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ARTICLE

# Application of neural networks for the reliability design of a tunnel in karst rock mass

Meho Saša Kovačević, Mario Bačić, and Kenneth Gavin

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**Abstract:** This paper offers a solution to overcome time-consuming numerical analysis for the evaluation of the impact of tunnel construction in a complex karst environment by implementing Monte Carlo Simulation (MCS) using a neural network (NN) tool. The rock mass is described using three parameters: Geological Strength Index, the uniaxial compression strength of the intact rock, and the Hoek–Brown parameter for the intact rock $m_i$. By using their probabilistic distribution as an input, a developed neural network NetTUNN produces probabilistic distributions of tunnel crown displacement, rock bolt axial load, and shotcrete uniaxial compression stress. A full MCS is then applied on these NetTUNN outputs to determine the reliability index and probability of failure for the relevant limit states. To demonstrate the potential of NN in tunnel design, a case study of Tunnel Pećine in Croatia is used, where the NetTUNN-assisted MCS assessment served as a benchmark to evaluate approximate reliability assessment techniques. It was shown that the developed NN can be used as an accurate surrogate model for determination of probabilistic distributions of tunnel design parameters. Further, it was shown that approximate reliability assessment techniques generally overestimate the reliability index and underestimate the probability of failure when compared to the NetTUNN-assisted MCS.

*Key words:* tunnel design, neural network, reliability methods, limit states, karst.

**Résumé :** Dans cet article, on propose une solution permettant de surmonter les longues analyses numériques pour l'évaluation de l'impact de la construction de tunnels dans un environnement karstique complexe en appliquant la simulation de Monte Carlo (MCS) au moyen d'un outil de réseau neuronal (NN). La description de la masse rocheuse est réalisée à l'aide de trois paramètres, l'indice de résistance géologique, la résistance à la compression uniaxiale de la roche intacte et le paramètre Hoek–Brown pour la roche intacte $m_i$. Grâce à leur distribution probabiliste, un réseau neuronal développé, NetTUNN, produit des distributions probabilistes du déplacement de la couronne du tunnel, de la charge axiale des boulons de la roche ainsi que de la contrainte de compression uniaxiale du béton projeté. Ensuite, on applique une MCS complète sur ces sorties de NetTUNN pour calculer l'indice de fiabilité et la probabilité de défaillance pour les états limites concernés. Pour démontrer le potentiel de la NN dans la conception des tunnels, on utilise une étude de cas de tunnel Pećine en Croatie, dans laquelle l'évaluation MCS assistée par NetTUNN a permis d'évaluer les techniques d'évaluation de la fiabilité approximative. On a démontré que la NN développée peut être utilisée comme un modèle de substitution précis pour la détermination des distributions probabilistes des paramètres de conception du tunnel. On a également démontré que les techniques d'évaluation de la fiabilité approximative surestiment généralement l'indice de fiabilité et sous-estiment la probabilité de défaillance lorsqu'elles sont comparées au MCS assisté par le NetTUNN. [Traduit par la Rédaction]

*Mots-clés :* conception des tunnels, réseau neuronal, méthodes fiables, états limites, karstique.

## Introduction

Given the complex response of rock masses and scale of tunnel construction relative to the volume of soil and rock that is tested during an extensive ground investigation, tunnel construction is by its nature an uncertain activity and quantification of risk is of upmost importance (Cerić et al. 2011). The need for risk assessment is even more pronounced in karst rock mass, which is highly susceptible to dissolution under the influence of water, the so-called karstification process. Karst phenomena, including caverns, voids, discontinuities, etc., significantly contribute to the tunnel design and construction complexity, as shown in Fig. 1.

One of the challenges of estimating the factor of safety during tunneling operations is that the rock mass contributes to both the load and the resistance terms, thus propagating uncertainties in the analysis. The use of sophisticated numerical analyses techniques usually relies on the best or conservative methods for estimating the material properties, depending on the limit state being considered. Hadjigeorgiou and Harrison (2011) noted that overlooking inherent variability will result in an uncertain design in rock engineering. Therefore, the application of probabilistic (or reliability) based methods is ideally suited to the design of tunnels in a rock mass. Although the application of probabilistic approaches to engineering problems in rock is considered in the relevant design code Eurocode EN 1997-1 (CEN 2004), Bačić (2019) noted that this is done in a rather vague way due to insufficient coverage of rock engineering as a discipline within the code,

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**Fig. 1.** Example of a tunnel construction in complex karst environment. [Colour online.]

and because of the code's recommendations for semi-probabilistic safety verification. At the same time, practical tunnel engineers appear reluctant to adopt reliability-based methods, which are perceived as too complex for practical use, with the prevailing misconception that these methods require considerably more effort in comparison to traditional design methods. However, the rock engineering community has been more progressive in the implementation of different reliability-based methods for the design of tunnels (see Oreste 2005; Mollon et al. 2009; Li and Low 2010; Lü and Low 2011; Fortsakis et al. 2011; Lü et al. 2012, 2013, 2017, 2018; Langford and Diederichs 2013; Zhao et al. 2014; Eshraghi and Zare 2015; Johanson et al. 2016; Song et al. 2016; Wang et al. 2016; Bjureland et al. 2017 and others).

Generally, reliability assessment methods can be classified into two categories: simulation-based and approximate methods. Even though they are more accurate, the simulation-based methods such as Monte Carlo Simulation (MCS) require a large number of numerically complex evaluations. These methods are usually implemented in relatively simple calculations, e.g., analysis of slope stability utilizing the limit equilibrium method or analysis of tunnel supports utilizing the closed-form solution. In finite element and finite difference analyses that include complex constitutive models, deterministic parameters are usually employed. Given the importance, Idris et al. (2011*a*) implemented MCS in a finite difference method (FDM) analysis to account for the variability of the rock mass material properties on the behaviour of a rock slope. In such analyses, the computational effort can be reduced if variance reduction schemes (Schoenmakers et al. 2002) are used. However, despite the processing powers of modern-day computers, simulation times remain long (Goh and Kulhawy 2005), precluding their use in general practice. To overcome this limitation for complex geotechnical numerical models, the utilization of the approximation methods — such as the First Order Second Moment (FOSM) method, Second Order Second Moment (SOSM) method, Point Estimate (PEM) method, and Hasofer–Lind (HL) method — is often adopted. Whilst faster, approximation methods are less accurate than full simulation and are therefore unlikely to find the true minimum of the reliability index. In this paper, a solution in the form of a custom-made neural network (NN) is presented to reduce computation time for MCS analyses. A trained, tested, and validated NN serves as an MCS auxiliary tool. NN utilizes a probabilistic distribution of Geological Strength Index (GSI), the uniaxial compression strength of the intact rock (UCS), and the Hoek–Brown parameter for the intact rock ($m_i$) as an input. From this input, a developed NN produces a probabilistic distribution of tunnel design parameters, including displacement of a tunnel crown, rock bolt axial load, and shotcrete uniaxial compression stress. A full MCS can then be applied on these output distribution curves to determine the reliability index and probability of failure for the serviceability and ultimate limit states of the tunnel. The MCS, due to its lack of approximations, is used as an ideal benchmark for comparison with the approximation reliability methods, as suggested by Langford and Diederichs (2011).

## The uncertain nature of rock mass parameters

### Rock mass strength and stiffness parameters

An elastic – perfectly plastic model that follows the Hoek–Brown failure criterion (Hoek et al. 2002) is usually employed to describe the strength characteristics of the heavily fractured rock mass. The model strength parameters ($m_b$, $s$, and $a$, as defined in Fig. 2) describe the nonlinear nature of the rock mass and are determined by established empirical correlations with GSI, UCS (sometimes referred to as $\sigma_c$), and $m_i$, which depends on the rock type. This empirical failure criterion is expressed as a nonlinear relationship between rock mass strength and principal stresses (see Fig. 2), where $\sigma'_1$ is the maximum effective principal stress, $\sigma'_3$ is the minimum effective principal stress, and $D$ is the disturbance factor that quantifies the effect of excavations on the rock mass.

An important parameter affecting tunnel behaviour is the rock mass deformation modulus $E_{rm}$. Hoek and Diederichs (2006) compiled a large database of $E_{rm}$ values and proposed an empirical equation that accounts for the intact rock modulus $E_i$, $D$, and GSI. However, Kovačević et al. (2011) presented intensive measurements from projects undertaken in karstic rock that show significantly higher measured rock mass deformation values than suggested by moduli correlated with rock mass classifications. Based on these observations, Jurić-Kaćunić et al. (2011) developed a new approach for determination of the karst carbonate rock deformation modulus, given by eq. 1. The equation shows that the parameters affecting deformation modulus of karst are the GSI, the dispersion velocity of longitudinal waves ($V_p$), and the rock mass deformation index ($ID_m$).

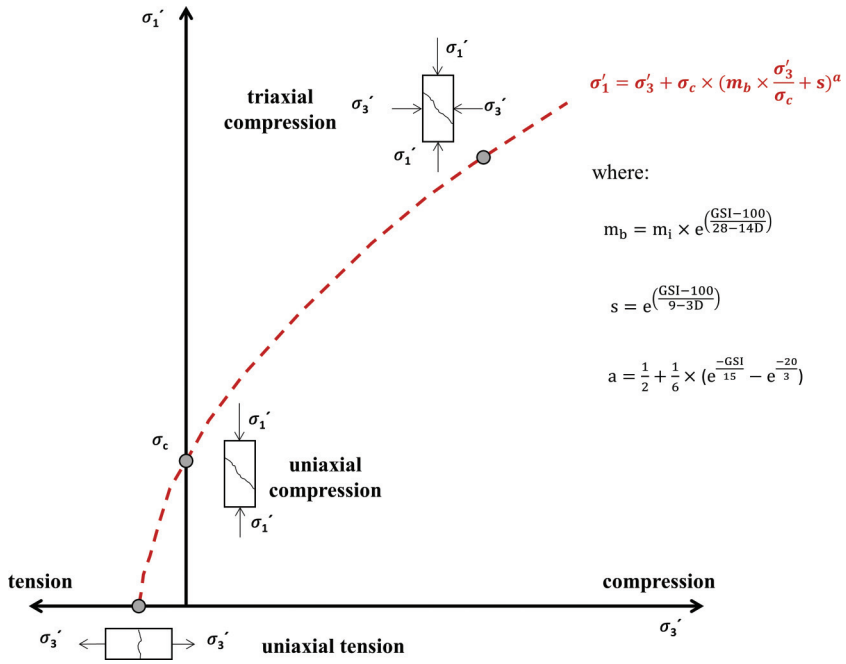
$$E_{rm} = ID_m(GSI^2)(V_p^2) \tag{1}$$

where the unit for $E_{rm}$ is GPa, for GSI is %, and for $V_p$ is km/s. The $ID_m$ for carbonate rocks is equal to the rock mass quality index ($IQ_s$) determined by allocating rock mass into one of the proposed models and weathering zones, whereas the GSI is adapted to the geological engineering properties of Croatian karst (Pollak 2007).

### Evaluation of rock mass parameter distribution

In a discussion on appropriateness of reliability design in rock engineering, Harrison (2019) focused on the statistical evaluation of rock mass parameters, considering that they provide a principal source of the structural resistance. Two approaches to determine rock mass properties are analysed in his study and it is concluded that the analytic approach, based on an assessment of the rock mass characteristics to obtain a rock mass rating value, is not suitable for determining rock mass properties for reliability-based design. This is due to epistemic uncertainty of these assessments, rather than allowing characterization of aleatory variability as required by reliability-based design. In contrast, the synthetic approach could be considered as appropriate for reliability-based design, owing to the fact that rock mass properties are represented as a combination of component factors associated with both intact rock and discontinuities, and these factors are available in a quantitative form. However, a challenge remains with respect to obtaining a sufficiently large database for the synthetic

**Fig. 2.** Hoek–Brown failure criterion (modified from Hoek et al. 2002). [Colour online.]




approach. If transformation models are used to obtain as large a database as possible to overcome the perennial problem of limited data for analysis of rock parameter variability, research conducted by Ching et al. (2018) could be considered. In that study, 184 previous studies were utilized to form a database of transformation models for several rock mass parameters, which was then adopted to calibrate the bias and variability of existing transformation models. Also, a challenge linked with limited data may be dealt with through application of Bayesian data analysis, as given by Bozorgzadeh and Harrison (2019). Harrison (2019) stated that the results for the strength and stiffness of intact rock demonstrate aleatory variability, where Bozorgzadeh and Harrison (2019) stressed that this variability has little similarity within and between rock types, so that reference values are unsuitable and variability needs to be determined case-by-case, as was done within this study. Some aspects of variability, such as variability of polyaxial rock strength, anisotropy of strength, and the elastic compliance matrix, need further research. Further, both geometrical and mechanical properties of discontinuities are known to be aleatory. However, state-of-the-art investigation techniques allow large quantities of discontinuity geometry data to be obtained, which would eventually aid their variability analysis in reliability-based design.

Whilst rock mass strength and stiffness characteristics are influenced by GSI, UCS, and $m_i$ parameters, the tunnel response is also influenced by the geometry, overburden height, excavation technique, and characteristics of the support system amongst other factors. However, Fortsakis et al. (2011) noted that variability of the geotechnical properties of the rock mass surrounding the tunnel have the largest impact in controlling the uncertainty of tunnel lining loads. This variability of rock mass properties along a tunnel, arising from the deposition and weathering processes, strongly affects the relevant failure mechanisms (see Phoon and Kulhawy 1999; Song et al. 2011; Cai 2011). In most cases, normal or lognormal distributions are suitable to describe the rock mass parameters; however, it is important to confirm this assumption and adopt an alternative distribution to ensure sufficient accuracy.

GSI is determined by the field observations of blocks and the surface condition of discontinuities. Fortsakis et al. (2011) presented the possibility of determining coefficient of variance (COV) values of GSIs, based on Marinos and Hoek (2000) and Marinos et al. (2005) estimation diagrams of GSI isolines density in the GSI charts. The scatter is assumed to be ±5 for GSI values lower than 30, ±7 for GSI between 30 and 40, and ±10 for GSI values higher than 40. In the case where GSI distribution is assumed uniform, Fortsakis et al. (2011) noted that the scatter defined the upper and lower limits, while in the case where the normal distribution was assumed it defined the 90% confidence interval, leading to the calculation of the standard deviation. The quantitative description of GSI is possible only if sufficient GSI data are available. For example, Idris et al. (2011*b*) used the GSI chart to estimate about 1000 GSI values from field observations at the same location. However, given the qualitative nature of the GSI assessment, quantitative description of the distribution is often not possible, and statistical tools can be applied. One of these tools is the three-sigma rule (Dai and Wang 1992), which identifies that 99.73% of all values of a normally distributed GSI will fall within three standard deviations of the mean. Using this rule, the mean value as the best estimate of the random variable — and the COV, as a representation of uncertainty — is defined for GSI.

The distributions of UCS and $m_i$ can be determined from measurements, when a sufficient amount of laboratory or field-testing data are available. To describe a distribution, a prevailing — however, often argued (e.g., Kar and Ramalingam 2013) — suggestion of a minimum sample size of 30 data points can be used. Hoek (1998) and Sari (2009) suggested a COV value of 30% for UCS values described with a normal distribution, noting that log-normal distributions are often used to avoid possible negative sampling values because of the relatively large COV. The material constant ($m_i$) depends on many factors, such as the type of rock and its mineral composition, grain size. It is determined either by triaxial testing in the laboratory or from published tables based on rock mass structure (Hoek et al. 2002). For different types of rock mass, Hoek and Diederichs (2006) assumed that the scatter of 17 ± 4 corresponds to a 90% confidence interval. However, in the event that a sufficient sample size is not available for UCS and $m_i$, the mentioned three-sigma rule can be adopted.

An example of the rock mass parameter variability is given in Fig. 3, for the case study tunnel presented in the paper. During



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the on-site excavation of an analysed tunnel section, a GSI value of 29 was determined. This value represents a mean value, while the GSI distribution was determined through application of the three-sigma rule. The UCS distribution was determined on the basis of a total of 56 triaxial, uniaxial, and point load tests (PLTs), while the $m_i$ distribution was determined on the basis of a total 36 triaxial tests.

The UCS and $m_i$ data from Fig. 3 are shown in form of histogram, where both experimental tests have passed the normal distribution hypothesis, using the chi-square goodness-of-fit test. Considering their dominant influence on tunnel behaviour, the GSI, UCS, and $m_i$ are treated within this study as random uncorrelated variables. Other variables such as disturbance factor $D$, as well as longitudinal velocity parameter from eq. 1, easily determined by the means of geophysical methods, are considered as deterministic within this study.

## Reliability index and probability of unsatisfactory performance

In this study, reliability methods consider the impact of uncertainties associated with the input parameters GSI, UCS, and $m_i$ on predictions of three quantities: (*i*) displacement of the tunnel crown related to the serviceability limit state (SLS), (*ii*) support rock bolt loads related to the ultimate limit state (ULS), and (*iii*) uniaxial compression stresses in the shotcrete lining related to the ULS. Therefore, limit state (performance) functions, $g(\boldsymbol{X})$, can be expressed as the difference between capacity $C$ and loading $B$, where the terms "loading" and "capacity" must be taken in their broadest sense, as they do not point only to "forces" and "stresses," but also to the displacement of a tunnel crown:

$$(2)\qquad g(\boldsymbol{X}) = C - B \begin{cases} < 0 & \text{safe state} \\ = 0 & \text{limit state} \\ > 0 & \text{failure state} \end{cases}$$

where $\boldsymbol{X}$ is the vector of different random variables ($x_i$) in the problem

$$(3)\qquad g(\boldsymbol{X}) = g(x_1, x_2, \ldots, x_n)$$

The basic random variables ($x_1$, $x_2$, . . ., $x_n$) represent the uncertain parameters of rock mass, in this case GSI, UCS, and $m_i$, so that eq. 3 has the form

$$(4)\qquad g(\boldsymbol{X}) = g(\mathrm{GSI}, \mathrm{UCS}, m_i)$$

It should be noted that a limit state surface, $g(\boldsymbol{X}) = 0$, is the boundary between the safe state and the state in which the SLS and ULS are exceeded.

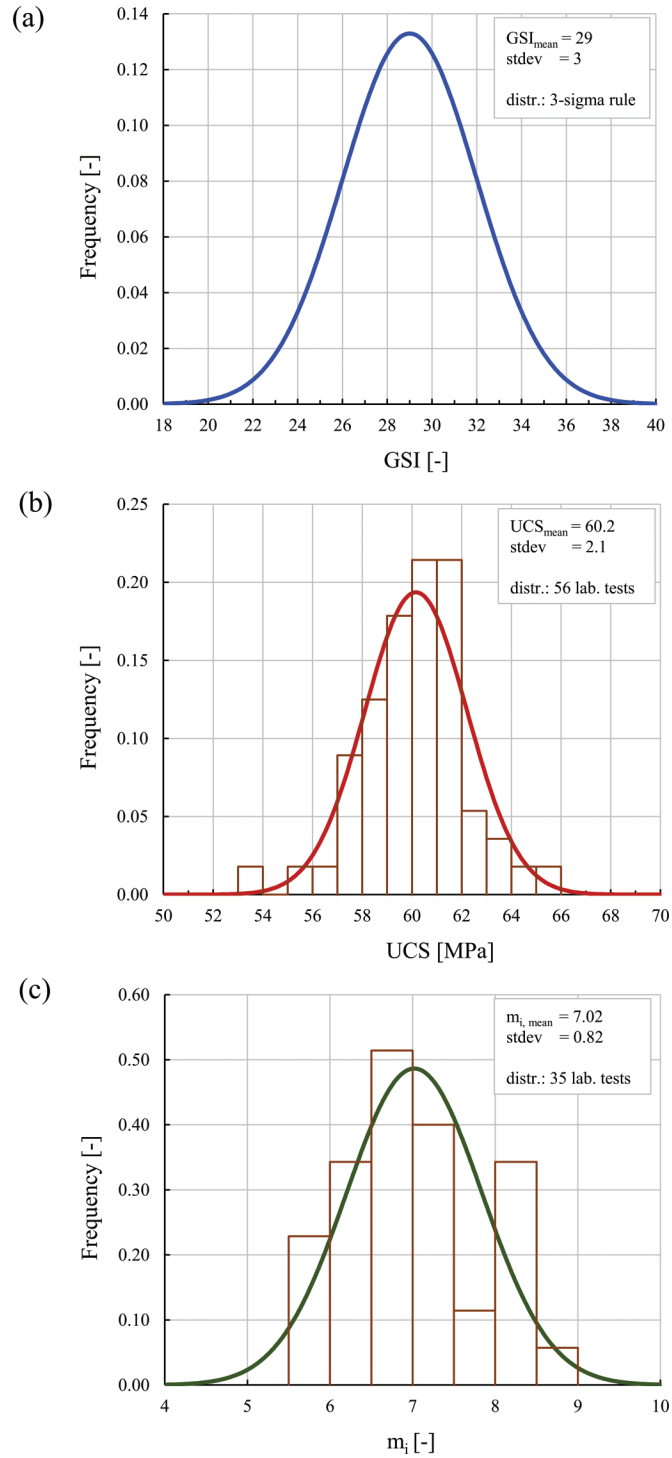
Probability density functions for typical capacity and load are shown in Fig. 4*a*. Assuming normal distributions of the capacity ($C$) and loading ($B$), the reliability index can be defined as the distance by which the failure function mean $\mathrm{E}[g(\boldsymbol{X})]$ exceeds zero in units of standard deviation $\sigma[g(\boldsymbol{X})]$ (Xue and Gavin 2007) (Fig. 4*b*). Therefore, the reliability index can be expressed as

$$(5)\qquad \beta = \frac{E\left[g(\boldsymbol{X})\right]}{\sigma\left[g(\boldsymbol{X})\right]} = \frac{E(C-B)}{\sqrt{\sigma^2(C) + \sigma^2(B)}}$$

The probability of exceeding SLS or ULS, $P_f$ in Fig. 4*b*, can be defined as the probability that the loading will equal or exceed capacity and is expressed by the equation

$$(6)\qquad P_f = P\left[g(\boldsymbol{X}) \le 0\right]$$

**Fig. 3.** (*a*) GSI, (*b*) UCS, and (*c*) $m_i$ distribution for an analysed section of a case study tunnel. [Colour online.]

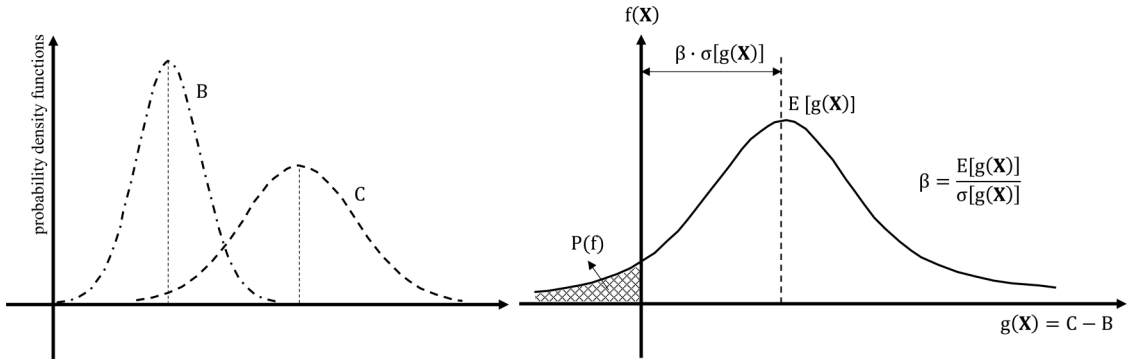



Considering eq. 2, the performance function (or limit state surface), for the serviceability limit state, i.e., tunnel crown displacement, is given by

$$(7)\qquad g(\boldsymbol{X}) = Y_{\mathrm{disp,SLS}} - Y_{\mathrm{disp,NN}}(\mathrm{GSI}, \mathrm{UCS}, m_i)$$

where $Y_{\mathrm{disp,SLS}}$ is the limiting displacement value while $Y_{\mathrm{disp,NN}}$ (GSI, UCS, $m_i$) is a normal distribution of displacements obtained

**Fig. 4.** Probability densities for (*a*) typical capacity and load and (*b*) probability density for $g(\boldsymbol{X})$.




by the NN. The value $Y_{\mathrm{disp,NN}}$ represents the maximum displacement values across the cross section and is usually the displacement of the tunnel crown.

The ULS performance functions for the axial load in a rock bolt (CA) and uniaxial compression stress within the shotcrete (SM) are given by

$$g(\boldsymbol{X}) = \mathrm{CA}_{\mathrm{max,ULS}} - \mathrm{CA}_{\mathrm{max,NN}}(\mathrm{GSI}, \mathrm{UCS}, m_{\mathrm{i}}) \tag{8}$$

and

$$g(\boldsymbol{X}) = \mathrm{SM}_{\mathrm{max,ULS}} - \mathrm{SM}_{\mathrm{max,NN}}(\mathrm{GSI}, \mathrm{UCS}, m_{\mathrm{i}}) \tag{9}$$

where $\mathrm{CA}_{\mathrm{max,ULS}}$ and $\mathrm{SM}_{\mathrm{max,ULS}}$ denote the axial capacity of a rock bolt and uniaxial compression stress capacity of shotcrete with regards to the ultimate limit state, respectively. The value $\mathrm{CA}_{\mathrm{max,NN}}$ is a normal distribution of maximum axial load within the rock bolt with the highest load in a given cross section determined by the NN. $\mathrm{SM}_{\mathrm{max,NN}}$ (GSI, UCS, $m_{\mathrm{i}}$) is a normal distribution of maximum values of shotcrete uniaxial compression stress within the cross section, obtained by the means of NN and determined as given by Oraee et al. (2011)

$$\mathrm{SM}_{\mathrm{max,NN}}(\mathrm{GSI}, \mathrm{UCS}, m_{\mathrm{i}}) = \frac{N_{\mathrm{max}}}{A} + \frac{M_{\mathrm{max}} h}{2I} \tag{10}$$

where $N_{\mathrm{max}}$ (kN) is the maximum axial load within shotcrete; $M_{\mathrm{max}}$ (kN·m) is the maximum bending moment within shotcrete; while $A$ ($\mathrm{m}^2$), $h$ (m), and $I$ ($\mathrm{m}^4$) are cross-sectional area, distance between axial force and neutral line, and moment of inertia of shotcrete, respectively. A detailed analysis of the shotcrete stress capacity procedures can be found in Hoek et al. (2008).

Within this study, a MATLAB (MathWorks 2019) code was written to obtain reliability indexes and probabilities of failures for both MCS and approximation techniques. MCS is an enumeration-based procedure used for estimation of the uncertainty of a system's output with consideration of uncertainty of the model input (Shreider 1964). The MCS requires the calculations of hundreds and thousands of performance function ($g[\boldsymbol{X}]$) values and, within this study, these values have been selected from the NN output database. Therefore, by utilizing a NN as an auxiliary tool, time-consuming numerical calculations of performance function values are avoided. Afterwards, MCS is used to serve as a benchmark for evaluating the accuracy of the approximate methods: First Order Second Moment Method (FOSM; Cornell 1971), First Order Reliability Method (FORM; Hasofer and Lind 1974), and Rosenblueth Point Estimate Method (PEM; Rosenblueth 1975).

## An architecture of the NetTUNN neural network

To overcome the time-consuming aspect of conducting a large number of numerical analyses for MCS, an artificial NN tool is employed among the large range of possible surrogate models. NN is used to establish the correlation between the rock mass parameters and tunnel design parameters. Li et al. (2016) gave an extensive literature overview of the response surface methods as surrogate modelling tools for soil slope reliability analyses, including Kriging-based response surface, quadratic polynomial, Support Vector Machine (SVM)-based response surface, and NN-based response surface. One of the most popular surrogate models among these is the Kriging model, mainly because of its recognized ability to provide high-quality predictions. As such, it has been used in the geotechnical domain (Brito et al. 1997) and has been incorporated in many software offering custom-built surrogate models for fundamental aspects of uncertainty quantification, such as the open-access platform UQLab (2020). Despite being popular and providing relatively high accuracy, some geotechnical studies showed that ordinary Kriging did not work well in estimating rock mass quality along tunnel alignments in complex geological settings, with a large difference between the estimated and actual values (Kaewkongkaew et al. 2015).

Long after the development of a Kriging method, a back-propagation NN algorithm was presented as an alternative in determining the limit state surface. NN represents an advanced machine learning technique that simulates processes of the human brain and nerve system. Interconnected artificial NN elements share information leading to development of awareness of the relationship between different parameters (Reale et al. 2018). The application of NN is particularly useful if these relationships are intuitively difficult to understand and describe, as is often the case with rock mass parameters. When used to map an input–output function, NN represents a special form of response surface in which the response function is a superposition of a class of smooth, sigmoidal-type squashing functions. Since its development, NN has been used in many applications including geological (Leu and Adi 2011) and geotechnical domain (Shahin et al. 2001; Goh and Kulhawy 2005; Miranda et al. 2007). Goh and Kulhawy (2005) stated that the NN approach is particularly useful for modelling the nonlinear limit state surface. This is especially the case with the evaluation of the serviceability limit state surface of geotechnical structures as the serviceability limit state is usually not known explicitly (Goh and Kulhawy 2003). Much research was conducted on the comparison of Kriging and NN, to determine which surrogate model performs better in establishing complex correlation between parameters. Many of these suggest that the NN models are superior to the geostatistical Kriging model and exhibit higher accuracy, e.g., in geodesy (Akcin and Celik 2013); groundwater contamination (Chowdhury et al. 2010); ionosphere mapping, especially when data set is spare (Jiang et al. 2015); geotechnical site characterization (Samui and Sitharam 2010) or mapping of rock depth below soft deposits (Sitharam et al. 2008). For the tunneling applications, Shi et al. (2019) stated that the NN surrogate model can accurately estimate the geological

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conditions prior to excavation when compared with the methods based on soft computing methods, while Santos et al. (2015) concluded that model errors obtained with the different estimation methods (linear regression, geostatistical Kriging, and NN algorithms) are very similar. As the utilization of NN generated using evolutionary algorithms can be considered as an advanced surrogate model, compared to the traditionally used statistical and experimental methods, many researchers utilized its benefits in rock tunneling and underground rock engineering (Lee and Sterling 1992; Moon et al. 1995; Benardos and Kaliampakos 2004; Yoo and Kim 2007; Mahdevari and Torabi 2012; Zhang and Goh 2015; Hasegawa et al. 2019).

The adaptability and learning capabilities of NN require a sufficient amount of training data, where the amount is even larger when complex nonlinear systems are analysed. In the NN regression analysis, used for the purpose of this study, the NN is used to approximate static nonlinear function *f(x)* through implementation of the so-called multi-layer Layer Perceptron (MLP) architecture consisting of an input layer, a hidden layer(s), and an output layer. While the number of input and output layers is based on the specific problem analysed, the number of hidden layers must be optimized. If the number of hidden layers and neurons is too small, it will result in a too general NN without the possibility of learning input–output relationships. In contrast, if the number of hidden layers and neurons is too large, it can lead to NN overtraining. An extensive literature overview of methods to determine the optimal number of hidden layers and hidden nodes, influencing the NN performance, is given by Sheela and Deepa (2013). Additionally, Trenn (2008) and Doukim et al. (2010) presented some NN optimization techniques for MLP architecture, while Majdi and Beiki (2010) conducted a study involving comparison of different types of NN architectures with different numbers of layers and nodes, for rock mass application.

After the number of hidden layers and neurons is determined, each input neuron connects with each hidden neuron, with each interconnection receiving a weighting. These weightings, developed and optimized within the hidden layer, determine how the NN predicts and adapts. Several characteristic phases in the development of an optimal NN can be distinguished and these include training, validation, and testing phase (Hammerstrom 1993). Based on the input–output sets given by the user, it is recommended that 70% of data are used for the training process to minimise the error function by changing the individual neural weightings to attain the optimum neural weightings. During the training phase, inputs and outputs are supplied to the NN, which allows learning of the sensitivity of each individual parameter. This phase continues until the NN can correctly model the system response or until all available training data have been utilised (Reale et al. 2018). Once the NN is trained, the validation phase follows and it includes simulation of output data with input data, where 15% of total data are used in process. The validation dataset, completely independent from the dat set used for NN training, provides an unbiased evaluation of a model fit on the training dataset while tuning the model's parameters. If the NN can correctly predict the outputs of this data, then it can be said that it models the system accurately. Finally, the test phase uses the remaining 15% of data, not used in the training or validation phase, to provide an unbiased evaluation of a final model fit on the training dataset. During this phase, only the inputs were supplied to the model and at the end of this phase, the NN system recalibrates itself based on the testing results so that system inputs are more accurately mapped onto system outputs.

To learn complex relationships between rock mass input values and tunnel design output values, a NN named NetTUNN was trained, tested, and validated within this study. The input set contains $n$ values of selected rock mass parameters: [$UCS_1$, $UCS_2$, . . ., $UCS_n$]; [$GSI_1$, $GSI_2$, . . ., $GSI_n$]; [$m_{i1}$, $m_{i2}$, . . ., $m_{in}$]. As the output, $n^3$ sets determined through $n^3$ deterministic numerical analysis are defined in the form [$y_1$, $CA_1$, $SM_1$]; [$y_2$, $CA_2$, $SM_2$]; [$y_n^3$, $CA_n^3$, $SM_n^3$]. After the calibration of NetTUNN, this NN could understand the nonlinear relationships between input and output sets. Along with three input nodes and three output nodes, the optimized network consists of four hidden layers, with utilization of total 34 distinct weightings. A sigmoid activation function for hidden neurons and a linear activation function for output neurons are used. A scheme of a developed NN is given in Fig. 5.

As NN outputs, this study evaluates the most loaded rock bolt and the most loaded shotcrete section, as well the point with the largest displacement, as in usual design practice these are treated as the critical parameters from the limit state point of view. To obtain a maximum displacement and internal forces values from numerical simulations, an algorithm is developed to search both the maximum values of the mentioned design parameters and their position along the cross section to ease the search procedure and to avoid potential overlooking of critical elements or sections. It was shown in all of the conducted numerical analyses that the position of the cross-sectional point with maximum displacement (SLS) differs from the position of the most loaded rock bolt and the position of the most loaded shotcrete section (both being ULS). Further, even within the ULS the position of the most loaded rock bolt and the position of the most loaded shotcrete section differed in all analysed numerical simulations, usually being on opposite sides of the cross section. Therefore, if only maximum values of these three design parameters are analysed, it could be stated that the correlations between NetTUNN outputs are statistically insignificant both between SLS outputs (crown displacement) and ULS outputs (rock bolt loads and shotcrete compression stresses), as well as between two ULSs (rock bolt loads and shotcrete compression stresses). Once the NN learned relationships between rock mass parameters and tunnel design parameters, it was ready to apply these relationships on normally distributed values of rock mass input parameters. The NN outputs, comprising fully defined distributed curves of tunnel displacements, rock bolt axial force, and shotcrete uniaxial compression stress, can be further subjected to MCS for the determination of the reliability index and probability of failure.

## Case study example: Tunnel Pećine

The efficiency of NetTUNN at obtaining representative distributions of design parameters for reliability analysis is validated using a case study of the construction of a road tunnel. Tunnel Pećine is located in a karstic rock mass formed of cretaceous deposits, breccias, dolomites, and limestones, of relatively good permeability. Because of their high susceptibility to the karstification process, karst phenomena including caverns, voids, etc., have been an additional challenge during tunnel construction. The surrounding rock mass is generally partially fractured, with the degree of fracturing being more pronounced near the fault zones. As a part of the D404 state road, the tunnel provides access to the city of Rijeka and its major port area. The tunnel, having an overall length of 1258.5 m with 60% of the tunnel constructed as a three-lane and 40% constructed as a four-lane highway, was constructed between 2005 and 2008. The tunnel section analysed in this paper is characterized by the relatively constant overburden depth and similar geological conditions. The primary support system consists of 20 cm thick shotcrete installed in several layers and 6 m long self-drilled steel rock bolts, with 23 rock bolts installed along the cross section. The tunnel section analysed is in close proximity to a railway tunnel constructed over 100 years ago (see Fig. 6), and therefore significant instrumentation was provided to confirm the design assumptions and prevent damage to the rail tunnel. A detailed description of the tunnel and excavation works is given by Kuželički and Ružić (2008).

**Fig. 5.** Scheme of a NetTUNN neural network.

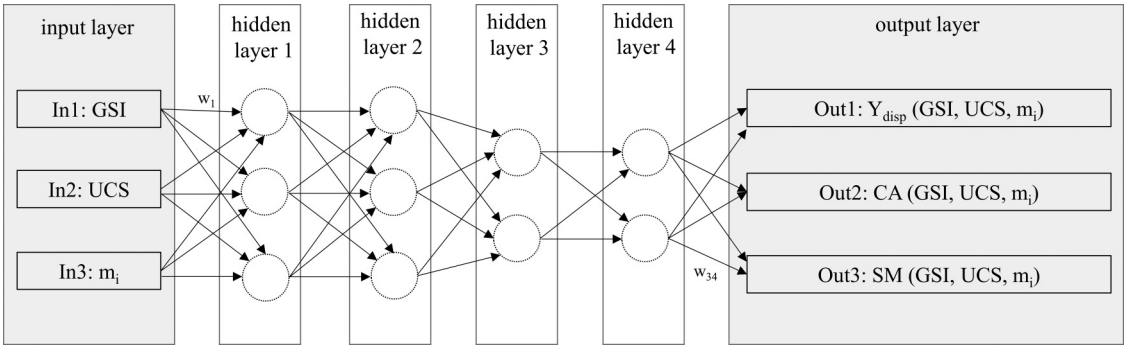
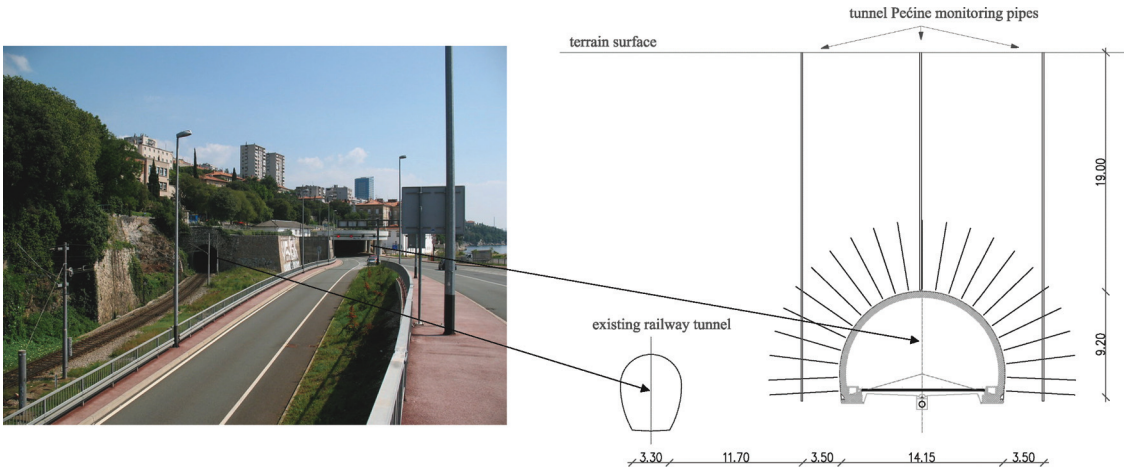



**Fig. 6.** Tunnel Pećine entrance and a scheme of one of the monitoring profiles. (All dimensions in metres.) [Colour online.]

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## Rock mass input distributions

During the design of a tunnel support system, a combination of numerical, empirical, and observation methods was used, where the design numerical models relied on average values of GSI, UCS, and $m_i$ for each characteristic tunnel section. However, this study uses the probabilistic distribution of rock mass parameters, as given in Fig. 3, where the UCS and $m_i$ distributions are determined on the basis of laboratory testing, while the GSI distribution is determined on the basis of the three-sigma rule. The disturbance factor ($D$) in this study is defined as the deterministic input value of 0.1, considering the excavation technology of combining blasting (in high-quality rock mass sections) and mechanical excavation (in poor-quality rock mass sections). These technologies resulted in minimal disturbance to the surrounding rock mass. This assumption of $D$ = 0.1 was verified on-site after excavation of the analysed section. Selection of the deterministic value of the disturbance factor is often encountered in the literature covering the uncertainties in tunneling projects (see Fortsakis et al. 2011; Idris et al. 2011*a*; Cai 2011; Lü et al. 2018). Further, implementation of the karst-adapted rock mass stiffness model, as given by eq. 1, included distributed GSI values (Fig. 3), a unique deterministic value 0.4 for $ID_m$, and deterministic values of longitudinal wave velocities ($V_p$) obtained by the means of the seismic refraction method. For carbonate karst rocks, $ID_m$ is equal to the rock mass quality index ($IQ_s$) determined by allocating rock mass into one of the models and weathering zones proposed by Pollak (2007) and it covers both stiffness reduction due to karstification of rock masses as well as the disturbance resulting from the excavation technology. Onodera (1963) proposed to estimate $IQ_s$ as the ratio of velocities of longitudinal seismic waves in rock mass and velocities of longitudinal seismic waves measured in laboratory on the intact rock ($IQ_s = V_p/V_{p,0}$). Therefore, acquired in situ velocities on the analysed section, as well as laboratory results of velocities of intact samples, yielded a mentioned deterministic value of $ID_m$. Considering the increase of the rock mass stiffness due to the $V_p$ increase, as given by Jurić-Kaćunić et al. (2011), a FISH programming language code representing the nonlinear increase of rock mass stiffness was implemented within the two-dimensional finite difference software FLAC (Itasca 2019). For calculation simplicity, the properties of the in situ stress as well as properties of the support system elements, including rock bolts and shotcrete, are regarded as deterministic.

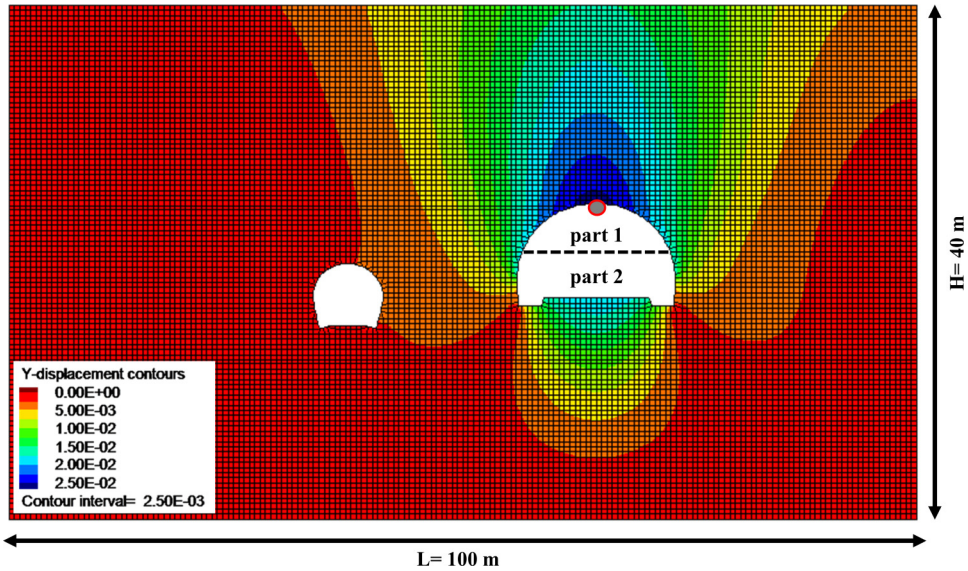
## NetTUNN neural network application

As a first step in applying the NN, 125 ($5^3$) deterministic numerical analyses were carried in FLAC using the following sets of input parameters:

GSI = [15; 25; 35; 45; 55]
UCS (MPa) = [30; 50; 70; 90; 110]
$m_i$ = [3; 5; 7; 9; 11]

The first numerical phase included calculation of the initial stress state, the second phase involved excavation of the first part of the cross section of the tunnel with installation of 13 rock bolts and shotcrete, while the third phase involved the excavation of the second part of the cross section, with installation of 10 rock bolts and shotcrete. The numerical model is shown in Fig. 7. A

**Fig. 7.** Vertical displacement contours (in metres) for numerical model with mean input values. [Colour online.]

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sensitivity analysis was performed to check for boundary effects and a FLAC model 100 m wide and 40 m high was found to satisfy the requirements. After conducting 125 deterministic numerical analyses, a set of outputs was determined in the form [$Y_1$; $CA_1$; $SM_1$], [$Y_2$; $CA_2$; $SM_2$], . . ., [$Y_{125}$; $CA_{125}$; $SM_{125}$].

The 125 input–output datasets were used for training, testing, and validating the NetTUNN NN by utilizing the MATLAB software (MathWorks 2019). While what the minimum number of data points required for NN training, testing and validation is often discussed, the utilized number of input–output sets (125) can be considered as appropriate for this particular case where the numerical modelling input–output sets were used for the NN development. The values of the numerical model outputs are dominantly conditioned by the numerical constitutive model, used to represent the rock mass behaviour. This allows minimal scattering of data, as the constitutive model is a "smooth" function with unambiguous description of the stress–strain behaviour (for a certain imposed stress value, a certain strain–displacement occurs). Therefore, the supply of larger numerical input–output datasets for NN development would not significantly increase the accuracy of NN in predicting outputs from predefined inputs. The difference would be if the experimental or observational datasets were used for NN development where the significant data scattering is present and where larger number of input–output pairs would be necessary for NN to find a meaningful relationship. However, even in the case when the NN is developed on small datasets, some techniques are available to increase the accuracy of NN (see Ingrassia and Morlini 2005; Feng et al. 2019). The regression coefficients were determined for tunnel displacement (maximum displacement of a tunnel crown), rock bolt axial load, and shotcrete stress. The regression coefficient values for training, testing, and validation datasets, as well for overall data, are shown in Fig. 8 for the stresses induced in shotcrete. The $R^2$ values for the target-output evaluations are 0.96 for training data, 0.92 for validation data, 0.94 for testing data, and 0.95 for overall data. The target-output data for rock bolt axial load and tunnel displacement result in even higher values of $R^2$, leading to the conclusion that NetTUNN performs very well in establishing the complex, nonlinear, relationships between rock mass parameters (UCS, GSI, and $m_i$) and tunnel design parameters ($Y$, CA, SM).

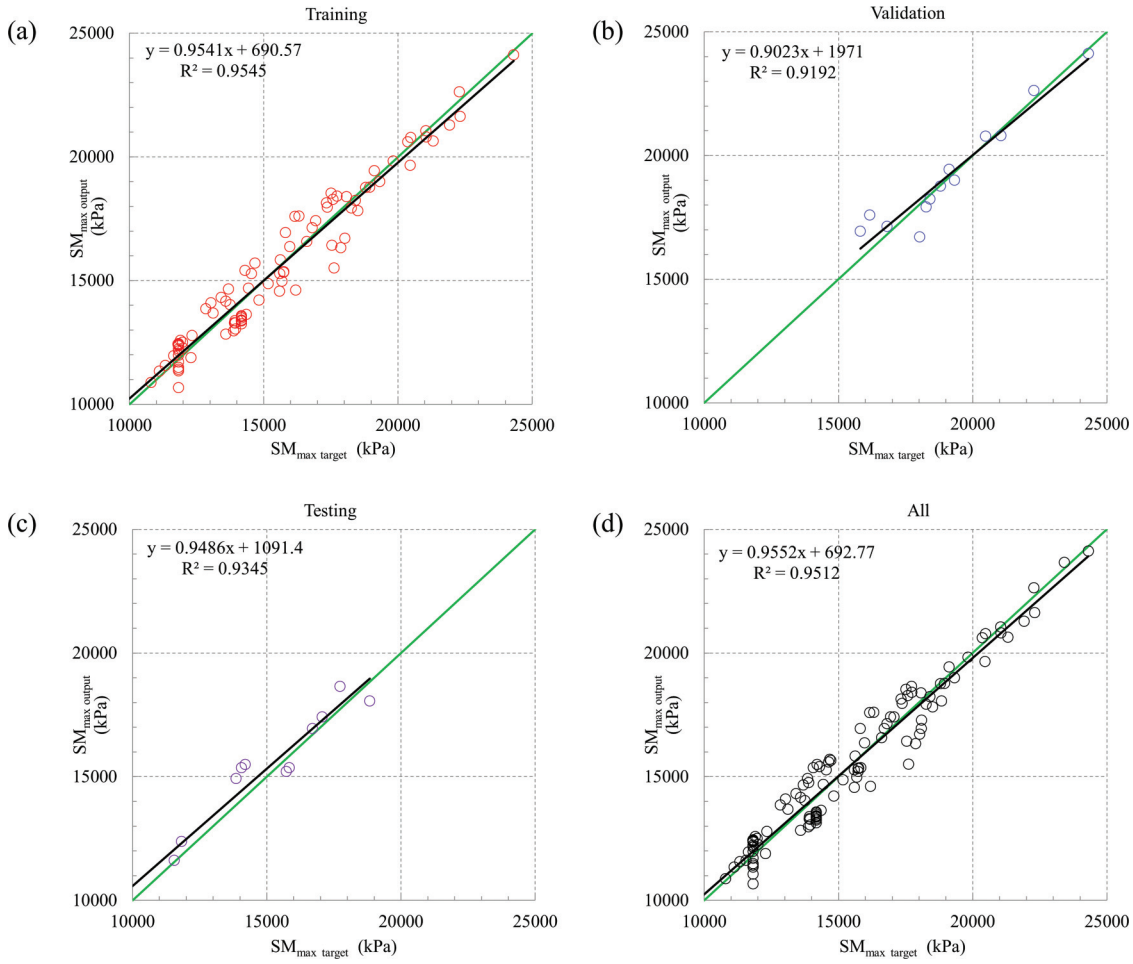
Further, the normal distribution of rock mass parameters (GSI, UCS, $m_i$), shown in Fig. 3, was used as an input for the developed NetTUNN to determine the distributed ($Y$, CA, SM) output, as shown in Fig. 9.

The distribution of tunnel crown displacement $Y_{disp\_NN}$, predicted by the model, is shown in Fig. 9*a*. The data have a mean value of 2.71 cm and standard deviation of 0.56 cm. Figure 9*b* shows several $CA_{i\_NN}$ ($i$ = 1, 2, 3, 4, 5) curves representing the distributions of axial load in the rock bolts, together with the distribution of capacity considered for the ULS condition. The curve $CA_{i\_NN}$ is a distribution of maximum load in the most highly loaded rock bolt along the analysed cross section. It is evident from Fig. 9*b* that a significant number of the predicted values exceed the ULS load. It is worth noting that this condition would lead to rock bolt failure, rather than failure of the tunnel itself. In the event of an individual rock bolt failing, plastic failure of a zone of rock around the bolt and tunnel displacement will occur (Carranza-Torres 2009) followed by load redistribution. To model this phenomenon, the curves of distribution of the second, third, fourth, and fifth most loaded rock bolts were determined. In these analyses, $CA_{2\_NN}$ represents the distribution of a maximum load within second most loaded rock bolt where the first most loaded rock bolt is considered as failed, which was achieved by simply eliminating it in numerical analyses. Similarly, $CA_{3\_NN}$ represents the distribution of a maximum load within third most loaded rock bolt where the first and second most loaded rock bolts are considered as failed, and so on. The axial load mean values of curves $CA_{1\_NN}$ to $CA_{5\_NN}$ reduced from 198 to 113 kN with a significant drop occurring (below the ULS distribution) when the second rock bolt failed. The sensitivity analysis shows that failure of the five most loaded rock bolts had limited impact on the overall tunnel displacement and stresses in the shotcrete lining. The distribution of the maximum predicted value of uniaxial compression stress within the shotcrete, $SM_{max\_NN}$, is shown in Fig. 9*c*. The position of $SM_{max\_NN}$ in a given cross section varies depending on the rock mass parameter's value and is determined as given in eq. 10. The data have a mean value of 18.5 MPa with standard deviation of 1.3 MPa. The interaction of axial force and bending moment is considered in this study, due to fact that all analyses yielded significantly higher shotcrete uniaxial compression stress values when compared to shear force – bending moment interaction.

## Comparison with in situ monitoring and testing results

An intensive monitoring program was implemented in Tunnel Pećine with data collected periodically during construction and

**Fig. 8.** (*a*) Training, (*b*) validation, (*c*) testing, and (*d*) overall datasets with correlation of NetTUNN-predicted shotcrete stress and the numerically obtained values. [Colour online.]




continuing to the present day. The data collected include measurement of deformations and displacements using standard survey points as well as inclinometers and deformeters installed from ground level to the depth of the tunnel for a number of cross sections (see Fig. 6). Data recorded by a deformeter placed above the centreline of the tunnel show the development in displacement during the construction process (see Fig. 10).

The monitored crown displacements measured, after the primary support system was installed, show a high match with the mean value of the $Y_{\text{disp\_NN}}$ distribution shown in Fig. 9*a*, with the monitored value being only 4% lower than the NetTUNN determined value.

In addition to the monitoring programme, an extensive quality-control testing programme was conducted. This included the pull-out tests for determination of installed rock bolt capacity, as well as laboratory testing of the shotcrete UCS on samples taken from installed shotcrete. The monitored crown displacement measured, after the primary support system was installed, was ≈26 mm, close to the mean value of displacement predicted with the model: 27 mm (see Fig. 9*a*). The pull-out tests were conducted with respect to the ISRM standard (ISRM 1974), where a total of 19 rock bolts were tested. The failure mode in all of these tests was yielding of the central steel bar of a rock bolt, rather than geotechnical failure of the rock. This is not surprising considering the very large values of pull-out capacity given through a combination of rock bolt length and the high unit shear strength between the grout and surrounding rock mass. In total, 77 samples of shotcrete were taken and tested in the laboratory using a hydraulic press apparatus. For the purpose of analysing the uniaxial compression stress data, and considering the C25/30 shotcrete class, the in situ strength requirements included a 0.85 reduction factor to allow for the effects of in situ coring, as recommended by EFNARC (1996).

## Reliability analysis using MCS and approximate techniques

Reliability analyses were conducted on the NetTUNN output distribution curves shown in Fig. 9, using both MCS and the approximate techniques to enable comparison between the methods.

Some definition of the SLS is required to define the "capacity." In this study, an allowable value for the tunnel crown displacement of 4 cm was chosen to represent convergence equal to 2.5% of tunnel width. The performance function thus becomes

$$g(\boldsymbol{X}) = 4.0 - Y_{\text{disp\_NN}}(\text{GSI}, \text{UCS}, m_{\text{i}})$$

This was solved by the means of MATLAB software (MathWorks 2019), with the MCS analysis giving a reliability index, $\beta$, value of 2.23, meaning that the probability ($p_{\text{f}}$) of the tunnel displacement exceeding 4.0 cm is 1.3%. A sensitivity analysis was performed to consider the impact of the maximum tunnel displacements on the results. Values of allowable displacement of between 3 and 6 cm were considered see (Table 1). The probability of exceeding the 3.0 cm displacement value is 31.1%, with a very low $\beta$ value of



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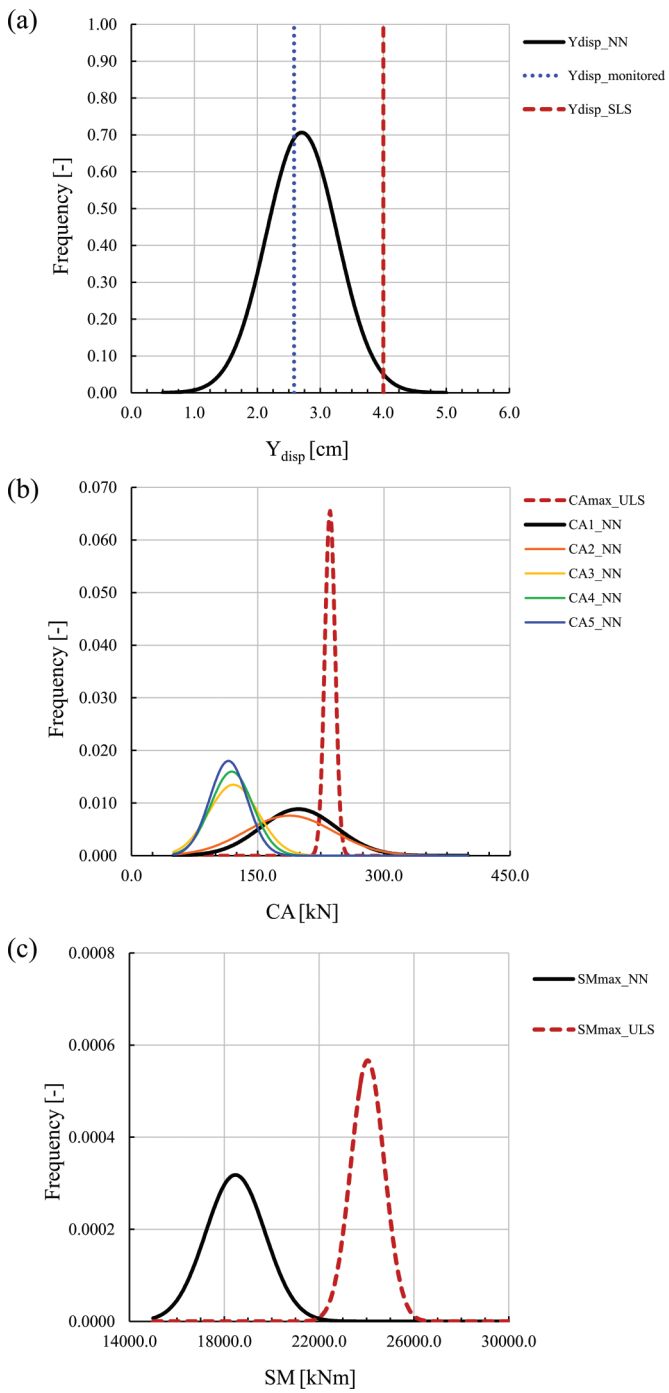
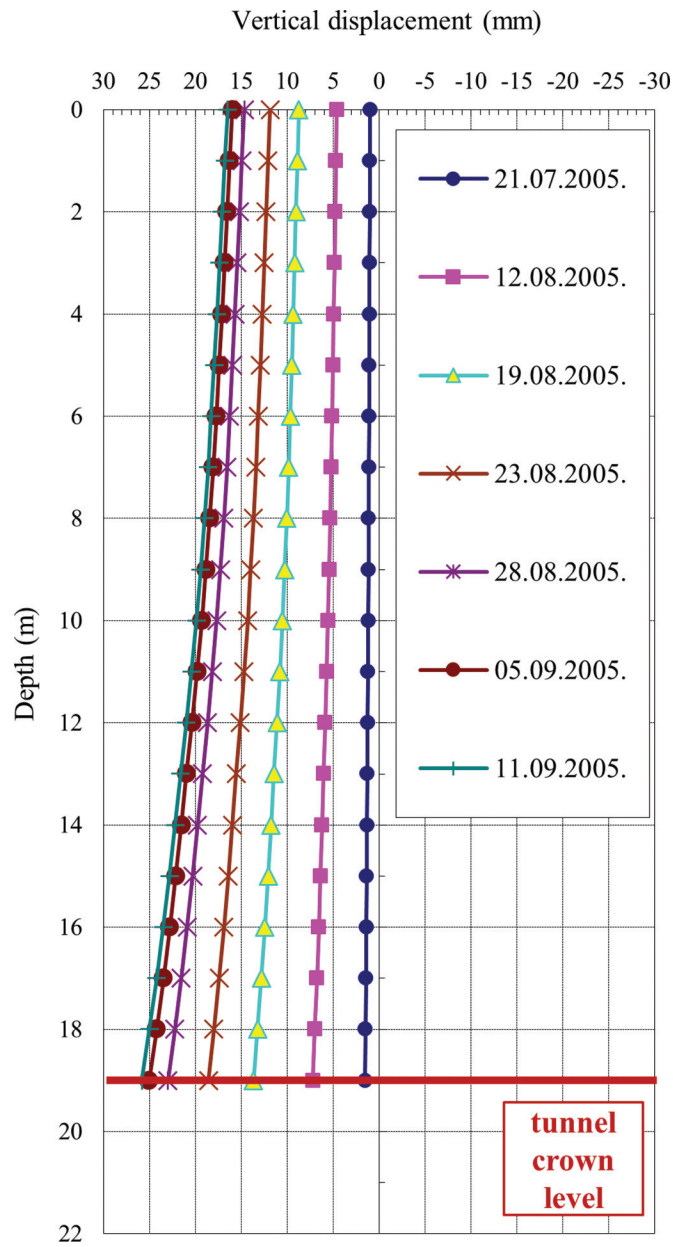
**Fig. 9.** (*a*) Displacement, (*b*) rock bolt axial force, and (*c*) shotcrete uniaxial compression stress distribution obtained from the NetTUNN. [Colour online.]




0.49. The probability of displacement exceeding the 6.0 cm limit has a significantly higher $\beta$ value of 5.67 and a $p_f$ of $7 \times 10^{-7}$. The $\beta$ and $p_f$ values were also evaluated using the approximate techniques (see Table 1), where it is shown that the MCS, evaluated on the full NetTUNN distribution, gives lower values of $\beta$ and $p_f$. Considering the minimum value of reliability index given by the Eurocode EN 1990 (CEN 2002), where the SLS $\beta$ for a 50 year reference period is recommended as 1.5, the obtained values of displacement can be considered as acceptable if the admissible value is 4.0 cm or higher. Of course, if it is assumed that the

**Fig. 10.** Vertical displacement obtained during construction from the deformeter measurements. [Colour online.]




design life of the tunnel is more than 100 years, the recommended values of $\beta$ would be even lower.

Given that the pull-out tests revealed yielding of the steel bars as being the critical failure mode for the installed rock bolts, a ULS capacity distribution curve (Fig. 9*b*) was developed based on the specification given by manufacturer of the steel section. The distribution curve has a mean value of 236 kN with a relatively low standard deviation of 6 kN. The performance function according to eq. 8 is

$$g(\boldsymbol{X}) = \mathrm{CA}_{\mathrm{distr,\,ULS}} - \mathrm{CA}_{i\_\mathrm{NN,\,max}}(\mathrm{GSI}, \mathrm{UCS}, m_i)$$

The MCS analysis shows that the probability that one rock bolt at the tunnel profile will exceed the ULS is 20.5%, with a low $\beta$ value of 0.82. Similar values were obtained when considering two rock bolts ($p_f$ = 18.2%, $\beta$ = 0.91), because the rock bolts were

**Table 1.** $\beta$ and $p_f$ for different reliability assessment methods (MCS, FORM, PEM, FOSM) applied on a case study tunnel.

| Limit state | Criteria | | | MCS | | FORM | | PEM | | FOSM | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | $\beta$ | $p_f$ (%) | $\beta$ | $p_f$ (%) | $\beta$ | $p_f$ (%) | $\beta$ | $p_f$ (%) |
| SLS displacement "Y" | Displacement exceeding admissible values | Admissible value (cm) | 3 | 0.49 | 31.1 | 0.53 | 29.9 | 0.54 | 29.5 | 0.75 | 22.8 |
| | | | 4 | 2.22 | 1.30 | 2.29 | 1.09 | 2.45 | 0.71 | 2.73 | 0.32 |
| | | | 5 | 3.95 | $4\times10^{-3}$ | 4.03 | $3\times10^{-3}$ | 4.30 | $9\times10^{-4}$ | 4.61 | $2\times10^{-4}$ |
| | | | 6 | 5.67 | $7\times10^{-7}$ | 5.81 | $3\times10^{-7}$ | 6.17 | $3\times10^{-8}$ | 6.54 | $3\times10^{-9}$ |
| ULS rock bolt capacity "$CA_{max}$" | Rock bolt load exceeding rock bolt capacity | No. of rock bolts exceeding capacity | 1 | 0.82 | 20.5 | 0.85 | 19.7 | 0.95 | 17.0 | 1.32 | 9.3 |
| | | | 2 | 0.91 | 18.2 | 0.93 | 17.5 | 0.97 | 16.6 | 1.22 | 11.2 |
| | | | 3 | 3.80 | $7\times10^{-3}$ | 3.92 | $4\times10^{-3}$ | 4.15 | $2\times10^{-3}$ | 4.49 | $4\times10^{-4}$ |
| | | | 4 | 4.58 | $3\times10^{-4}$ | 4.62 | $2\times10^{-4}$ | 4.68 | $1\times10^{-4}$ | 4.78 | $9\times10^{-5}$ |
| | | | 5 | 5.25 | $8\times10^{-6}$ | 5.31 | $6\times10^{-6}$ | 5.37 | $4\times10^{-6}$ | 5.48 | $2\times10^{-6}$ |
| ULS shotcrete capacity "$SM_{max}$" | Shotcrete stress exceeding shotcrete capacity | | | 3.88 | $5\times10^{-3}$ | 3.72 | $9\times10^{-3}$ | 3.71 | 0.01 | 3.12 | 0.09 |

positioned on opposite sides of the tunnel cross section. However, the probability that the loads within a third rock bolt will exceed the ULS is significantly lower with a value of 0.0072% with a correspondingly high value of $\beta$ = 3.8. The probability of failure of the fourth or fifth rock bolt is very low, as seen in Table 1. From this, it can be concluded that overall failure of the tunnel due to rock bolt failure is of low probability. $\beta$ and $p_f$ were also evaluated using the approximate techniques and, similar to the SLS analysis, it is demonstrated that the MCS results in lower values of both $\beta$ and $p_f$. With respect to the recommended values of reliability index for ULS, as given in the Eurocode EN 1990 (CEN 2002), the minimum $\beta$ value for a 50 year reference period is 3.8. All of the considered reliability analysis methods yield larger $\beta$ values than the recommended one, if failure of three of more rock bolts is considered.

The distribution of the uniaxial compression stress capacity of the shotcrete was determined based on the laboratory tests results, and the ULS curve is shown in Fig. 9*c*. It has a mean value of 24.1 MPa with a standard deviation of 0.7 MPa. The performance function was determined by the means of eq. 9 as

$$g(\boldsymbol{X}) = \mathrm{SM}_{\mathrm{distr,\,ULS}} - \mathrm{SM}_{\mathrm{NN,\,max}}(\mathrm{GSI}, \mathrm{UCS}, m_i)$$

The MCS analysis resulted in a $\beta$ = 3.88 value, meaning there is 0.0052% probability that the most loaded part of shotcrete will exceed the shotcrete uniaxial compression stress capacity, higher than the values recommended by the Eurocode for a 50 year reference period. However, unlike the SLS and rock bolt ULS analysis, when compared to the approximate techniques, here MCS yields the lowest values. The reliability indexes are 3.72 (FORM), 3.71 (PEM), and 3.12 (FOSM), meaning a 0.009% (FORM), 0.01% (PEM), and 0.09% (FOSM) probability that the shotcrete uniaxial compression stress capacity will be exceeded.

## Conclusions

The complex geological character of the rock mass surrounding a tunnel suggests that reliability-based methods are more suitable for tunnel design than deterministic methods. This is especially the case for a karstic rock mass due to its susceptibility to rapid local deterioration. In a number of papers, rock mass parameters — such as GSI, UCS, and $m_i$ — are considered as uncertain inputs for the tunnel design process. The parameters are used for numerical stress–strain analysis of tunnel – rock mass interaction, but when it comes to application of reliability techniques, these numerical models usually rely on approximate reliability assessment techniques. The reason for this is that simulation-based methods, such as MCS, require a large number of numerically complex evaluations of the tunnel behaviour, which is usually not feasible in practice despite the high processing powers of modern-day computers. At the same time, MCS is often regarded as the "more accurate and reliable" method when compared to approximation techniques. To overcome the time-consuming aspect of MCS, this paper offers a solution in the form of a custom-made NN called NetTUNN, trained to learn complex nonlinear relationships between rock mass parameters and tunnel design parameters.

It was found that NetTUNN can be used as a tool for defining design parameters for tunneling in karstic rock masses, significantly reducing the time necessary for probabilistic determination of tunnel design parameters. For a defined rock mass parameter distribution, NetTUNN gives a complete distribution of the tunnel displacement, rock bolt forces, and stresses in the tunnel lining. The efficiency of NetTUNN is demonstrated on a case study of the construction of the Pećine road tunnel in Croatia. It was shown that approximate reliability assessment techniques generally overestimate the reliability index and underestimate probability of failure when compared to the NetTUNN-assisted MCS. The probability of exceeding the SLS admissible value is generally higher for MCS than for approximation techniques, and the same is the case for the probability of exceeding ULS for rock bolt elements. However, when considering the probability of exceeding the uniaxial compression stress capacity in the shotcrete, the approximation techniques underestimate the MCS values. Further, additional validation of NetTUNN is given through comparison of predicted tunnel displacement with the displacement values obtained through tunnel monitoring during construction being within 4% of the mean value predicted using the model. This clearly demonstrates the benefits of using NN as a tool in reliability design of a rock mass tunnel.

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