An Adaptive Network-based Fuzzy Inference System for Rock Share Estimation in Forest Road Construction

Ismael Ghajar, Akbar Najafi, Seyed Ali Torabi, Mashalah Khamehchiyan, Kevin Boston

Abstract – Nacrtak

This paper presents a new Rock Share Estimation (RSE) procedure that can estimate the cost of forest road construction. One of the key elements of the total cost in road construction is the cost of embankment. The proportion of the rock directly influences the price of this activity. Hence, a reliable estimation of rock proportion should be made within the entire project area, especially in rocky areas. The objective of the study is to introduce a practical expert system to estimate the share of rock as a function of terrain slope and geological formations using the Adaptive Network – based Fuzzy Inference System (ANFIS) and Analytic Hierarchy Process (AHP). This approach can be very useful first to show the variability of rock proportion and second to model the excavation costs in an area, which are essential for planning forest roads. This study treats geological composition as a decision variable that is solved by AHP method and applies the ANFIS to model and predict the share of rock in different physiographic and geological conditions. In order to investigate the impact of change in membership functions (MF), four types of MFs were adopted to generate the hybrid RSE–ANFIS models. Furthermore, to show the applicability of the proposed approach, the optimum model was applied to a mountainous forest, where additional forest road network should be constructed in the future periods.

Keywords: Rock Proportion, ANFIS, AHP, Forest Road Cost, Membership Function

1. Introduction – *Uvod*

Estimation of rock proportion of subsoil as a real life problem is an important element in both the design and construction stages of road projects. All road planners and contractors prefer to construct the road in a soft terrain with the least rock excavation as this is the most cost-effective construction. However, it is very hard to exactly calculate the rock ratio of subsoil before the excavation of a project begins. In this regard, a number of methods have been suggested for assessment of slope stability and excavation quantities (Hoek and Bray 1981; Goodman 1989; Pettifer and Fookes 1994). Additionally, rock mass classification concept, which provides quantitative data and guidelines for engineering purposes, has been applied extensively for tunneling and underground excavation.

The main shortcoming of the existing traditional rock mass classification systems such as Rock Structure Rating, RSR (Wickham et al. 1972), the Rock Mass Rating, RMR (Bieniawski 1975), and the Q-system (Barton et al. 1974) is that they ignored the regional and local geological features and rock properties, and they were developed with the fixed weight for each rating factor (Liu and Chen 2007). On the other hand, other researchers that have developed tools to estimate the rock share related to forest topics are so limited (e.g. Inaba et al. 2001; Stuckelberger et al. 2006). In most prior studies, the share of rock is introduced as a function of terrain slope and geology information. Inaba et al. (2001) developed a numerical model to estimate the share of rock excavation volume. They assigned a coefficient for each geological unit and used this coefficient along with the slope and road crown width as inputs of the model to estimate rock portion for each geological unit. Stuckelberger et al. (2006) have adopted the current model and the above mentioned coefficients to estimate rock excavation volume and cost for each geological unit. They calculated the rock excavation cost as a function of earth embankment costs to be used as one of the cost elements of forest road construction cost model. However, considering a fixed coefficient for each type of geological unit regardless of local conditions could lead to inaccurately estimating the rock share and consequently inaccurately estimating the construction costs. The approach performed in practice in Iran is as follows: after visiting the proposed alignment of forest road, three general classes of rock, soft, medium, and hard, are assigned to several parts of the road project by experts. In fact, these linguistic values are used to describe the difficulty levels of the earthwork and to calculate the base price of project appraisal. As a result, providing a framework that could be practical and at the same time have a justifiable analytic foundation is essential for forest managers.

From another perspective, developing a model to estimate the share of rock is problematic due to the uncertainty associated with geological information and environmental variables. The numerical modeling and optimization approaches have long been employed in forest researches worldwide. The traditional simulation and optimization tools are appropriate when data are known well enough, while in many real-world problems, there are many uncertain variables, and/or vague and ambiguous input data that should be handled for modeling. A computing system that has the ability to analyze these kinds of data should be more flexible and adaptive than the traditional approaches. In other words, a Real-World Computing (RWC) system should be capable of distributed representation of information, massively parallel processing, learning and self-organization to achieve enough flexibility in information processing (Sreekanth et al. 2010). In this relation, soft computing techniques as the open, robust, and real-time processing systems can be adopted efficiently to cope with the RWC systems. Hereafter, a brief introduction of relevant techniques and literature are provided.

Fuzzy logic (Zadeh 1965) is increasingly used in various fields of science and technology for prediction purposes (Gail et al. 2002). Fuzzy systems are stable, easily tunable and could be validated conventionally. One of the significant advantages of linguistic methodology in fuzzy rule based systems is that a well-defined physical relationship is not required to systematically convert an input to an output (ASCE Task Committee on Applications of Artificial Neural Networks in Hydrology 2000). These properties make them sufficiently flexible for solving the real time problems especially when the input or output data are defined by several linguistic values. Fuzzy sets theory has been applied in forest management (Mendoza and Sprouce 1989; Mendoza et al. 1993; Zandik 2006), water runoff, sediment yield, and recreation (Tecle et al. 1994), resource allocation (Ghajar et al. 2010), and forestry planning problems (Kangas et al. 2006).

Artificial Neural Networks (ANNs) are another type of soft computing and data driven techniques that, because of their heuristic problem-solving capabilities, have been applied successfully in many fields of geological engineering problems (Shahin et al. 2008). Among them, ANNs have been employed in predicting the settlement and bearing capacity of shallow foundations (Shahin et al. 2005; Padmini et al. 2008), applications concerning earth retaining structures (Kung et al. 2007), site characterization (Najjar and Basheer 1996), mining (Rankine and Sivakugan 2005), groutability of soils (Tekin and Akbas 2010) and many other problems. A comprehensive overview of ANN application in geological engineering problems can be found in Shahin et al. (2008). To gain more efficiency from fuzzy logic and ANNs, a combined approach called neuro-fuzzy was developed by Jang (1993). Neuro-fuzzy systems are fuzzy systems that use ANN theory in order to determine their properties (i.e. the respective fuzzy sets and fuzzy rules) by processing of available data set (Andrews et al. 1995). In this regard, »the adaptive network-based fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions« (Wang et al. 2010) is of particular interest. The important contribution of Jang (1993) to ANFIS development was the establishment of the universal approximant nature of ANFIS, and the functional equivalency of the Sugeno fuzzy inference systems with radial neural networks, providing the essential theoretical support for the practical application of ANFIS to nonlinear system modeling (Roger and Sun 1993). The membership function parameters in the ANFIS representing the system behavior are extracted from input data patterns. ANFIS learns features in data patterns and then adjusts the consequent parameters according to a given error criterion. There is a lack of literature in the application of ANFIS in forestry but, successful implementations of ANFIS in geological engineering have been reported recently (for example for strength prediction, Yilmaz and Yuksek 2009). Determination of compressive strength of a rock material is time consuming, expensive and involves destructive tests. If

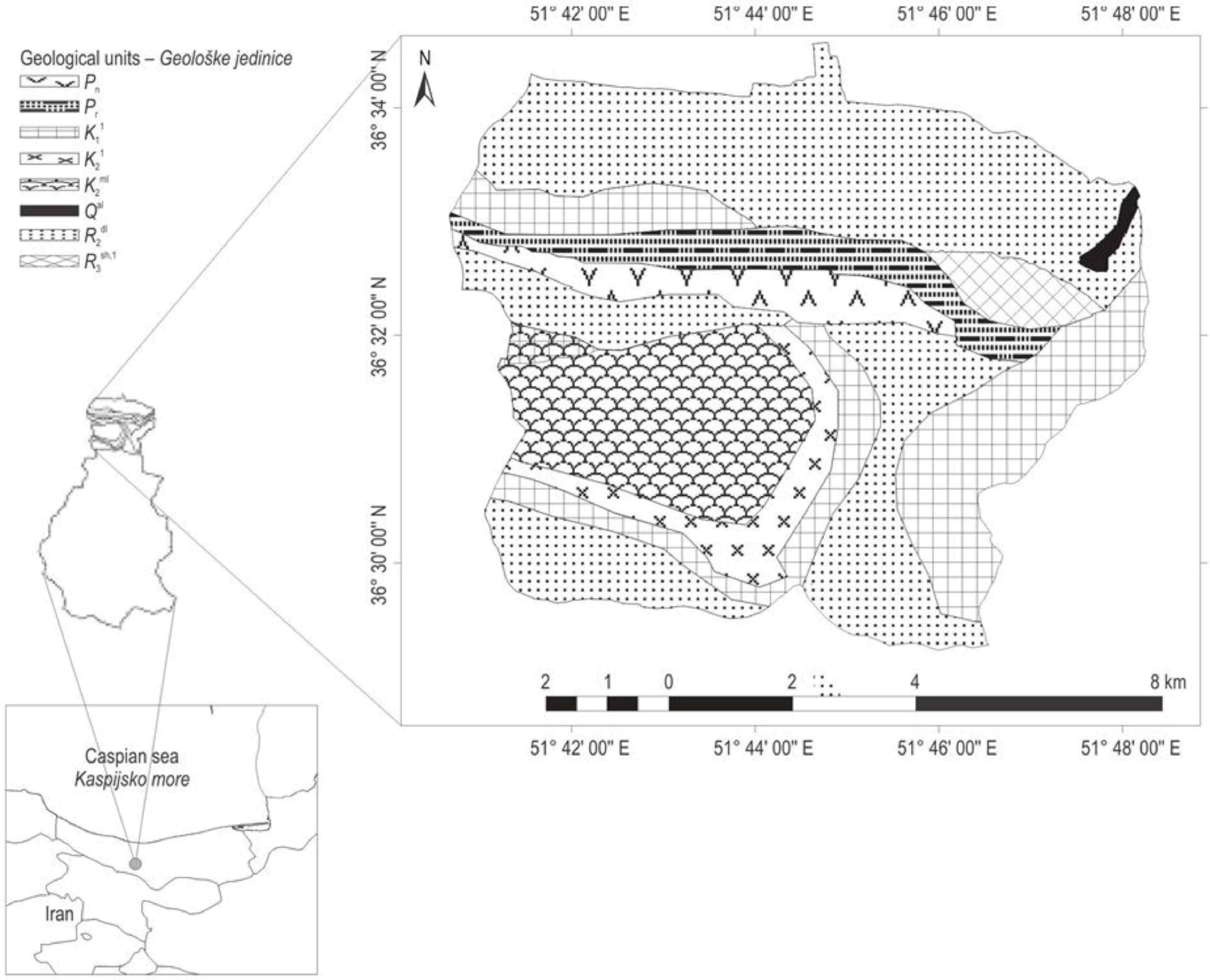

Fig. 1 Geological units of study area
Slika 1. *Geološke jedinice na području istraživanja*

reliable predictive models could be obtained to correlate unconfined compressive strength to quick, cheap, and non-destructive test results, they would be very valuable for at least the preliminary stage of designing a structure (Yilmaz and Yuksek 2009). In the present paper, the Analytic Hierarchy Process (AHP) method was used to prioritize geological units of the study area with respect to strength factor. AHP originally developed by Saaty (1977; 1980), is one of the most popular Multi-Criteria Decision Making (MCDM) methods, which has been widely used in many fields, including natural resource management. AHP, as a comprehensive framework for modeling the real-world problems has the ability to incorporate both tangible and intangible criteria into the decision making process. Murray and von Gadow (1991); Kangas (1992); Vacik and Lexer (2001) and; Kangas and Kangas (2005) have used AHP in forestry applications. Furthermore, the number of AHP applications in other fields, such as geology, is continuously increasing. As a successful application of fuzzy logic and AHP in Engineering geology problems, Liu and Chen (2007) presented a systemic procedure by combining the AHP and the Fuzzy Delphi method (FDM, Kaufmann and Gupta 1988) for assessing the quality of slope rock mass, and classifying the stability of rocks using Linear Discriminant Analysis (LDA) model.

This paper proposes an approach that applies the ANFIS technique along with AHP to develop a novel knowledge-based model for rock share estimation. The model is developed based on two input variables of terrain slope and geological units. Furthermore, the impacts of different membership functions on the static parameters of rock share estimation, which are used in the ANFIS model, were investigated. As a case study, the best resulted model is implemented in the 7938 (ha) of Educational and Research Forest of Tarbiat Modares University (TMU) in the northern Iran,

Table 1 Description of geological units of study area
Tablica 1. *Opis geoloških jedinica*

Era (groups) *Geološke ere*	Period *Geološki periodi*	Abr. *Oznaka*	Description – *Opis*
Mesozoic *Mezozoik*	Cretaceous *Kreda*	K_1^1	Orbitolina limestone and calcareous shale – *Vapnenci s orbitolinama i vapneni škriljevci*
		K_2^1	Conglomerate in lower part, limestone, marly limestone and sandy limestone – *Konglomerati u donjem dijelu, vapnenac, laporoviti vapnenac i pjeskoviti vapnenac*
		K_2^{ml}	*Limestone, marl, limy marl and silty marl – Vapnenac, lapor, vapnenasti lapor i pjeskoviti lapor*
	Triassic *Trijas*	$R_3^{sh,1}$	Shale, sandstone and limestone – *Škriljevac, pješčenjak i vapnenac*
		R_2^{dl}	Thick bedded to massive dolomitic limestone, dolomite and limestone – *Debeli do masivni dolomitni vapnenac, dolomiti i vapnenci*
Paleozoic *Paleozoik*	Permian *Perm*	P_n	Cherty limestone, calcareous and sandy shale – *Čertni vapnenac, vapneni i pjeskoviti škriljevci*
		P_r	Gray, thick bedded to massive limestone and dolomite (Fuzulinid limestone) – *Sivi, debeli do masivni vapneci i dolomiti (fuzulinidni vapnenac)*
Cenozoic *Cenozoik*	Quaternary *Kvartar*	Q^{al}	Recent alluvium in river beds – *Rani aluvij u koritima rijeka*

where a 24 (km) forest road has already been constructed and additional forest road alignment should be planned and constructed in the future periods.

2. Materials and Methods – *Materijal i metode*

2.1 Study area and data collection – *Područje istraživanja i prikupljanje podataka*

The research was carried out in districts 2, 3, 4, and 5 of Educational and Research Forest of TMU situated between longitudes 51°40′37′′E–51°51′36′′E and latitudes 36°29′08′′N–36°34′33′′N. The topographic elevation is about 2 to 2 206 m above mean sea level. The slope classes and their area percentage ranged from 0 to 10% (6.3%); 10–25% (21.6%); 25–45% (31.6); 45–70% (22.3%), and more than 70% (18.2%). In order to make adaptable data that could be applied in the study area, similar geological units to the project area and their constructed road network were investigated to find where the sample data should be collected.

Fig. 1 shows the map of geological units in the study area. The cut slope of the constructed road in each geological unit was divided into 10 (m) non-overlapping intervals (Fig. 2).

In each sample the type of geological unit and slope degree of terrain were recorded as inputs and the amount of rock share was estimated by an expert in the form of linguistic values as the observed output. A total of 130 samples, including all combination of input variables, were recorded. In the current study, we determined the share of rock for cut-slope areas in three groups of geological units; Mesozoic sediment formations, Paleozoic geological units and Quaternary formation of alluvial deposit (Table 1).

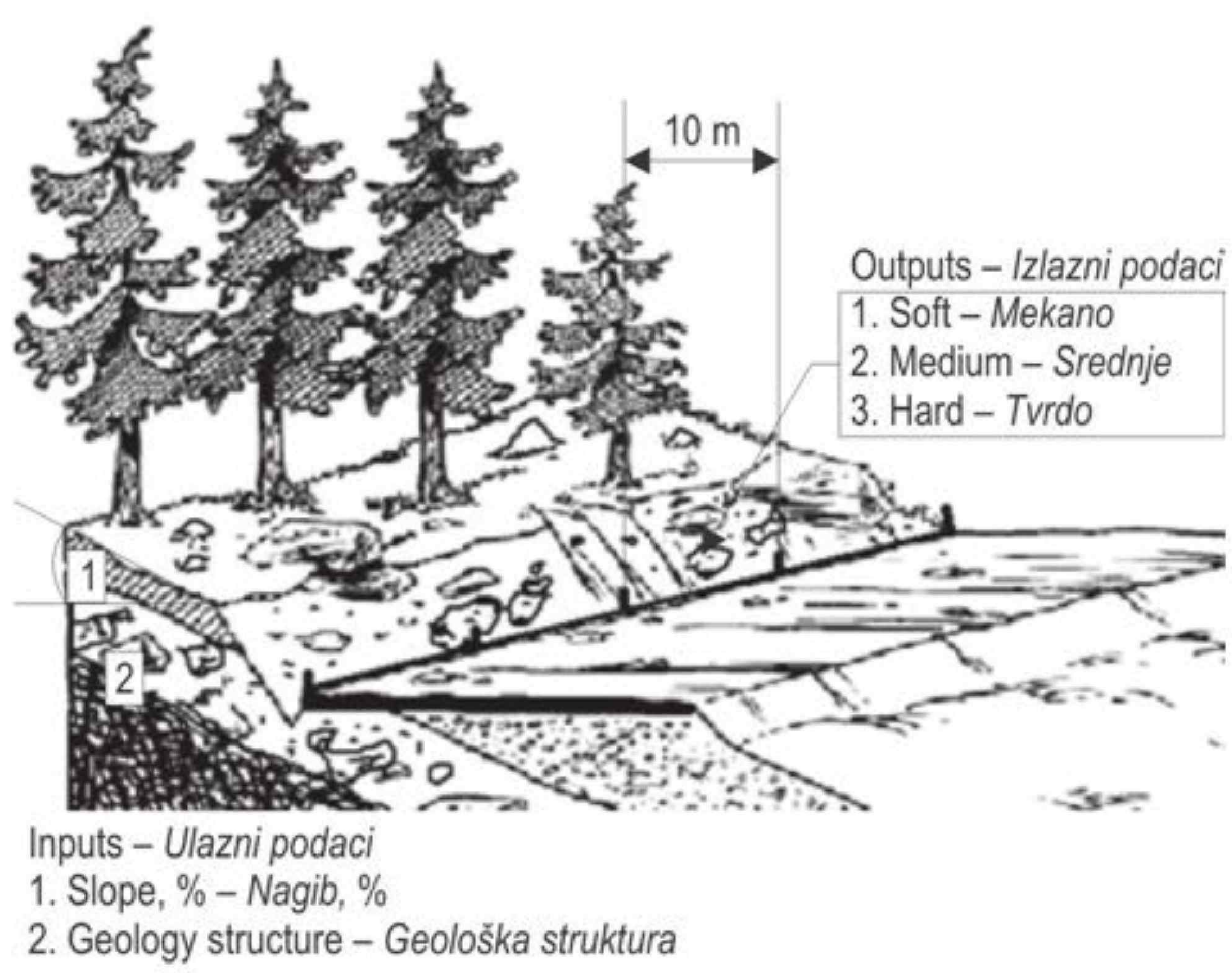

Fig. 2 Input and output data collection
Slika 2. *Ulazni i izlazni podaci*

To quantify the geological information, Analytical Hierarchy Process (AHP) was used to prioritize the geological units regarding strength against the earth embankment. Since the allowable terrain slope for road construction is up to 70%, to collect a complete set of data, additional samples were collected from higher ter-

Table 2 Linguistic values of input and output variables
Tablica 2. *Vrijednosti ulaznih i izlaznih podataka*

Variables – *Varijable*		Rating values *Ocjene vrijednosti*				
Inputs *Ulazni podaci*	Terrain Slope, % – *Nagib terena*, %	Flat *Ravnica*	Gentle *Blago*	Moderate *Umjereno*	Steep *Strmo*	Very Steep *Vrlo strmo*
		0–10	10–25	25–45	45–70	70<
	Strength of geological units (normalized AHP priorities) *Ocjena geološkoh jedinica (normalizirani AHP)*	Very Low *Izrazito nisko*	Low *Nisko*	Medium *Srednje*	High *Visoko*	Very High *Izrazito visoko*
		0	0.25	0.5	0.75	1
Output *Izlazni podaci*	Share of Rock – *Udio stijena*	Soft – *Mekano*		Medium – *Srednje*		Hard – *Tvrdo*
		≤30%		50%		70%≤

rain slopes so that the minimum and maximum slope of the entire area were included in the samples. The observed rock share, as the output of the model, was recorded as three linguistic values »soft«, »medium« and »hard« according to the practical expert-based method of rock share estimation. The linguistic values of input and output variables specified by the fuzzy sets as well as their ranges are shown in Table 2.

2.2 Data division – *Razdioba podataka*

The purpose of the training process in ANNs and fuzzy systems is to interpolate (generalize) the data used for calibration in high dimensional space. Having a large number of model parameters (connection weights), ANNs and neuro-fuzzy systems can overfit the training data when the data are little or noisy. In other words, if the number of degrees of freedom of the model is large compared with the number of data points used for calibration, the model might no longer fit the general trend, as desired, but might learn the idiosyncrasies of the particular data points used for calibration leading to *»memorization«*, rather than *»generalization«* (Shahin et al. 2008). To prevent overfitting and evaluate the generalization power of the model, a separate validation and test sets, respectively, are needed. In this research, in order to develop the ANFIS, we used a modified data division method, i.e. cross-validation (Stone 1974), in which the data are divided to three sets:

⇒ Training set used to adjust the connection weights, membership functions and model parameters,

⇒ Validation set that checks the performance of the model through the training process and stops the training to avoid overfitting,

⇒ Testing set used to evaluate the trained ANFIS performance and generalization power.

About 20% of the data were used for testing and the remaining data were divided to training – 80% and validation – 20%.

2.3 Analytic Hierarchy Process – *Analitički hijerarhijski proces (AHP)*

2.3.1 Fundamentals – *Osnove i temelji*

AHP is a mathematical method for analyzing complex decisions with multiple attributes (Saaty 1977; Saaty 1980). AHP can consider the objective information, expert knowledge, and subjective preference at the same time. It aggregates separate performance indicators into an integrated performance indicator (Bouma et al. 2000). In addition, both qualitative and quantitative criteria can be included in the judgments and comparisons of alternatives. By decomposing the decision problem into its elements, a hierarchical decision structure is constructed in the AHP that helps decision makers to view the problem. The preferences for the attributes (or alternatives) are compared in a pairwise manner and numerical techniques are used to derive quantitative values from these comparisons (Kurttila et al. 2000).

Unlike other related methods that require quantitative values of criteria, which are measured in ratio or interval scales in their analysis; AHP can transfer the qualitatively expressed measures into a ratio scale through the pairwise comparison. The intensity of preference between alternatives can be expressed on a nine-point scale. If two alternatives are of equal importance, a value of 1 is given in the comparison, while a 9 indicates the absolute importance of one criterion over the other (Saaty 1980). Pairwise comparison data can be analyzed using either regression methods or the eigenvalue technique (Ananda and Herath 2007). The Eigenvalue is calculated for every pair of components. If there are n components to be computed the matrix I, is defined as follow:

$$I=\begin{bmatrix} w_1/w_1 & w_1/w_2 & > & w_1/w_n \\ w_2/w_1 & w_2/w_2 & > & w_2/w_n \\ \vdots & \vdots & \square & \vdots \\ w_n/w_1 & w_n/w_2 & > & w_n/w_n \end{bmatrix}=\begin{bmatrix} 1 & a_{12} & > & a_{1n} \\ 1/a_{12} & 1 & > & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & > & 1 \end{bmatrix}$$

After computing all pairwise comparisons the priority weight vector (w) is computed as the unique solution of equation 1.

$$I_w=\lambda_{max}\, w \qquad (1)$$

Where:

λ_{max} is the largest Eigenvalue of matrix I.

The priority vector w is often normalized by $a=\Sigma_i^n=$ $_1w_i$. This ensures the uniqueness of w and provides that a becomes unity (Saaty 1980). The Consistency Index (CI) of derived weights is a parameter that measures the consistency of pairwise comparisons and could be calculated by:

$$CI=\frac{\lambda_{\max}-n}{n-1} \qquad (2)$$

As a rule of thumb, a CR value of 10% or less is considered acceptable (Saaty 1977).

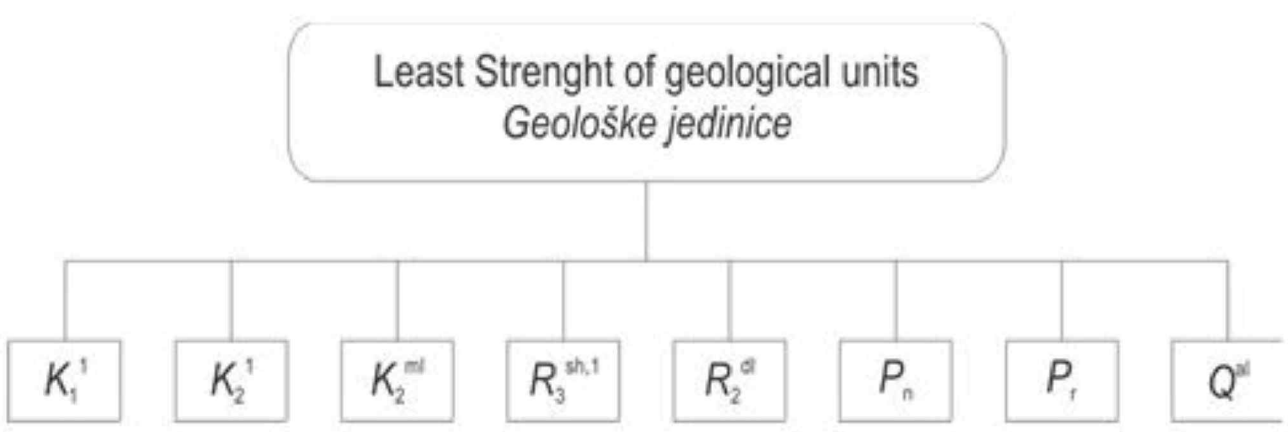

Fig. 3 The Structure of AHP for prioritization of geological units with respect to their strength variable

Slika 3. *Ustrojstvo AHP-a i ocjene geoloških jedinica*

2.3.2 Applying AHP to rank the geological units *Primjena AHP-a za ocjenjivanje geoloških jedinica*

AHP approach was adopted to calculate the degree of preference of geological units from the viewpoint of rock strength.

The structure of AHP model is shown in Fig. 3. Otherwise AHP was applied to quantify the preference of each of the eight units with respect to the strength against the earth embankment. The less strength against the earthwork, the more value of computed preference. The weighting process to synthesize the ranking of geological units was performed in Super Decision software ver.1.6.0.

2.3.3 Normalization technique – *Normalizacija*

Due to different scales of input and output variables, and in order to increase the speed and accuracy of data processing, input and output data were *normalized* in a boundary of (0.1) before using them in the ANFIS. As a result, the synthesized priorities of geological units in AHP and terrain slope, as the inputs, and also the percent of rock share (estimated by expert knowledge), as the output of the ANFIS, were normalized using the equation 3. As shown in the equation, the normal forms of each input and output were calculated by dividing each value minus the minimum value by the maximum value minus the minimum value so that the largest individual had a priority of 1.0. The normalized values are also used to create the membership function of input and output variables.

$$X_n=\frac{X_i-X_{min}}{X_{max}-X_{min}} \qquad (3)$$

2.4 The Adaptive Network-based Fuzzy Inference System – *Prilagodljivi mrežno-fazni sustav*

2.4.1 Architecture – *Arhitektura sustava*

ANFIS proposed by Jang (1993) is one of the most applied fuzzy inference systems especially in modeling of the real-world physical objects. ANFIS is a combination of Fuzzy Logic (FL) and Artificial Neural Network (ANN), which applies the learning process developed in ANN approaches to a fuzzy inference system (FIS). The selection of the FIS is the main concern in designing the ANFIS. Several FIS were developed in the literature, each of which was based on the type of fuzzy reasoning and the employed fuzzy if-then rules (e.g. Mamdani and Assilian 1974; Tsukamoto 1979; Takagi and Sugeno 1983). In the current study, ANFIS uses a Sugeno inference system (Sugeno and Kang 1988). The consequent part of the linear equations and the parameters can be estimated by a simple least squares method (Farokhnia et al. 2010). ANFIS structured by a five-layered network and a hybrid algorithm is used to tune this system based on the structure of input and output data. A mathematical-schematic representation of Takagi-Sugeno's type of ANFIS with two inputs x and y, one output z, two MFs for each input and two rules is shown in Fig. 4.

It is a simple example of a fuzzy inference system, known as the first-order Sugeno FIS. The fuzzy rule-

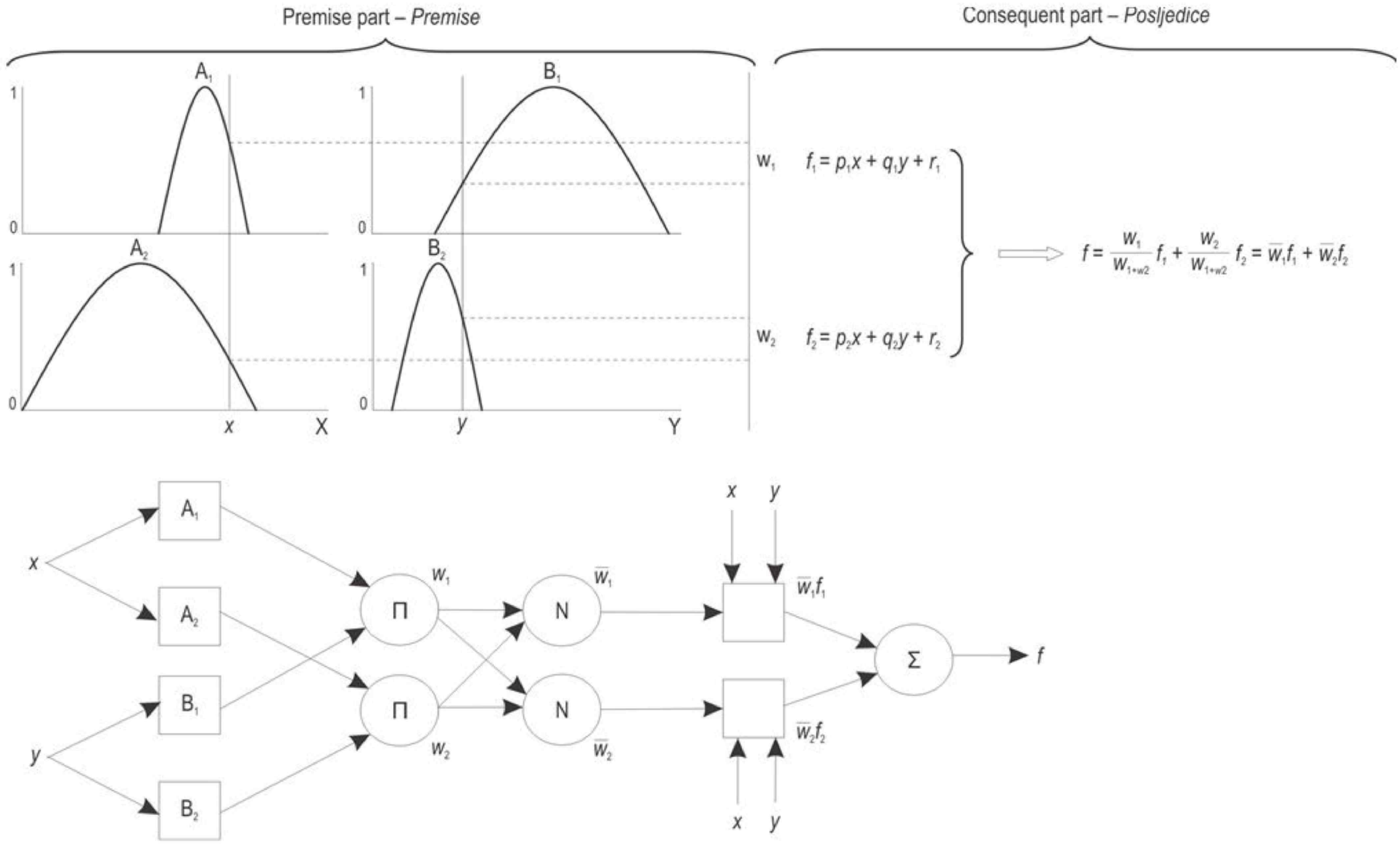

Fig. 4 Schematic-Mathematical representation of Takagi-Sugeno's type of ANFIS for two rules
Slika 4. *Shematsko-matematički prikaz modela Takagi-Sugeno ANFIS s dva pravila*

base of this example including two if-then rules can be presented as follows:

Rule 1: If x is A_1 and y is B_1; Then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2; Then $f_2 = p_2x + q_2y + r_2$

(4)

Where:

A_1, A_2 and B_1, B_2 are the membership functions of inputs X and Y, respectively,

p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of output function.

The modeling process of ANFIS is described layer by layer:

Input variables are uncertain in the first hidden layer. Every node i in this layer is an adaptive node with a node function:

$$OP_i^1 = \mu_{Ai}(x) \text{ for } i = 1, 2 \tag{5}$$

$$OP_i^1 = \mu_{Bi-2}(y) \text{ for } i = 3, 4$$

Where:

x or y are the input variables to node *i*,

A_i, B_{i-2} are the linguistic label (such as *low* or *high*) associated with this node, characterized by the appropriate MFs in this node.

To investigate the impact of different MFs on the result of the ANFIS model in this research, the Gaussian, generalized bell-shaped, trapezoidal-shaped, and triangular-shaped functions were applied.

Fig. 5 illustrates an overview of development of the RSE-ANFIS models with different MFs based on input variables applying first-order Sugeno reasoning method. There are a total of 25 rules for each model.

The first layer is one of the two adaptive layers of this ANFIS architecture, because three modifiable parameters $\{a_i, b_i, c_i\}$ are related to MFs present in this layer. These parameters are so-called premise (antecedent) parameters used to calculate the fuzzy output of each node function. The shape of MFs varies with any change of the above mentioned parameters at various stages of training, thus exhibiting various forms of membership functions on linguistic label A_i,

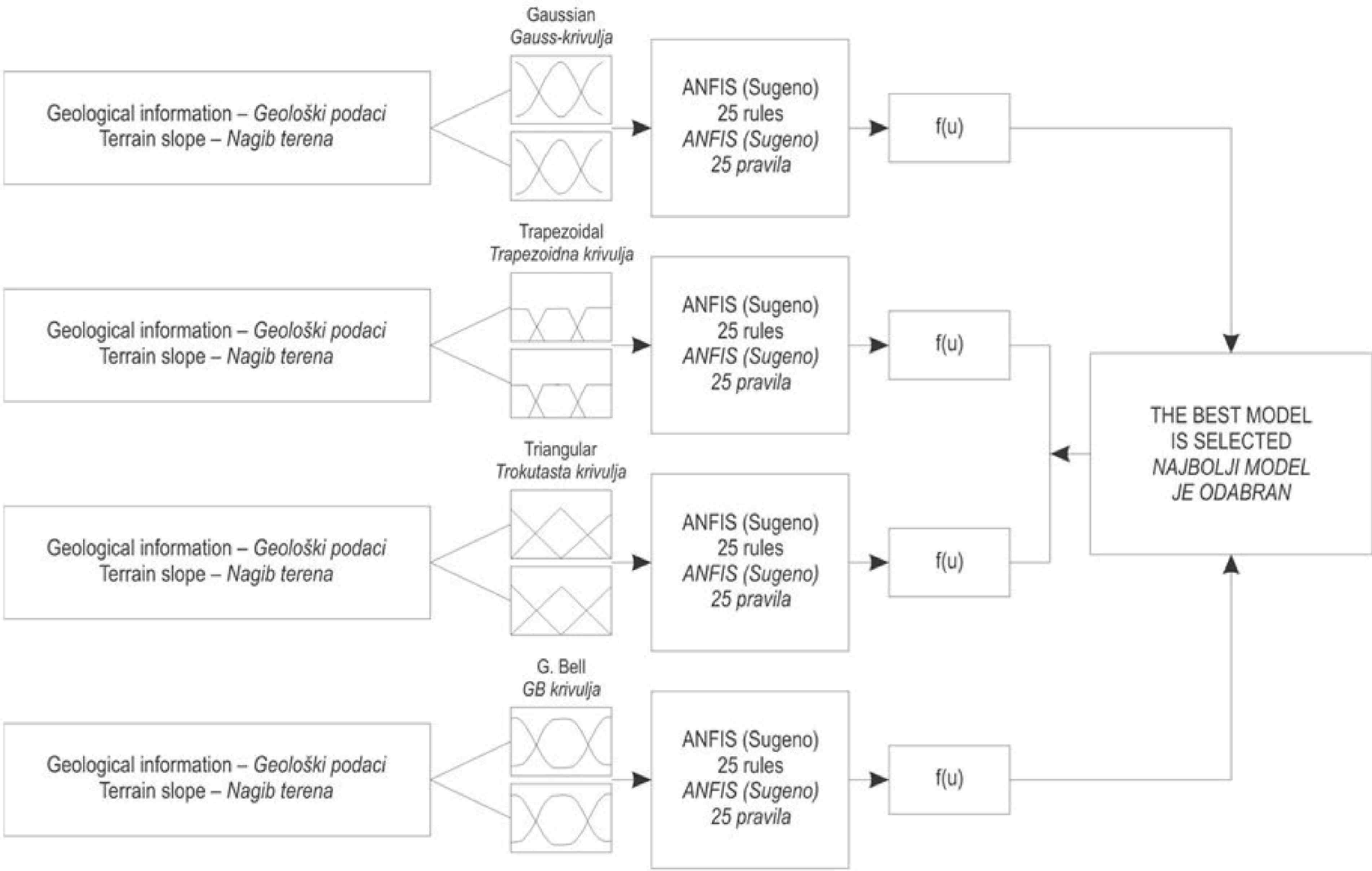

Fig. 5 Architecture of adopted approach for modeling of rock share using ANFIS
Slika 5. *Sustav preuzetoga modela ANFIS za procjenu udjela stijena u tlu*

with a maximum equal to 1 and minimum equal to 0 (Jang 1993), and consequently, results in more fuzzy values of input variables for each type of MF.

The antecedent parts of rules are computed in the second hidden layer using *T-norm* operators. This layer consists of the nodes labeled $\prod$, which multiplies the incoming signals and sends the product out. For instance:

$$OP_i^1 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \; i = 1, 2 \tag{6}$$

The output (w_i) represents the firing strength of a rule.

The third hidden layer is used for normalization of the rules' firing strength (FS). Every node in this layer labeled as N calculates the ratio of i^{th} rules' FS to the sum of all rules' FS.

$$OP_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \; i = 1, 2 \tag{7}$$

The fourth hidden layer determines the consequent part of the rules. Node i computes the contribution of i^{th} rule toward the model output using the following function:

$$OP_i^4 = \overline{w}_i f_i = w_i(p_i x + q_i y + r_i) \tag{8}$$

The fourth layer is the second adaptive layer of ANFIS architecture. Like with the first layer, there are three modifiable parameters (e.g. p_i, q_i, r_i), the so-called consequent parameters (Jang 1992). Finally the single node in fifth layer labeled with $\sum$, computes the overall output as the sum of all incoming signals. The corresponding function can be as follows:

$$OP_i^4 = \sum_i \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i w_i} \tag{9}$$

2.4.2 Learning algorithm – *Algoritam učenja*

Since there are two adaptive layers in the ANFIS, the task of learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ (premise parameters) and $\{p_i, q_i, r_i\}$ (consequent parameters), to make the ANFIS output match the training data (Polat et al. 2008). Similar to conventional statistical models, the model parameters are adjusted in the model calibration phase (training) using a hybrid learning algorithm, so as to minimize the error between model outputs and the corresponding measured values for a particular data set, e.g. the training

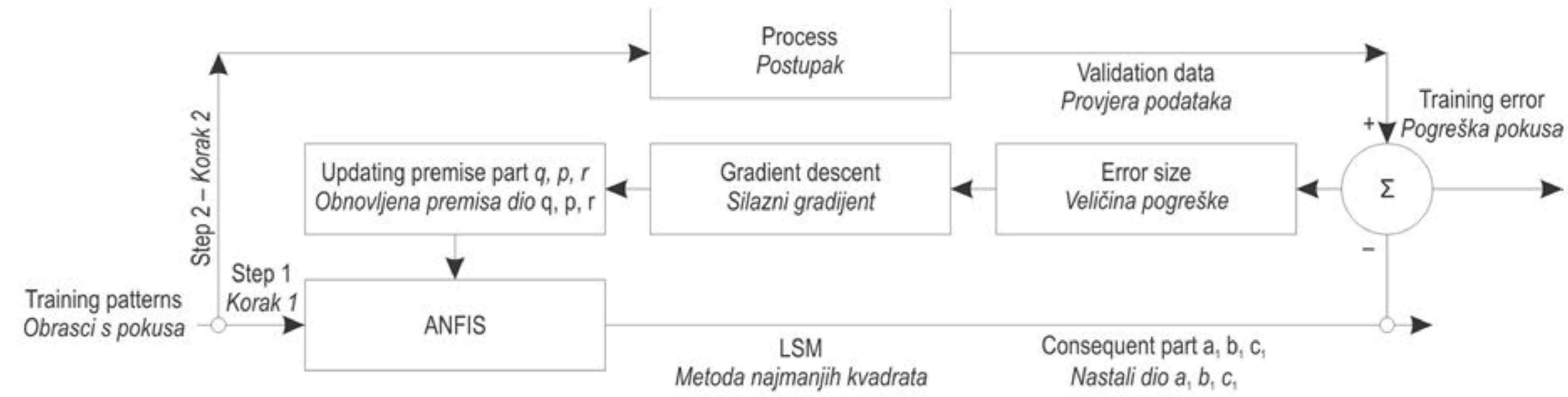

Fig. 6 ANFIS learning process by Hybrid algorithm

Slika 6. *Postupak učenja modela ANFIS pomoću hibridnoga algoritma*

set. The learning process of ANFIS by this Hybrid algorithm is shown in Fig. 6.

ANFIS implements a hybrid algorithm for the learning process. This algorithm combines the gradient descent method used to learn and modify the premise parameters, and least squares method (LSM) which determines the consequent part. The reason for this combination is that when the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. Thus, the training process that results in learning has two steps in each iteration.

Step 1 In the first epoch, the input patterns are propagated and the optimal consequent parameters are identified by the LSM, while the premise parameters are assumed to be fixed for the current cycle through the training set.

Step 2 In the second epoch, the patterns are propagated again; the error signals propagate backward to modify or update the premise parameters, by gradient descent (A back propagation gradient descent method).

2.4.3 Evaluation of model performance – *Ocjena modela*

The ANFIS models were developed in *MATLAB ver.7.6* environment. In order to evaluate the predictability, performance and validity of models as well as consistency of results, three well-known statistical criteria, including coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), were used (equations 10, 11 and 12).

$$R^2 = \left[\frac{\sum_{i=1}^{n}(X_i^o-\overline{X^o})(X_i^p-\overline{X^p})}{\sqrt{\sum_{i=1}^{n}(X_i^o-\overline{X^o})}\sqrt{\sum_{i=1}^{n}X_i^p-\overline{X^p}}}\right]^2 \qquad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i^o - X_i^p)^2} \qquad (11)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_i^o - X_i^p\right| \qquad (12)$$

Where:

n denotes the number of data,

X_i^o and X_i^p are the observed and predicted output of pattern number I, respectively.

The optimal performance of the model will tend to the R^2 of 1 and 0 for other criteria. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data in a robust fashion, rather than simply having memorized the input-output relationships that are contained in the training data (Shahin et al. 2008). To achieve this, the performance of trained ANFIS is tested on an independent test data set, which has not been used as a part of the model building process. If such evaluation is adequate, the model is considered to be able to generalize and is deemed to be robust.

2.4.4 Model implementation – *Primjena modela*

One of the goals of this research was to create a reliable framework for forest managers or stakeholders to estimate the volume of rock in the ground before road construction begins. The assignment of a given area element (i.e. pixel) to any rock share classes was encountered with the problems due to the variation of physiographic and geological properties within the area and matching these properties with rock share of the underground layers, which would affect the cost of earth embankments. After developing an appropriate ANFIS model, it was implemented to estimate the rock ratio of the ground in the study area. Geographic information system (ArcGIS 9.3), as the best suited tool for handling the spatial data, was used to extract the input data (e.g. slope and geological information) of the ANFIS model from each pixel of the study area rasterized slope and geology maps. By entering these data as the input data to the optimum developed ANFIS, the output value of each record was calculated. The obtained values were transferred to the attribute table of original map to produce the final rock share map, which illustrates the spatial variability of rock ratio in the study area. The resulted map was classified to three classes based on the primary expert-based classes, which were considered at the beginning of the research.

3. Results – *Rezultati*

In the present research, the AHP method was applied to obtain the priority of existing geological units with respect to the least strength against the earthwork in forest road construction. There were eight types of geological units in the study area that had to be prioritized. The final results synthesized from the AHP model are presented in Table 3.

Table 3 Final priorities of geological units with respect to the least strength against the earthwork

Tablica 3. *Ocjene geoloških jedinica s obzirom na količinu zemljanih radova (iskop)*

Geological units *Geološke jedinice*	AHP priorities *ocjena AHP-a*	Total Ranking for excavation *Ocjena za iskapanje*	Strength *Težina*
Q^{al}	0.315	1	Low *Nisko*
P_n	0.234	2	↓
K_2^{ml}	0.168	3	
$R_3^{sh,1}$	0.106	4	
K_2^1	0.071	5	
P_r	0.047	6	
K_1^1	0.032	7	
R_2^{dl}	0.023	8	High *Visko*

CI=0.0266 < 0.1 (OK)

As shown in this table, the structure Q^{al} took the highest priority and it is the least strength unit and R_2^{dl} is the most resistant structure to the earthwork from the viewpoint of geology experts. The judgments and comparisons between alternatives in this AHP model were based on the question as to which geological unit showed less strength against the earthwork.

The results of normalization of input and output field data, calculated by equation (3), are shown in Table 4.

The prepared normalized values were, then, transferred into the ANFIS models. Table 5 shows a part of normalized data that were fed to the model as the training, validation, and testing data.

All models were developed using the first-order Sugeno FIS and Hybrid optimization method. The adopted strategy for obtaining the model with the best performance was the incorporation of four different membership functions in designing the ANFIS models. The best result obtained from this strategy was related to triangular-shaped MF (Table 6).

The main preference criteria of the models were the coefficient of determination (R^2) and Root Mean Square Error (RMSE) of validation data set. R^2 and RMSE for triangular-shaped MF were 94.89% and 9.23%, respectively, obtained after training epoch 12. The step size adaptation for the parameters of optimum ANFIS is shown in Fig. 7.

The process of each epoch presented in this figure is illustrated in Fig. 6. Fig. 7 shows that the training process stopped at epoch 12 and the model could not improve its own performance after this stage. These results showed that the ANFIS model developed using the triangular MFs had the highest power of generaliza-

Table 4 Maximum and minimum values of input and output variables before and after normalization

Tablica 4. *Najveće i najmanje vrijednosti varijabli prije i poslije normalizacije*

		Inputs – *Ulazni podaci*		Output – *Izlazni podaci*
		Slope, % – *Nagib, %*	Geology formation priorities *Ocjena geoloških tvorbi*	Rock share *Udio stijena*
Before normalization *Prije normalizacije*	Min.	5	0.023	Low – *Nizak* (≤ 30%)
	Max.	140	0.315	High – *Visok* (≥ 70%)
After normalization *Poslije normalizacije*	Min.	0	0	0
	Max.	1	1	1

Table 5 A part of data used as training, validation and testing data
Tablica 5. *Dio podataka korištenih za vježbu i ispitivanje valjanosti modela*

Geology *Geologija*	Slope *Nagib*	Observed rock share *Procijenjeni udio stijena*
0.753	0.185	0
0.753	0.269	0.5
0.030	0.704	0
1	0.481	1
0.164	0.667	0
0.284	0.444	0
0.753	0.444	1
0.753	0.222	0.5

tion and performance in rock share estimation. Consequently, this model was selected as the optimum ANFIS. The results of incorporation of Gaussian MF were very close to triangular ones. The obtained R^2 and RMSE of Gaussian MF were 93.74% and 10.03%, respectively. These results of this study also showed a robust perfor-

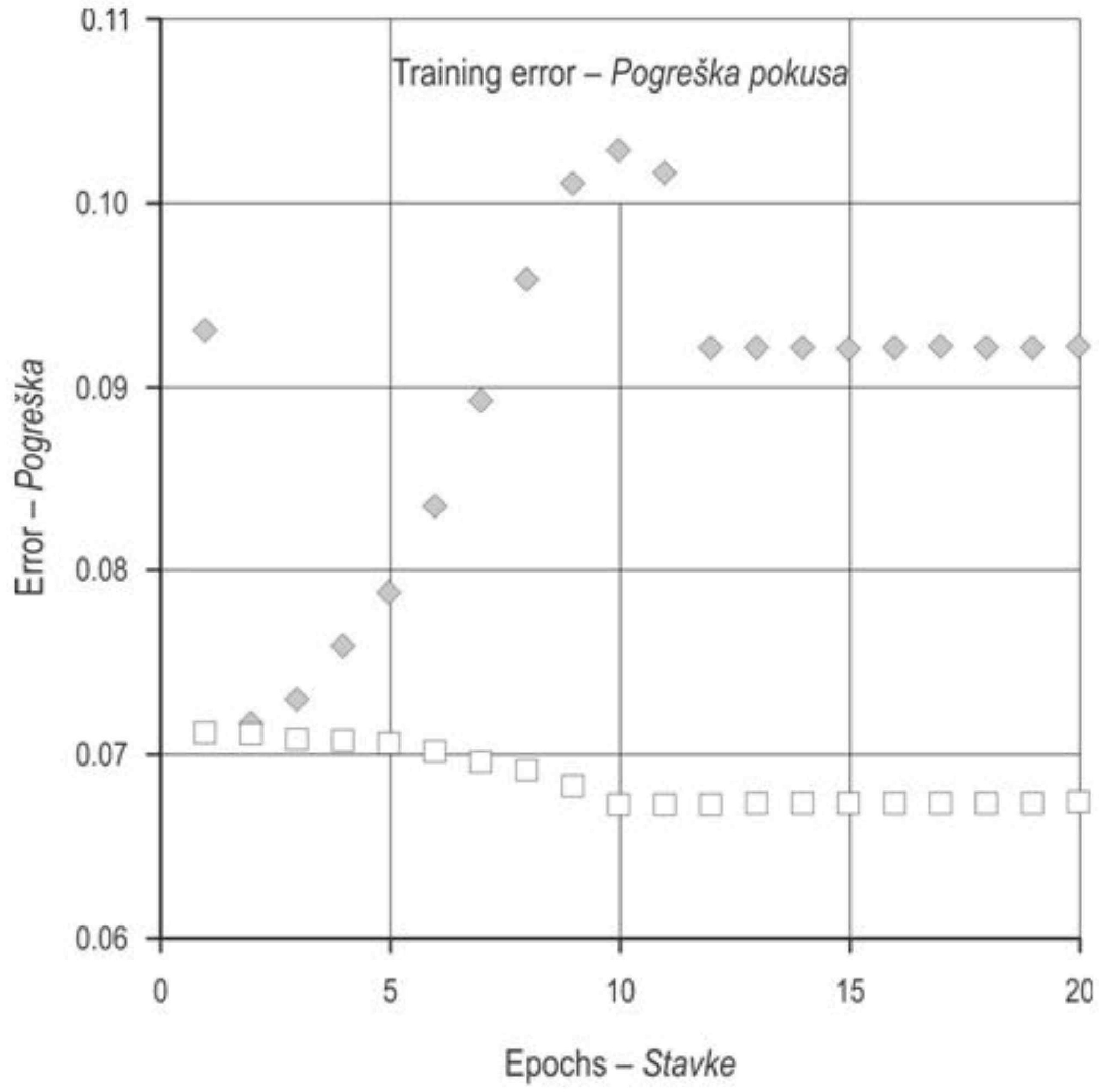

Fig. 7 Step size diagram of training process of optimum ANFIS (stopped at epoch 12)
Slika 7. *Razvijanje modela ANFIS »korak po korak« (zaustavljeno u 12. stavki)*

Table 6 Result of application of different MFs in rock share ANFIS model
Tablica 6. *Primjena različitih funkcija članstva (MFs) u modelu ANFIS*

Type of FIS *Vrsta modela sustava neizrazitoga zaključivanja*	Adaptive network based Fuzzy Inference System (Takagi-Sugeno) *Prilagodljivi mrežno-fazni sustav za modeliranje (Takagi-Sugeno)*			
Learning algorithm *Algoritam učenja*	Hybrid *Hibridni sustavi*			
Type of MF *Vrsta funkcije članstva*	G.Bell *GB*	Gaussian *Gauss*	Trapezoidal *Trapezoidna*	Triangular *Trokutasta*
R2 (training data) % *Koeficijent determinacije (podaci za vježbu modela), %*	96.87	96.40	93.31	96.90
R2 (validation data) % *Koeficijent determinacije (podaci za ispitivanje valjanosti modela), %*	81.50	64.00	88.80	85.60
R2 (test data) % *Koeficijent determinacije (podaci za ispitivanje modela), %*	82.50	93.74	78.05	94.89
RMSE (training data) % *Pogreška korijena usrednjenih kvadrata (podaci za vježbu modela), %*	6.77	7.18	7.28	6.37
RMSE (validation data) % *Pogreška korijena usrednjenih kvadrata (podaci za ispitivanje modela), %*	18.25	30.58	14.39	16.33
RMSE (test data) % *Pogreška korijena usrednjenih kvadrata (podaci za ispitivanje modela), %*	21.25	10.03	19.28	9.23
MAE (training data) % *Srednja apsolutna pogreška (podaci za vježbu modela), %*	2.09	2.31	2.14	1.94
MAE (validation data) % *Srednja apsolutna pogreška (podaci za ispitivanje valjanosti modela), %*	8.37	8.24	3.63	4.61
MAE(test data) % *Srednja apsolutna pogreška (podaci za ispitivanje modela), %*	9.89	4.23	6.63	4.06
Epochs *Stavke*	10	2	4	12

Table 7 Estimated areas for rock share classes

Tablica 7. *Procjena površine ovisno o udjelu stijena u tlu*

Rock share classes *Udio i vrsta tla*	Area, ha *Površina,* ha	Relative area, % *Udio površine,* %
Soft – *Mekano*	2137.44	26.92
Medium – *Srednje*	3240.11	40.83
Hard – *Tvrdo*	2560.26	32.25

mance in modeling the ratio of rocks in the ground. Application of other types of MFs resulted in either less R^2 or more RMSE than triangular and Gaussian ones.

The result of application of the developed ANFIS in predicting the rock share in the study area is shown in Fig. 8. The results of final estimated areas that were assigned to each class of rock share are presented in Table 7.

The best coefficient of determination, related to the ANFIS model with triangular MF, is shown in Fig. 8. The predicted results driven from this optimum ANFIS have been plotted with the results of field data (i.e. real data). The total set of field data were used to calculate the result of the optimum ANFIS.

4. Discussion – *Rasprava*

The ultimate purpose of this modeling was to provide a practical approach for estimating the proportion of rock for the purpose of estimating the cost of forest roads. In other words, by estimating the rock proportion in various conditions of a mountainous forest before planning the forest road network, a planner

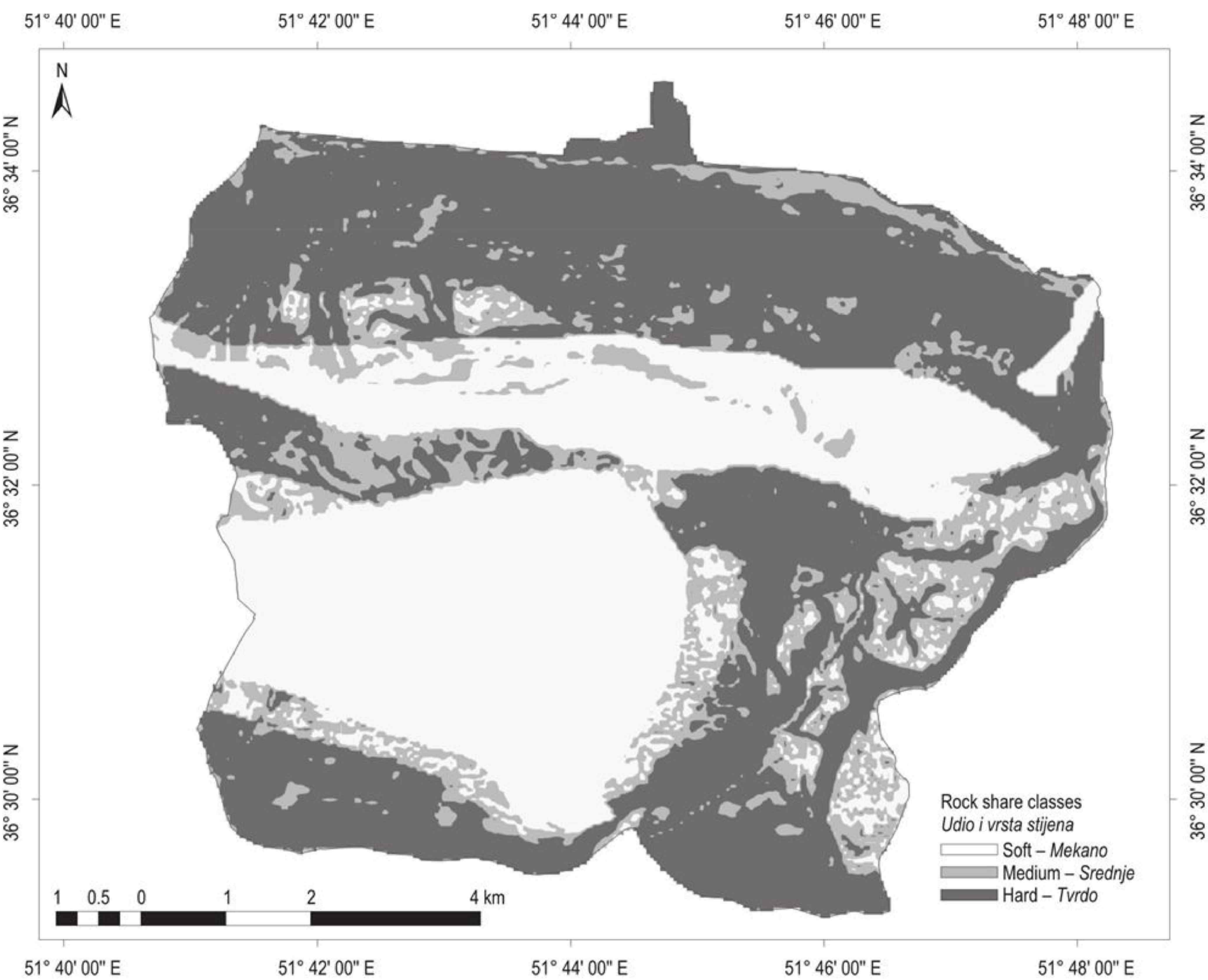

Fig. 8 Spatial variability of rock share based on ANFIS model with triangular-shaped MFs

Slika 8. *Prostorna promjenjivost udjela stijena u tlu prema modelu ANFIS s trokutastom funkcijom članstva*

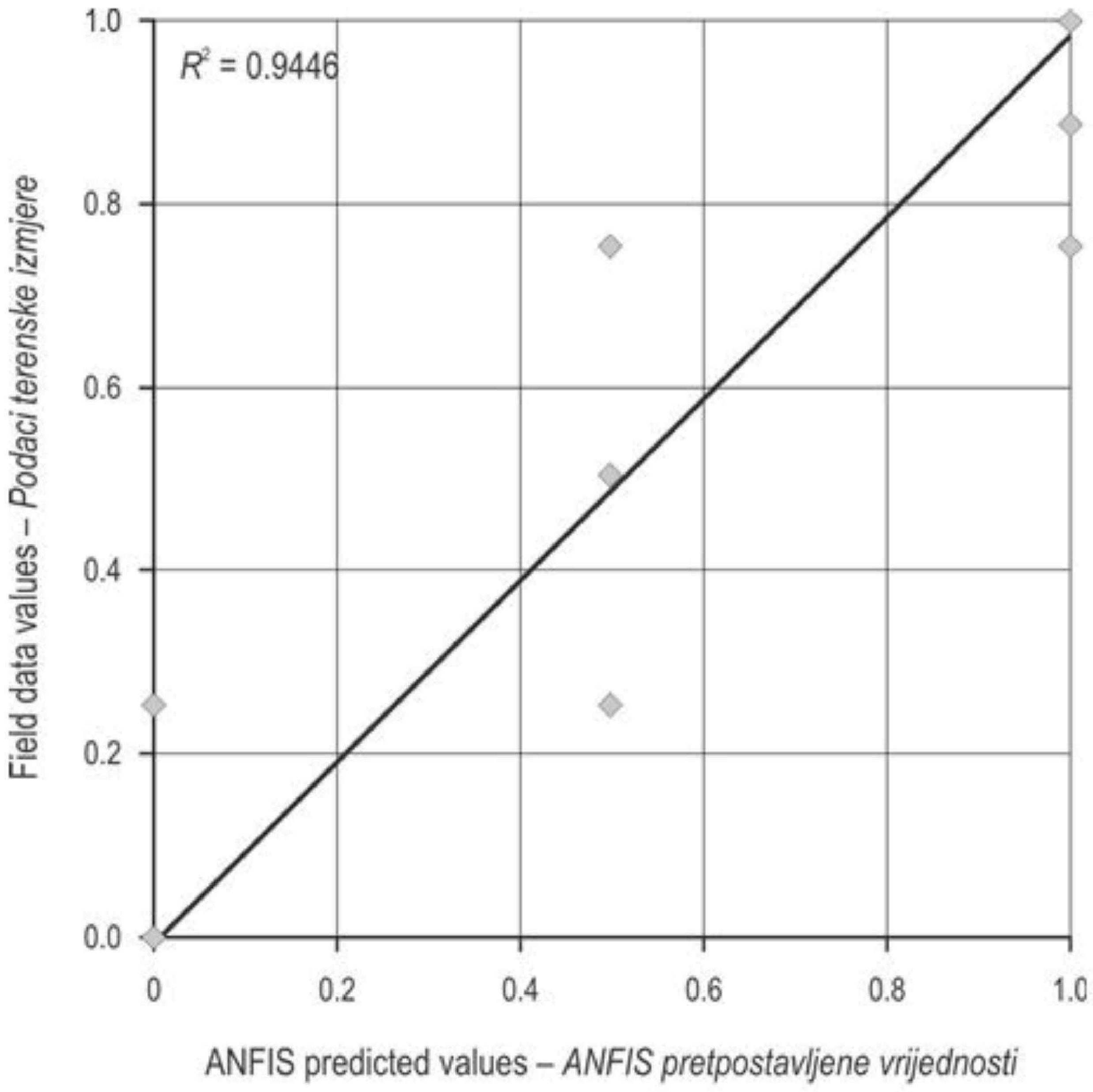

Fig. 9 The optimum ANFIS predicted values of rock share estimation versus field data values

Slika 9. *Najtočnije predviđeni podaci modelom ANFIS*

can effectively decide where to place the road to decrease the time and cost of earthwork. In this research, AHP and ANFIS methods were applied to model the share of rock in different geological and physiographic conditions. In addition, four different types of membership function were adopted for the analysis in ANFIS training to compare their differences regarding statistical parameters. Although the presented ANFIS approach is an experimental method in which just two main input variables (e.g. geological structures and terrain slope) were considered, the acceptable ranges of statistical parameters of R^2 and RMSE were obtained from all four developed models. The result of this study showed that an ANFIS can obtain a higher level of accuracy and generalization power for rock share estimation when triangular membership function is used to conduct system training. The coefficient of determination for ANFIS with triangular MF was 0.94. This result means that 94.89% of changes of rock proportion are related to the changes of the two considered variables, i.e. geological information and terrain slope. The RMSE is the most popular measure of error and has the advantage that large errors receive much greater attention than small errors (Hecht-Nielsen 1990). The result of RMSE for applied MFs indicated that the use of triangular MF produced the least RMSE compared to other three MFs. In contrast with RMSE, MAE eliminates the emphasis given to large errors. Both RMSE and MAE are desirable when the evaluated output data are smooth or continuous (Twomey and Smith 1997). Since the defined output linguistic variables, i.e. Low, Medium, and High, as well their corresponding normalized values, i.e. 0, 0.5, and 1 created a relatively discrete space (Fig. 9), MAE was not a determinant criteria for preference of a model to another.

Nevertheless, a conclusion can still be drawn from the MAE results. According to the results of MAE shown in Table 6, it can be seen that the ANFIS developed by triangular MF still has the least error compared to other models. Thus it could be concluded that the ANFIS developed by triangular MF can be selected as the optimum model for rock share estimation. After triangular MF-based ANFIS, which produced the best results, the adaptation of Gaussian MF was determined as the second robust model from the viewpoint of statistical criteria. The application of Gaussian MF resulted in a R^2 of 93.74%, an RMSE of 10.03%, and a MAE of 4.23%. Hence, it could be expected that the use of Gaussian MF in RSE-ANFIS model will generate robust performance and high generalization power. The g.bell and trapezoidal MFs results were less favorable than those of triangular and Gaussian MFs and therefore they were not proposed as acceptable models in the present research.

In order to produce a zoning map of rock proportion, the ANFIS value calculated for each pixel was transferred to the corresponding point on the map of the study area. The current map included a continuous set of data that needed to be changed into two or more categories. A number of classifiers are available and namely natural breaks, quantile, equal intervals, *K*-means, etc; each of them may lead to different clustering results because of their different statement about the method of dividing. The final classification of rock share map in this study was based on the practical procedure used by the experts to determine the price of embankments for forest road projects. Thus, the normalized scores on the map were grouped into three categories of rock ratio: »Soft« (0–0.3), »Medium« (0.3–0.7), and »Hard« (0.7–1). This classification may differ from a country to another but it is a common principle in forest management that the least rock ratio areas should be traversed in forest road construction to minimize the total time and cost of construction.

The weathering condition of geological structure is one of the factors in determining the cost of excavating the rocks; however this factor was neglected since the investigation of the nature of rocks was not the purpose of this study and the focus was on the proportion of rocks in the underground layers.

Although it is more expensive to use geotechnical rock testing facilities than experts' opinions, the investigation of mechanical and physical properties of near–surface rocks, and performing the strength and deformation tests for the evaluation of the possibility of excavation, could give more accurate data for such models. In the current study, the AHP technique was used to quantify the geology formations with respect to their strength against earthwork to persuade forest managers to apply practical fuzzy models for various construction purposes in forest management. The advantages of the presented procedure are as follows:

Easy sampling and applied methodology that allow other researchers to repeat the study with lower costs in other regions with specific local conditions,

Ability of handling several types of data (numerical, ordinal, or nominal) in fuzzy inference systems, which makes it flexible for the use in modeling natural resources,

Acceptable statistics with the emphasis on effective input factors and reliability of the results in the present study.

A comparison between the applied soft computing method and other traditional statistical methods such as multiple regressions could indicate the degree of robustness or fault tolerance of presented models. It appears that there is a possibility of estimating rock share of subsoil by using the proposed soft computing models. The number of the analyzed data is relatively limited in this study. Therefore, the practical outcome of the proposed model could be used, with acceptable accuracy, for the estimation of earthwork cost at the preliminary stage of planning the forest roads in the study area.

5. References – *Literatura*

Ananda, J., Herath, G., 2008: Multi-attribute preference modeling and regional land-use planning. Ecological Economics 65(2): 325–335.

Andrews, R., Diederich J., Tickle, A., 1995: A survey and critique of techniques for extracting rules from trained artificial neural networks. Knowledge-Base Systems 8(6): 373–389.

ASCE Task Committee on Applications of Artificial Neural Networks in Hydrology 2000: Artificial neural networks in hydrology: I: preliminary concepts; II: hydrologic applications. Journal of Hydrological Engineering 5(2): 115–137.

Barton, N., Lien, R., Lunde, J., 1974: Engineering classification of rock masses for the design of tunnel support. Rock Mechanics 6(4): 189–236.

Bieniawski, Z. T., 1975: Case studies: prediction of rock mass behavior by the geomechanics classification. Proc. 2nd Australia–New Zealand Conference Geomechanics, Brisbane, 36–41 pp.

Bouma, J., Brouwer, R., Van Ek, R., 2000: The use of integrated assessment methods in Dutch water management: a comparison of cost-benefit and multi-criteria analysis. Third International Conference of the European Society for Ecological Economics, Vienna, 3–6 pp.

Farokhnia, A., Morid, S., Byun, H. R., 2010: Application of global SST and SLP data for drought forecasting on Tehran plain using data mining and ANFIS techniques. Theoretical and Applied Climatology 10(1–2): 71–81.

Gail, M., Brion, T. R., Neelakantan, S. L., 2002: A neural-network-based classification scheme for sorting sources and ages of fecal contamination in water. Water Research 36(15): 3765–3774.

Ghajar, I., Najafi, A., Ezzati, S., 2010: Skidding Machines Allocation (SMA) using fuzzy set theory. Croatian Journal of Forest Engineering 31(2): 99–110.

Goodman, R. E., 1989: Introduction to Rock Mechanics. (2nd ed.). Wiley, 562 pp, New York.

Hecht-Nielsen, R., 1990: Neurocomputing, Addison-Wesely Publishing Company, Reading, MA.

Hoek, E., Bray, J. W., 1981: Rock Slope Engineering. (3rd ed.). Institute of Mining and Metallurgy, 358 pp, London 1981.

Inaba, S., Heinimann, H. R., Shiba, M., 2001: A Model to estimate rock excavation volume of forest roads in steep terrain conditions. In: Anonymous (Ed.): Proceedings of the 112th Meeting of the Japanese Forestry Society. April 2–4, Japan.

Jang, J.S.R., 1992: Self-learning fuzzy controllers based on temporal backpropagation. IEEE Transactions on Neural Networks 3(5): 714–723.

Jang, J.S.R., 1993: ANFIS: Adaptive-Network-based Fuzzy Inference Systems. IEEE Transactions on Systems, Man, and Cybernetics 23(3): 665–685.

Kangas, J., 1992: Multiple-use planning of forest resources by using the analytic hierarchy process. Scandinavian Journal of Forest Research 7(1–4): 259–268.

Kangas, J., Kangas A., 2005: Multiple criteria decision support in forest management – the approach, methods applied, and experiences gained. Forest Ecology and Management 207(1–2): 133-143.

Kangas, A., Kangas, J., Laukkanen, S., 2006: Fuzzy multicriteria approval method and its application to two forest planning problems. Forest Science 52(3): 232–242.

Kung, G. T., Hsiao, E. C., Schuster, M., Juang, C. H., 2007: A neural network approach to estimating deflection of diaphram walls caused by excavation in clays. Computers and Geotechnics 34(5): 385–396.

Kurttila, M., Pesonen, M., Kangas, J., Kajanus, M., 2000: Utilizing the analytic hierarchy process (AHP) in SWOT analysis – a hybrid method and its applications to a forest certification case. Forest Policy and Economics 1(1): 41–52.

Liu, Y. C., Chen, C. S., 2007: A new approach for application of rock mass classification on rock slope stability assessment. Engineering Geology 89(1–2): 129–143

Mamdani, E. H., Assilian, S., 1974: An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies 7(1): 1–13.

Mendoza, G. A., Sprouse, W., 1989: Forest planning and decision making under fuzzy environments: an overview and illustration. Forest Science 35(2): 481–502.

Mendoza, G. A., Bare, B. B., Zhou, Z., 1993: A fuzzy multiple objective linear programming approach to forest planning under uncertainty. Agricultural Systems 41(3): 257–274.

Murray, D. M., Von Gadow, K., 1991: Prioritizing mountain catchment areas. Journal of Environmental Management 32(4): 357–366.

Najjar, Y. M., Basheer, I. A., 1996: Neural network approach for site characterization and uncertainty prediction. ASCE Geological Special Publication 58(1): 134–148.

Padmini, D., Ilamparuthi K., Sudheer, K. P., 2008: Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models. Computers Geotechnics 35(1): 33–46.

Pettifer, G. S., Fookes, P. G., 1994: A revision of the graphical method for assessing the excavatability of rock. Journal of Engineering Geology 27(2): 145–164.

Polat, K., Yosunkaya, S., Güneş, S., 2008: Pairwise ANFIS Approach to Determining the Disorder Degree of Obstructive Sleep Apnea Syndrome. Journal of Medical Systems 32(5): 379–387.

Rankine, R., Sivakugan, N., 2005: Prediction of paste backfill performance using artificial neural networks. Proceedings of 16th international society for soil mechanics and foundation engineering, Osaka, 1107–1110 pp.

Roger, J. S., Sun, C., 1993: Functional equivalence between radial basis function networks and fuzzy inference systems. IEEE Trans Neural Netw 4:156–159. doi:10.1109/72.182710

Saaty, T. L., 1977: A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 15(3): 234–281.

Saaty, T. L., 1980: The Analytic Hierarchy Process. McGraw-Hill, New York.

Shahin, M. A., Jaksa, M. B., Maier, H. R., 2005: Neural network based stochastic design charts for settlement prediction. Canadian Geotechnical Journal 42(1): 110–120.

Shahin, M. A., Jaksa, M. B., Maier, H. R., 2008: State of the art of artificial neural networks in geotechical engineering. Electronic Journal of Geotechnical Engineering 8: 1–26.

Sreekanth, P. D., Sreedevi, P. D., Ahmed, S., Geethanjali, N., 2010: Comparison of FFNN and ANFIS models for estimating groundwater level. Environmental Earth Sciences, DOI 10.1007/s12665-010-0617-0.

Stone, M., 1974: Cross-validatory choice and assessment of statistical predictions. Journal of Royal Statistical Society 36(2): 111-147.

Stuckelberger, J. A, Heinimann, H. R., Burlet, E. C., 2006: Modeling spatial variability in the life-cycle costs of low-volume forest roads. European Journal of Forest Research 125(4): 377–390.

Sugeno, M., Kang, G. T., 1988: Structure identification of fuzzy model. Fuzzy Sets and Systems 28(1): 15–33.

Takagi, T., Sugeno, M., 1983: Derivation of fuzzy control rules from human operator's control actions. In: Proc IFAC Symp Fuzzy Inf, 55–60 pp.

Tecle, A., Duckstein, L., Korhonen, P., 1994: Interactive, multiobjective programming for forest resources management. Applied Mathematics and Computations 63(1): 75–93.

Tekin, E., Akbas, S. O., 2011: Artificial neural networks approach for estimating the groutability of granular soils with cement-based grouts. Bulletin of Engineering Geology and the Environment 70(1): 153–161.

Tsukamoto, Y., 1979: An approach to fuzzy reasoning method. In: Gupta MM, Ragade RK, Yager RR (eds) Advances in fuzzy set theory and applications. Elsevier, Amsterdam, 137–149 pp.

Twomey, J. M., Smith, A. E., 1997: »Validation and verification«. Artificial neural networks for civil engineers: Fundamentals and applications, N. Kartam, I. Flood, and J. H. Garrett, eds., ASCE, New York, 44-64.

Vacik, H., Lexer, M. J., 2001: Application of a spatial decision support system in managing the protection forests of Vienna for sustained yield of water resources. Forest Ecology and Management 143(1–3): 65–76.

Wang, C. H., Liu, B. J., Wu, L. S. H., 2010: The Association Forecasting of 13 Variants Within Seven Asthma Susceptibility Genes on 3 Serum IgE Groups in Taiwanese Population by Integrating of Adaptive Neuro-fuzzy Inference System (ANFIS) and Classification Analysis Methods. Journal of Medical Systems 36(1): 175–185.

Wickham, G. E., Tiedemann, H. R., Skinner, E. H., 1972: Support determination based on geologic predictions. Proc. Conf. Rapid Excavation and Tunneling, 43–64 pp.

Yilmaz, I., Yuksek, G., 2009: Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. International Journal of Rock Mechanics & Mining Sciences 46(4): 803–810.

Zadeh, L. A., 1965: Fuzzy sets. Inf Control. 8: 338–353.

Sažetak

Prilagodljivi mrežno-fazni sustav za procjenu udjela stijena pri izgradnji šumskih prometnica

Ovo je istraživanje novi model procjene udjela stijena u tlu (RSE). Postupak je koristan za izračun troškova zemljanih radova koji se ubrajaju među glavne troškove izgradnje šumskih prometnica. Udio stijena u tlu izravno *utječe na cijenu izgradnje prometnica. Dakle, postoji potreba za pouzdanom procjenom udjela stijena unutar cijeloga područja izgradnje prometnice, osobito u stjenovitim područjima gdje je udio stijena visok. Nije poznato numeričko svojstvo ni pouzdan numerički parametar za mjerenje udjela stijena u tlu, a nestalnost udjela stijena u tlu bio je i dodatan razlog ovoga istraživanja.*

Cilj je istraživanja bio uvesti stručni sustav za procjenu udjela stijena u tlu u različitim uvjetima pomoću prilagodljivoga mrežno-faznoga sustava za modeliranje (ANFIS) i analitičkih hijerarhijskih procesa (AHP). Nagib terena i vrste geoloških tvorbi smatrani su ulaznim varijablama za stvaranje modela ANFIS. Kako bi se smanjili troškovi uzorkovanja udjela stijena u tlu, razvijen je praktičan pristup koji osam postojećih geoloških jedinica obrađuje kao nositelje problema u odlučivanju. AHP-i na temelju znanja stručnjaka korišteni su za rješavanje problema procjene udjela stijena u tlu. Rezultat modela ANFIS jest razradba na tri vrste tla, ovisno o udjelu stijena: meko, srednje i tvrdo. Nakon uzorkovanja, normalizacije podataka te podjele Sugeno sustav neizrazitoga zaključivanja prvoga reda i hibridna metoda optimizacije usvojeni su kako bi se stvorio model ANFIS. Izlazni podaci modela predstavljaju funkciju prvoga reda čiji su parametri prilagođeni svakoj stavki sustava optimizacije.

Trokutaste funkcije članstva (MF) dale su najbolje rezultate. Sustav je primijenjen u planinskim šumama u Iranu gdje će u skoroj budućnosti biti izgrađena mreža šumskih prometnica. Predviđene vrijednosti zatim su opisane prostorno odnosno u okruženju GIS-a. Procijenjeni udjeli stijena u tlu po razredima: meko, srednje i tvrdo iznosili su 6,92 %, 40,83 % i 32,25 %. Ovaj je pristup koristan kao prvo za pokazivanje nestalnosti udjela stijena u tlu te drugo kao model za izračun troškova izgradnje šumskih prometnica koji će uz pomoć ostalih matematičkih modela još točnije prikazati izračun troškova šumskih prometnica i potom omogućiti odabir zamjenskih trasa u slučaju previsokih troškova izgradnje.

Ključne riječi: udio stijena u tlu, ANFIS, AHP, troškovi izgradnje šumskih prometnica, funkcije članstva

Authors' address – *Adresa autorâ*:

Ismael Ghajar, MSc.
e-mail: ismael.ghajar@modares.ac.ir
Assist. Prof. Akbar Najafi, PhD.
e-mail: a.najafi@modares.ac.ir
Tarbiat Modares University
Faculty of Natural Resources
Department of Forestry
Noor, PO Box: 64414–356
IRAN
Assoc. Prof. Seyed Ali Torabi, PhD.
e-mail: satorabi@ut.ac.ir
University of Tehran
College of Engineering
Department of Industrial Engineering
Tehran
IRAN
Assoc. Prof. Mashalah Khamehchiyan, PhD.
e-mail: khamechm@modares.ac.ir
Tarbiat Modares University
Department of Engineering Geology
Tehran
IRAN
Assoc. Prof. Kevin Boston, PhD.
e-mail: kevin.boston@oregonstate.edu
Oregon State University
Department of of Forest Engineering
Corvallis, OR
USA

Received (*Primljeno*): February 08, 2012
Accepted (*Prihvaćeno*): August 18, 2012