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An Alternative Approach for Estimating the Shear Behavior of Rock Discontinuities by Using Radial Basis Function Neural Networks

Uma abordagem alternativa à previsão do comportamento cisalhante de descontinuidades rochosas utilizando redes neurais de funções de base radial

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Abstract: This paper aims to present predicting models for the shear stress and dilation in rock discontinuities by using artificial neural networks with radial basis functions. These models were developed based on a database obtained from 116 large-scale direct shear tests carried out on different types of discontinuities and boundary conditions. The input variables of the proposed models are the external normal stiffness, the initial normal stress, the roughness of the discontinuity, the uniaxial compressive strength of the intact rock, the thickness and the friction angle of existing infill material, the basic friction angle and the shear displacement imposed on the rock discontinuity. The results have shown that the RBF networks are capable of satisfactorily estimating the shear behavior of rock discontinuities, once coefficients of determination greater than 0.98 were obtained in the training and testing phases. In addition, the performance analyses of the models have shown that they can represent the influence of the input variables on the shear behavior of rock discontinuities. It can therefore be concluded that the models obtained are useful and simple tools for predicting the shear behavior of rock discontinuities.

Keywords: Neural Network Artificial; Radial Basis Function; Rock Discontinuities.

Resumo: Este artigo tem como objetivo apresentar modelos de predição da tensão cisalhante e dilatância em descontinuidades rochosas por meio de redes neurais artificiais que empregam funções de base radial. Para tanto, foi utilizado um banco de dados obtido de 116 ensaios de cisalhamento direto em grande escala realizados em diferentes tipos de descontinuidades e condições de contorno. As variáveis de entrada dos modelos propostos são a rigidez normal externa, a tensão normal inicial, a rugosidade da descontinuidade, a resistência uniaxial da rocha intacta, a espessura do preenchimento, o ângulo de atrito do material de preenchimento, quando houver, o ângulo de atrito básico e o deslocamento cisalhante imposto na descontinuidade. Os resultados mostraram que as redes RBF são capazes de estimar de forma satisfatória o comportamento cisalhante das descontinuidades rochosas uma vez que foram obtidos coeficientes de determinação superiores a 0,98 nas fases de treinamento e teste. Além disto, nas análises de desempenho dos modelos observou-se que eles são capazes de representar de forma coerente a influência das variáveis de entrada no comportamento cisalhante das descontinuidades rochosas. Logo, pode-se concluir que os modelos obtidos se apresentam como ferramentas úteis e simples para a previsão do comportamento cisalhante de descontinuidades rochosas.

Palavras-chave: Redes Neurais Artificiais; Funções de Base Radial; Descontinuidades Rochosas.

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1. Introduction

Over the last few decades there has been a great effort to develop models for predicting the mechanical behavior of rock masses that realistically consider the influence of the main parameters that govern the shear mechanism in these rock structures. In this sense, several analytical models have been proposed based on large-scale direct shear tests carried out on different types of discontinuities and boundary conditions, including the proposals of Barton (1973, 1976), Ladanyi and Archambault (1969), Barton and Choubey (1977), Skinas, Bandis and Demiris (1990), Indraratna and Haque (2000), Indraratna, Oliveira and Brown (2010), among others. The results obtained in these studies indicated that the shear behavior of rock discontinuities is governed by the following factors: filling material, roughness, imposed boundary conditions, as well as the characteristics of the intact rock.

Despite satisfactorily representing the shear behavior of rock discontinuities for the conditions in which they were developed, the various existing analytical models present numerous limitations, given the difficulties in obtaining the parameters necessary for their application (DANTAS NETO et al., 2017; LEITE et al, 2019a; MATOS, 2018). In this way, there is a need to employ alternative methods that allow the prediction of the shear behavior of rock discontinuities in a practical and simple way, but that consider all their governing variables. In this regard, we can mention artificial neural networks (ANN), which have shown good performance in solving complex, multivariate, and non-linear problems, with increasingly frequent use in geotechnical engineering. In rock mechanics, numerous works demonstrate the capacity of these tools in predicting parameters (MAJDI; REZAEI, 2013; SAYADI et al., 2013; ZHOU et al., 2020).

Regarding the shear behavior of rock discontinuities, the works of Dantas Neto et al. (2017), Leite et al. (2019a), and Leite et al. (2019b) used multilayer perceptrons (MLP) in the development of prediction models. The results obtained by these authors showed that neural models have provided results that are closer to experimental data than the estimates made by analytical models. However, as MLPs have complex architectures and are designed to perform a global approximation of the input-output mapping, with all parameters being computed at the same time, a high computational effort is required, resulting in a slower learning process compared to that obtained with other types of ANNs (SOARES; TEIVE, 2015; FERREIRA, 2020).

In this context, radial basis function (RBF) networks are an alternative to the tools used to estimate the shear behavior of rock discontinuities due to their ability to adequately deal with non-linear problems with a single hidden layer, enabling the training process (network parameter adjustments), whose computational effort is significantly lower when compared to other types of artificial neural networks, especially MLPs, as highlighted by Gan, Peng, and Chen (2012), Ferreira (2020), and Souza, Batista, and Silva (2021).

In relation to the less intensive computational effort presented by RBF, for a given input vector, typically only a few hidden neurons will present significant activations, which makes its training faster, unlike the MLP, which presents a more complex connectivity pattern since it is based on multiple layers of neurons. In addition, the process of estimating the parameters (weights and thresholds) is sequential, requiring several passes through all the samples in the training set. This, in turn, requires a high computational effort due to the need to back-propagate the error, resulting in a slow convergence learning curve when compared to the RBF network (VIEIRA; LEMOS; LING, 2003; BISHOP, 1997; HAYKIN, 2009). This network divides its training into two very distinct and fast-executing phases, not relying on a training process lasting several epochs as required by the MLP network. Furthermore, the RBF network has only two hyperparameters, namely, the number of hidden neurons and the common width of the Gaussian basis functions. The MLP network requires the specification of several hyperparameters, such as the number of hidden layers, the number of neurons in each hidden layer, the learning rate, the momentum factor, and the number of training epochs. Regarding its application, several authors have highlighted the potential of RBF networks in predicting geotechnical parameters (QIN et al., 2018; MENDES, 2021; SAYADI et al., 2013).

Therefore, this article aims to present models developed with neural networks of the radial basis function type to predict the shear behavior of rock discontinuities as a function of their governing variables, namely, the shear displacement, the boundary conditions represented by the tension initial normal and normal boundary stiffness, and the characteristics of the discontinuities, such as roughness, basic friction angle, uniaxial compressive strength of the intact rock, t/a ratio for the fill, and internal friction angle of the fill material, when applicable. case. In this case, the use of RBF networks aims to take advantage of their ability to model complex and non-linear phenomena in a simpler way, with less computational time and better performance than those obtained with other types of ANN.

2. Radial Basis Function (RBF) Neural Networks

An ANN is formed by a set of artificial neurons distributed in multiple layers linked together by synaptic connections whose function is to transmit signals from the input layer to the output layer, with the responses of the artificial neurons being given by activation functions, which can be mentioned the linear, sigmoidal, hyperbolic tangent functions, among others (HAYKIN, 2009). Considering the main advantages of ANN, the ability to universally approximate functions stand out, which is used to establish input-output relationships through a data-based learning process. Once subjected to an appropriate training process, the network has the ability to generalize knowledge about the modeled phenomenon, allowing predictions to be made for input patterns different from those used during the adjustment of the network parameters (GETAHUN; SHITOTE; ABIERO GARIY, 2018).

There are different types of ANN, each with its own architecture and learning algorithms (TURCATO, 2015). Among them, we can mention the simple perceptron, which is characterized as the simplest architecture of an ANN and whose processing occurs in a single layer, whose neurons are activated by non-linear functions (HAYKIN, 2009). One can also mention multilayer perceptrons (MLP), which can be considered an extension of the simple perceptron with the ability to interpolate non-linear and more complex problems due to the presence of one or more layers of hidden neurons. In general, MLP networks are the most used in geotechnics, as highlighted by Erzin, Rao, and Singh (2008), probably due to their ability to allow the modeling of non-linear and complex multivariate phenomena due to the use of a greater number of non-linear hidden layers and neurons.

Neural networks that use radial basis functions (RBF) also present a structure in which information is propagated from the input layer to the output layer, however, without feedback loops (SOUZA, BATISTA, SILVA, 2021). Unlike other types of neural networks, an RBF uses radial basis functions as the activation function of hidden layer neurons, which are characterized as non-linear functions (KAWASE, 2015). However, the connection between the neurons of the hidden layer and the output layer is made through linear neurons, making such networks have a simpler structure and learning process than that used in MLP. Among the different types of radial basis functions are linear, cubic, Gaussian, multiquadric, and inverse multiquadric functions (MENDES, 2021).

In general, an RBF network can be used for practically every type of problem handled by an MLP (CHAOWANAWATEE; HEEDNACRAM, 2012). Because it has a simple topological structure, fast training, good generalization, and an output activated by a linear function, the RBF network becomes a competitive alternative to MLP networks in modeling engineering problems (NASERI, TATAR, and SHOKROLLAHI, 2016).

According to Haykin (2009), the basic structure of an RBF network includes three layers: the first layer refers to the input of the ANN, consisting of the nodes into which information from the input variables is fed and which will be propagated to the second layer. Hidden; the second layer of the network is the hidden layer, in which a non-linear transformation of the input space is carried out using radial basis functions to activate its constituent neurons; and the output layer returns the ANN response through a linear transformation from the high-dimensional space of the hidden layer to the (usually) low-dimensional space given as a function of the modeled problem.

Figure 1 shows a schematic representation of the structure of an RBF network in which $\mathbf{x}$ corresponds to the input vector of dimension n; φ_i refers to the i-th radial basis activation function, i=1, 2, …, q, whose value increases with decreasing distance of the input vector $\mathbf{x}$ in relation to the center $\boldsymbol{\mu}_i$ that defines the position of the i-th radial basis function in the input space. Each hidden neuron is centered on a particular coordinate of the multidimensional input space. Thus, each of these coordinates is characterized by defining the center of a region of greater agglomeration of points, or cluster, in the input data space. Thus, the centers of the radial basis functions are determined as part of the learning process and their quantity and position must cover a representative set of the data sample (NEVES; CARVALHO, 2010). The parameter ω_i corresponds to the synaptic weight that connects the i-th hidden neuron (or equivalently, the i-th basis function) to the output y by means of the linear transformation mentioned above, representing the network's response to the input vector $\mathbf{x}$.

According to Soares and Teive (2015) and Souza, Batista and Silva (2021), the radial basis function commonly used for the hidden layer neurons is the Gaussian function, which is given by:

$$\varphi(\mathbf{x}, \boldsymbol{\mu}_i) = exp\left(-\frac{||\mathbf{x}-\boldsymbol{\mu}_i||^2}{2\sigma^2}\right) \tag{1}$$

Where $||\mathbf{x} - \boldsymbol{\mu}_i||$ is the Euclidean distance between the input vector ($\mathbf{x}$) and the center $\boldsymbol{\mu}_i$ of the i-th radial basis function. The width parameter σ (a.k.a., radius) defines the receptive field of the Gaussian radial basis functions. This parameter is named *spread* in the Matlab's newrb function which was used to implement the RBF version in this paper.

According to Heshmati et al. (2009), RBF networks with a Gaussian radial basis function are universal approximators, that is, they are capable of approximating non-linear input-output mappings with a good degree of accuracy. Regarding the output layer, the response of the RBF network is calculated as a linear combination of all the outputs of the radial basis functions. Therefore, the ANN response (y) is represented by the sum of the outputs of the q Gaussian functions weighted by their synaptic weights (ω_i) plus the threshold (ω_0), as shown in the following equation:

$$y(\mathbf{x}) = \sum_{i=1}^{q} \omega_i \varphi(\mathbf{x}, \boldsymbol{\mu}_i) + \omega_0 \qquad (2)$$

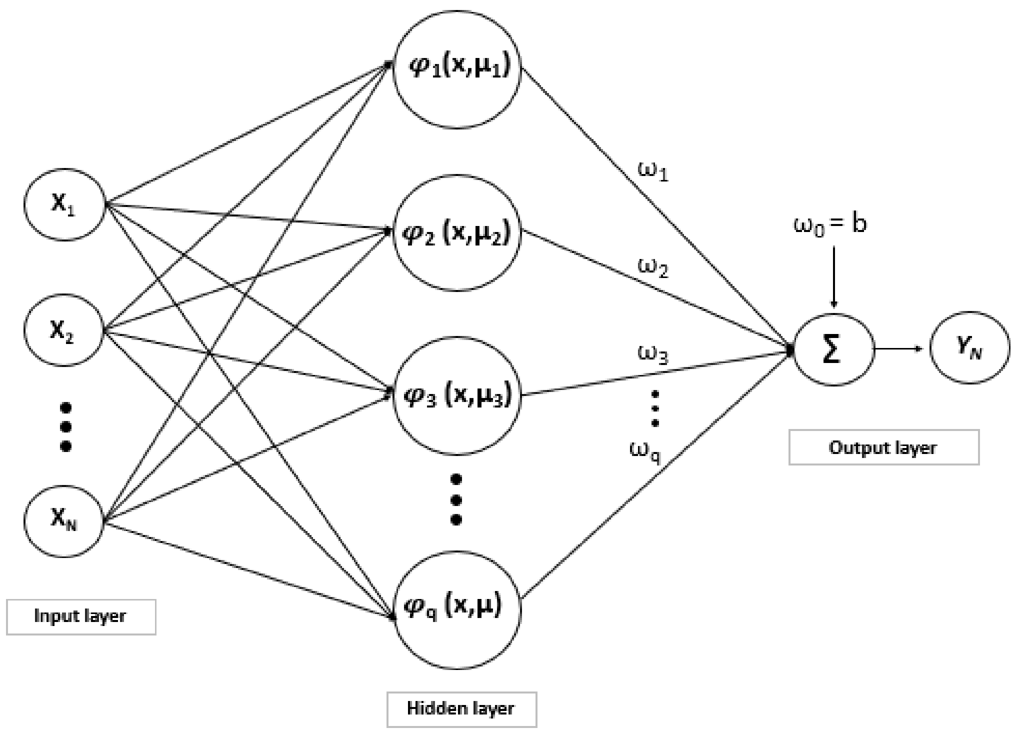

Figure 1 – General architecture of a single-output RBF network.
Source: Haykin (2009).

3. Materials and methods

3.1. Definition of input variables

In general, it is observed that the boundary conditions acting on a rock discontinuity, its roughness characteristics, presence of filling and its resistance parameters, properties of the intact rock and level of shear displacement are the main factors that govern the shear behavior of discontinuities in rock masses (INDRARATNA; OLIVEIRA; BROWN, 2010; OLIVEIRA; INDRARATNA, 2010; PAPALIANGAS et al., 1993; SKINAS; BANDIS; DEMIRIS, 1990).

Therefore, for the development of the shear behavior prediction models, the following were adopted as input variables: the contour normal stiffness (k_n), the ratio between the thickness of the fill and the height of the asperity (t/a), the initial normal stress (σ_{n0}), the roughness coefficient of the discontinuity (JRC), the uniaxial compressive strength of the intact rock (σ_c), the basic friction angle (ϕ_b), the friction angle of the fill (ϕ_{fill}) and the shear displacement (δ_h). The output variables of the proposed models are the shear stress (τ_s) and the dilation (δ_v) as representative parameters of the shear behavior of rock discontinuities.

3.2. Database

The data used to develop the neural models was obtained from the results of 116 large-scale direct shear tests presented in the works by Benmokrane and Ballivy (1989), Skinas, Bandis and Demiris (1990), Papaliangas et al. (1993), Haque (1999), Indraratna and Haque (2000), Oliveira (2009), Indraratna, Oliveira and Brown (2010), Mehrishal et al. (2016) and Shrivastava and Rao (2017).

The database has a total of 2098 input-output examples. Of these, 58% correspond to results obtained in tests carried out under conditions of constant normal stiffness (CNS) and 42% carried out under conditions of constant normal loading (CNL). In addition, both filled (55%) and unfilled (45%) rock discontinuities are included.

The data used to develop the models also includes the results of tests carried out on discontinuities that are not very rough to very rough, as well as on soft to very resistant rocks. Table 1 shows the measures of dispersion and central tendency for the values of the input and output variables in the data set used to develop the proposed neural models.

Table 1 – Descriptive statistics of the variables in the database.

Parameters	Minimum	Maximum	Mean	Median	Standard Deviation
k_n (Kpa/mm)	0.00	7515.00	266.06	90.96	601.99
t/a	0.00	2.00	0.51	0.00	0.68
σ_{n0} (MPa)	0.05	46.50	2.02	0.56	5.77
JRC	2.00	20.00	9.19	8.00	4.75
σ_c (MPa)	3.50	150.00	21.05	12.00	30.66
ϕ_b (Graus)	30.00	37.50	33.99	35.00	3.44
ϕ_{fill} (Graus)	0.00	35.50	14.62	0.00	15.98
δ_h (mm)	0.01	26.00	8.03	7.00	5.81
τ_s (MPa)	0.01	6.68	0.86	0.61	0.84
δ_v (mm)	-2.43	4.97	0.39	0.20	0.83

Source: Authors (2024).

3.3. Training and testing RBF models

According to Souza, Batista and Silva (2021), network training consists of changing synaptic weights and thresholds according to a specific learning algorithm. In this article, the construction of RBF network models was carried out using the newrb function[1] developed by Hagan, Demuth and Beale (1996) and available in Matlab's Neural Network Toolbox.

Mota et al. (2011) point out that in the test phase, input patterns not used in training are used and it is at this stage that the performance achieved by the RBF network is effectively evaluated by means of performance indices compatible with the task of interest. In regression, it is common to use the correlation between the actual output values and the values predicted by the model. The coefficient of determination, usually denoted R2, is also widely used to assess how well the regression model fits the data. Once trained and tested, the neural network allows the models to be validated with field data, which in this study was done by evaluating the ability of the models developed to represent the behavior of the modeled parameters, according to the studies by Dantas Neto et al. (2017), Leite et al. (2019a), Leite et al. (2019b) and Dantas Neto et al. (2022). To build the regression models based on the RBF network, a source code was developed in the Matlab script language (version 13a), the flowchart of which is illustrated in Figure 2.

Initially, the input and output patterns are loaded and read. Such data must be arranged in lines and in a single file with the .dat extension. Possetti (2009) points out that, for example, normalization techniques can be implemented to the data set to be modeled using RBF, to make the training process more efficient. In this way, the data used in the training and testing phases were normalized between 0 and 1. The next stage consists of randomly selecting the samples to be used in the training and testing phases. In this work, 80% of the available experimental data was used for the training phase and 20% for the test phase, obtained randomly from the available data set, as suggested by Turcato (2015).

Next, the adjustment parameters required by the algorithm are defined, namely the width of the radial basis function (σ) and the largest mean squared error (MSE) allowed in the training stage. In the newrb function, this parameter is denoted by the term goal. In this work, we made σ = 0.5 and tested 10 values for the goal parameter, varying it from

[1] https://www.mathworks.com/help/deeplearning/ref/newrb.html

0.0001 to 0.001, so that we could satisfactorily assess the influence of the MSE value on the generalization capacity of the models (DIAS, 2005).

The centers of the radial basis functions are defined using clustering techniques so that the Euclidean distance between each center and the input vectors in the training set is as small as possible. The centers of the radial basis functions represent the synaptic weights between the input layer and the intermediate layer of the RBF network. Once obtained, their values are used to calculate the radial basis functions that represent the neurons of the intermediate layer according to Equation 1 presented above. The output of the RBF network is calculated as the linear combination of the activations of the hidden neurons weighted by the synaptic weights linking them to the output neuron.

According to the newrb function, developed by Hagan, Demuth and Beale (1996), the outputs corresponding to the training samples have their values compared to the observed values to generate the mean squared error for that training epoch. After calculation, the input vector for which this mean squared error was the maximum among those calculated is identified, and if this value is higher than the value set for the target MSE in the training process, a new hidden neuron is added, and the radial functions of the hidden layer are adjusted again. This process takes place iteratively and training is terminated when the maximum MSE value allowed in training, called the goal, is reached or the maximum number of neurons is reached (i.e. the total number of examples in the training set).

After the iterations made during the training process, the statistical performance in the training and testing phases is calculated in the source code, considering 50 different simulations in which randomly chosen input-output data is used. The performance of the RBF network is evaluated by the mean, standard deviation, maximum and minimum values and the median of the coefficients of determination (R^2).

The last stage of the modeling process consists of storing the topology of the RBF network with the best performance, considering the highest geometric mean of the coefficients of determination of the 2 output variables of interest using test samples. The stored network allows the models to be validated, so it is necessary to insert a .dat file containing data that was not used in the previous stages.

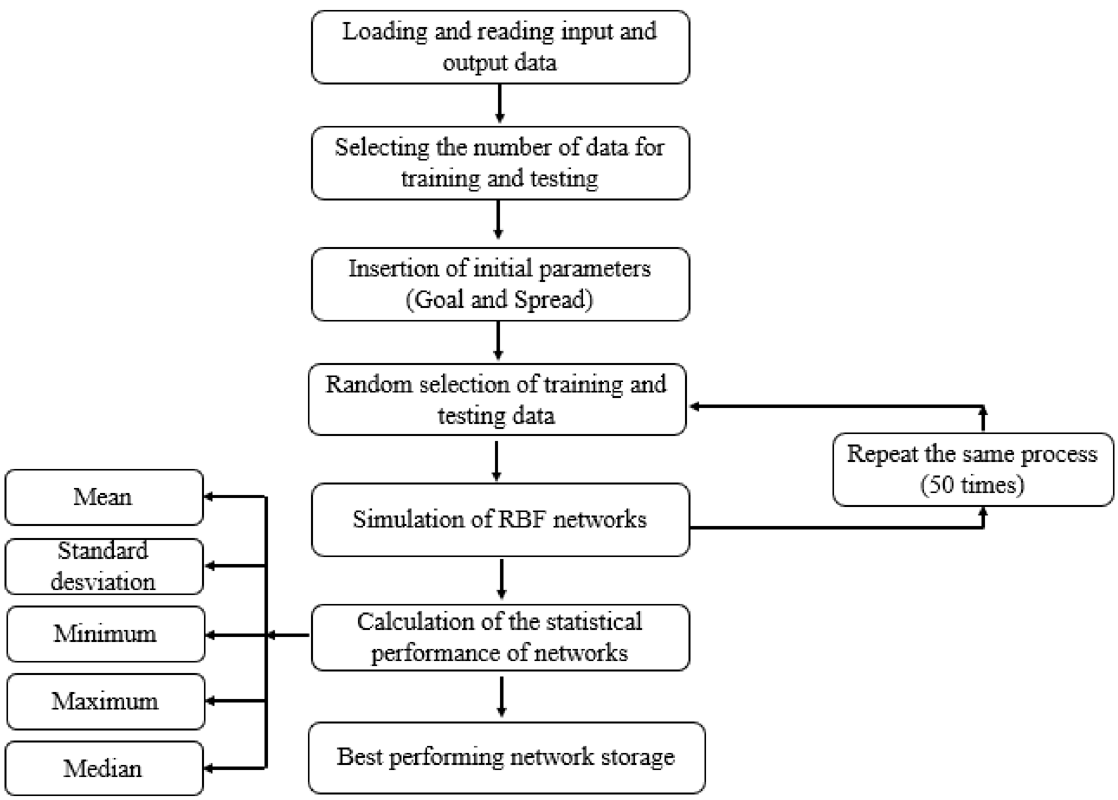

Figure 2 – Illustration of the RBF network training and testing processes.
Source: Authors (2024).

3.4 Regression model validation and selection stage

Once all the models had been developed, an analysis was carried out to select as suitable models for validation those with coefficients of determination (R2) greater than 0.95 and root mean square errors (RMSE) closer to zero in the training and testing phases. Lower RMSE values suggest a better fitting model, as they indicate a smaller error between the actual data and that estimated by the RBF, which in statistical terms indicates a good fitting model.

Validation consists of evaluating the models in terms of their ability to satisfactorily represent the influence of the input variables on the predicted values for shear stress and dilation in hypothetical rock discontinuities, in a similar way to what was done in the works by Dantas Neto et al. (2017), Leite et al. (2019a), Leite et al. (2019b), and Dantas Neto et al. (2022). The model for predicting the shear behavior of rock discontinuities was then selected using the best performance in the validation phase as the final criterion.

4. Results and discussion

Table 2 shows the values of the coefficients of determination (R2) and the RMSE obtained during the training and testing phases of the RBF models proposed for predicting the shear behavior of rock discontinuities represented by shear stress and dilation.

Table 2 – Coefficients of determination and RMSE of the training and test sets for shear stress and dilation.

Configurations			Shear stress				Dilation			
			Training		Test		Training		Test	
Models	*Goal*	Archictecture	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
M1	0.0002	8-242-2	0.9840	0.0153	0.9872	0.0157	0.9872	0.0127	0.9840	0.0141
M2	0.0003	8-129-2	0.9760	0.0189	0.9828	0.0185	0.9798	0.0184	0.9800	0.0178
M3	0.0004	8-103-2	0.9686	0.0217	0.9787	0.0205	0.9719	0.0182	0.9742	0.0203
M4	0.0005	8-87-2	0.9632	0.0235	0.9748	0.0223	0.9624	0.0210	0.9669	0.0230
M5	0.0006	8-76-2	0.9593	0.0247	0.9709	0.0240	0.9528	0.0235	0.9638	0.0241
M6	0.0007	8-72-2	0.9566	0.0255	0.9687	0.0248	0.9374	0.0271	0.9507	0.0280
M7	0.0008	8-64-2	0.9552	0.0266	0.9643	0.0244	0.9285	0.0297	0.9347	0.0301
M8	0.0009	8-51-2	0.9419	0.0295	0.9579	0.0288	0.9214	0.0304	0.9399	0.0311
M9	0.0001	8-49-2	0.9388	0.0313	0.9480	0.0286	0.9193	0.0320	0.9280	0.0299

Source: Authors (2024).

The results show that considering a very low goal leads to overfitting, which is when a statistical model fits the training data set very well but proves ineffective at predicting the output values for test samples. Therefore, the model built with a goal of 0.0001 was discarded. In accordance with the established criteria, models M1, M2, M3, M4, and M5, with R2 greater than 0.95 and RMSE close to 0 in the training and testing phases, were chosen as suitable for the validation process. To this end, hypothetical discontinuities were used to ascertain whether they could express the influence of the variables that govern the shear behavior of filled and unfilled rock discontinuities, under CNL and CNS conditions. These discontinuities have as constant variables σ_c = 12 MPa, JRC = 5, ϕ_b= 37.5º, and to verify the influence of the fill we used σ_{fill} = 35.5° and different values of $t/a \in \{0, 0.6, 1.0, 1.4\}$.

The results obtained in the validation phase indicate that the M1 model best represented the influence of the input variables on the shear behavior of the rock discontinuities. The results provided by the RBF were coherent, and as expected, there was an increase in shear stress (Figures 3a and 4a) as well as a decrease in dilation (Figures 3b and 4b) with the increase in contour normal stiffness and initial normal stress, respectively.

It can also be seen that for high levels of initial normal stress, there is a marked decrease in dilation (Figure 4b). This is due to the degradation of the asperities of the unfilled discontinuity, as shown in the experimental results presented by Indraratna and Haque (2000), Indraratna, Oliveira and Brown (2010), Oliveira, Indraratna and Nemcick (2009) and Oliveira and Indraratna (2010), indicating the model's ability to understand this phenomenon.

To evaluate the behavior of the model with the change in roughness, JRC values of 5 and 10 were assumed for hypothetical discontinuity without filling, under CNS (560 kPa/mm). Figures 5a and 5b show the increase in both shear stress and dilation with roughness represented by the JRC value, as expected.

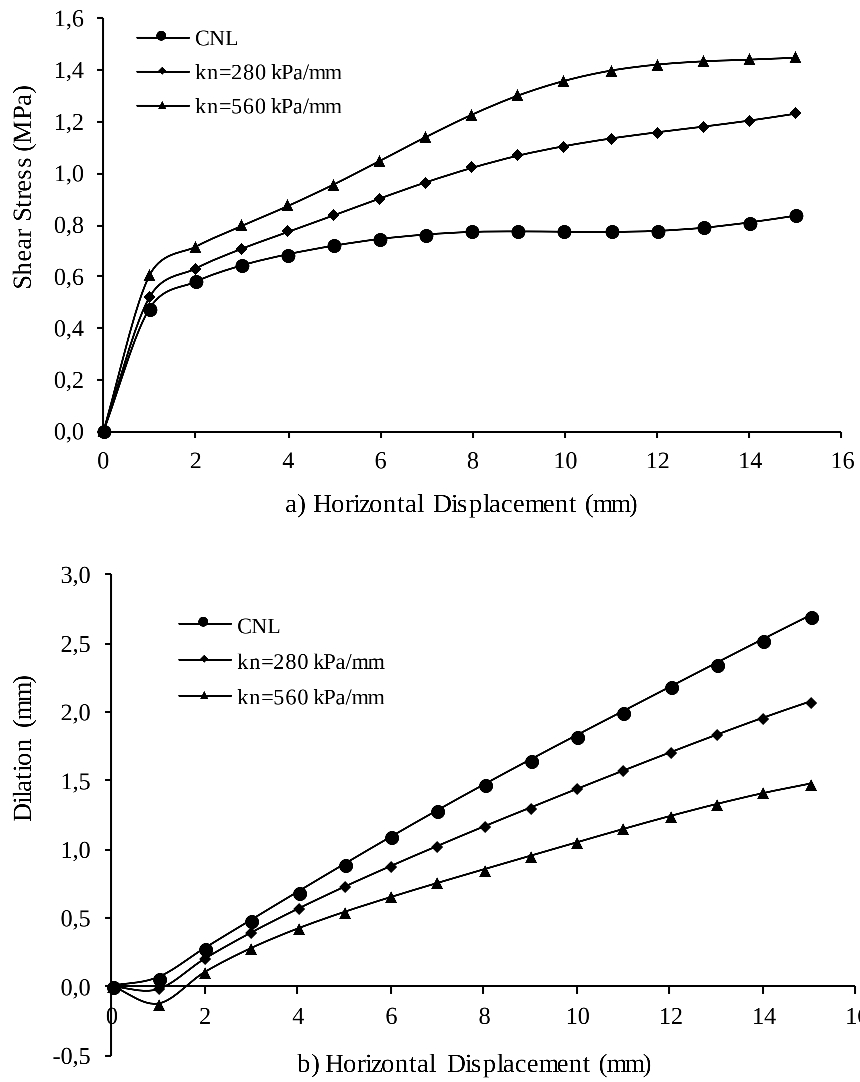

Figure 3 – Influence of normal stiffness on shear stress (a) and dilation (b) (σ_{no}= 0,5 MPa, t/a =0).
Source: Authors (2024).

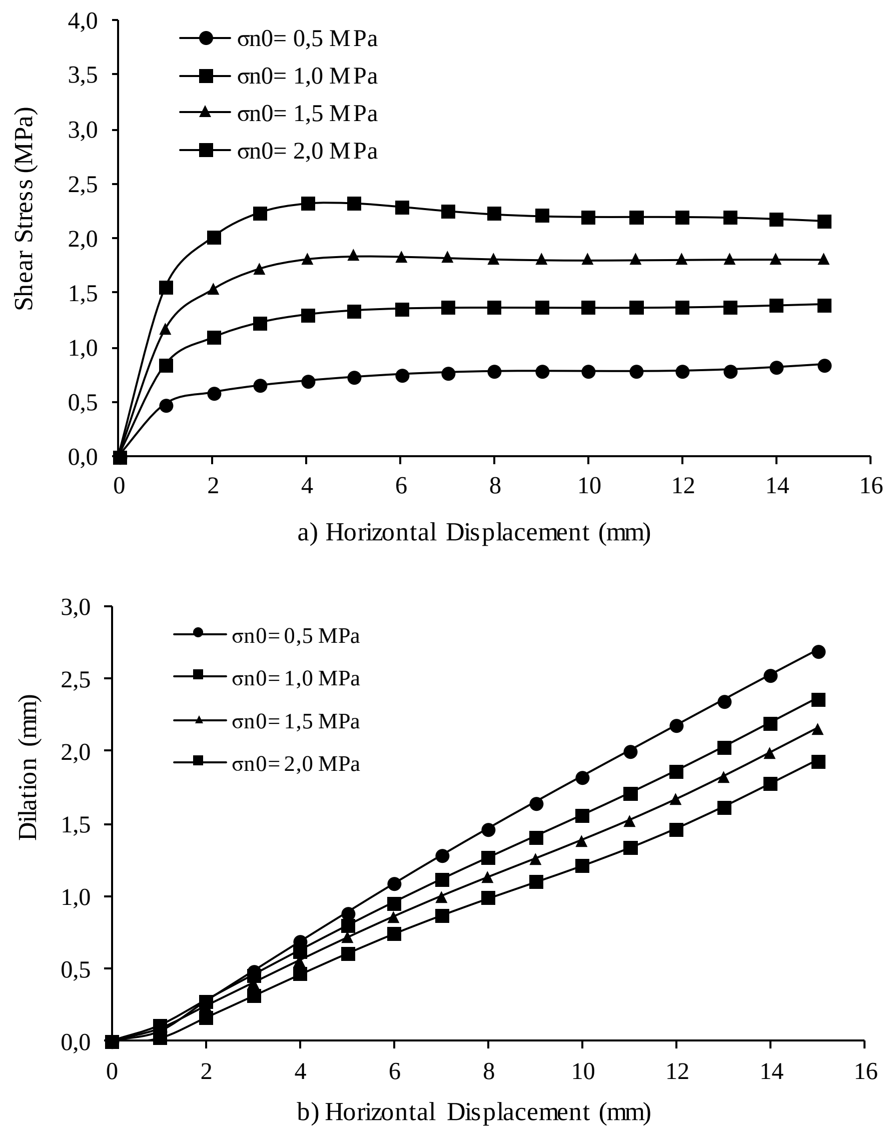

Figure 4 – Influence of initial normal stress on shear stress (a) and dilation (b) (k_n = 0 kPa/mm and t/a = 0).
Source: Authors (2024).

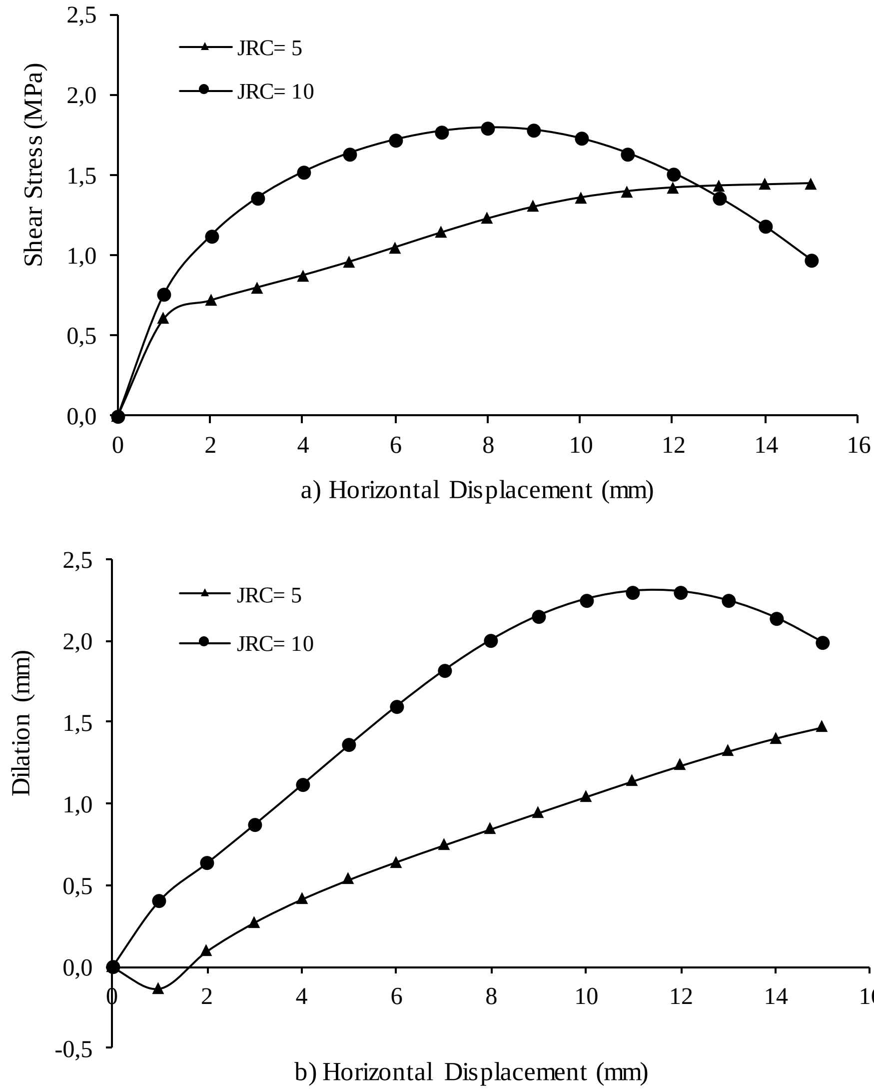

Figure 5 – Influence of roughness on shear stress (a) and dilation (b) (k_n = 560 kPa/mm, σ_{no} = 0,5 MPa and t/a=0)
Source: Authors (2024).

For hypothetical discontinuities with filling, the following parameters were considered: k_n = 560 kPa/mm; σ_{no} = 0.5 MPa; ϕ_{fill} = 35.5°; t/a values ranging from 0 to 1.4; JRC=5; σ_c = 12 MPa and ϕ_b=37.5. The results shown in Figures 7a and 7b indicate that the M1 model can represent in a very satisfactory way the reduction in shear stress and dilation with increasing fill thickness, according to results obtained by different authors, such as Indraratna and Haque (2000), Indraratna, Oliveira and Brown (2010), Oliveira, Indraratna and Nemcick (2009), and Oliveira and Indraratna (2010).

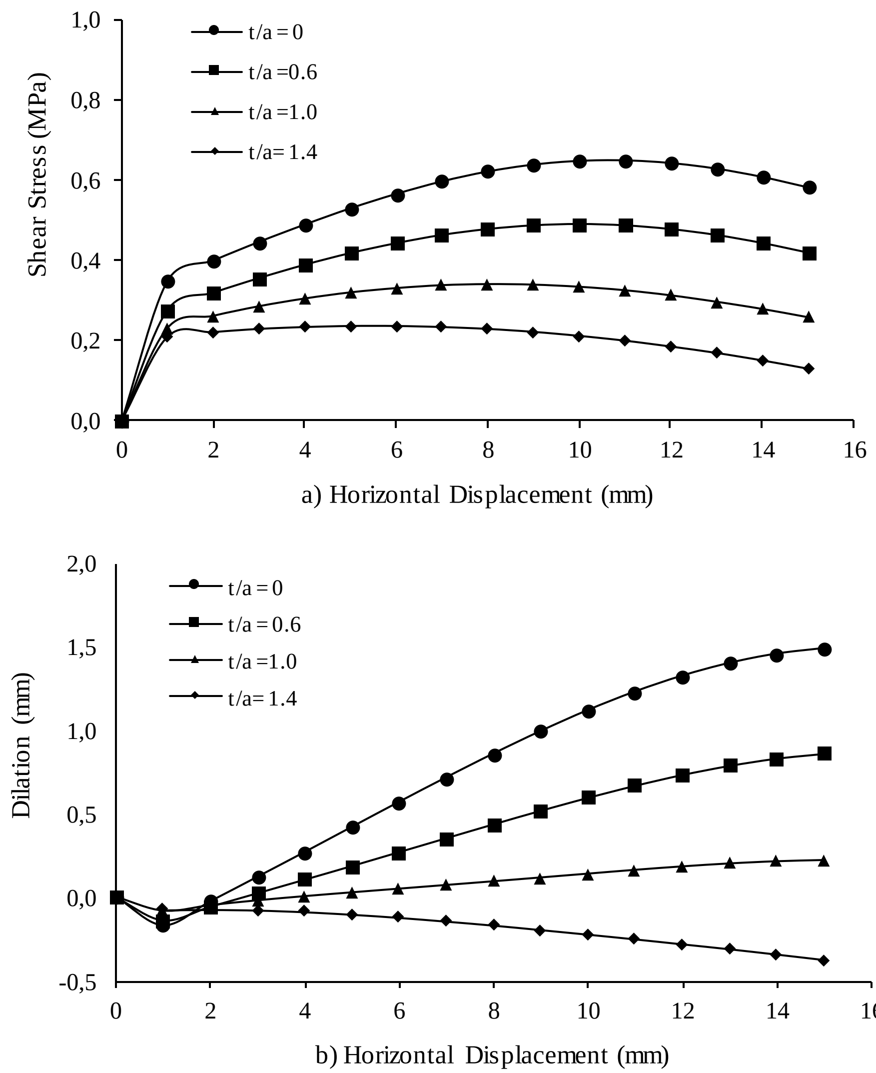

Figure 6 – Influence of filling under CNS on shear stress (a) and dilation (b) (k_n = 560 kPa/mm and σ_{no} = 0,5 MPa)
Source: Authors (2024).

The M1 model presents an architecture composed of 8 neurons in the input layer, 242 neurons in the hidden layer and 2 neurons in the output layer, as illustrated in Figure 7. The determination coefficients and RMSE values for the shear stress and dilation obtained by Said model are presented in Figures 8a and 8b, respectively.

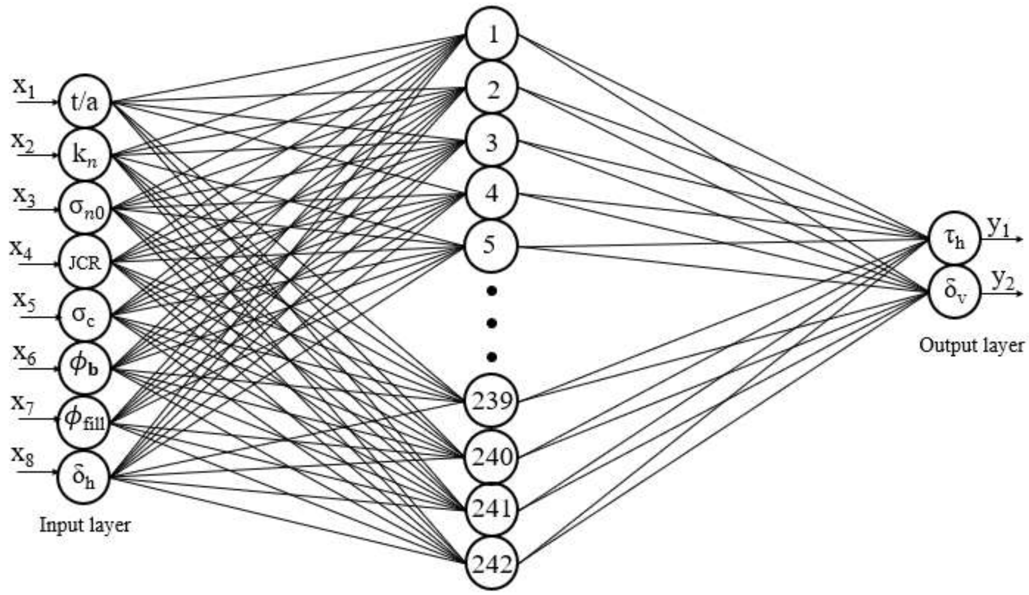

Figure 7 – Architecture of the best performing RBF model (8-242-2).
Source: Authors (2024).

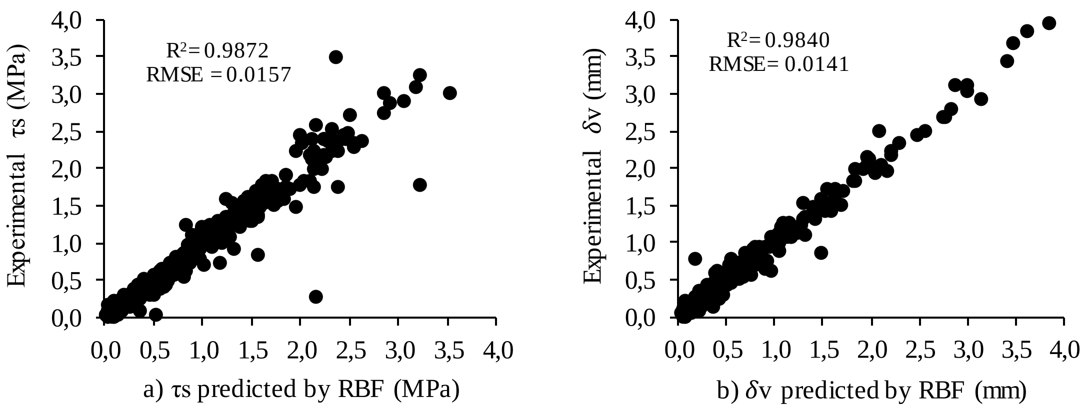

Figure 8 – Correlation between experimental data and those predicted by the RBF network for shear stress for the training and test sets.
Source: Authors (2024).

Figure 9 presents the comparison between the results provided by the RBF model, the experimental data and the analytical model of Indraratna and Haque (2000) and the neural models of Dantas Neto et al. (2017) and Leite (2019) for the shear stress (a) and dilation (b) for an unfilled rock discontinuity tested under conditions of constant normal stiffness with k_n=453 kPa/mm, σ_c= 12 MPa, JRC=8 and $\phi_b = 37{,}5°$.

The results show that for both output variables, the M1 model fits better to the experimental data than the other models considered, showing that neural networks of the radial basis function type have provided better results than those obtained by traditional analytical models and by multilayer perceptrons.

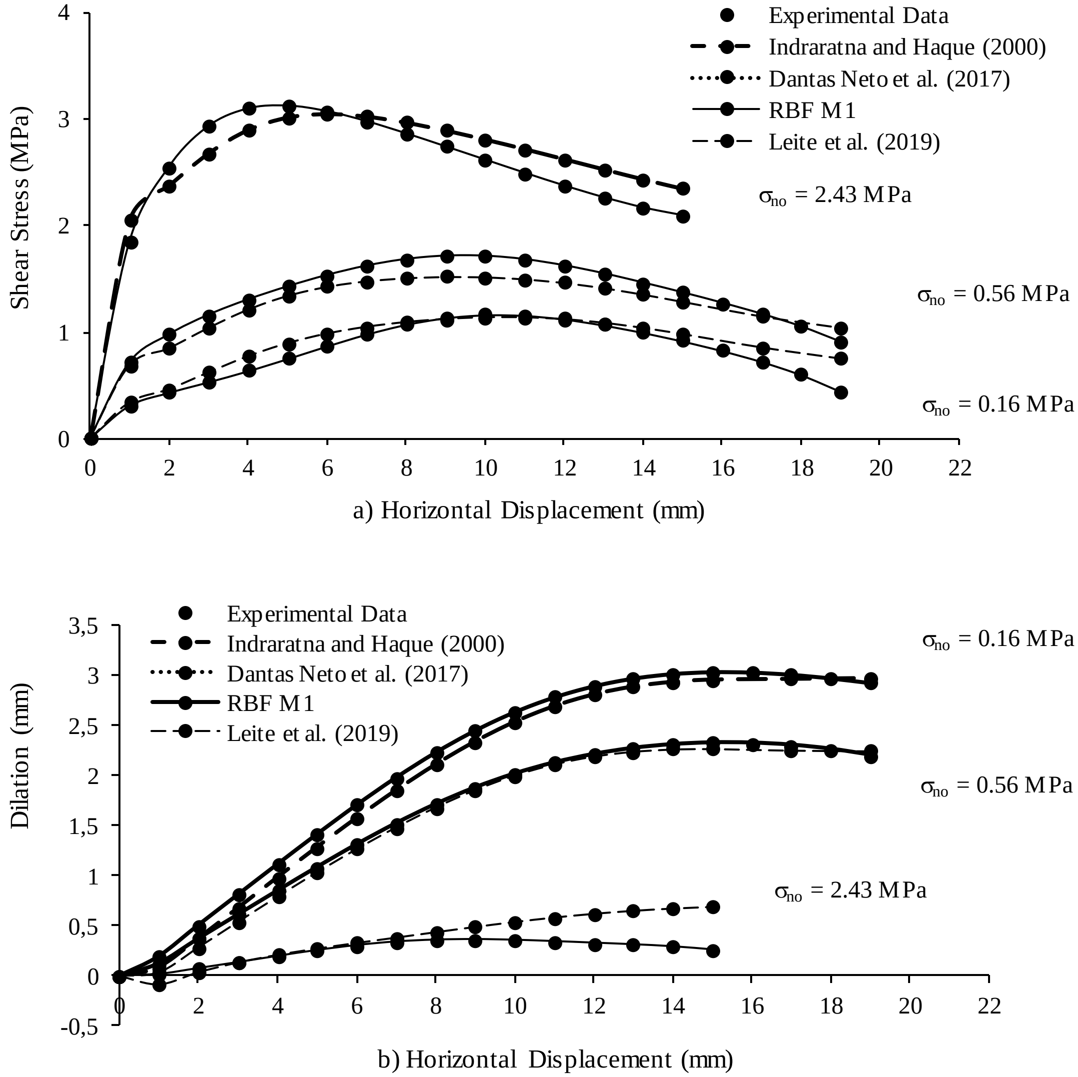

Figure 9 – Comparison between experimental data and neural and analytical models for shear stress (a) and dilation (b).
Source: Authors (2024).

5. Conclusions

In this work, an alternative approach was proposed for estimating the shear behavior of filled and unfilled rock discontinuities under CNL and CNS conditions. The model called M1 was obtained with a spread equal to 0.5 and a goal of 0.0002, having as input variables the normal stiffness (kn) given in kPa/mm, initial normal stress (σ_{n0}) in MPa, the coefficient of joint roughness (JRC), the resistance to uniaxial compression of the intact rock (σ_c) in MPa, the basic friction angle ($\square_b$) in degrees and shear displacement (δ_h) in mm, while the predictor variables refer to resistance to shear (τ_s) given in kPa and the corresponding dilation (δ_v) in mm, presenting an architecture of 8-242-2.

The coefficients of determination were greater than 0.98 for shear stress and dilation and the RMSE values were equal to or less than 0.0157 in the training and testing phases, indicating excellent agreement between the experimental data and the results obtained by the proposed RBF model. Considering the various characteristics of hypothetical filled and unfilled rock discontinuities, the model chosen can satisfactorily represent the influence of the variables that govern their shear behavior and some specific mechanisms, such as the degradation of roughness at high levels of initial normal stress.

The limitations of the proposed model include the need to implement a source code to test and validate the results, given that the software interface only allows the data to be trained. In addition, the proposed model did not consider other important factors that are currently being investigated, such as some characteristics of the fill material, such as its degree of compaction, degree of saturation and the cohesive portion of its shear strength, as well as the effect of weathering on the walls of rock discontinuities. In short, the proposed model is an alternative method for acquiring shear stress and dilation quickly and economically for everyday applications in the field of rock mechanics.

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