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USING ARTIFICIAL NEURAL NETWORKS TO PREDICT PROFESSIONAL MOVEMENTS OF GRADUATES

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ABSTRACT

The aim of this paper is to examine the possibility of predicting professional choices of secondary school graduates using artificial neural networks for the needs of enrolment policy planning at the Faculty of Mechanical Engineering in Belgrade. The research on predicting professional choices of graduates has been carried out on a sample of 119 graduates from two Belgrade vocational schools. The factors influencing professional choices of secondary school students grouped as twelve input variables proved to be suitable for predicting professional movements of graduates. The results of this research represent a basis for further researches aiming to improve the Faculty enrolment policy.

Keywords*: predictive techniques, faculty enrolment policy, prediction of professional choice*

INTRODUCTION

The University has a central role in developing an integrated Europe by producing experts of all profiles that model the future European society. Globalization of education, with its multiple associations within the knowledge society, the increasing penetration of market forces into higher education and the treatment of education as an exportable product, supplied in different forms and by various providers, exerts the need for systematic and quality assurance in higher education. The Bologna Process, with the aim to create the European Higher Education Area (EHEA) by 2010, has improved the quality of all activities at the university (teaching, research, services and management) while recognizing and retaining the diversity of national specificities (culture, language, traditions). But, the degree to which higher education policy is converging in the course of the Bologna Process is still unknown as well as the reasons for national differences in the convergence (Heinze, 2008).

The Higher Education Area in Serbia consists of state and private universities. Universities in Serbia accepted the Bologna Declaration in 2003. The New University Law, which was enacted in 2005, provided all reform elements and set the frame for their implementation. Following the signing of the Bologna Declaration Serbia officially joined other European countries in this Trans-European process aiming to create the European Space in Higher Education by the year 2010. The effort to achieve a more efficient and better quality higher education is still under way.

The young generations completing their secondary school education in Serbia, nowadays, enter the world which is undergoing rapid changes in all its fields – economy, culture, politics, science, technology, and social relationships. Such changes also demand from the management of higher education institutions a more flexible approach in the organization and more efficiency in carrying out activities. Modern business management policy of higher education institutions is characterized by the concept of active management based on planning, communication and flexibility (Karavidić, 2006).

In order to adapt to the changes and market trends, faculties develop their activities and programs based on continual monitoring of educational needs. To define the target group whose education needs should be fulfilled, faculties intensify cooperation with secondary schools, engage in professional orientation of students as well as in the promotion of their own curriculum. One of the research activities is predicting the number of potential students on the basis of secondary school students' professional choices.

Professional preferences of graduates significantly depend on the socio-political and economic context (Vondraček et al., 1999). Research on value orientations and preferences of graduates' life styles in Serbia at the end of the 20th century (Mladenović and Knebl, 2000), showed that no important changes occurred in the value system of the young nor in preferences of some of the life styles in comparison with 1994. Among the most important expectations from professions the graduates select (Havelka, 1995): personal improvement, cooperation, job security, job agreeability, and work independence. Preference of certain professions is conditioned by previous experience in those professions. Graduates of secondary vocational schools have the advantage over graduates of secondary grammar schools, because they know some professions at the operational level and already have some professional skills considering their school and practical experiences. Both, graduates from vocational and grammar schools, can develop a relationship towards certain professions on the basis of surrounding models.

Possibilities in professional choices of secondary vocational school graduates by using artificial neural networks (ANNs) have been researched in this paper.

METHODOLOGY

Recent research has showed that ANNs have several advantages over traditional statistical methods (Gonzalez and DesJadins, 2002). The advantage of neural networks is in the high flexibility of disturbances of input data and in the ability of learning, ability to work with non-structured input data as well as in cases when data are missing (Garson, 1998). One great advantage of neural networks is the possibility of parallel data processing, especially when calculating output values which are independent from one another. ANNs proved to be very successful in the field of classification and prediction in many fields of science. For the research presented in this paper, specially designed software for prediction using neural networks – BPnet was applied.

The software BPnet was developed in the Laboratory for Industrial Robotics and Artificial Intelligence at the Faculty of Mechanical Engineering in Belgrade for the needs of implementing sensor-motor coordination of learning robot and camera calibration (Miljković, 2003). This software was planned for a wide range of applications which have the need to use the results of training of backpropagation neural network, with the established application in the domain of intelligent robot control (Miljković and Babić, 2007). Nowadays, BPnet software is used in the domain of machine learning by mobile robots (Miljković and Aleksendrić, 2009), as well as for predicting professional choices of secondary school graduates in order to contribute to the institutional recruitment efforts.

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Sample or Description of Data Sets

Higher education in Serbia together with the lower level of education is faced with a decrease of interest of young people for education in sciences, technology and mechanics. The results of professional orientation of graduates from different schools show that the most desirable professions are in the fields of medicine and economy while the mechanical engineer profession was on the list of professions not desired (Dunjić-Mandić et al., 2005). This problem, together with more competition in the field of higher education, resulted from the establishment of private universities as well as an imperative conditioned by the Bologna Declaration which places students in the centre of the educational process and thus influenced the change of enrollment policy of the Faculty of Mechanical Engineering in Belgrade. With the new enrollment policy the Faculty is focused on market research of potential students, checking graduates' interest for studying technology. In order to determine the target group, an analysis of the structure of students enrolled in the first year of the Mechanical Engineering Faculty in Belgrade for the previous three academic years 2005/06, 2006/07, 2007/08 was carried out. This analysis showed that students coming from secondary vocational schools such as Mechanical Engineering and Electrical Engineering are dominant. The percentage of these students was between 54.46% and 56.86%. The rest included students of other vocational and secondary schools.

The research regarding the problem of predicting professional choices of graduates was carried out on a sample of 119 graduates from two Belgrade vocational schools which were at the top of the enrollment list at the Faculty of Mechanical Engineering in the analyzed generations. The research was carried out in the spring of 2009 when the tested students had already made their decisions about their further professional education.

Defining the model's input and output parameter

Empirical researches have shown that the most influential factors concerning professional orientation of secondary school students are: attraction of activities, expectations of their own abilities, success probability, attitudes and opinions of parents and/or friends (Andrilović and Čudina, 1988). All these components act formatively on making professional decision and they are extremely dependent on the influence of social processes and differences of social groups.

According to developmental theories, adolescents choosing a profession are influenced by: parents, teachers, social circumstances, their (students') current interests, balance between personal abilities and demands of the chosen profession, friends. The listed determinants and recent research findings have defined influential factors which have also been used in this paper for predicting graduates' professional choice. Socioeconomic status, personal characteristics, the economic and political climate also affect students' inclination to attend a specific institution. The influence of parents, peers, and close friends was also determined to be substantial at the stage of gathering information (Hossler et al., 1989). Parents who have completed a postsecondary education will be more capable of giving their children good advice, and this relationship is especially important since children typically depend on their parents for guidance and support. Higher levels of socioeconomic status commonly permit families to supply better material resources for their children in the form of conducting more sophisticated university searches and collecting information on application procedures (Gonzalez and DesJadins, 2002).

A questionnaire has been created on the basis of the identified factors which influence professional choice of secondary school students. The listed factors are grouped in 12 input variables: gender, success in the second, third and fourth grades of secondary school, level of education and work status of parents, schooling financial support, self-assessment of acquired knowledge from Mathematics for continuing education, self-assessment of acquired professional competences for professional work, assessment of employment possibilities with completed secondary school. Professional choice of graduates after finishing secondary school is grouped into three categories presented by output variables: job, continuation of schooling at the Faculty of Mechanical Engineering in Belgrade or at some other faculty.

The uncertainty in the process of making decisions by secondary school students about their future professional status was the reason why neural networks were used as paradigms of artificial intelligence for solving the mentioned problem. Using the existing experience, further research was carried out with the aim to create a model of neural networks which would be used for solving the problem of classification of graduates' professional choice.

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Artificial neural networks – basic concept

ANNs are computational modeling tools that have been extensively used in many disciplines to model complex, real-world, problems (Liao and Wen, 2007). They have been found to be both reliable and effective when applied to applications involving prediction, classification, and clustering (Adriaans and Zantinge, 1997). The most frequent areas of ANNs applications are production/operations (53.5%) and finance (25.4%) (Wong et al., 1997), but in the field of educational research they are quite unexplored as a tool to aid educational researchers (Gonzalez and DesJardins, 2002).

ANNs are used when: data is 'noisy'; underlying distributions are unknown; the application is data intensive; data contains complex relationships between many factors; and other technologies are not adequate (Hardgrave et al., 1994). The advantage of ANNs comes from their information processing characteristics such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and their capability to generalize (Liao and Wen, 2007). Thus, on the basis of these factors, predicting professional choices of secondary school graduates appears to be an ideal neural network application.

ANNs can be defined as structures composed of simple processing elements called artificial neurons or nodes that are capable of performing massive parallel computations for data processing and knowledge representation (Schalkoff, 1997). Artificial neurons are divided into at least three layers: input, hidden, and output layer (Fig. 1).

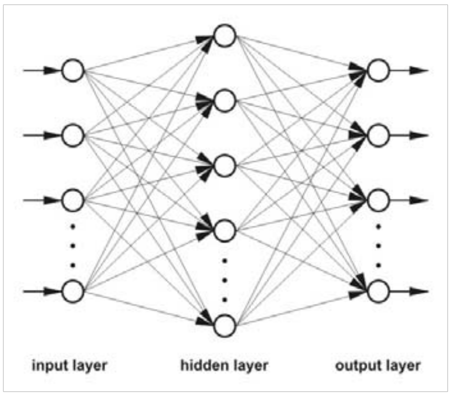

Figure 1. The three-layer backpropagation neural network architecture

Each input corresponds to an attribute (an input parameter). An output of the network represents the resolution of the problem. A key element of ANNs is weight. A network learns by adjusting weights or fails to adapt to the specific data, as to find hidden rules between the data.

The processing element of each network is a neuron. It is a unit that processes received information and as a result gives an output. The basic model shown in Figure 2 includes the inputs, weights, threshold, activation function and an output. The two components model the actual activity within the neuron cell: adding and activation function. An adder sums up all the inputs modified by their respective weights, while an activation function controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1.

This is the mechanism of translating inputs to an output for each neuron. The first step is to create the net input value for a neuron. Some inputs may be more important than the others, so there is a corresponding weight with each input presented to a neuron. These weights are the strength of connection between neurons. The second step of the translation is to create the activation value for each neuron through activation (transfer) function. So, the transfer function is used to convert the activation value for each neuron into its output value. The most commonly used type of nonlinear transfer function is sigmoid transfer function. According to Kros et al., (2006) there are two advantages of transfer function characteristics. First, the values in the network remain in a reasonable range, and second, a nonlinear transfer function is necessary to enable feedforward neural networks to map input values to a desired output. Finally, the neuron will generate the output if the net weighted input is greater than its threshold value.

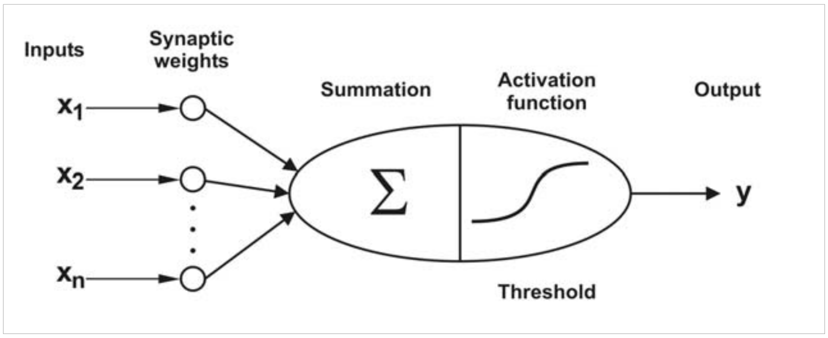

Figure 2. The components of a basic artificial neuron

In order to get an acceptable output response a neural network goes through the following phases: training, cross-validation and testing. Training

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a neural network means feeding it with teaching patterns and letting it adjust its weights using a feedback method. One of the most common feedback methods is known as backpropagation (Rumelhart et al., 1986). Backpropagation (BP) is an iterative gradient-descent algorithm designed to minimize the mean squared error (MSE) between the actual output of a node and the desired output as specified in the training set.

In the validation phase a neural network tends to optimize the length of network training, the number of hidden neurons and learning parameters (learning rate and momentum). The best network obtained is stored and tested in the next phase.

In the testing phase a trained network is tested on a new sample, and the result is taken as the assessment of the network. The network with the best test results is used in practice.

ANALYSIS AND RESULTS

A supervised multilayer feedforward BP neural network is used as it was implemented in the original version of the software BPnet. The architecture of tested networks consisted of three and four layers. The neural network had 12 input nodes (12 input variables), and three output nodes (one for each category) (Fig. 3).

Building of ANNs model consisted of the following steps: preparation of data and modeling, training and testing neural networks, analysis of results and selecting the best model.

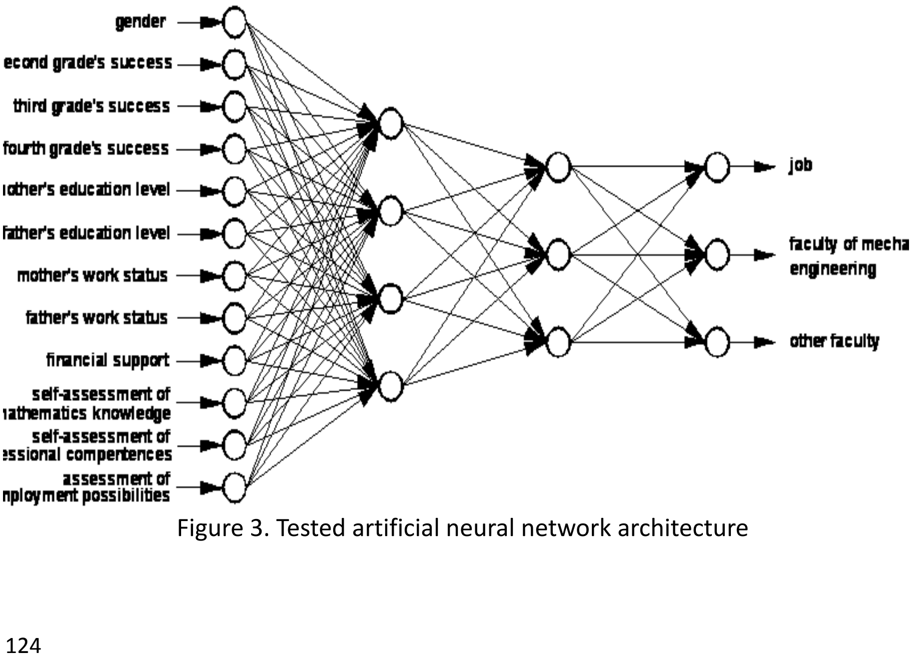

Figure 3. Tested artificial neural network architecture

Suggestions are made for the number of appropriate neurons in the hidden layer range from one-half the number of input neurons (Lawrence, 1991), to two times the number of input neurons plus one (Wilson, 1992). The number of neurons in the hidden layer estimated as (Flitman, 1997):

The number of neurons in the hidden layer = 2* √ (number of inputs + number of outputs).

Different number of hidden layers and neurons in them are presented in Table 1.

Table 1. Neural network configurations

Number of hidden layers	Number of neurons in hidden layer /layers
1	3
1	6
1	8
2	4-3
2	6-3
2	5-4
2	4-4
2	8-4
3	5-4-3
3	6-4-3
3	8-7-6

Determining the size of the network (the number of neurons in hidden layers) is important for network performances. If the network is too small it may not reach an acceptable level of accuracy. On the other hand, if there are too many neurons it may result in an inability for the network to generalize as a universal approximator.

Since this research is designed to test the predictive effectiveness of various neural network structures, the following data sets were made: training, validation and testing set. A data partitioning strategy is employed in this research that follows the experiences of earlier works (West et al., 2005; Breiman, 1996; Zhang, 1999). A training set comprised 60% of the randomized observations. The number of iterations was obtained in a cross-validation procedure, while network in the iterative procedure learns from the training sample using different parameters (e.g. number of hidden neurons). Each combination was tested on a validation sample (20% total sample). The aim was to find the number of iterations and structure of the learning network, which gives the best result on the validation sample. Finally, the obtained networks were tested on a testing sample (20% total

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sample). A sigmoid function was used as an activation function, and the learning rule was the delta rule, with momentum λ = 0.2 and learning parameter μ = 0.2. MSE was used to calculate the error in the neural network training phase (MSE = 0.05) (Fig. 4).

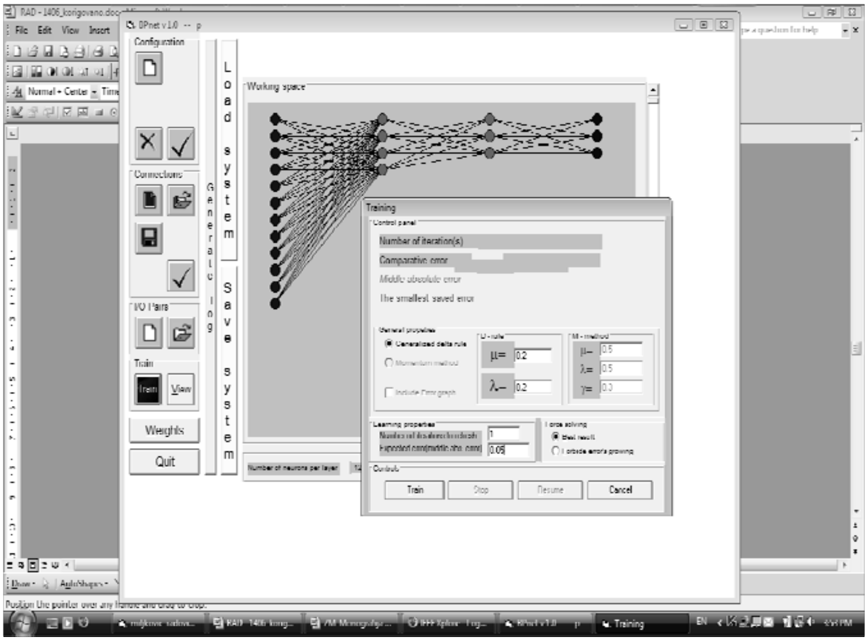

Figure 4. Process of BP neural network training – basic windows of the BPnet software

It has been empirically confirmed (Larose, 2005) that the increase in value of these λ and μ parameters makes the process of learning unstable thus giving worse results. On the other hand, by decreasing the values of these parameters the learning process is prolonged with an uncertain result in the sense of their improvement.

All selected neural network configurations (Table 1) are trained on the same sample and with the same starting learning parameters. The training of each network separately was stopped when the network would reach a predefined expected error.

After training each network separately, the network parameters are preserved. The classification rate at all networks on cross-validation set varies from 90% to 95% for all three output categories (job, further education at the Faculty of Mechanical Engineering, and further education at some other faculty) (Figure 5).

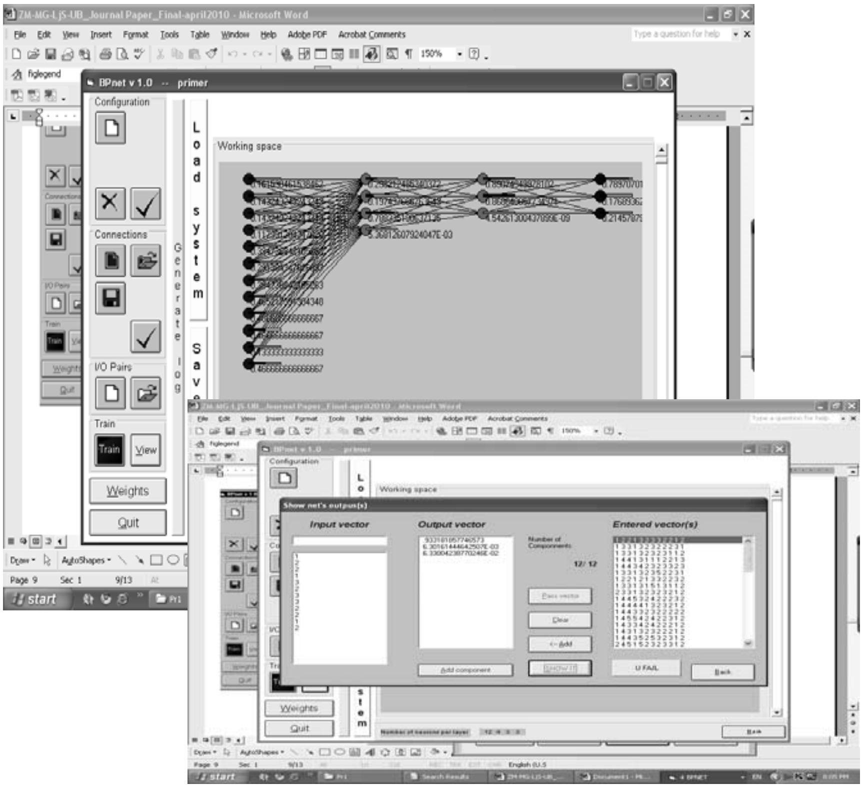

Figure 5. Cross-validation

As the problem of classification was treated, after the testing phase, the neural network classification rate was calculated for each class individually as well as the average classification rate. It served as a performance measurement for ANNs model evaluation. The results of neural networks testing are shown in Table 2.

The best average classification rate of the testing sample is achieved by network 4, 77% (Table 2). This neural network had 2 hidden layers with 4 and 3 hidden neurons, respectively. The obtained result means that 77% of the cases in the testing sample were correctly classified, while 23% of the cases were placed in the wrong class.

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Table 2. Testing results obtained by BPnet software

No.	Number of hidden layers	Number of neurons in hidden layer	Expected error	The classification rate			Average classification rate
				Job	Faculty of mechanical engineering	Other faculty	
1.	1	3	0.05	69%	75%	68%	71%
2.	1	6	0.05	76%	75%	78%	76%
3.	1	8	0.05	68%	64%	68%	67%
4.	2	1) 4 2) 3	0.05	80%	81%	71%	77%
5.	2	1) 6 2) 3	0.05	78%	71%	61%	70%
6.	2	1) 8 2) 4	0.05	71%	71%	64%	69%
7.	2	1) 5 2) 4	0.05	75%	76%	61%	71%
8.	2	1) 4 2) 4	0.05	73%	73%	68%	71%
9.	3	1)5 2)4 3)3	0.05	75%	73%	66%	71%
10.	3	1)6 2)4 3)3	0.05	80%	75%	64%	73%
11.	3	1)6 2)4 3)3	0.024	80%	76%	68%	75%
12.	3	1)6 2)4 3)3	0.021	78%	71%	59%	69%
13.	3	1)8 2)7 3)6	0.05	80%	68%	66%	71%

Looking at the classification rates for each class individually, it could be realized that the classification rate for the class Job is 80%, for the class Faculty of Mechanical Engeenering the classification rate is 81%, while for the class Other faculty is 71%. Greater accuracy of classification for the Faculty of Mechanical Engeenering indicates that students who have chosen to enter the studies at the Faculty of Mechanical Engineering have common characteristics which this model of neural networks succeedes to recognize and connect more succefully than in the case of students who are choosing a job or education at another faculty.

The results of testing indicated the following: decrease of expected error or increase of the number of iterations in the phase of network's testing doesn't lead to a greater rate of classification, because it leads to overtraining of the network.

More layers slow down the training time because the gradient of the error is more unstable and there is a higher risk of local minima.

CONCLUSION

The results shown in the paper emphasize the great possibility of ANNs application in the process of prediction secondary school students' professional choices. The factors influencing the professional choice of secondary school students such as gender, success in the second, third and fourth grades of secondary school, level of education and work status of parents, schooling financial support, self-assessment of acquired knowledge from Mathematics for continuing education, self-assessment of acquired professional competences for professional work, assessment of employment possibilities with completed secondary school, proved to be suitable for predicting professional movements of graduates. The result of this analysis indicates the possibility of improving the obtained values by introducing new input variables together with keeping three defined output categories. Further directions of the research can be in finding the best combination of input variables which would improve the prediction results of neural networks. Our strong opinion is that the results of this research represent the basis for further researches aiming to improve the Faculty's enrolment policy.

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UPORABA UMJETNIH NEURONSKIH MREŽA U PREDVIĐANJU PROFESIONALNIH KRETANJA MATURANATA

SAŽETAK

Svrha ovog rada je istražiti mogućnosti predviđanja izbora profesije maturanata uporabom umjetnih neuronskih mreža zbog potrebe planiranja upisne politike Strojarskog fakulteta u Beogradu. Istraživanje predviđanja odabira profesije provedeno je na uzorku od 119 maturanata dvije beogradske strukovne srednje škole. Svrstavanje čimbenika koji utječu na izbor profesije kod srednjoškolaca u dvanaest ulaznih varijabli pokazalo se odgovarajućim za predviđanje profesionalnih kretanja maturanata. Rezultati ovog istraživanja predstavljaju osnovu za daljnja istraživanja usmjerena poboljšanju upisne politike Fakulteta.

***Ključne riječi**: tehnike predviđanja, upisna politika fakulteta, predviđanje izbora profesije*

UVOD

Sveučilište ima središnju ulogu u razvoju i povezivanju Europe, stvarajući stručnjake svih profila koji će oblikovati buduće europsko društvo. Globalizacija obrazovanja, višestruko povezanog s rastućim društvom znanja, sve većim prodorom tržišnih sila u visoko obrazovanje i odnosom prema obrazovanju kao prema izvoznom proizvodu, dobavljivom u različitim oblicima i od različitih dobavljača, ukazuje na potrebu za sustavnim osiguravanjem kakvoće u sustavu visokog obrazovanja. Bolonjski je proces, s ciljem stvaranja Europskog prostora visokog obrazovanja (EHEA – Eurpean Higher Education Area) do 2010., unaprijedio kakvoću svih aktivnosti na sveučilištu (poučavanje, istraživanje, usluge i upravljanje), istodobno prepoznajući i zadržavajući raznolikosti nacionalnih posebnosti (kultura, jezik i tradicija). Ali stupanj do kojeg je politika visokog obrazovanja konvergirala s bolonjskim procesom još uvijek je nepoznat kao i razlozi u nacionalnim razlikama u tom procesu (Heinze, 2008).

Područje visokog obrazovanja u Srbiji sastoji se od privatnih i državnih sveučilišta. Sveučilišta u Srbiji prihvatila su bolonjsku deklaraciju

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2003. godine. Novi sveučilišni zakon, usvojen 2005. Godine, omogućio je sve elemente potrebne za provođenje reforme i postavio okvir za njenu implementaciju. Potpisivanjem bolonjske deklaracije Srbija se službeno pridružila drugim europskim zemljama u tom trans-europskom procesu usmjerenom stvaranju europskog prostora visokog obrazovanja do 2010. godine. Napori u postizanju učinkovitijeg i kvalitetnijeg visokog obrazovanja i dalje traju.

Mlade generacije koje završavaju svoje srednjoškolsko obrazovanje u Srbiji stasaju u svijet koji prolazi strjelovite promjene u svim područjima – ekonomija, kultura, politika, znanost, tehnologija i društveni odnosi. Takve promjene od uprava visoko obrazovnih ustanova također traže fleksibilniji pristup organizaciji i veću učinkovitost u provođenju raznih aktivnosti. Suvremenu politiku poslovnog upravljanja visokoobrazovnim ustanovama karakterizira koncept aktivnog upravljanja temeljen na planiranju, komunikaciji i fleksibilnosti (Karavidić, 2006).

S ciljem prilagođavanja promjenama i tržišnom kretanju fakulteti razvijaju aktivnosti i programe temeljene na kontinuiranom praćenju obrazovnih potreba. Da bi se odredila ciljna skupina čije obrazovne potrebe treba zadovoljiti, fakulteti intenziviraju suradnju sa srednjim školama, sudjeluju u profesionalnoj orijentaciji studenata kao i u promociji vlastitih kurikula. Jedna od aktivnosti istraživanja je i predviđanje potencijalnog broja studenata temeljemnog na odabiru profesije koji su iskazali srednjoškolci.

Profesionalno usmjerenje maturanata značajno ovisi o socio-političkom i ekonomskom kontekstu (Vondraček et al., 1999). Istraživanje vrijednosnih stavova i željenog stila života među maturantima u Srbiji na kraju 20. stoljeća (Mladenović i Knebl, 2000) pokazalo je da se u navedenom nisu dogodile nikakve značajne promjene u odnosu na rezultate istraživanja iz 1994. godine. Kao najvažnija očekivanja od budućeg zanimanja maturanti su naveli (Havelka, 1995): osobno usavršavanje, suradnju, siguran posao, zadovoljstvo poslom i samostalnost u radu. Sklonost određenom zanimanju uvjetovana je prethodnim iskustvom u tom zanimanju. Maturanti srednjih strukovnih škola su u prednosti pred maturantima gimnazija jer su upoznati s određenim zanimanjem na operacijskoj razini i već posjeduju određene profesionalne vještine s obzirom na školu koju pohađaju, kao i na praktično iskustvo. Obje skupine maturanata mogu razviti stav prema određenom zanimanju temeljem modela koji ih okružuju.

U ovom radu se istražuju mogućnosti primjena umjetnih neuronskih mreža – UNM (eng. Artificial Neural Networks – ANN) na odabir profesionalnog usmjerenja maturanata srednjih strukovnih škola.

METODOLOGIJA

Novija istraživanja su pokazala da uporaba UNM-a ima značajne prednosti pred tradicionalnim statističkim metodama (Gonzales i DesJadins, 2002). Prednost neuronskih mreža je u visokoj fleksibilnosti poremećaja ulaznih podataka i u mogućnosti učenja, sposobnosti baratanja s nestrukturiranim ulaznim podacima kao i u slučajevima kad podatci nedostaju (Garson, 1998). Velika prednost neuronskih mreža je i mogućnost paralelne obrade podataka, posebice kod izračunavanja međusobno neovisnih izlaznih vrijednosti. UNM su dokazano vrlo uspješne u polju klasificiranja i predviđanja u mnogim znanstvenim poljima. Za istraživanje prikazano u ovom radu primijenjen je program izrađen za predviđanje uporabom neuronskih mreža – BPnet.

BPnet je razvijen u Laboratoriju za industrijsku robotiku i umjetnu inteligenciju pri Strojarskom fakultetu u Beogradu za potrebe implementiranja senzomotorne koordinacije robota koji uče i kalibracije kamera (Miljković, 2003). Softver je planiran za široka područja primjene koja imaju potrebu za rezultatima obučavanja neuronske mreže sa svojstvom širenja unatrag, s već ostvarenom značajnom primjenom u području inteligentne kontrole robota (Miljković i Babić, 2007). Danas se BPnet softver koristi u području strojnog učenja mobilnih robota (Miljković i Aleksandrić, 2009), kao i za predviđanje odabira profesije maturanata, na taj način pridonoseći institucionalnim težnjama pri odabiru kandidata.

Uzorak ili opis podatkovnog seta

Visoko obrazovanje u Srbiji, zajedno s nižim razinama obrazovanja, suočeno je s pomanjkanjem interesa mladih ljudi za obrazovanjem u području znanosti, tehnologije i tehnike. Rezultati profesionalnog usmjerenja maturanata iz različitih škola pokazuju da se najpoželjnije profesije nalaze u poljima medicine i ekonomije dok je profesija inženjera strojarstva na popisu neželjenih profesija (Dunjić-Mandić et al., 2005). Navedeni problem, zajedno s povećanom kompetitivnošću na polju visokog obrazovanja koja je rezultat pojavljivanja privatnih sveučilišta kao i imperativa uvjetovanih Bolonjskom deklaracijom, koja u središte obrazovnog procesa stavlja studente i na taj način utječe na promjene u politici prijavljivanja kandidata na Strojarski fakultet u Beogradu. S novom upisnom politikom Fakultet je usredotočen na istraživanje tržišta potencijalnih studenata i provjeravanje interesa maturanata za studij tehnologije. Sa željom utvrđivanja ciljne skupine provedena je analiza

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strukture studenata prijavljenih na prvu godinu Strojarskog fakulteta u Beogradu za tri prethodne akademske godine, 2005/2006, 2006/2007, 2007/2008. Analiza je pokazala da dominiraju studenti koji dolaze iz srednjih strukovnih škola kao što su Strojarska škola ili Elektrotehnička škola. Postotak tih studenata je bio između 54,46% i 58,86%. Ostatak obuhvaća studente ostalih strukovnih i srednjih škola.

Istraživanje koje se tiče problema predviđanja profesionalnog odabira maturanata provedeno je na uzorku od 119 maturanata iz dvije Beogradske škole koje su bile pri vrhu uspješnosti prijavljenih na Strojarskom fakultetu u analiziranoj generaciji.

Određivanje ulaznih i izlaznih parametara modela

Empirijska istraživanja su pokazala da su najutjecajniji čimbenici na odabir profesije kod srednjoškolaca: privlačnost aktivnosti, očekivanja od njihovih sposobnosti, vjerojatnost uspjeha, stavovi i mišljenja roditelja i/ili prijatelja (Andrilović i Čudina, 1988). Sve te sastavnice djeluju formativno u stvaranju odluke o odabiru profesije i izrazito su ovisne o utjecaju društvenih procesa i razlikama među društvenim skupinama.

Prema razvojnim teorijama, adolescenti su prilikom odabira profesije pod utjecajem: roditelja, učitelja, društvenih okolnosti, trenutnog interesa pojedinca, ravnoteže između vlastitih sposobnosti i zahtjeva odabrane profesije te prijatelja. Navedene determinante i aktualna istraživanja su odredila čimbenike utjecaja koje smo koristili u ovom radu kao i za predviđanje koju profesiju će maturanti odabrati. Socioekonomski status, osobne karakteristike, ekonomska i politička klima također utječu na sklonost maturanata pohađanju određene institucije. Utjecaj roditelja, kolega i bliskih prijatelja također je određen kao značajan u fazi prikupljanja informacija (Hossler et al., 1989). Roditelji koji su završili neko više obrazovanje bit će sposobniji djeci dati dobar savjet i ta je veza iznimno bitna jer djeca primarno ovise o roditeljskoj podršci i vođenju. Viša razina socioekonomskog statusa uobičajeno obiteljima dopušta bolju materijalnu potporu djeci u obliku sofisticiranije pretrage sveučilišta i prikupljanja informacija o postupku prijave (Gonzales i DesJadins, 2002).

Upitnik je kreiran temeljem identifikacije čimbenika koji utječu na profesionalnu orijentaciju srednjoškolaca. Čimbenici su grupirani prema 12 ulaznih varijabli: spol, uspjeh ostvaren u drugom, trećem i četvrtom razredu srednje škole, razina obrazovanja i radni status roditelja, financijska potpora školovanju, samoprocjena stečenog znanja matematike za daljnje obrazovanje, samoprocjena stečenih profesionalnih kompetencija za profesiju, procjena mogućnosti zapošljavanja sa završenom srednjom školom. Odabir profesije maturanata po završetku srednjoškolskog obrazovanja grupiran je u tri kategorije predstavljene izlaznim varijablama: posao, nastavak obrazovanja pri Strojarskom fakultetu u Beogradu ili nekom drugom fakultetu.

Nesigurnost u procesu donošenja odluke kod maturanata o njihovom odabiru buduće profesije razlogom je uporabe neuronskih mreža kao paradigme umjetne inteligencije za rješavanje navedenog problema. Uporabom postojećeg iskustva provedena su daljnja istraživanja s ciljem stvaranja modela neuronske mreže koja bi bila korištena za rješavanje problema klasifikacije profesija koje su odabrali maturanti.

Umjetne neuronske mreže – temeljni koncepti

UNM su računalni alati za modeliranje čija uporaba je rasprostranjena u mnogim disciplinama da bi se modelirali složeni problemi iz realnog svijeta (Liao i Wen, 2007). Ustanovljeno je da su pouzdani i učinkoviti kad ih se primijeni u aplikacijama koje uključuju predviđanje, klasificiranje i stvaranje klastera (Adriaans i Zantinge, 1997). Najčešća područja uporabe UNM-a su proizvodnja/operacionalizacija (53,5%) i financije (25,4%) (Wong et al., 1997), no u području obrazovanja primjena UNM-a, kao alata za pomoć obrazovnih istraživanja, još je prilično neistražena (Gonzales i DesJardins, 2002).

UNM se upotrebljavaju kad: u podacima postoji "šum"; nije nam poznata osnova rasporeda; aplikacija je zasićena podatcima; podatci sadrže složene odnose među mnoštvom čimbenika; i kad ostale tehnologije nisu zadovoljavajuće (Hardgrave et al. 1994). Prednost UNM-a proizlazi iz njihovog svojstva procesuiranja informacija poput nelinearnosti, visokog stupnja paralelnosti, robusnosti, tolerancije na pogreške, učenja, sposobnosti baratanja nepreciznim i izmiješanim informacijama, te sposobnošću uopćavanja (Liao i Wen, 2007). Temeljem svih tih čimbenika predviđanje profesionalne orijentacije maturanata izgleda kao idealan zadatak za primjenu neuronskih mreža.

UNM se može definirati kao strukture sastavljene od jednostavnih elementa za obradu nazvanih umjetni neuroni ili čvorovi koji su sposobni izvoditi ogroman broj paralelnih izračuna pri obradi podataka i predstavljanje znanja (Schalkoff, 1997). Umjetni neuroni su podijeljeni u najmanje tri sloja: ulazni, skriveni i izlazni sloj (Slika 1).

Slika 1.

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Svaki ulaz korespondira jednom svojstvu (ulazni parametar). Izlaz mreže predstavlja rješenje problema. Ključni element UNM-a je težinski čimbenik. Mreža uči prilagođavajući težinski čimbenik ili se ne uspijeva prilagoditi specifičnim podatcima, kao što je pronalaženje skrivenih pravila među podatcima.

Element za procesiranje svake mreže je neuron. To je jedinica koja procesuira zaprimljenu informaciju i kao rezultat daje neki izlaz. Osnovni model prikazan na *slici 2* uključuje ulaze, težinske čimbenike, pragove, funkcije aktivacije i izlaz. Dvije komponente modeliraju stvarnu aktivnost unutar neuronske stanice: zbrajač i funkcija aktivacije. Zbrajač zbraja sve ulaze ovisno o njihovoj težinskoj vrijednosti, dok funkcija aktivacije kontrolira amplitudu izlazne vrijednosti neurona. Prihvatljiv raspon vrijednosti je obično između 0 i 1 ili -1 i 1.

Slika 2.

To je mehanizam prevođenja ulaza u izlaz za svaki neuron. Prvi korak je stvaranje mrežne ulazne vrijednosti za neuron. Neki ulazi mogu biti važniji od drugih, stoga se svakom ulazu koji se predstavlja neuronu dodjeljuje određena težinska vrijednost. Te težinske vrijednosti čine snagu veze između neurona. Drugi korak prevođenja je stvaranje vrijednosti aktivacije za svaki neuron kroz funkciju aktivacije (transfera). Funkcija transfera se koristi da bi se aktivacijska vrijednost svakog neurona pretvorila u svoju izlaznu vrijednost. Najčešće korišten tip nelinearne funkcije transfera je sigmoidna funkcija transfera. Prema (Kros et al., 2006.) postoje dvije prednosti svojstava funkcije transfera. Prvo, vrijednosti u mreži ostaju u razumnom rasponu, I, drugo, nelinearna funkcija transfera je nužna da bi se omogućilo jednosmjernim neuronskim mrežama mapiranje ulaznih vrijednosti prema željenom izlazu. Na kraju, neuron će proizvesti izlaznu vrijednost ako je težinska vrijednost ulaza veća od vrijednosti postavljenog praga.

U svrhu dobivanja prihvatljivih izlaznih odgovora neuronska mreža prolazi kroz sljedeće faze: učenje, unakrsno vrednovanje i testiranje. Učenje neuronske mreže znači punjenje mreže uzorcima za učenje i puštanje da sama odredi težinske vrijednosti koristeći metodu povratne sprege. Jedna od najpoznatijih metoda povratne sprege poznata je kao širenje unatrag (eng. *Backpropagation – BP*) (Rumelhart et al., 1986). Širenje unatrag (BP) je ponavljajući postupno-silazni algoritam dizajniran u svrhu minimiziranja srednje kvadratne grješke (MSE) između stvarne izlazne vrijednosti čvora i željene vrijednosti određene u skupu podataka za učenje.

U fazi vrjednovanja neuronska mreža teži optimizaciji dužine trajanja učenja, broja skrivenih neurona i parametara učenja (brzina učenja i učinkovitost). Najbolja mreža se pohranjuje i testira u sljedećoj fazi.

U fazi testiranja utrenirana mreža se testira s novim uzorkom, a rezultat se uzima kao vrjednovanje mreže. Mreža s najboljim rezultatom testiranja koristi se u praksi.

ANALIZA I REZULTATI

S obzirom da je već bila implementirana u originalnu inačicu programa BPnet, korištena je nadzirana, višeslojna, jednosmjerna BP neuronska mreža. Arhitektura testirane mreže sastoji se od tri i četiri sloja. Neuralna mreža je imala 12 ulaznih čvorova (12 ulaznih varijabli), i tri izlazna čvora (po jedan za svaku kategoriju) (Slika 3).

Izgradnja UMN modela sastojala se od sljedećih koraka: priprema podataka i modeliranje, učenje i testiranje neuronskih mreža, analiza rezultata i odabir najboljeg modela.

Slika 3.

Pretpostavljen je broj odgovarajućih neurona u skrivenom sloju mreže u rasponu od polovine broja ulaznih neurona (Lawrence, 1991), do dvostrukog broja ulaznih neurona plus jedan (Wilson, 1992). Broj neurona u skrivenom sloju je procijenjen kao (Flitman, 1997):

Broj neurona u skrivenom sloju=2* √ (broj ulaza + broj izlaza).

Različiti brojevi skrivenih slojeva i pripadajućih im neurona prikazan je u Tablica 1.

Tablica 1.

Određivanje veličine mreže (broja neurona u skrivenim slojevima) važno je zbog performansi mreže. U slučaju da je mreža premala možda ne će doseći prihvatljivu razinu točnosti. S druge strane, prevelik broja neurona može rezultirati nemogućnošću mreže da uopćava kao univerzalni aproksimator.

S obzirom da je ovo istraživanje dizajnirano da bi testiralo učinkovitost predviđanja različitih neuronskih struktura, načinjeni su sljedeći skupovi podataka: skup za učenje, vrednovanje i testiranje. U istraživanju je primijenjeno particioniranje podataka temeljeno na iskustvima ranijih radova (West et al., 2005; Breiman, 1996; Zhang, 1999). Set za učenje se sastoji od 60% nasumičnih opažanja. Broj ponavljanja je pribavljen postupkom unakrsnog vrjednovanja, dok je mreža u postupku iteracija učila koristeći uzorak za učenje upotrebljavajući različite parametre (npr. broj skrivenih neurona). Svaka kombinacija je testirana na uzorku za vrjednovanje (20% ukupnog uzorka). Cilj je bio pronaći broj iteracija i strukturu mreže koja uči, koji daju najbolji rezultat na uzorku za vrjednovanje. Na kraju su prikupljene mreže testirane na testnom uzorku (20% ukupnog uzorka). Kao aktivacijska funkcija upotrijebljena je sigmoidna funkcija i delta pravilo za pravilo učenja s momentumom $\lambda = 0,2$ i parametrom učenja $\mu = 0,2$. MSE je korišten da bi se izračunala greška u fazi učenje neuronske mreže (MSE=0,05) (Slika 4).

Slika 4.

Iskustveno je potvrđeno (Larose, 2005) da je povećanje vrijednosti λ i μ parametara čini proces učenja nestabilnim rezultirajući lošijim rezultatima. S druge strane, smanjivanjem vrijednosti tih parametara proces učenja se produžava s neizvjesnim rezultatom da će konačni ishod biti bolji.

Sve odabrane konfiguracija neuronskih mreža (Tablica 1) su učene na istom uzorku s istim početnim parametrima učenja. Postupak učenja svake mreže bi se prekidao kad bi mreža dostigla predefiniranu očekivanu pogrešku.

Nakon što je svaka mreža zasebno prošla postupak učenja, parametri svake mreže su sačuvani. Stupanj klasifikacije pri svim mrežama na skupu unakrsnog vrednovanja je varirao između 90% i 95% za sve tri izlazne kategorije (posao, daljnji studij na Strojarskom fakultetu, daljnje studiranje na nekom drugom fakultetu) (Slika 5).

Slika 5.

Kako je problem klasifikacije tretiran, nakon faze testiranja, stupanj klasifikacije neuronske mreže se računao za svaku klasu posebno kao i prosječan stupanj klasifikacije. To je poslužilo za mjerenje performansi pri evaluaciji UNM modela. Rezultati testiranja neuronskih mreža prikazani su u Tablici 2.

Tablica 2.

Najbolji prosjek stupnja klasifikacije testiranog uzorka postigla je mreža br. 4, 77% (Tablica 2). Navedena neuronska mreža je imala 2 skrivena sloja s 4 i 3 skrivena neurona. Dobiveni rezultati znače da je 77% slučajeva klasifikacije testnog uzorka ispravno klasificirano, dok je 23% bilo određeno pogrješno.

Gledajući stupanj klasifikacije za svaku klasu posebno, mogli bismo zaključiti da je stupanj klasifikacije za klasu "Posao" 80%, za klasu "Strojarski fakultet" 81%, dok je za klasu "Ostali fakulteti" 71%. Veća točnost klasifikacije za klasu Strojarski fakultet ukazuje na to da su učenici koju su se opredijelili za navedeni fakultet imali više zajedničkih svojstava koja je sustav uspio bolje prepoznati i ispravno povezati nego u slučaju učenika koji su odabrali klasu "Posao" ili klasu "Ostali fakulteti".

Rezultati testiranja ukazuju na sljedeće: smanjenje očekivane pogrješke ili povećanje broja iteracija u fazi testiranja mreže ne povećava uspješnost klasifikacije, jer to vodi prekomjernom učenju mreže.

Veći broj slojeva usporava proces učenja jer je gradacija grješke nestabilnija i povećava se rizik lokalnih minimuma.

ZAKLJUČAK

Rezultati prikazani u ovom radu naglašavaju ogromne mogućnosti primjene UNM u procesu predviđanja profesionalnog usmjerenja maturanata. Čimbenici koji utječu na profesionalnu orijentaciju maturanata kao što su spol, uspjeh ostvaren u drugom, trećem i četvrtom razredu srednje škole, razina obrazovanja i radni status roditelja, financijska potpora školovanju, samoprocjena stečenog znanja matematike za daljnje obrazovanje, samoprocjena stečenih profesionalnih kompetencija za profesiju, procjena mogućnosti zapošljavanja sa završenom srednjom školom, pokazali su se kao prikladni za predviđanje profesionalnog kretanja maturanata. Rezultati analize ukazuju na mogućnost poboljšanja dobivenih vrijednosti uvođenjem novih ulaznih varijabli istodobno zadržavajući tri postojeće izlazne kategorije. Daljnje mogućnosti istraživanja mogu biti u pronalaženju najbolje kombinacije ulaznih varijabli, koje bi poboljšale rezultate predviđanja neuronskih mreža. Smatramo da rezultati ovog istraživanja predstavljaju dobar temelj za daljnja istraživanja usmjerena razvoju upisne politike Fakulteta.