Artificial Neural Networks in the Assessment of Stand Parameters from an IKONOS Satellite Image

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Abstract – Nacrtak

The paper explores the possibilities of assessing five stand parameters (tree number, volume, stocking, basal area and stand age) with the application of a multi-layer perceptron artificial neural network. An IKONOS satellite image (PAN 1 m x 1 m) was used to asses parts of stands in the sixth (121–140 yrs) and seventh (141–160 yrs) age class of pedunculate oak management class in the »Slavir« Management Unit of Otok Forest Office. Six features extracted from the first order histogram and five texture features extracted from the second order histogram were used as input data for neural network training. Data from the Management Plan were used as outputs of the neural network. An early stopping method and scaled conjugate gradient algorithm with error back propagation were used to improve generalization property of the neural network. Two neural network models were applied to assess the required stand parameters. The first model has one neuron in the output layer, where separate neuron network training was conducted for each stand parameter. The second model has five neurons in the output layer related to five assessed stand parameters. Both networks were trained and tested simultaneously. The conducted research showed that both of these neuron network models have good generalization properties. However, further analysis gave precedence to the second neural network model. Assessment of five quantitative stand parameters did not show any statistically significant differences between the Management Plan data and the neuron network model in terms of tree number, volume, stocking, basal area and stand age analysis.

Keywords: artificial neuron networks, IKONOS – 2, stand parameter assessment, texture

1. Introduction – *Uvod*

At present, remote sensing information is generally gathered using digital procedures (De Jong et al. 2006). Image analysis and scene interpretation are complex problems that require knowledge of the objects contained in a scene and spatial distribution of objects. Image analysis and scene interpretation are one of the most difficult issues in the sphere of intelligent systems (Gonzalez and Woods 2002).

In addition to statistical methods and operational research methods, based on the theory of learning, artificial intelligence has advanced the possibility of using previous knowledge (e.g. expert systems or neural networks) to foster more effective decision-making processes (Haykin 1999).

For a number of years, empirical statistical methods or complex mathematical models have been applied in forest research and management to complement valid decision making processes. These models are expressed as mathematical equations. However, some decision making procedures contain qualitative components, which do not allow integration into mathematical equations. The technology of artificial intelligence makes it possible to process knowledge that will be used in decision making as an additional tool. The application of artificial neural networks in predictions of non-linear systems behaviour has become an alternative to traditional statistical methods (Peng and Wen 1999).

In the years to come an increasing number of research teams will be dealing with artificial neural networks and artificial intelligence in general. An interdisciplinary approach to this issue has become the imperative of our time. The degree of interdisciplinarity is expected to rise. At present, artificial neural networks have such broad applications that we can safely say that this is the period of transition to artificial neural network technology.

Extensive research has been conducted in the applicability of satellite images to the study of the Earth's surface. Satellite images used in forest research have proven their applicability in a number of issues: determining methods of land use, identifying tree species and monitoring the condition of forest stands, making forest inventories, assessing biomass, monitoring and identifying changes in a forest, detecting fires, assessing the conditions immediately after natural disasters (floods, volcano eruptions, earthquakes, etc.), hunting, etc.

The advent of the new era in remote sensing (late 1990s) and the launching of the new generation of high resolution satellites (IKONOS) have enabled scientists to investigate their applications in natural resource monitoring.

Scientific research predominantly focused on radiometric and geometric accuracy of IKONOS satellite images (Helder et al. 2003, Pagnutti et al. 2003, Zanoni et al. 2003), and on automatic detection of forms (features), recognition and regeneration. Their applicability to interpretation, mapping and photogrammetry was also investigated (Kristof et al. 2002, Dial et al. 2003).

Some authors also used IKONOS satellite images in forestry to evaluate structural variables: age, height, number of trees, volume and basal area (Astola et al. 2000, Kayitakire et al. 2006). In their research, Shresta and Zinck (2001), Hagner (2002), classify and compare stand volumes from satellite images with different spatial resolutions (IKONOS, IRS, LANDSAT ETM+, SPOT). Katoh (2004) studies and describes tree species classification in mixed stands and their spectral characteristics. Kawamura et al. (2004) describe a method of parameter recognition necessary for the discrimination and identification of forest types on IKONOS satellite images, as well as spectral and textural features of these species. Chubey et al. (2006) describe object-based classification for the assessment and acquisition of soil cover, stand height and stand age parameters.

1.1 Artificial neural networks – Umjetne neuronske mreže

The application of artificial intelligence in forestry and natural resource management began with the development of an expert system for problem solving and decision making (Coulson et al. 1987). Initial experiments in the application of neural networks to forestry began in the USA and Canada in the late 1980s.

In order to understand an artificial neural network model, it is necessary to have some basic knowledge of biological neuron structure.

There are a number of criteria for discriminating the architecture of neural networks. The basic discrimination factors are: number of layers, type of learning, direction in which a signal travels through the network, type of connection between neurons, input and transfer functions.

According to Peng and Wen (1999) and Liu et al. (2003), the advantages of artificial neural networks stem from:

$\Rightarrow$ the possibility of learning complex patterns and monitoring data trends,

$\Rightarrow$ significant tolerance of imperfect data (absence of values),

$\Rightarrow$ robustness towards highly interconnected data.

Artificial neural networks have been developed as an alternative approach to modeling non-linear and complex phenomena in forestry science (Gimblett and Ball 1995, Lek et al. 1996, Peng and Wen 1999, Liu et al. 2003). They are generally used for segmentation and classification purposes and are recommended for solving problems with highly diverse data. Such a use is forest inventory.

Sui (1994) groups the application of artificial neural networks in spatial data handling into two main categories: the application of neural networks in remote sensing and integration of neural network with GIS for purposes of spatial modeling.

In general, the application of artificial neural networks in remote sensing began in the early 1990s (Benediktsson et al. 1990, Civco 1993, Paola and Schowengerdt 1995).

The most commonly used neural network model in remote sensing is the multi-layer perceptron (Atkinson and Tatnall 1997, Kanellopoulos and Wilkinson 1997, Foody 2001, Ashis 2002, Cetin et al. 2004, Shah and Gandhi 2004, Berberoglu and Curran 2006), whereas neural networks with radial basis functions (RBF) and probabilistic neural networks (PNN) (Foody 2001) are used less frequently.

Neural networks with unsupervised learning, such as a self-organizing neural network (Beamish 2001) are also used.

In their research authors use different types of images, but the focus is on satellite images with varied spectral, sensor and temporal characteristics.

Skidmore et al. (1997) apply the error back propagation algorithm to forest mapping using GIS data and data obtained with Landsat TM images.

Wang and Dong (1997) apply the multi layer perceptron to determine stand parameters using radar scenes.

Ardö et al. (1997) use the error back propagation algorithm to classify conifer damage with multitemporal satellite images (Landat TM) and topographic data. They compare this algorithm with multinominal logistic regression and do not favor any of these approaches.

Moisen and Frescino (2002) compare five techniques of forest features predictions and confirm that the neural network technique is equally valuable as statistical methods.

Ingram et al. (2005) map the structure of tropical forests using the multi layer perceptron with error back propagation on the basis of Landsat ETM+ scenes.

Kuplich (2006) uses artificial neural networks in the analysis of satellite scenes (SAR, Landsat TM) to discriminate between forests and pastures, or to classify the age structure of forests.

Joshi et al. (2006) use the feed forward multi layer network with feedback error propagation and Landsat ETM+ scene to determine (the density of) forest canopy. They compare the neural network with three methods: multiple linear regression, forest canopy density mapper and the highest probability classification. Their research confirms higher accuracy of the neural network model in relation to the three methods.

Verbeke et al. (2006) also use the feed forward multi layer network with feedback error propagation and CIR aerial photographs to assess the number of trees.

Research in the field of remote sensing use in forestry has shown the merits of artificial neural networks as an alternative approach to classical statistical methods.

2. Research aim– *Cilj istraživanja*

The basic goal is to investigate the simplest and the most acceptable procedure for operational application of artificial neural networks in the assessment of five stand parameters: volume, tree number, basal area, stocking and stand age from an IKONOS satellite image (PAN 1 m x 1 m).

In order to achieve the set goal, the research was carried out as follows:

⇒ assessment of stand parameters in the images using the neural network method,

⇒ experimental validation of the obtained results,

⇒ analysis and comparison of the obtained results,

⇒ analysis of the strengths and weaknesses of artificial neural networks in remote sensing as support in forest management.

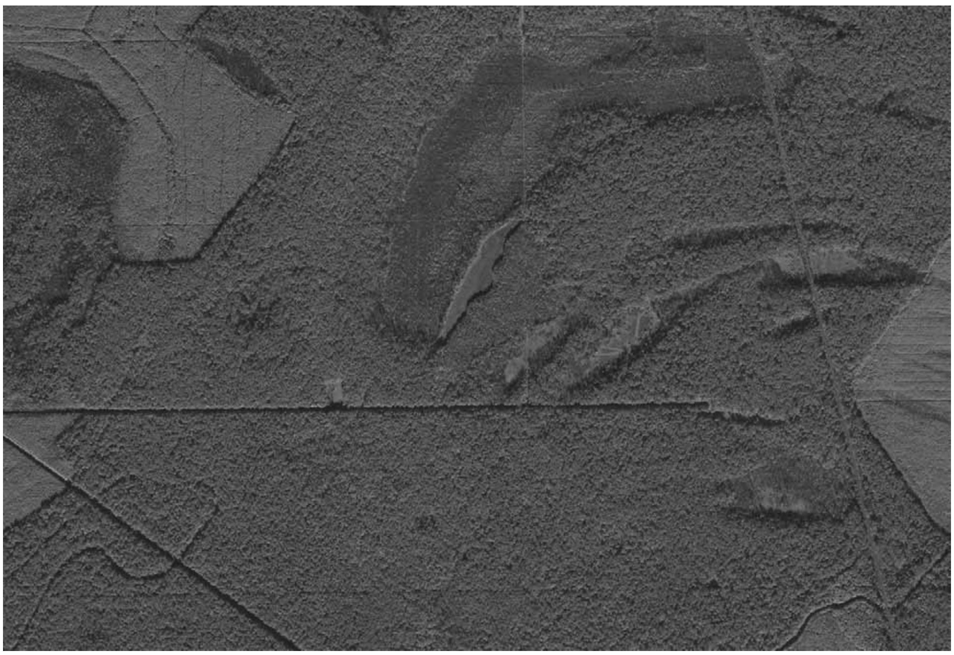

Fig. 1 IKONOS satellite image of a part of the study area (Spačva basin – Croatia)
Slika 1. *IKONOS-ov satelitski snimak dijela istraživanoga područja (Spačva – Hrvatska)*

3. Materials and Methods – *Materijal i metode*

3.1 Research Area – Područje istraživanja

This research was conducted in a part of the Spačva forest basin. The forests of the Spačva Basin cover about 40,000 ha. They are predominantly developed in the floodplain area of the Sava River and its tributaries. The part of the Spačva basin, where the research was carried out, relates to the age class VI (121–140 yrs) and VII (141–160 yrs) of pedunculate oak management class in the »Slavir« Management Unit (MU). An IKONOS satellite image of the Spačva basin covering an area of 132 km^2 was obtained in 5 spectral channels: PAN (1 x 1 m) and 4 MS Bundle. The satellite image was processed (Fig. 1) with ERDAS IMAGINE 9.2 software.

3.2 Extracting textural features of the stand scene – Ekstrakcija teksturnih značajki sastojinske scene

In order to determine the textural features, a sample of the satellite image was cut out for each stand scene. A total of 120 compartments/subcompartments (stand scenes) in the sixth and seventh age class of pedunculate oak management class were cut out. The reason for choosing these two age classes lies in the fact that this management unit has an irregular age structure and that in terms of surface area these are the two best represented age classes (64% of the management class area, or 76% without the first age class).

A typical procedure in texture analysis relates to statistical intensity features of the first order histogram. The MATLAB statxture function (Gonzales and Woods 2004) was used, and it yielded six statistical values: arithmetic mean, standard deviation, smoothness, third moment, uniformity and entropy.

Texture measures calculated only from the first order histogram data have a drawback, because they do not provide information on the relative relationship between the pixels themselves (Gonzales and Woods 2002).

According to Coburn and Roberts (2004), remote sensing researchers commonly use data obtained with second order histograms to make texture analyses and classifications, while first order histograms are used less frequently.

Kayitakire et al. (2006) state that features obtained with second order histograms were often used in texture classification or segmentation (Hay et. al. 1996, Franklin et al. 2000, 2001, Coburn and Roberts 2004), and however they were very rarely used in stand parameter assessments (Kayitakire et al. 2006).

Berberoglu and Curran (2006), Kayitakire et al. (2006) report that only six out of 14 defined textural features of the second order (Haralick et al. 1973), (energy, contrast, variance, homogeneity, correlation and entrophy) are used in remote sensing more frequently.

To determine the features of the second order histogram, the MATLAB imtexfeat function was used on blocks sized [M N] with a certain vector shift [Dx Dy]. In this case the block was represented by the cut stand scene, while the shift was [1 1]. Five textural features were calculated: the absolute difference value, inertia, covariance, entropy and energy.

The following three facts were taken into account to select the sample size:

⇒ image features are extracted for stand scenes (compartments/subcompartments) that were already stratified according to forest management criteria,

⇒ selection of matrix size (window) is not important only for calculation reasons, but also for purposes of defining a representative sample (Hodgson 1994, Franklin et al. 2000),

⇒ MATLAB is the interpreter language, and the implementation of the function imtexfeat, which was used to calculate features of the second order histogram, may take some time.

Accordingly, stand scene features were extracted using spatial features of the first and second order histograms. A total of eleven texture features were extracted for each stand scene (compartment/subcompartment) using the described procedure. A data set (vectors) was formed as an input to the neural network model. Data from Management Plans were used as output values.

3.3 Construction of an Optimal Structure of Multi Layer Perceptron – Izrada optimalne strukture višeslojnoga perceptrona

After extracting textural features of stand scenes for 120 compartments/subcompartments, the optimal neural network architecture was produced in MATLAB 6.5 software program.

According to Davies (2005), there are generally two approaches to optimizing the network architecture. The first approach involves gradual upgrade of the network by adding one by one neuron. The second approach involves the construction of a complex network structure, which is gradually reduced until the optimal network structure is obtained. The same author also states that research so far favors the first approach, and that the universal optimization

Table 1 Results of repeated-measures analysis of variance for the MU »Slavir«

Tablica 1. *Rezultati analize varijance ponovljenih mjerenja za GJ »Slavir«*

Volume, m^3/ha – *Obujam*, m^3/ha					
	SS	df	MS	*F*	*p*
Intercept	44501936	1	44501936	33458.07	0.000000
Error	78475	59	1330		
Model	694	2	347	0.43	0.649579
Error	94512	118	801		
Trees number per ha – *Broj stabala po ha*					
Intercept	14216695	1	14216695	4205.503	0.000000
Error	199449	59	3380		
Model	629	2	315	0.310	0.734021
Error	119777	118	1015		
Stand age, years – *Dob sastojine, godine*					
Intercept	2745109	1	2745109	37145.96	0.000000
Error	4360	59	74		
Model	121	2	60	2.14	0.122463
Error	3329	118	28		
Stocking – *Obrast*					
Intercept	162.8612	1	162.8612	94398.69	0.000000
Error	0.1018	59	0.0017		
Model	0.0080	2	0.0040	**3.16**	**0.045852**
Error	0.1485	118	0.0013		
Basal area, m^2/ha – *Temeljnica*, m^2/ha					
Intercept	163557.1	1	163557.1	39572.03	0.000000
Error	243.9	59	4.1		
Model	9.5	2	4.7	1.60	0.205497
Error	348.9	118	3.0		

process has not yet been formulated. Generalization is the property of the network to work »well« with vectors, which were not contained in the set of examples used for network training.

An early stopping method and scaled conjugate gradient algorithm with error back propagation were used to improve generalization property of the neural network. The early stopping method actually involves a statistical cross-validation method in which the total data set is divided into three sets: for training, validation and testing. Out of the total data set, 50% or 60 compartments/subcompartments were allocated to the training set, while the two remaining sets were divided in equal amounts: 25% (30 compartments/subcompartments) accounted for the validation set and 25% (30 compartments/subcompartments) accounted for the testing set.

Prior to neural network training, the data were preprocessed. In this sense two operations were performed using MATLAB functions: input-out value normalization and analysis of the main input value components. Normalization yielded the mean value equal to zero, or standard deviation equal to one of input and output data. The main components analysis reduced the input vectors dimension. In this case, all those components participating with less than 1% in the total input data variance were eliminated, thus reducing the number of extracted texture features from 11 to 5.

After the data were trained, generalized and normalized, they were converted into standard units.

To construct a neural network model, we used an algorithm with one hidden layer and the logarithmic sigmoidal function at its output and the hyperbolic-tangential-sigmoidal function in the output layer.

A total of 14 architectures were trained (the number of neurons in the hidden layer: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 25, 30), starting with one neuron in the hidden layer, and adding one more neuron with each new iteration until 10 neurons were obtained in the hidden layer, after which the number of neurons increased by 5 until there were 30 neurons in the hidden layer.

Two models were used to determine stand parameters.

In model 1, there was one neuron in the output layer. For each stand parameter, separate neural network training was performed.

A neural network with five neurons in the output layer was also applied (Model 2), while the number of input and hidden neurons, as well as the applied activation functions were identical to Model 1. The five neurons in the output layer relate to the five listed stand parameters, which were trained, i.e. tested simultaneously in this case.

The minimal value of the mean square error in the testing set was applied for both models so as to select the optimal architecture. As mentioned before, this set consists of 30 compartments/subcompartments. In the operative stage of neural network application, 30 additional compartments (15 compartments from each age class) were subsequently tested. Consequently, generalization for both models was conducted in 60 compartments/subcompartments.

4. Results – *Rezultati*

The minimal value of the mean square error of the testing set was used to select the optimal archi-

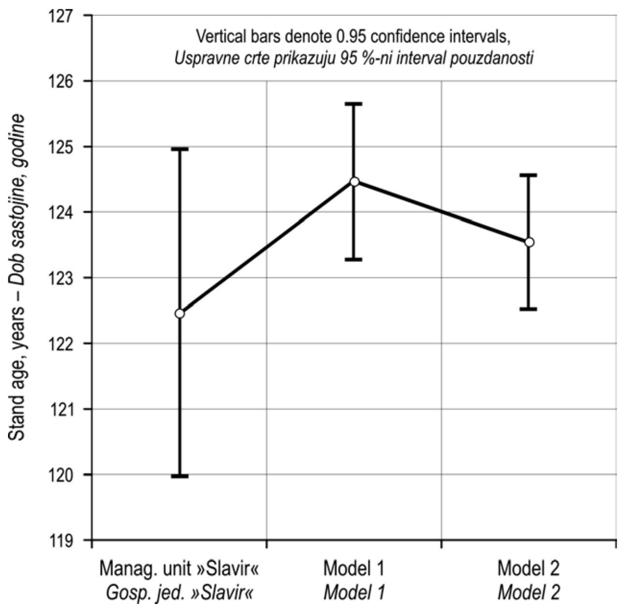

Fig. 2 Means and 95% confidence intervals of stand age for MU »Slavir«, Model 1, Model 2

Slika 2. *Aritmetičke sredine i 95 %-ni intervali pouzdanosti dobi sastojina za GJ »Slavir«, model 1, model 2*

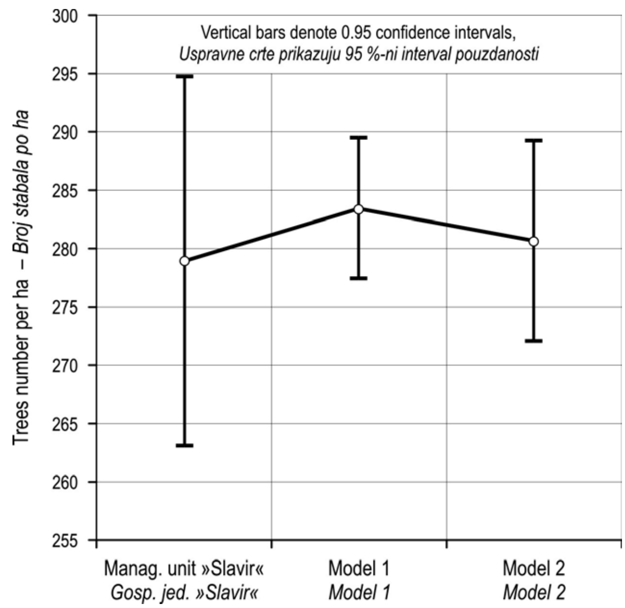

Fig. 3 Means and 95% confidence intervals of tree number per ha for the MU »Slavir«, Model 1, Model 2

Slika 3. *Aritmetičke sredine i 95 %-ni intervali pouzdanosti broja stabala po hektaru za GJ »Slavir«, model 1, model 2*

tecture of the multi layer perceptron. In Model 1, to determine basal area/ha, stocking and number of trees/ha the optimal architecture had two neurons in the hidden layer (5 – 2 – 1), to determine volume/ha the optimal architecture had three neurons in the hidden layer (5 – 3 – 1), and to determine stand age 20 neurons in the hidden layer were used (5 – 20 – 1). The following values of the mean square testing set error were determined: basal area/ha (0.0473), stocking (0.0633), number of trees/ha (0.1092), volume/ha (0.0468) and age (0.1631).

In Model 2, the optimal architecture contained five neurons in the hidden layer (5 – 5 – 5), and the obtained mean square error of the testing set was 0.1804.

To test the differences in the values of five quantitative stand parameters of the MU »Slavir« Management Plan and the artificial neural networks model, repeated-measures analysis of variance was used (Table 1) as well as Tukey's HSD test for multiple comparisons in STATISTICA 7.1 software. The results obtained with Model 1 and Model 2 were compared with those of the Management Plan data.

According to Table 1, the statistically significant difference between the Management Plan data and the neural network model related only to the assessment of the stocking. The application of Tukey's HSD test revealed the difference related to Model 1 and Model 2.

Fig. 2 shows the relationship of stand ages from the Management Plan and their assessment with neural network models. It is clear that Model 2 shows slightly higher correspondence with the Man-

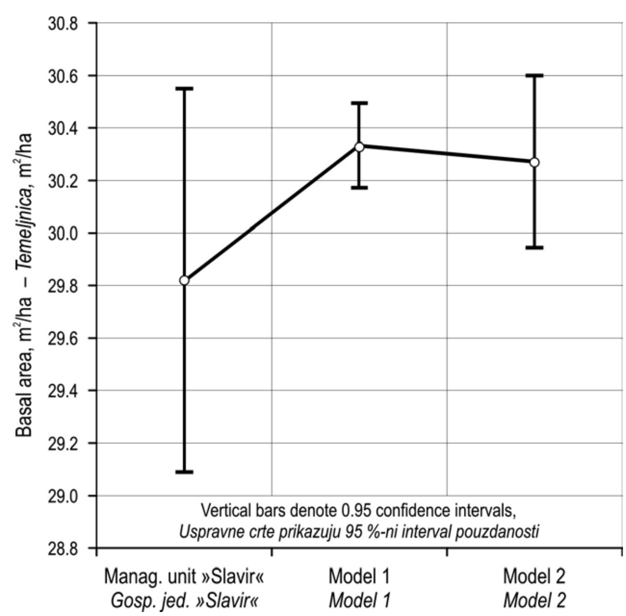

Fig. 4 Means and 95% confidence intervals of basal area per ha for the MU »Slavir«, Model 1, Model 2

Slika 4. *Aritmetičke sredine i 95 %-ni intervali pouzdanosti temeljnice po hektaru za GJ »Slavir«, model 1, model 2*

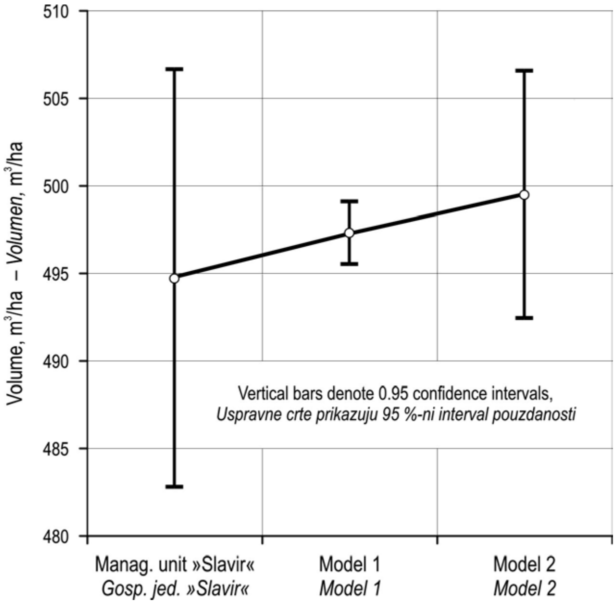

Fig. 5 Means and 95% confidence intervals of volume per ha for the MU »Slavir«, Model 1, Model 2

Slika 5. *Aritmetičke sredine i 95 %-ni intervali pouzdanosti volumena po hektaru za GJ »Slavir«, model 1, model 2*

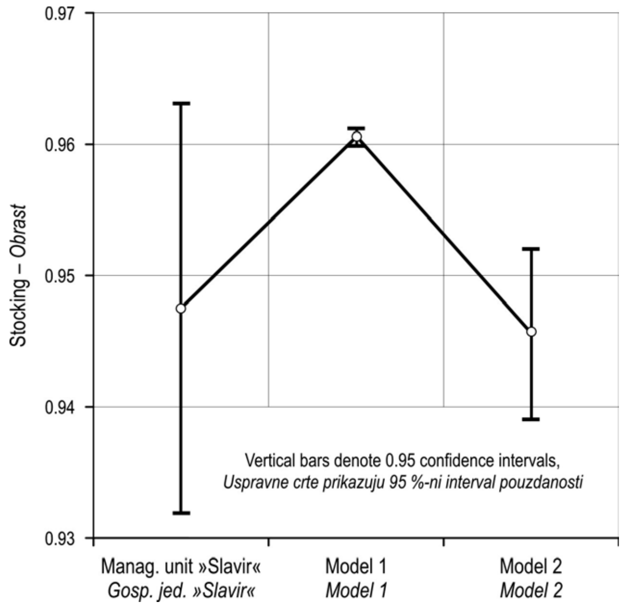

Fig. 6 Means and 95% confidence intervals of stocking for the MU »Slavir«, Model 1, Model 2

Slika 6. *Aritmetičke sredine i 95 %-ni intervali pouzdanosti obrasta za GJ »Slavir«, model 1, model 2*

agement Plan value range, but also that assessment did not include the bottom part of confidence interval in both models; however, the difference is not significant.

In tree number assessment (Fig. 3), the arithmetic means of neural network models showed high correspondence with the mean value of tree number (279 trees/ha) in the Management Plan. It is also clear that both models for the most part encompass the value range contained in the Management Plan.

In the assessment of basal area (Fig. 4), values from the upper part of confidence interval from the Management Plan were assessed in both models. Model 2 showed a slightly higher value range.

In terms of stand volume assessment, both neural network models showed good generalization properties, which is reflected in the values of arithmetic means, as well as in correspondence with the value range of interval confidence in the Management Plan (Fig. 5).

In the assessment of stocking, Model 2 has better generalization properties in relation to Model 1, where the assessed values show a small value range (Fig. 6).

5. Discussion – *Rasprava*

Table 1 and graphs (Fig. 2–6) clearly show that Model 1 and Model 2 have good generalization properties. In the assessment of five quantitative parameters there was no statistically significant difference between the Management Plan data and the results obtained by neural network in the analyses of tree number, volume, stocking, basal area and stand age.

Data obtained for basal area correspond to the research by Kayitakire et al. (2006) according to which it is not recommended to determine basal area per ha with remote sensing methods for intensively managed stands without additional (ancillary) information. The present research did not show high accuracy of basal area assessment despite the application of additional information (Model 2).

Further, it is clear that Model 2 responds better to the value range of stand parameters contained in the Management Plan. The conclusion is that in order to assess stand parameters with remote sensing methods it is better to use the architecture of a neural network which has a higher number of neurons in the output layer; in other words, the network is trained for simultaneous assessment of a higher number of stand parameters, as is the case with Model 2.

Compared to terrestrial measurements, the applied procedure is much more acceptable from material and temporal aspects. To assess five quantitative stand parameters for 60 compartments/subcompartments in the generalization procedure, the total time needed to extract textural features of stand scenes and simulate (assess) them with a trained (optimal architecture) neural network was one working day. The area in question was 1326.96 ha.

Image feature extraction, i.e. preparation of a data set for the neural network, is faced with the problem of heterogeneity and complexity of data from natural surroundings. The problem, described by Cherakassky et al. (2006), relates to temporal, dynamic, spatial, biometric and other components of data collection, whether quantitative and qualitative variables are determined terrestrially or with remote sensing. Another problem occurring in remote sensing research relates to the difficulty of having at our disposal aerial and satellite images, as well as terrestrial data that are gathered in the same time period (Foody and Curran 1994, Ingram et al. 2005).

From the aspect of forestry profession, the results obtained from remotely-sensed five quantitative stand parameters using artificial neural network models from a high-resolution IKONOS panchromatic satellite image (PAN 1 m x 1 m) for stands in the management class of pedunculate oak in the sixth and seventh age class can be considered acceptable.

Forestry is a field of economy in which multitudinous and varied measurements are performed almost every day. The artificial neural network model based on the theory of learning could considerably improve the handling of such a large number of data. Until now, the problem has been dealt exclusively with statistical methods and methods of operational research. Artificial neural networks are more accurate than statistical methods, especially when the problem is poorly defined or incomprehensible, or when the solution is not *a priori* know by the user.

6. Conclusions – *Zaključci*

The conclusions can be summarized into the following statements:

⇒ Artificial neural networks have proved to be a robust remote sensing tool in forest management,

⇒ The multi layer perceptron has good generalization properties in the assessment of quantitative stand parameters (volume per ha, number of trees per ha, age, stocking, basal area per ha) from an IKONOS (PAN 1 m x 1 m) satellite image,

⇒ Based on the conducted research and experience with the use of the multi layer perceptron with error back-propagation, one hidden layer has proved sufficient for solving problems in the field of using artificial neural networks in remote sensing for the needs of forest management,

⇒ This research has also confirmed the strengths (no need to know the data model, possibility of application in the analysis of new conditions, tolerance of data imperfections) and weaknesses (determination of the optimal architecture, impossibility of assessment outside the value range of learning data) of artificial neural networks.

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Sažetak

Umjetne neuronske mreže u procjeni sastojinskih parametara s IKONOS-ova satelitskoga snimka

Danas se pridobivanje informacija u daljinskim istraživanjima uglavnom provodi digitalnim postupkom (De Jong i dr. 2006). Polazišne osnove analiza slike i interpretacija scena su kompleksni problemi koji zahtijevaju znanje o objektima sadržanim na sceni te o međusobnom prostornom rasporedu objekata. Navedene analize slike interpretacije scena jedne su od najtežih u području inteligentnih sustava (Gonzalez i Woods 2002).

Već mnogo godina u istraživanju i rukovođenju u šumarstvu koriste se empiričke statističke metode ili složeni matematički modeli, koji upotpunjuju donošenje pravovaljanih odluka. Ti su modeli izraženi kao matematičke jednadžbe. Međutim, neki postupci donošenja odluka sadrže kvalitativne komponente koje ne dopuštaju integraciju u matematičke jednadžbe. Tehnologija umjetne inteligencije omogućuje procesiranje znanja koje će biti uključeno kao dodatni alat u odlučivanju. Primjena umjetnih neuronskih mreža u predikciji ponašanja nelinearnih sustava postaje alternativa tradicionalnim statističkim metodama (Peng i Wen 1999).

Naime, umjetna inteligencija temeljena na teoriji učenja unaprijedila je mogućnost korištenja prethodnoga znanja (npr. ekspertni sustavi ili neuronske mreže) i podataka radi donošenja učinkovitih odluka (Haykin 1999).

Stoga se u radu istražuju mogućnosti procjene pet sastojinskih parametara (broja stabala, obujma, obrasta, temeljnice i dobi sastojina) primjenom višeslojnoga perceptrona, kao najkorisnijega modela umjetnih neuronskih mreža u daljinskim istraživanjima. Za tu je potrebu korišten IKONOS-ov satelitski snimak (PAN 1 m x 1 m) dijela sastojina VI. (121 – 140 god.) i VII. (141 – 160 god.) dobnoga razreda, uređajnoga razreda hrasta lužnjaka, gospodarske jedinice »Slavir«, Šumarije Otok.

Za ulaz u neuronsku mrežu uzeto je šest vrijednosti teksturnih značajki histograma prvoga reda i pet vrijednosti teksturnih značajki histograma drugoga reda. Za izlazne vrijednosti korišteni su podaci Osnove gospodarenja.

Radi unapređenja generalizacije primijenjena je metoda ranijega zaustavljanja (engl. early stopping), te scaled conjugate gradient algoritam s povratnom propagacijom pogreške. Prije treniranja neuronske mreže provedeno je preprocesuiranje podataka, dok je za izradu optimalnoga modela neuronske mreže korišten jedan skriveni sloj s različitim brojem neurona. Primijenjene aktivacijske funkcije su logaritamsko-sigmoidna u skrivenom, odnosno hiperboličko-tangentno-sigmoidna funkcija u izlaznom sloju.

Da bi se procijenili sastojinski parametri primijenjena su dva modela: model 1 s jednim neuronom u izlaznom sloju, gdje je za svaki sastojinski parametar provedeno zasebno treniranje neuronske mreže, i model 2 s pet neurona u izlaznom sloju koji se odnose na pet procjenjivanih sastojinskih parametara, koji su u ovom slučaju trenirani, odnosno testirani istodobno.

Kod oba modela u odabiru optimalne arhitekture primijenjena je najmanja vrijednost srednje kvadratne pogreške na setu za testiranje. Za testiranje razlike u vrijednostima pet kvantitativnih parametara sastojine podataka Osnove gospodarenja GJ »Slavir« i modela umjetnih neuronskih mreža primijenjena je analiza varijance ponovljenih mjerenja te Tukey HSD test za međusobne višestruke usporedbe u programu STATISTICA 7. 1.

Svi postupci koji se odnose na tehnologiju umjetnih neuronskih mreža odrađeni su u programu MATLAB 6.5. Satelitski je snimak obrađen pomoću programskoga paketa ERDAS IMAGINE 9.2.

Provedenim istraživanjem utvrđeno je da oba modela neuronskih mreža imaju dobra generalizacijska svojstva, s tim da je daljnjom analizom prednost dana modelu 2. Naime, u procjeni pet kvantitativnih parametara nema statistički značajne razlike između podataka Osnove gospodarenja i modela neuronske mreže u analizi broja stabala, obujma, obrasta, temeljnice i dobi sastojina.

Šumarstvo je područje gospodarstva u kojem se gotovo svakodnevno provodi velik broj različitih mjerenja, a upravo umjetne neuronske mreže predstavljaju model temeljen na teoriji učenja, kojim bi se značajnije moglo unaprijediti korištenje tako velikoga broja podataka, gdje su se problemi do sada rješavali isključivo statističkim metodama i metodama operacijskih istraživanja. Umjetne su neuronske mreže točnije od statističkih metoda, pogotovo kada je problem slabo definiran ili nerazumljiv, odnosno kada korisnik a priori ne zna rješenje.

Ključne riječi: umjetne neuronske mreže, IKONOS – 2, procjena sastojinskih parametara, tekstura

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Received (*Primljeno*): August 20, 2008
Accepted (*Prihvaćeno*): November 29, 2008