

Application of fuzzy methods in tunnelling

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Full-face tunnelling machines were used for the tunnel construction in Slovakia for boring of the exploratory galleries of highway tunnels Branisko and Višňové-Dubná skala. A monitoring system of boring process parameters was installed on the tunnelling machines and the acquired outcomes were processed by several theoretical approaches. Method IKONA was developed for the determination of changes in the rock mass strength characteristics in the line of exploratory gallery. Individual geological sections were evaluated by the descriptive statistics and the TBM performance was evaluated by the fuzzy method. The paper informs on the procedure of the design of fuzzy models and their verification.

Key words: computer monitoring system, tunnel boring machine, cluster analysis

Introduction

The process of the rock mass disintegration by the full-profile tunnelling machines (TBM) is affected by a whole range of factors that can be divided into three main groups:

1. Factors of rock environment (geological formation, rock mass properties),
2. Factors of the boring machine (constructional parameters of the boring machine and the cutting tools, effect of disk tool wear on the TBM cutterhead),
3. Applied boring regime and operational conditions affected by a work organization.

All of these factors affect the input and output variables of the boring process and determine their mutual relations. The relations between several variables of the process have been explored in the previous theoretical research using the mathematical and statistical procedures. The effects of disintegrated rock, applied boring regime and of the wear of cutting tools on the boring effectiveness were investigated primarily. Linear or non-linear regressions were used in their description. A model of the interaction between the rock mass and the tunnelling machine was developed based on previous research findings, experience and knowledge using the conventional mathematical approaches [1, 2, 3, 4]. The model, named IKONA, provided the determination of rock characteristics on the tunnel face during the drilling. Recently, the research team has focused on modelling the effectiveness or performance of the TBM using the fuzzy methods.

Modelling of the TBM performance by the application of fuzzy methods and selection of model variables

The long-term experience from the research of rock disintegration process, the outcomes from the data analysis obtained from the boring process monitoring, as well as the complexity of the system rock-tool were leading to the idea to use a fuzzy approach for the modelling of the TBM performance.

Fuzzy modelling is an approach realized by searching for the main relation between the system variables described in the terms of fuzzy sets. Intervals represented by the fuzzy sets enable a mathematical description of the inaccuracy of the system (rock mass-TBM), as the sets are overlapped and provide a subsequent transition from one field of the universe values to another one.

Fuzzy model was designed in the Matlab environment using the Fuzzy Logic Toolbox. The design used a Takagi-Sugeno fuzzy modelling method, which provides generation of fuzzy *If-Then* rules from numerical data.

The model consists of a set of fuzzy rules, which describe a local linear relation between the input variables and the output in the following form:

$$R_i : \text{If } x_1 \text{ is } A_{i1} \text{ and } \dots \text{ and } x_n \text{ is } A_{in} \text{ Then } \hat{y}_i = a_i x + b_i, \quad i = 1, 2, \dots, K, \quad (1)$$

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where R_i is the i -th rule, $x=[x_1, \dots, x_n]^T \in X$ is an input vector of the variables (antecedent), A_{i1}, \dots, A_{in} are fuzzy sets defined in the antecedent space and \hat{y}_i is an estimate of the output (consequent) of the model for the given rule, K denotes the total number of rules. The total output $\hat{y} \in Y$ of the model is calculated using the weighted average of the shared outputs of the rules, where the conditions of its assumption part were fulfilled:

$$\hat{y} = \frac{\sum_{i=1}^K \beta_i(x) \hat{y}_i}{\sum_{i=1}^K \beta_i(x)}, \tag{2}$$

where $\beta_i(x)$ is a degree of the fulfilment of the i -th rule.

The base knowledge for the selection of variables entering the presented fuzzy model was the fact that insufficient adjustment of the applied boring regime (M_k, F) to the particular geological conditions ($\sigma, RQD, \text{quartz}$, all variables explained later) causes an oscillation of the advance rate of the TBM, which significantly affects the TBM performance, thus affecting the effectiveness of the TBM use, cost-efficiency of the tunnel construction process and the time period of the tunnel construction. The advance rate v [mms^{-1}] is a function of the tool penetration depth into the rock h [mm] and of the cutterhead revolutions n [s^{-1}].

$$v = h.n, \quad [\text{mm.s}^{-1}] \tag{3}$$

Advance rate v is then determined from the output variable of the model, i.e. from the penetration depth h . A multiple of the advance rate v and the surface of the excavated tunnel face S define the performance of the TBM boring Q . Full-face boring uses the following formula for the calculation of the instantaneous performance of excavation

$$Q = v.S = h.n.S, \quad [\text{m}^3.\text{h}^{-1}] \tag{4}$$

where S [m^2] is a size of excavated tunnel face surface and this value is a constant for a given machine.

Following values enter the fuzzy model presented in this paper: a torque M_k , thrust F , rock disturbance RQD , model strength of rock mass σ and the quartz content (expressed as a degree of 4-degree scale informing on the presence of the quartz dikes on the tunnel face). Torque and thrust represent the boring regime parameters; the model strength, quartz content and RQD contain the information on the rock mass properties. The output variable is a penetration depth. The scheme of the fuzzy model is presented in the Fig. 1.

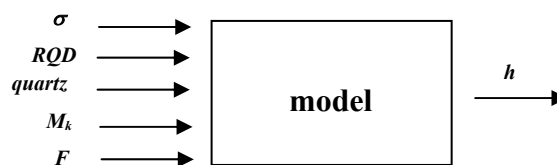


Fig. 1. Scheme of fuzzy model of penetration depth.

Training data set was formed by the data from the boring section 680 – 700 m from the eastern portal of the Branisko exploratory gallery. The range of tested variables was defined from the real minimal and maximal measured values in the observed section. Individual variables were examined in the intervals presented in the Table 1.

Tab. 1. Range of values of training data set in the stationing 680-700 m.

Variable	M_k [kNm]	F [kN]	RQD [-]	σ [MPa]	<i>quartz</i>	h [mm]
Min.	90.6	1036	47	32	1	1.8
Max.	165.0	2147	89	224	4	7.8

The section 680 – 700 m is formed by the amphibolites exclusively regarding the geological structure. The Fig. 2 shows the behaviour of the variables entering the model.

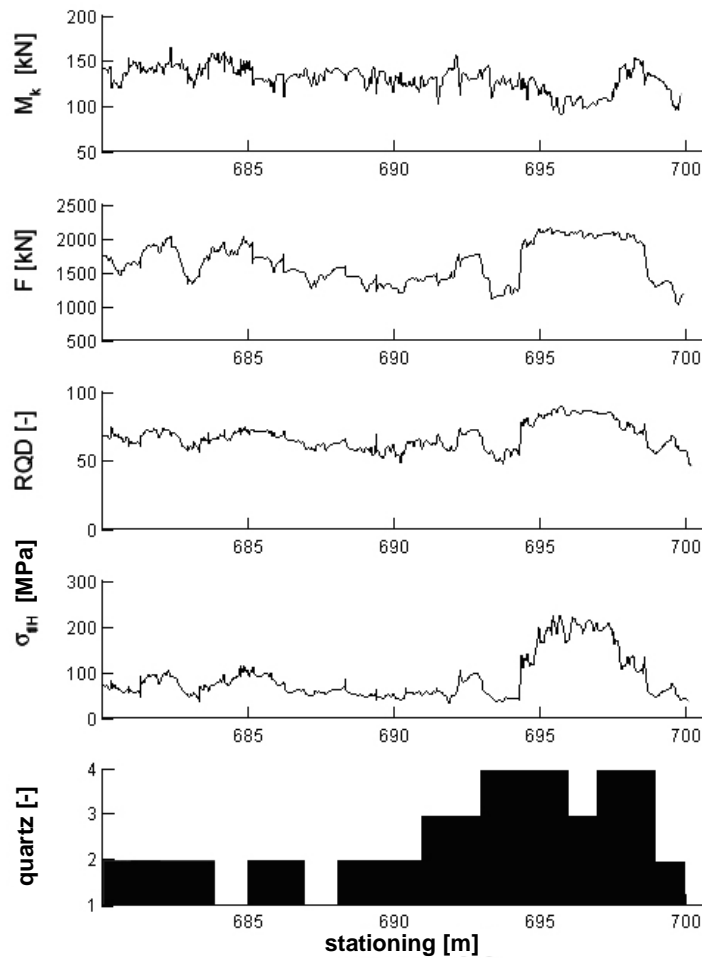


Fig. 2. Visualization of behaviour of input parameters depending on stationing in the section 680-700m of the Branisko exploratory gallery.

Adjustment and complementation of monitored data – program support

Initial database for the model design was comprised from the archived data files from the boring process recorded during the boring of the Branisko exploratory gallery. The data were monitored and scanned by a computer system developed at the Institute of Geotechnics SAS, which was installed on the full-profile tunnelling machine WIRTH that bored the eastern part of the exploratory gallery on total length of 2340 m. The system provided scanning of basic parameters of boring process in the interval of approximately 2,3 s in order to optimize the whole process and obtain relevant data complementing the results of detailed engineering-geological investigation. Monitored and scanned parameters were thrust, torque, revolutions and the position of the cutterhead protrusion. Several useful variables were calculated in real-time directly during the boring, such as instantaneous boring rate, specific disintegration energy and recommended optimal thrust. Secondary outputs of the system were large archived data files, which formed the training data in further theoretical research.

Tunnelling machine crossed the paleogene formation in initial tunnel sections; further only rocks of crystalline complex were present. Crystalline complex was represented by high-grade metamorphic rocks and bodies of granitoids, mainly by amphibolite gneisses, biotite-amphibolite gneisses, biotite gneisses, amphibolites and leucocratic granitoids. The part of the exploratory gallery bored by a TBM was divided into 42 geological sections. The contribution uses the analysis of the first 27 geological sections. The data on stationing (location), rock type and percentage of monitored data (expressing a share of the monitored section length to total length of particular geological section) in individual section are shown in Tab. 2.

Tab. 2. Brief description of 27 geological sections and percentage of monitored data in geological sections.

Geological section	Stationing	Rock type	% of data
	from - to [m]		
1	139-183	sandstone	48.4
2	183-191	contact of paleogene and crystalline complex	68.8
3	191-200	biotite gneiss	100.0
4	200-226	biotite gneiss	50.0
5	226-298	muscovite-biotite granitoid	94.4
6	298-348	biotite to quartz gneiss	100.0
7	348-426	biotite-amphibolite gneiss	78.2
8	426-482	biotite- to biotite-amphibolite gneiss	28.6
9	482-526	biotite- to biotite-amphibolite gneiss	72.7
10	526-540	biotite-amphibolite gneiss, mylonitized significantly	57.1
11	540-590	biotite-amphibolite paragneiss	100.0
12	590-652	biotite-amphibolite paragneiss	93.5
13	652-680	biotite- to biotite-amphibolite gneiss, amphibolites	67.9
14	680-720	amphibolites	91.3
15	720-770	amphibolites, amphibolite gneiss	89.0
16	770-850	amphibolites, amphibolite gneiss	100.0
17	850-916	amphibolites, amphibolite gneiss	100.0
18	916-947	amphibolites, amphibolite gneiss, mylonitized	90.3
19	947-1025	amphibolites, amphibolite gneiss	55.1
20	1025-1054	amphibolites, amphibolite gneiss, locations of blastomylonites	72.4
21	1054-1072	amphibolites, amphibolite gneiss	55.6
22	1072-1108	amphibolites, amphibolite gneiss	100.0
23	1108-1193	amphibolites, amphibolite gneiss	45.9
24	1193-1234	amphibolites, amphibolite gneiss	78.0
25	1234-1263	amphibolites, amphibolite- to biotite-amphibolite gneiss	3.4
26	1263-1295	amphibolites, amphibolite- to biotite-amphibolite gneiss; rocks exhibit cleavage (schistosity)	56.3
27	1295-1320	amphibolites, amphibolite- to biotite-amphibolite gneiss	16.0

Data were processed using a new developed software application, [5]. Designed program provided fast preview and access to the archived files, data reading according to geological sections, calculation of further necessary variables, and visualization of their behaviour. Database was complemented by the results of engineering-geological investigation. Adjustment of the behaviour using the smoothing algorithm [6] eliminated the extreme values from the original data.

Utilization of algorithms of fuzzy clustering analysis

Fuzzy clustering method was used for the searching for the relation between the variables. Cluster analysis using the mathematical methods reveals the structure in multidimensional data, i.e. it locates the clusters in multidimensional feature space. Its aim is to classify the data in a way that the similarities between them within the formed clusters are very large and the similarity between the data from different clusters is very small. Non-hierarchic method classifying the data into predefined number of clusters was used for data classification into the clusters. Relations between the variables presented in Fig.1 were searched in such manner. The records are then constituted of the samples of such variables in discrete time steps.

Suppose N records in measurement. Application of clustering evokes a division of the set of records N into c subsets – clusters in a manner that the distance between the records and their centres is minimized. Analysed data are collected into the matrix Z created by chaining the regression data matrix X and output vector y :

$$\mathbf{X} = \begin{bmatrix} x_1^T \\ x_2^T \\ \dots \\ x_N^T \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{bmatrix}, \quad Z^T = [Xy]. \quad (5)$$

Every record is described by $n+1$ dimensional vector $\mathbf{z}_k = [x_{1k}, \dots, x_{nk}, y_k]^T = [\mathbf{x}_k^T, y_k]^T$. A cluster analysis is realized for such arranged data, producing the decomposition matrix \mathbf{U} :

$$\mathbf{U} = \begin{bmatrix} \mu_{1,1} & \mu_{1,2} & \dots & \mu_{1,c} \\ \mu_{2,1} & \mu_{2,2} & \dots & \mu_{2,c} \\ \dots & \dots & \dots & \dots \\ \mu_{N,1} & \mu_{N,2} & \dots & \mu_{N,c} \end{bmatrix}, \quad (6)$$

where its elements $\mu_{k,i}$ represent the membership degrees of the record z_k to the cluster i . Variables $\mu_{k,i}$ gain the values from the interval $\langle 0, 1 \rangle$, while following is valid:

$$0 < \sum_{k=1}^N \mu_{ki} < N, \quad 1 \leq i \leq c, \quad \sum_{i=1}^c \mu_{ki} = 1, \quad 1 \leq k \leq N. \quad (7)$$

Analysis of extremes of evaluating indexes was realized in order to determine the number of clusters, which is described in details in PhD. thesis of Tréfová [5]. Based on the results from the thesis, an optimal number of clusters was determined for the description of relations between the evaluated data, i.e. sufficient number is 8 clusters. Fuzzy C-means (FCM) algorithm was used for the classification of the records into clusters, which enables to each record to belong into several clusters. Membership to cluster is expressed by a membership degree in interval $\langle 0, 1 \rangle$, where the contributions in cluster for one record must be equal to 1. Boring section with length of 20 m, comprising of 10 000 records, was analyzed. Fig. 3 presents a program for data clustering designed in Matlab environment, which used Fuzzy Clustering and Data Analysis Toolbox developed at the Veszprem University in Hungary [7]. Fig. 4 graphically illustrates the cluster centres using the FCM method.

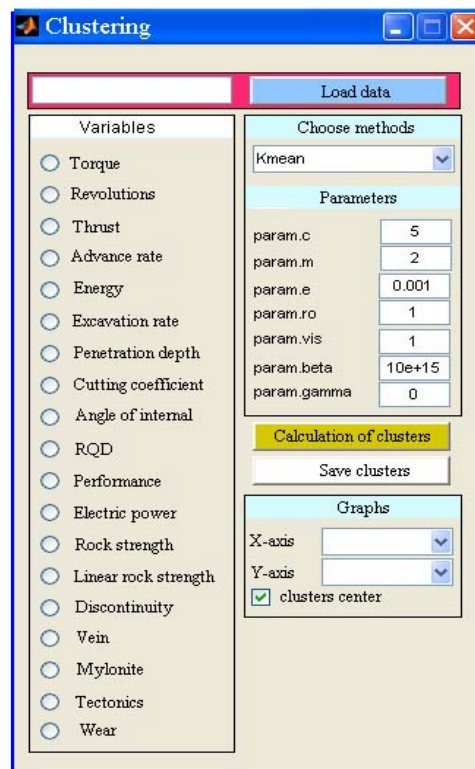


Fig. 3. Program for data clustering [5].

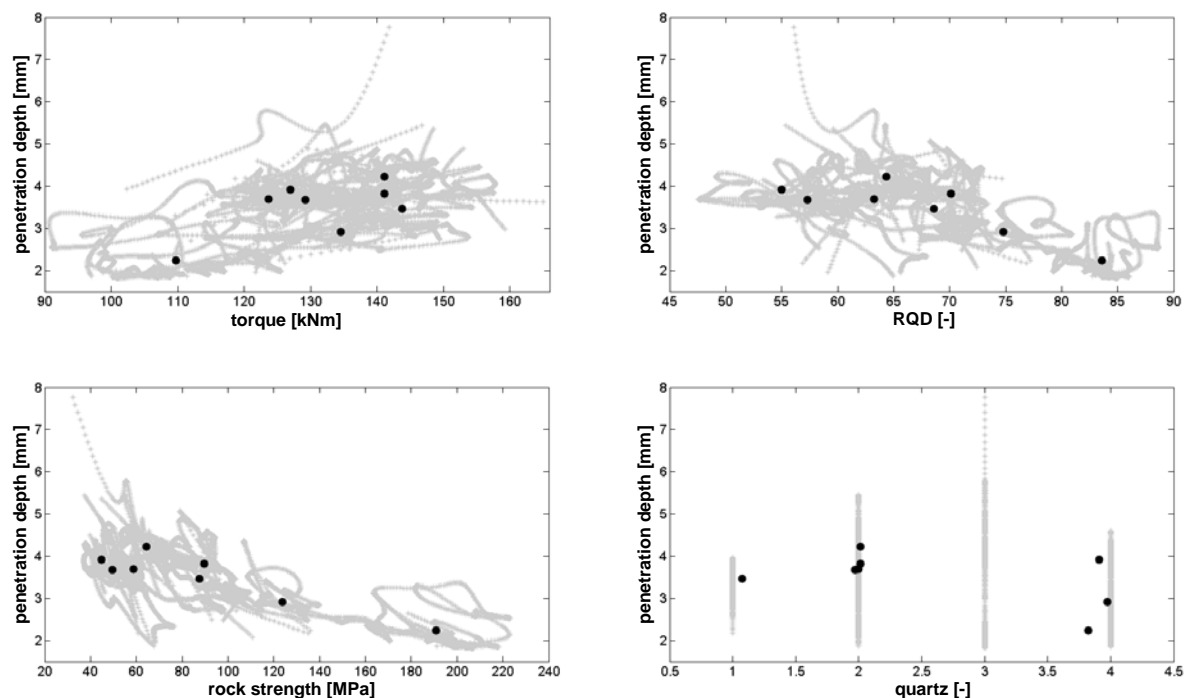


Fig. 4. Overview of cluster centres obtained from records in stationing of 680-700m.

Memberships of variables into the clusters were acquired by a spot projection of membership degrees of records into the space of individual variables. Fig. 5 presents memberships of variables to one cluster. Areas, where the highest values (i.e. approaching to 1) were obtained, represent the strongest relations between the variables. Such areas may be characterized as a definition domain of the cluster. The relations weakened or faded with decreasing values.

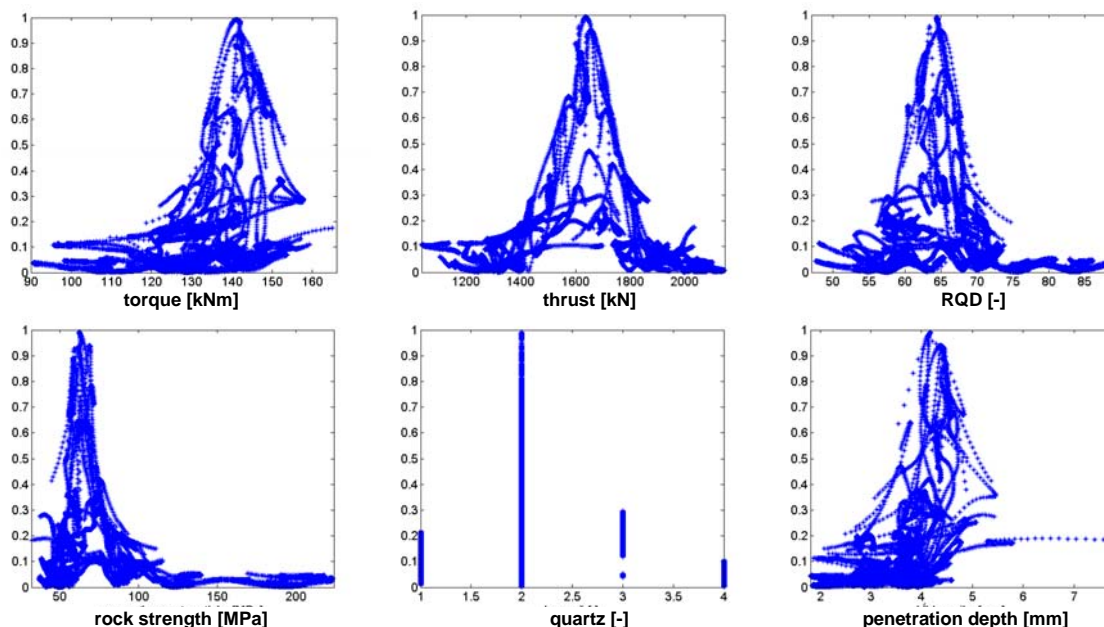


Fig. 5. Membership degrees of evaluated variables for one cluster.

Application of cluster analysis technique brought an algorithm for clusters formation from records based on their similarity. State space was decomposed into multidimensional non-linear boring process into individual areas with similar behaviour of variables. This analysis was realized in order to linearize the data dependencies in acquired areas using the local linear models of TBM performance.

Formation of rules

Number of clusters defines an optimal number of rules describing the relations of analysed variables behaviour acting in model. 8 rules are sufficient for parametrization of presented model. Approximation of spot projections of decomposition matrix into the space of five input variables of the model provided a definition of 8 membership functions, for every variable entering the model, Fig. 6.

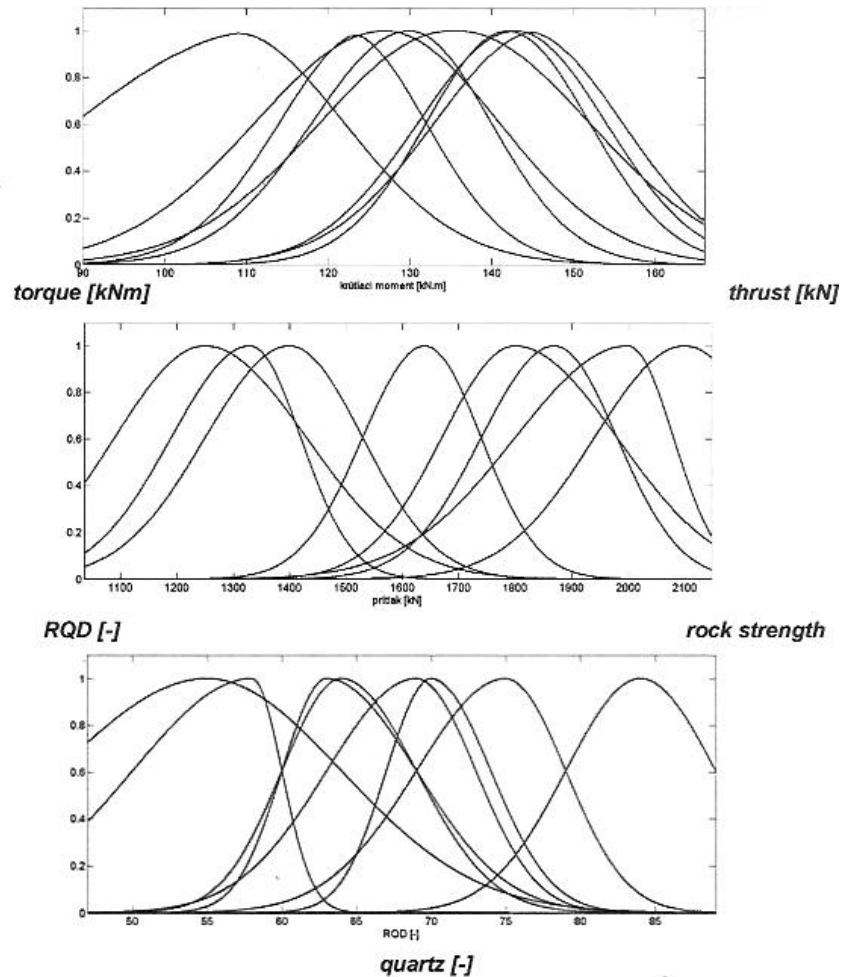


Fig. 6. Membership degrees of variables entering the model.

Following linear equations for individual rules were determined by parametrisation of the consequent:

$$\begin{aligned}
 h_1 &= -0,1021.M_k + 0,0112.F - 0,1682.RQD - 0,0559.\sigma + 0,0351.quartz + 14,4902 \\
 h_2 &= -0,1043.M_k + 0,0118.F - 0,2122.RQD - 0,0559.\sigma + 0,1543.quartz + 16,4664 \\
 h_3 &= -0,1269.M_k + 0,0118.F - 0,2427.RQD - 0,0629.\sigma + 0,1298.quartz + 18,3206 \\
 h_4 &= -0,1261.M_k + 0,0129.F - 0,2515.RQD - 0,0558.\sigma + 0,1243.quartz + 20,0992 \\
 h_5 &= -0,0955.M_k + 0,0091.F - 0,1896.RQD - 0,0385.\sigma - 0,1349.quartz + 17,3109 \\
 h_6 &= -0,0915.M_k + 0,0091.F - 0,1896.RQD - 0,0457.\sigma + 0,1812.quartz + 15,6384 \\
 h_7 &= -0,0962.M_k + 0,0115.F - 0,1698.RQD - 0,0582.\sigma + 0,1293.quartz + 13,3230 \\
 h_8 &= -0,1226.M_k + 0,0101.F - 0,2075.RQD - 0,0423.\sigma - 0,1181.quartz + 20,6049
 \end{aligned}$$

Model consists of following rules, which join the membership functions of input variables with corresponding linear equations, Fig. 7.

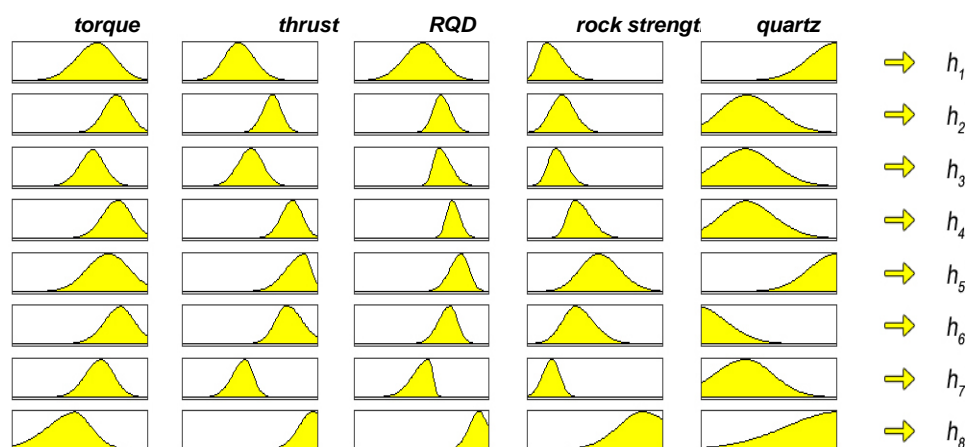


Fig. 7. Rules of fuzzy model.

Outcome of the model and rules adjustment

Comparison of measured and modelled results of the penetration depth exhibits a good accordance of data in analysed section after application of the above presented ranges of trained data. Average standard deviation between the real penetration depth and the one presented in the model in training section was 0,29 mm, Fig. 8. Regarding the range of the penetration depth, the coefficient of variation corresponds to 4,85 %. In reality, this 20 m long section was bored in approximately two days, with 171 m³ of rock excavated by the WIRTH machine with 16 retractions. Boring took place in amphibolites and the section belonged to the geological section number 14. The Fig.8 shows that more substantial deviations were present in the areas of significant increase of penetration depth. Apparently, larges pieces of rocks were chipped in these areas, which happens at favourable orientation of discontinuities filled with crushed rock material. The model did not cover such areas, probably due to the lack of local model, i.e. cluster analysis was not able to identify the clusters describing such behaviour of the system TBM – rock mass due to insufficient number of records.

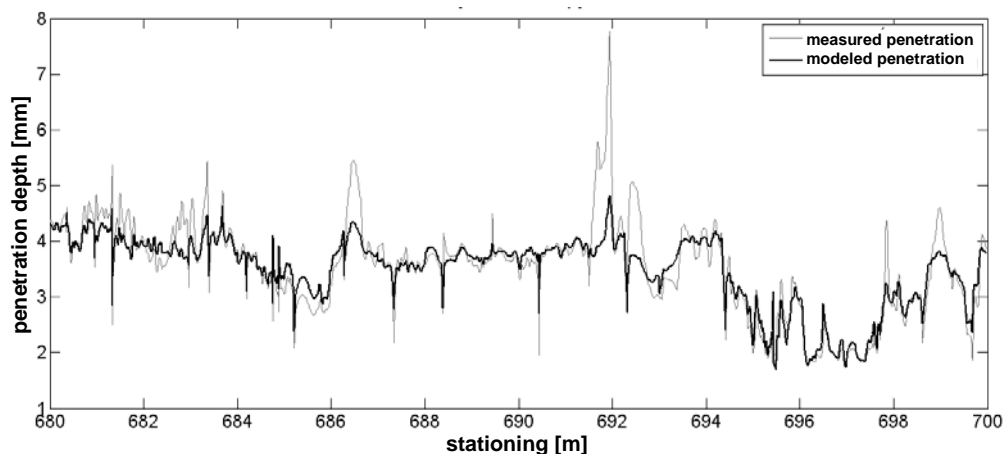


Fig. 8. Comparison of monitored and fuzzy modelled values of penetration depth.

Designed model was applied in further sections. Application of the model on the data in stationing 590-652 m is presented in the Fig. 9.

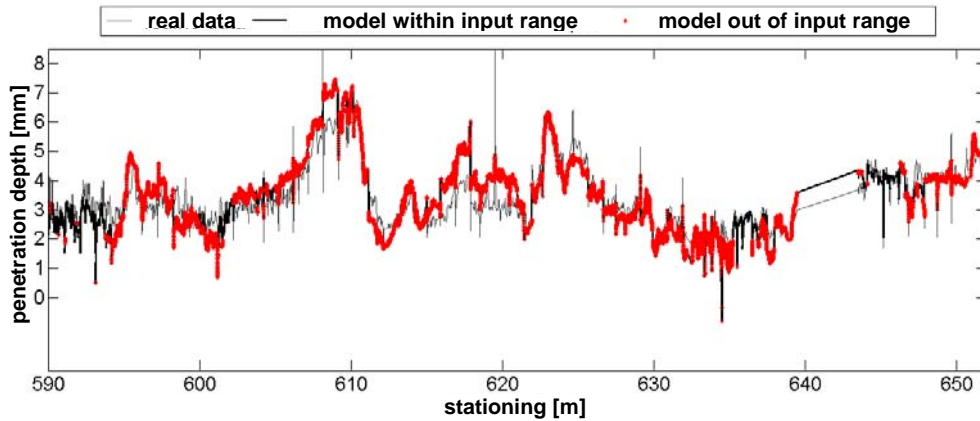


Fig. 9. Comparison of monitored and fuzzy modelled values of penetration depth in geological section 12.

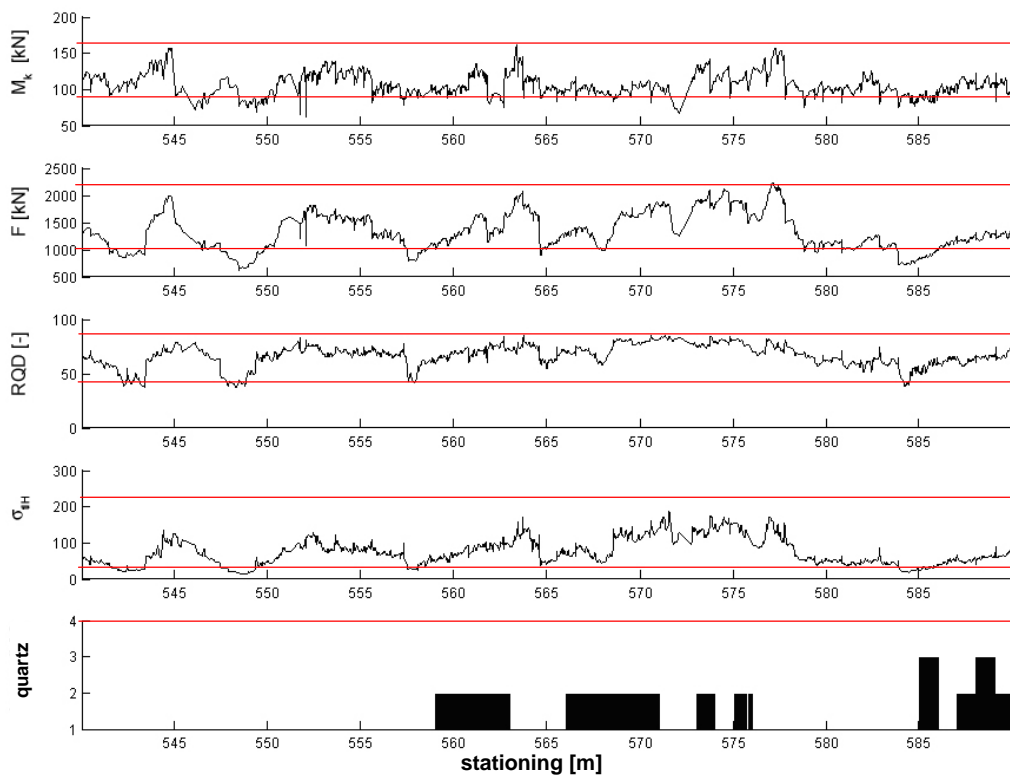


Fig. 10. Visualization of the range of training data in geological section 11.

Red colour in Fig. 9 and Fig. 10 indicates the segments from geological sections 12 and 11, respectively, that were not covered by the rules, i.e. at least one input variable of the model was out of the range of training data. In such cases, fuzzy model uses a boundary value (minimum or maximum) of relevant variable for the calculations. Increasing of the model deviations applied out of training data range was expected. Analysis of geological sections with insufficient coverage of input data approved that the most significant deviations from real penetration depth origin in the sections with the thrust lower than its boundary value, i.e. lower than 1037 kN. This evoked an adjustment of the rules. Geological section 12 was selected for this purpose. Data confined into the ranges of initial training set were filtered out of the section 12 in order to omit the duplication of initial rules.

Analysis of clustering coefficients for complementing training dataset determined 4 rules as optimal ones. New rules extended the data range of the model according to Table 3.

Tab. 3. Ranges of extended training data set.

Variable	M_k [kNm]	F [kN]	RQD [-]	σ [MPa]	quartz	H [mm]
Min.	60.0	609.0	18.7	9.7	1.0	1.7
Max.	165.0	2147.0	89.0	224.0	4.0	7.8

New ranges of data in the model were described by 4 membership functions. Following linear equations correspond to formed complementing rules:

$$\begin{aligned}
 h_9 &= -0,2072.M_k + 0,0254.F - 0,2396.RQD - 0,1269.\sigma + 0,0764.quartz + 17,03 \\
 h_{10} &= -0,2003.M_k + 0,0244.F - 0,2476.RQD - 0,1056.\sigma + 0,0789.quartz + 16,98 \\
 h_{11} &= -0,1869.M_k + 0,0250.F - 0,2098.RQD - 0,1492.\sigma - 0,0280.quartz + 15,00 \\
 h_{12} &= -0,2554.M_k + 0,0338.F - 0,2841.RQD - 0,1638.\sigma + 0,1364.quartz + 17,64
 \end{aligned}$$

Applications of extended model to individual geological sections led to the improvement results in studied geological section, which implies also from the comparison of Fig. 9 and Fig. 11.

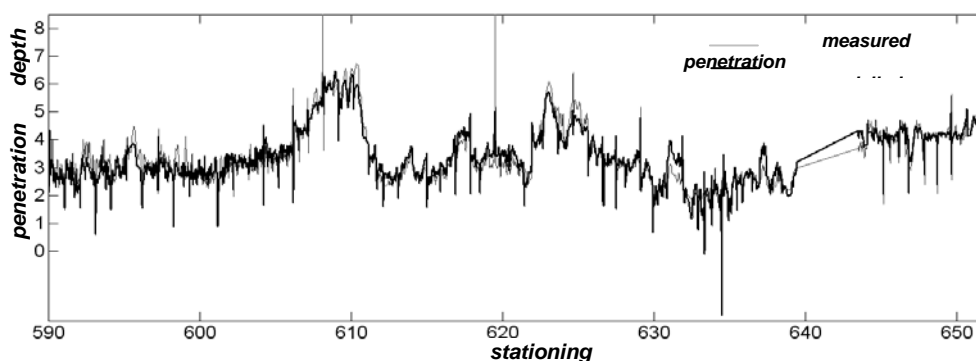


Fig. 11. Comparison of monitored and fuzzy modelled values of penetration depth in geological section 12 after complementing the rules.

Average deviation in the section 12 decreased from 0,53 mm to 0,30 mm after the above-presented adjustment. Modified model was applied on the other geological sections. The application of the improved model enhanced the sections 10-14 and 17-27 and slightly declined the sections 15 and 16. However, unsatisfactory results were obtained in the geological sections 1-9. These sections differ from the others in geological formation. The sections 1-9 comprised of the paleogene rocks and of the transition zone from paleogene to crystalline complex.

Authors supposed that the error was caused by the rock strength entering the model. A fuzzy model of rock strength was designed in order to confirm the hypothesis. Fig. 12 shows a scheme of the applied fuzzy model.

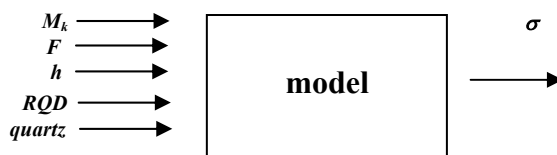


Fig. 12. Scheme of fuzzy model of rock strength.

Twelve clusters, which describe the relations of analysed behaviour of variables entering the model, were determined based on the outcomes of the analysis of the extremes of evaluating indexes. Following linear equations were determined for individual rules:

$$\begin{aligned}
 \sigma_1^F &= -2,309.M_k + 0,2341.F - 5,8231.h - 3,5987.RQD + 0,1477.quartz + 265,38 \\
 \sigma_2^F &= -2,7157.M_k + 0,2676.F - 7,7226.h - 5,2953.RQD + 0,4217.quartz + 379,78 \\
 \sigma_3^F &= -2,5522.M_k + 0,2575.F - 8,1249.h - 4,6732.RQD + 0,7971.quartz + 336,22 \\
 \sigma_4^F &= -2,7245.M_k + 0,2571.F - 9,1520.h - 5,1048.RQD + 1,8829.quartz + 388,50
 \end{aligned}$$

$$\begin{aligned}\sigma_5^F &= -2,9463.M_k + 0,2807.F - 11,3220.h - 5,7903.RQD - 2,8548.quartz + 444,16 \\ \sigma_6^F &= -2,6706.M_k + 0,2595.F - 8,8356.h - 5,0763.RQD + 1,8202.quartz + 375,39 \\ \sigma_7^F &= -2,3362.M_k + 0,2398.F - 6,8221.h - 3,9534.RQD + 0,48387.quartz + 285,61 \\ \sigma_8^F &= -3,0440.M_k + 0,2633.F - 14,2300.h - 5,1160.RQD - 4,0990.quartz + 452,00 \\ \sigma_9^F &= -1,3400.M_k + 0,1729.F - 4,0930.h - 1,2609.RQD + 0,1118.quartz + 85,75 \\ \sigma_{10}^F &= -1,3774.M_k + 0,1797.F - 4,5351.h - 1,3443.RQD + 0,3042.quartz + 89,04 \\ \sigma_{11}^F &= -1,2723.M_k + 0,1681.F - 4,5292.h - 1,2530.RQD - 0,2257.quartz + 85,81 \\ \sigma_{12}^F &= -1,2851.M_k + 0,1778.F - 3,3563.h - 1,1852.RQD + 0,4316.quartz + 69,79\end{aligned}$$

Designed fuzzy model of rock strength refuted such hypothesis. Detailed analysis of results proved that the model behaved in the sections 1-9 as TBM was excavating the rocks of the crystalline complex, according to the training data set. After implementation of fuzzy strength into the model, which simulated the crystalline complex conditions, the average deviations of both model and measured penetration depth improved significantly also in the geological sections 1-9. The coefficient of variation decreased in these sections from 30,36 % to 9,23 %. Improvement of the results in whole stationing of the section 8 was obtained after the application of model, where the coefficient of variation decreased from 12,98 % to 4,39 %. Maximal error of the model remained in the geological section 2, in the transition zone from paleogene to crystalline complex, with the coefficient of variation value 23 %. The section 2 is represented by the highest disturbance (rock jointing) degree and the largest inhomogeneity of present rock material. Table 4 shows average deviations between the monitored and fuzzy modelled penetration depth before and after extension of the rules and after the implementation of fuzzy strength into the model in geological sections 1-27.

Tab. 4 Comparison of average deviation between measured and fuzzy modelled penetration depth values in geological sections 1- 27.

Geological section	Deviation [mm]		
	Before rules extension	After rules extension	After application of fuzzy strength
1	0.9767	2.4613	0.4622
2	2.0887	2.8570	1.3777
3	2.8255	3.0009	0.6685
4	3.3254	3.5223	0.3264
5	3.5493	3.6264	0.3438
6	1.1666	1.3808	0.7627
7	0.7627	0.8408	0.5529
8	0.8824	0.9640	0.2987
9	1.0911	1.1013	0.2770
10	0.4735	0.4410	0.4132
11	0.5222	0.4644	0.3596
12	0.5274	0.3044	0.3973
13	0.8164	0.6631	0.4625
14	0.2897	0.2888	0.3029
15	0.6856	0.7264	0.4020
16	0.4948	0.5361	0.3445
17	0.5077	0.3785	0.3817
18	0.4480	0.3690	0.3877
19	0.2197	0.2097	0.4046
20	0.6072	0.5285	0.4742
21	0.7426	0.3935	0.3106
22	1.5269	0.4798	0.6186
23	1.0963	0.4234	0.5237
24	0.6166	0.6171	0.3963
25	0.4705	0.4672	0.2758
26	0.5202	0.5202	0.2182
27	0.5018	0.5018	0.2391

Conclusions

Use of cluster analysis algorithms for the design of fuzzy model of boring process and of expert system appears to be a promising method of better understanding and control of the process. Expert systems designed for the geotechnical purposes are subject to the specifics of the geotechnics, as the rock

environment cannot be describes explicitly and only approximate and simplified concepts of the rock environment are used. The results presented in the paper were obtained ex-post from monitored data acquired in boring of the Branisko exploratory gallery, which caused that it is not possible to identify the sources of significant differences between measured and modelled penetration depth of the disc rollers into the rock in several short sections of the tunnel. However, obtained average deviations between measured and calculated fuzzy values of penetration depth signalise a good accordance for in-situ conditions. After the application of the fuzzy strength, the model was modified for a wide scale of excavated rocks, i.e. the model was generalized for whole TBM-bored section of the tunnel.

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