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STEM PROFILE MODELING USING NEURAL NETWORKS

Pero Radonja[1]

Abstract: Stem profile modelling by neural networks, NN, by method based on the artificial intelligence is presented in this paper. The programs *newff, train* and *sim,* which are part of the program package MATLAB were used. The method of obtaining stem profile models or stem profile functions based on the use of NN, was illustrated with several examples. Since the modelling is based on the use of modified Brink's function, MBF, proved to be most suitable method until now, we compared these two methods. The size of the standard error of modelling was the base of the comparison. The data from the enclosed tables show the superiority of the modelling method based on NN.

Key words: stem profile function, neural networks, standard error of modeling, stem volume.

MODELIRANJE PROFILNE FUNKCIJE DEBLA POMOĆU NEURONSKIH MREŽA

Izvod: U radu je prikazano modeliranje profilne funkcije debla pomoću neuronskih mreža, NM, odnosno pomoću postupka baziranog na veštačkoj inteligenciji. Iskorišćeni su programi koji se nalaze u programskom paketu MATLAB. Postupak dobijanja modela profilne funkcije na osnovu korišćenja NM, ilustrovan je sa više primera. S obzirom da se do sada kao najpogodniji postupak pokazalo modeliranje bazirano na primeni modifikovane Brinkove funkcije, MBF, uporedili smo ova dva postupka. Veličina standardne greške modeliranja bila je osnov poređenja. Podaci iz priloženih tabela jasno pokazuju superiornost postupka modeliranja baziranog na NM.

Ključne reči: profilna funkcija debla, neuronske mreže, standardna greška modeliranja, zapremina debla.

[1] Pero Radonja, Ph.D, Intitute of Forestry, Belgrade, Serbia
Translation: Marija Stojanović

1 INTRODUCTION

It is clear that in the practice the real stem profile (morphological curve), must be presented analytically, i.e. approximated with some function. In this paper the approximations of the real stem profile, i.e. *stem profile functions* are obtained in two ways.

The method of obtaining profile function based on the use of neural networks, NN, (of the appropriate configuration) i.e. artificial intelligence is presented in a great detail. The basic data on the profile functions obtained by use of the classic method based on the use of the modified Brink's function, MBF, are also presented.

Accuracy of stem profile modeling is obviously of a great importance in the forestry, which is reflected in numerous papers related to this topic which have been published so far. For instance: Max and Burkhart, 1976; Kozak, 1988; Riemer et al., 1995; Bi, 2000; Kozak, 2004; Rojo et al., 2005; Radonja et al., 2005a, etc. Artificial intelligence is also widely used for modeling of different biological processes (Zhang et al., 2000; Radonja et al., 2003; Radonja et al., 2004; Radonja et al., 2005b; Hanewinkel, 2005, etc.). The programs which refer to NN were used from the voluminous program package MATLAB (Beale, 1993). The programs which define, train and test NN were used. It is needed to define the input parameters which depend on the practical usage and readily available data.

2 MATERIAL AND METHOD

2.1 Data

The data used in this paper refer to 31 even-aged spruce stands (*Picea abies* L. Karst.) from the region of Bosnia (Maunaga, 1995). The measurements were made on one or two trees from each stand, so there are 42 trees in total, and on each tree 13 pairs of data were measured (diameter-height). Diameter was measured on very surface (zero level), at breast height, of the same relative heights, (Hohenadl sections, *0.1H, 0.3H,....,0.9H*) and some other characteristic stem heights (lengths). The studied stands are situated at the altitude of 550-1350 meters, and the age of the tree ranges from 12 to 130 years. Site quality ranges from I to V. The sizes of the sample plots depend on the number of trees per ha and age of the trees and range from 0.05 and 0.5 ha.

The basic data of some trees (tree stem), height, radius (measured diameter/2) at breast height, age, and the habitat altitude, depending of the ordinal number, are presented in the Tables 1-4.

Table 1 - Basic data of the trees, ordinal number 1-10

Sprouce, Ordinal number N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Age [years]	130	127	105	103	100	95	90	81	68	63
Height H [m]	32.6	29.7	29.8	28.31	34.1	36.15	29.2	24.22	19.7	19.95
Radius, $d/2$ [cm]	21.6	21.6	16.95	16.2	24.2	17.4	14.7	15.0	12.1	9.45
Altitude [m]	1, 350	1,300	1,000	1,000	1,060	1,000	900	1,260	900	900

Table 2- Basic data of the trees, ordinal number 11-20

Sprouce, Ordinal number N	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Age [years]	56	53	50	44	39	36	33	30	16	14
Height *H* [m]	19.5	18.7	21.6	19.8	16.5	16.3	15.7	13.2	6.3	5.8
Radius, *d*/2 [cm]	9.2	10.4	9.0	8.6	9.0	6.9	6.7	6.7	3.5	3.0
Altitude [m]	1,300	1,160	1,000	900	1,000	950	1,050	990	550	635

Table 3- Basic data of the trees, ordinal number 21-30

Sprouce, Ordinal number N	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Age [years]	12	97	130	127	88	85	92	70	67	82
Height *H* [m]	5.65	35.0	31.45	30.6	34,82	34.35	34.52	29.5	28.10	25.50
Radius, *d*/2 [cm]	4.4	23.5	21.65	21.35	17.55	17.90	17.40	17.3	17.20	15.90
Altitude [m]	800	1,060	1,350	1,300	1,000	1,000	1,000	1,100	1,100	1,260

Table 4 - Basic data of the trees, ordinal number 31-42

Sprouce Ordinal number N	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**
Age [years]	84	86	71	71	83	82	47	72	83	53	54	78
Height *H* [m]	25.18	31.44	27.2	26.45	24.36	22.50	21.01	26.80	23.15	22.46	22.38	20.40
Radius, *d*/2 [cm]	14.95	14.30	14.2	14.15	14.10	14.10	10.85	14.00	13.60	13.35	13.00	12.10
Altitude [m]	1,260	900	1,050	1,050	1,260	1,270	1,000	1,080	1,270	1,155	1,155	900

2.2 Method

In this paper the focus of attention is the determination of the profile function by applying NN. For each tree, i.e. obtained profile function, the standard errors of modelling will be calculated. Also, we will present the results of the application of the classic method, i.e. value of the standard error of modelling of profile functions obtaining by the use of MBF, (Riemer et al.,1995; Radonja et al., 2005a).

In order to apply NN, we need to configure it first. Configuration of NN is done by **newff** program (Beale, 1993). From experience, for this problem, we choose the number of the layers of the NN and form of the transfer, i.e. activation function of the individual neuron. For training, i.e. learning of NN we will use Levenberg-Marquardt algorithm. In this way we have defined all parameters relevant to the configuration feed-forward NN. This network implies that we bring the data to its entrance, and that the coefficient adjusting is done by feedback from the exit.

The procedure of training is performed by another special program, **train,** which is stopped when the assigned total error of training is achieved. This program can also be stopped by specification of the maximum number of steps of estimation, EPOCHS. Testing of NN, i.e. of the obtained profile function is done by program **sim,** which the parameters are: trained NN and arbitrary entrance data.

3 PROCEDURE OF OBTAINING PROFILE FUNCTION

The procedure of obtaining profile function can be divided in three phases. In the first phase the parameters of program ***newff*** are defined. It is in the first place the range of the values of the input data, the number of layers and number of neurons per NN layers, the type of neuron (*tansig* or *purelin)* and training method (*trainlm* or some other). In the analyzed case it is needed to apply two-layer NN with two *tansig* neurons in the hidden layer (Haykin, 1994). *Tansig* neuron has hyperbolic tangent sigmoid transfer function. The stated problem can be solved in two-dimensional space, so the greater number of NN layers is not needed. One *tansig* neuron can not provide real variability of the profile function, whereas three neurons introduce the variability which do not exist in real profile functions. In the output layer of NN we will use one neuron with linear transfer function.

In addition, it is needed to define how frequently (after how many steps, iterations) the current value of the training error is to be shown, *trainParam.show*, what is the size of the adjusting step (size of the adjusting increment) *trainParam.Ir*, maximum number of adjusting steps *trainParam.epochs,* and target size of the training error *trainParam.goal.* It is clear that the training procedure finishes before the maximum number of adjusting steps is achieved, if the target error is achieved earlier. If the training method fails, i.e. the target error is not achieved, the procedure is finished after the maximum number of adjusting steps. At the end of the first phase we have **c**onfigured NN by **o**rdinal **n**umber, *ON*, *netCNNON.*

In the second phase program ***train**,* with three input parameters, vectors, is used. The first parameter is NN, *netCNNON,* with the set of the initial coefficients. The input vectors are also input data, height vector and radius vector. Training of the specified, configured NN is done with 13 measured pairs of data, height-radius. Upon the training procedure, the trained NN, *netTNNON*, is obtained.

Testing of the trained NM, *netTNNON* is done in the third phase by the program ***sim**,* for which the input parameters, vectors, *netTNNON,* and new input data vector, are indepent variables. In the aim of the accurate realization of the form of the profile function we use a few hundred, and even thousand, input data representing independent variable.

4 ILLUSTRATING OF THE PROCEDURE OF OBTAINING PROFILE FUNCTIONS

We will illustrate the procedure of obtaining concrete profile functions with the data which refer to a 130-year-old and an 83-year-old spruces. The basic data for these spruces are given by ordinal numbers 23 and 39 in the Tables 3 and 4.

Depending on the initial coefficients which depend on the configured NN and values generated by generators of the random numbers, in the case of 130-year-old spruce, the course of NN training can have different forms, which is presented in figures 1 and 2.

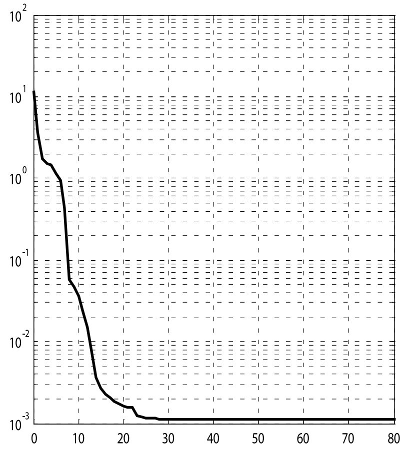

Fig. 1- Training error (I case)

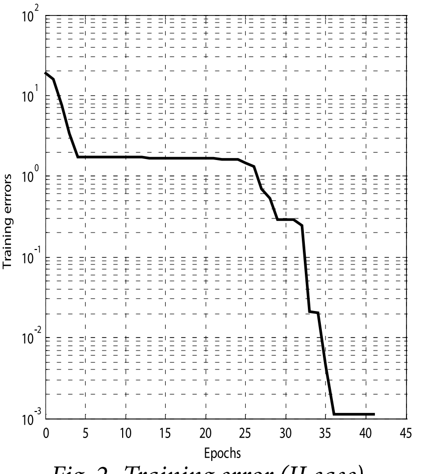

Fig. 2- Training error (II case)

At the end of the training procedure, the training errors in both cases have similar values, about 10^{-3}, and the obtained profile functions are very similar, which is presented in Figs. 3 and 4. The modelling error of the profile function presented in Fig. 3 is 0.1683, which is almost half the size of the error when MBF is used, which is 0.3378, as presented in the table 7, by the ordinal number 23.

Modelling errors in Fig. 5 range between -0.5 and +0.2, whereas the symmetrical limits of the of the maximal error in Fig. 6 range between -0.3 and +0.3. However, the initial values of the coefficients can be such that the training error converges to significantly greater value, as it is presented in Fig. 7, where it reached only $4 \cdot 10^{-1}$, therefore 400 time greater value. If the training procedure fails, the linear profile function is obtained, Fig. 8.

Now we are going to simultaneously observe the successful and unsuccessful modellings for a 83-year-old spruce. The successful training procedure of NN is presented in Fig. 9. We see that at the end of the training procedure, training error (sum of the squared errors in all points of adjustment) is about $3 \cdot 10^{-4.}$ When the training procedure fails, Fig. 10, the training error is approximately $3 \cdot 10^{-2}$, i.e. about 100 times bigger.

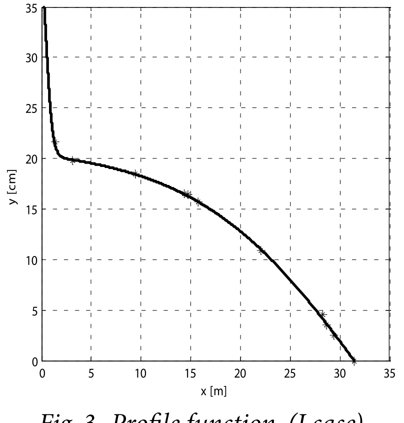

Fig. 3- Profile function (I case)

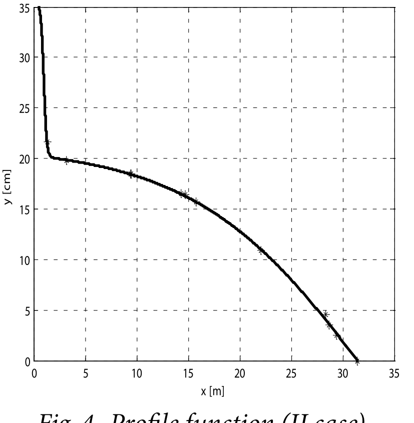

Fig. 4- Profile function (II case)

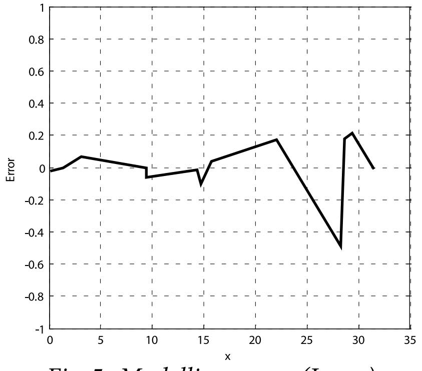

Fig. 5- Modelling errors (I case)

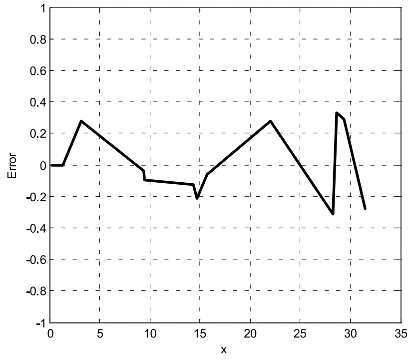

Fig. 6- Modelling errors (II case)

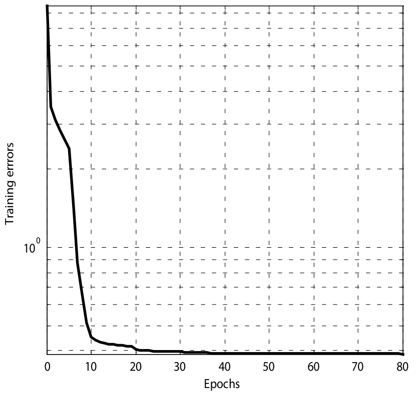

Fig. 7- Training error

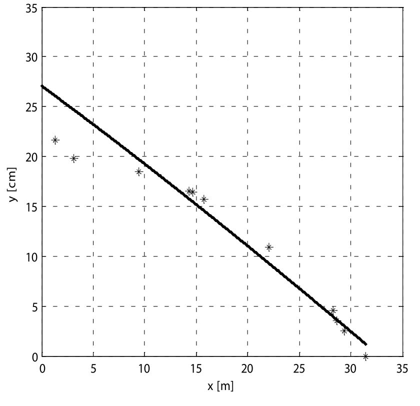

Fig.8- Profile function

(training procedure failed)

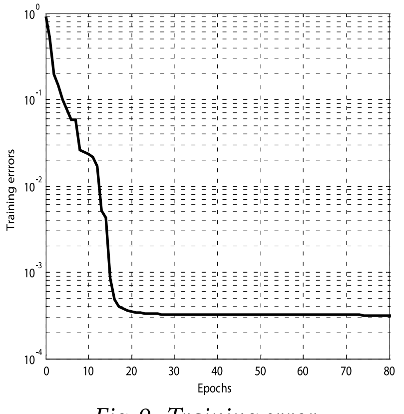

Fig. 9- Training error

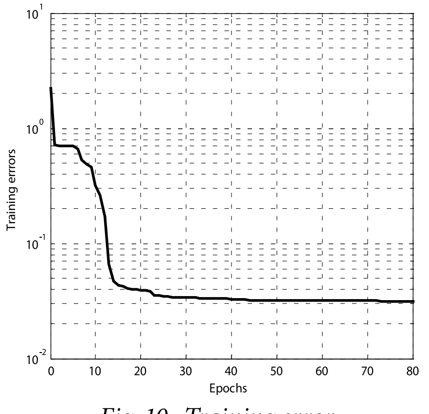

Fig. 10- Training error

(training procedure failed)

In Fig. 11 the obtained profile function which has the standard modelling error 0.0891, which is almost half size of the error obtained when MBF is used, which is 0.1746, as it is presented in Table 8, by ordinal number 39. When the training procedure fails, the profile function has very slightly convex shape, which is presented in Fig. 12.

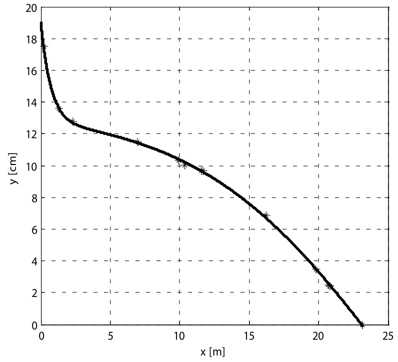

Fig.11- Profile function (83-year-old spruce)

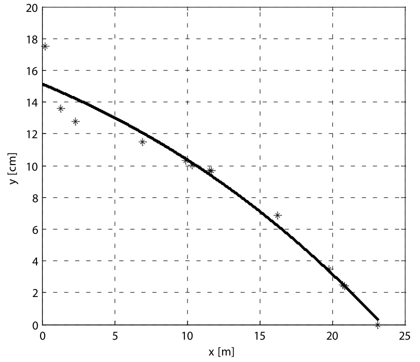

Fig. 12- Profile function (training procedure failed)

The individual modelling errors are presented in Figs. 13 and 14. When the training procedure fails, modelling errors are approximately ten times bigger.

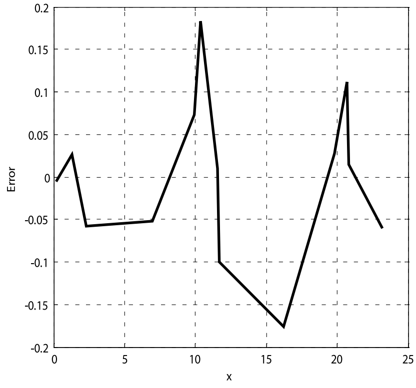

Fig. 13- Modelling errors

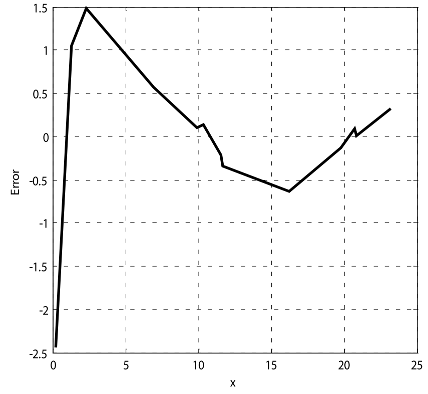

Fig. 14- Modelling errors (training procedure failed)

5 REZULTS

In the previous chapter the method of obtaining profile functions for two spruce trees was presented. Likewise, the modelling standard error of the models obtained in this way, ***Sem*[NN],** was compared with the ***Sem*[MBF],** when the profile function was obtained by application of MBF. In the following Tables, Tables 5-8, the modelling standard errors for the profile functions obtained by both aforesaid methods for the all analyzed spruce trees are presented.

Table 5- Size of the modelling standard error, ordinal numbers , 1-10

Spruce, Ordinal number N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Sem[NN] [cm]	0.335	0.099	0.226	0.1544	0.2580	0.1500	0.089	0.068	0.087	0.0785
Sem[MBF] [cm]	0.3880	0.2910	0.2610	0.1708	0.3850	0.4000	0.094	0.148	0.156	0.0908

Table 6- Size of the modelling standard error, ordinal numbers , 11-20

Spruce, Ordinal number N	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Sem[NN] [cm]	0.065	0.0571	0.0707	0.1718	0.0897	0.0595	0.0983	0.0638	0.0651	0.0399
Sem[MBF] [cm]	0.1726	0.0938	0.1263	0.3470	0.1072	0.079	0.122	0.0721	0.0897	0.0463

Table 7- Size of the modelling standard error, ordinal numbers 21-30

Spruce Ordinal number N	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Sem[NN] [cm]	**0.0793**	**0.2299**	**0.1683**	**0.1300**	**0.2341**	**0.1263**	**0.0697**	**0.1288**	**0.1422**	**0.0861**
Sem[MBF] [cm]	**0.1355**	**0.2613**	**0.3378**	**0.2204**	**0.2967**	**0.1516**	**0.0859**	**0.1341**	0.1658	0.0937

Table 8- Size of the modelling standard error, ordinal numbers 31-42

Spruce Ordinal number N	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**
Sem[NN] [cm]	0.1138	0.1166	0.1045	0.1456	0.0411	0.1145	0.1092	0.0787	0.0891	0.0957	0.0729	0.0622
Sem[MBF] [cm]	0.2596	0.2095	0.1182	0.1647	0.0861	0.1226	0.3024	0.1881	0.1746	0.0987	0.3251	0.0684

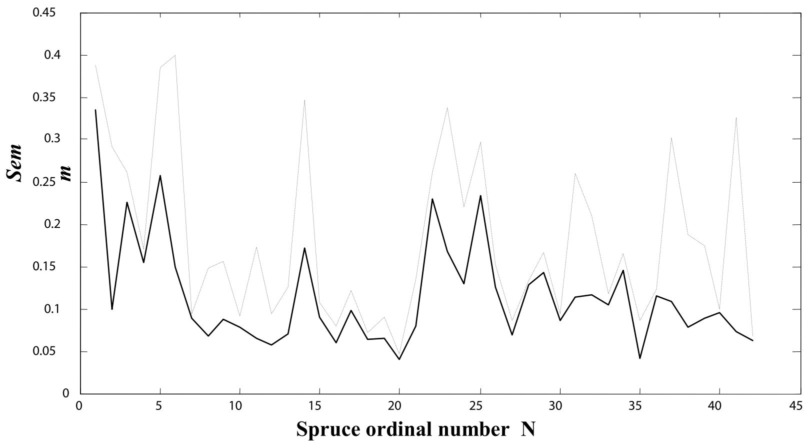

Fig. 15- Sem[NN] and Sem [MBF] for all the observed trees

The analysis of the results presented in Tables 5-8 show that there are several cases when ***Sem*[NN]** is between 2.5 and three times smaller than ***Sem*[MBF]**, the spruce by ordinal numbers 2, 6, 11 and 37. Also, there are several cases when ***Sem*[NN]** is two times smaller than ***Sem*[MBF]**, the spruce by the ordinal numbers 8, 14, 23, 31, 32, 35, 38 i 39. The superiority of the method based on the application of NN with regard to the size of ***Sem*** is most easily perceived when they are graphically presented in the same picture ***Sem*[NN],** solid line and ***Sem*[MBF],** dotted line, for all the observed trees, as it is done in Fig. 15.

6 CONCLUSION

The base for comparison of the stem profile models, i.e. stem profile functions, obtained by using neural networks and modified Brink's function, was the size of the standard modelling error. The analysis of the obtained results shows the superiority of models based on neural networks. The smaller standard modelling error is the result of the fact that the hyperbolic tangent sigmoid function in models based on the use of neural networks better approximates the biological process than the exponential functions which are used in modified Brink's function.

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STEM PROFILE MODELING USING NEURAL NETWORKS

Pero Radonja

Summary

Stem profile modelling was performed by the method based on the artificial intelligence, i.e. by neural networks, NN. The programs *newff, train*, and *sim*, which are part of the programme package MATLAB were used. The method of obtaining model of stem profile based on the application of NN, is illustrated with two examples, of the spruces 130-year-old and 83-year-old. The data used in this paper refer to 31 even-aged spruce stands (*Picea abies* L. Karst.) from the region of Bosnia (Maunaga, 1995). The measurements were made on one or two trees from each stand. There are 42 trees in total and 13 pairs of data, diameter-height, were measured on each tree. The studied stands are situated at the altitude of 550-1350 meters, and the age of the tree ranges from 12 to 130 years. Site quality is between I and V. The sizes of the sample plots depend on the number of trees per **ha** and age of the trees and range from 0.05 and 0.5 **ha**. Since the modelling based on the application of the modified Brink's function, MBF, has proven to be the most suitable method so far, we compared these two methods. The size of the standard error of modelling was the base of the comparison. The data from the enclosed Tables as well as their graphic presentation clearly demonstrate the superiority of the modelling method based on NN. The smaller standard modelling error in models based on the use of NN is the result of the fact that hyperbolic sigmoid function better approximates the biological process than the exponential functions which are used in modified Brink's function.

MODELIRANJE PROFILNE FUNKCIJE DEBLA POMOĆU NEURONSKIH MREŽA

Pero Radonja

Rezime

Modeliranje profilne funkcije debla izvršeno je pomoću postupka baziranog na veštačkoj inteligenciji odnosno pomoću neuronskih mreža, NM. Iskorišćeni su programi *newff, train* i *sim*, koji se nalaze u programskom paketu MATLAB. Postupak dobijanja

modela profilne funkcije na osnovu korišćenja NM, ilustrovan je sa dva primera, smrča starosti 130 i 83 godine. Podaci koji se koriste u ovom radu potiču iz 31 jednodobne sastojine smrče (*Picea abies* L. Krast.) iz regiona Bosne. Merenja su obavljena na jednom ili na dva stabla iz svake sastojine. Ukupan broj stabala iznosi 42 i na svakom stablu izmereno je 13 parova podataka, prečnik-visina. Posmatrane sastojine nalaze se na nadmorskim visinama od 550-1.350 metara a starost stabala je od 12 do 130 godina. Bonitet staništa se kreće u granicama od I do V. Veličine oglednih površina zavise od broja stabala po hektaru i od starosti stabala i kreću se od 0.05 do 0.5 ha. S obzirom da se do sada kao najpogodniji postupak pokazalo modeliranje bazirano na primeni modifikovane Brinkove funkcije, MBF, uporedili smo ova dva postupka. Veličina standardne greške modeliranja bila je osnov poređenja. Podaci iz priloženih tabela kao i njihova grafička prezentacija jasno pokazuju superiornost postupka modeliranja baziranog na NM. Manja standardna greška modeliranja kod modela baziranih na primeni NM javlja se zbog toga što tanges hiperbolična sigmoidna funkcija bolje aproksimira biološki proces od eksponencijalnih funkcija koje se koriste kod modifikovane Brinkove funkcije.

Reviewer: Prof. Srđan Stanković, PhD, School of Electrical Engineering, Belgrade, Serbia