.164	91	77	0.15385	A	C	0	5	4	0
7	0.000	0.000	7.625	56	58	0.03571	E	E	1	3	3	1
8	100.000	100.000	100.000	93	100	0.07527	A	A	1	5	5	1
9	86.906	75.515	90.596	90	93	0.03333	A	A	1	5	5	1
10	74.657	73.457	79.237	93	94	0.01075	A	A	1	5	5	1
11	33.263	48.397	48.038	85	86	0.01176	B	B	1	4	4	1
12	48.574	64.543	74.408	92	93	0.01087	A	A	1	5	5	1
13	68.110	62.573	65.735	87	90	0.03448	B	A	0	4	5	0
14	65.998	76.331	89.102	97	96	0.01031	A	A	1	5	5	1
15	57.761	20.937	25.719	55	67	0.21818	E	D	0	3	3	1
16	50.898	19.764	17.808	55	66	0.20000	E	D	0	3	3	1
17	83.949	65.395	63.892	89	89	0.00000	B	B	1	4	4	1

Fig. 3. The results of calculations based on the data of the new group

Conclusions

The conducted studies proved that the application of the method of artificial neural networks for predicting the grades of higher education seekers in a separate discipline depending on the quality of the prior acquisition of subject competencies leads to satisfactory results. By conducting a series of numerical experiments, the optimal architecture of the neural network was selected, a two-hidden-layer perceptron with five neurons in each.

The obtained results can be used to assess the quality of the structural and logical scheme of the EPP and in the work of the department during the analysis of seekers' success, etc.

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Oleksandr MELNYKOV **Олександр МЕЛЬНИКОВ**	PhD in Technics (Candidate of Technical Sciences), Associate Professor of the Department of Intelligent Decision Making Systems, Donbas State Engineering Academy, Kramatorsk, Ukraine, e-mail: alexandr@melnikov.in.ua https://orcid.org/0000-0003-2701-8051 , Scopus Author ID: 57221045380, ResearcherID: B-3142-2016	кандидат технічних наук, доцент, доцент кафедри інтелектуальних систем прийняття рішень, Донбаська державна машинобудівна академія, Краматорськ, Україна.
Veniamin GITIS **Веніамін ГІТІС**	PhD in Technics (Candidate of Technical Sciences), Associate Professor of the Department of Intelligent Decision Making Systems, Donbas State Engineering Academy, Kramatorsk, Ukraine, e-mail: veniamin.gitis@gmail.com https://orcid.org/0000-0002-7434-8259	кандидат технічних наук, доцент, доцент кафедри інтелектуальних систем прийняття рішень, Донбаська державна машинобудівна академія, Краматорськ, Україна.
Iryna GITIS **Ірина ГІТІС**	student in Kharkiv National University of Radio Electronics, Kharkiv, Ukraine, e-mail: gitis.iryna@gmail.com https://orcid.org/0009-0009-9091-8854	студентка групи ІТШІ-20-2, Харківський національний університет радіоелектроніки, Харків, Україна.