



Modelling the High Strain Rate Tensile Behavior of Steel Fiber Reinforced Concrete Using Artificial Neural Network Approach

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Abstract. Conventional concrete material shows relatively low ductility and energy dissipation capacity under high strain rate tensile loads. The use of steel fibers into concrete can significantly improve the tensile behavior of concrete subjected to high strain rate loads by fibers bridging the concrete crack surfaces, resulting in a high impact resistance and energy dissipation capacity. Experimental research evidenced that the parameters of volume fraction, aspect ratio and tensile strength of steel fibers affect the characteristics of steel fiber reinforced concrete (SFRC) composite materials under high strain rate tensile loads. However, the existing design codes, i.e. CEB-*fib* model code 1990 and *fib* model code 2010, recommend design formulations for the prediction of the behavior of normal concrete under different strain rate loads, which are only function of strain rate of the loads. Accordingly, development of the design models to predict the behavior of SFRC materials when subjected to high strain rate loads is still lacking in the literature. Hence, the current paper aims to improve the design models recommended in the existing design codes (e.g. *fib* model code 2010). An artificial neural network approach is adopted to predict more accurately the tensile behavior of SFRC materials. Besides the strain rate load effect, this approach considers the effects of the volume fraction, aspect ratio and tensile strength of steel fibers. Finally, the predictive performance of the proposed model was evaluated by simulating relevant experimental tests.

Keywords: Steel fiber reinforced concrete · High strain rate load · Analytical model · Artificial neural network

1 Introduction

The experimental studies in the literature evidence that normal concrete shows low ductility and energy dissipation capacity under high strain rate loads, while introducing various types of fibers into the concrete mixtures, especially steel fibers, can significantly improve its behavior under high strain rate loads (Nili and Afroughsabet 2010; Soufeiani

et al. 2016). The crack bridging effects of steel fibers in concrete causes higher impact resistance and energy dissipation capacity of steel fiber reinforced concrete (SFRC) composite materials under high strain rate loads. In other words, the fiber bridging mechanism, mainly those of fiber pull-out and snubbing effect at the fiber exit point, limits crack propagation and enhances the energy dissipation capacity. In this regard, prediction of the behavior of SFRC materials under tensile impact tests is complex due to the nonlinear relationship between the impact force and the effective variables. However, some researchers developed analytical models to predict the behavior of SFRC under impact tests (Soufeiani et al. 2016). In this area, proposing a formulation with a design framework to accurately predict the behavior of SFRC composite materials under impact loads considering the influence of effective parameters is an issue that needs to be addressed.

Mathematical methodologies in the field of machine learning, such is the case of artificial neural network (ANN), can be helpful for the development of models to accurately predict the impact behaviour of SFRC materials. In this regard, the present study focuses on proposing an analytical model with design framework for predicting the tensile behavior of SFRC composite materials under high strain loads using ANN method and considering the effective parameters.

2 Architecture of the ANN Models

Artificial neural networks (ANN) are inspired by the architecture of the human central nervous system. It is composed of an input layer that includes the variables, and an output layer, and more layers are added between these input and output layers, called hidden layers (for more details see Cascardi et al. 2017; Pham and Hadi 2014, 2016, Ramezansfat et al. 2020).

In this study, the proposed ANN-model was developed in Python programming language to estimate dynamic increase factor (DIF) of SFRC composite materials under high strain rate tensile loads. For the training and testing purposes of the ANN-model, a database of experimental tests results of SFRC under high strain tensile loads were collected from the literature. The analyzed database includes 42 SFRC samples tested under strain rates of less than 10s^{-1} and 115 SFRC samples under strain rates higher than 10s^{-1} , thus 157 SFRC samples form the database utilized in this study. The effective parameters adopted in the proposed model include volume fraction of steel fibers (V_f), aspect ratio of steel fibers (l_f/d_f), tensile strength of steel fibers (σ_{fu}), and concrete tensile strength (f_{ct}), were all reported for the specimens used in this database.

80% of the specimens was randomly selected as the training data, while the remaining 20% was the test data. Four neurons were adopted in the input layer for considering the four variables, while one neuron was defined in the output layer (Fig. 1). For the sake of simplicity, and for proposing a closed form formulation derived from the ANN-model, two neurons were adopted in the hidden layer. A sigmoid and a linear transfer function was used, respectively, in the hidden layer and in the output layer. After the network has been designed, and the value of the input parameters has been standardized to improve the ANN-model and make the training faster, the network has started being trained.

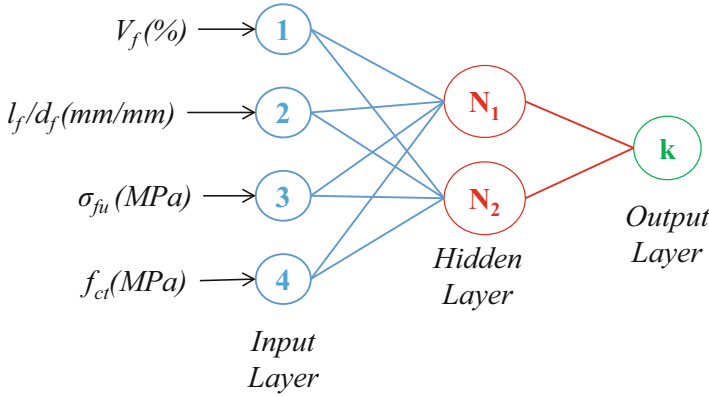


Fig. 1. Architecture of the proposed network.

3 Proposed Model for Predicting the Dynamic Increase Factor (DIF)

Dynamic increase factor (DIF) is defined as the ratio of dynamic to static strength, to determine the effects of strain rate on the concrete properties. Accordingly, DIF parameter is usually considered as a function of strain rate of loading. In this regard, the CEB-FIP Model Code 1990 (MC1990) and CEB-FIP Model Code 2010 (MC2010) have proposed design formulations for estimating the DIF of concrete under compression and tension as a function of strain rate of loading (CEB-FIP 1990, 2010). The authors already developed design formulations for the prediction of DIF of SFRC materials under compression, by considering the effective parameters based on modifying the proposed formulations in MC2010 (Ramezansafat et al. 2020). Figure 2 shows the comparison of the experimental compressive DIF with the corresponding DIF obtained from MC 1990, MC 2010 and the developed model, evidencing the good predictive performance of the developed model compared to the design codes recommendations. The details of this model can be found elsewhere (Ramezansafat et al. 2020).

In the current section, the ANN-model is developed based on modifying the proposed formulation in MC2010, to predict the DIF of SFRC materials under tension, considering the steel fiber effects in concrete. The performance of the developed model is compared with the proposed formulations in MC1990 and MC2010 to predict the tensile DIF of SFRC materials.

MC1990 proposed Eqs. 1–2 to estimate the tensile strength of normal concrete under high rates of loading. These Eqs. were established using appropriate underlying theory derived from thermodynamics and fracture mechanics analysis (CEB-FIP 1990).

$$f_{ct,Dyn}/f_{ct} = (\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{1.016\delta_s} \quad \text{for } \dot{\epsilon}_{ct} \leq 30 \text{ s}^{-1} \quad (1)$$

$$f_{ct,Dyn}/f_{ct} = \beta_s (\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{1/3} \quad \text{for } \dot{\epsilon}_{ct} > 30 \text{ s}^{-1}$$

$$\log \beta_s = 7.112\delta_s - 2.33$$

$$\delta_s = 1/(10 + 6f_{ct}/f_{c0}) \quad (2)$$

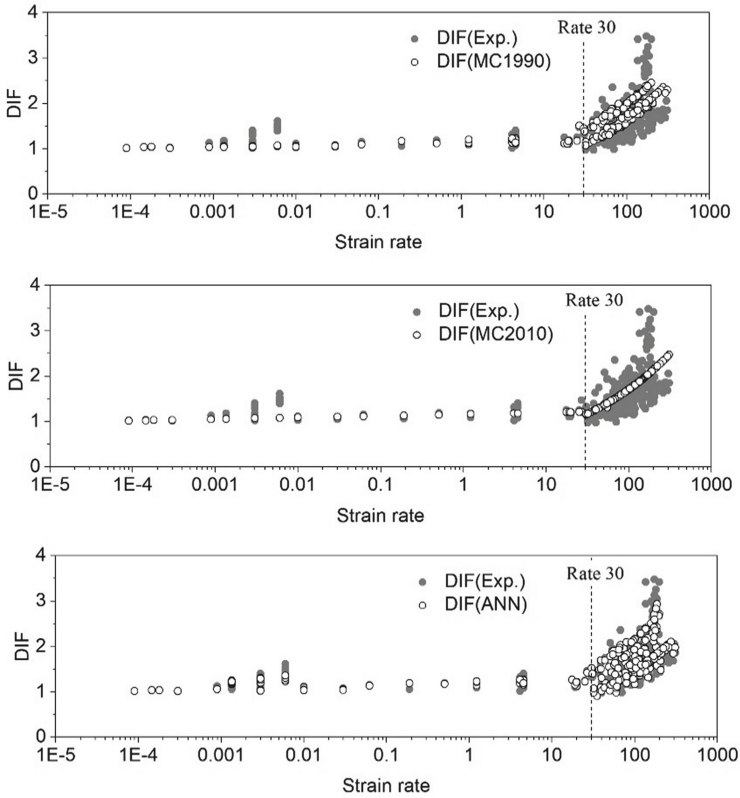


Fig. 2. Comparison of DIF values obtained experimentally and from MC 1990, MC 2010 and proposed ANN model (Ramezansfat et al. 2020).

where $f_{ct,Dyn}$ is the dynamic tensile strength under high rates of loading, f_{ct} is the static tensile strength, $\dot{\epsilon}_{ct}$ is the tensile strain rate, $\dot{\epsilon}_{ct0} = 3 \times 10^{-6} \text{ s}^{-1}$, and $f_{c0} = 10 \text{ MPa}$.

In this regard, MC2010 proposed the following equations for the tensile DIF of normal concrete:

$$f_{ct,Dyn}/f_{ctm,St} = (\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{0.018} \quad \text{for } \dot{\epsilon}_{ct} \leq 10 \text{ s}^{-1} \quad (3)$$

$$f_{ct,Dyn}/f_{ctm,St} = 0.0062(\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{1/3} \quad \text{for } \dot{\epsilon}_{ct} > 10 \text{ s}^{-1} \quad (4)$$

where $f_{ct,Dyn}$ is tensile strength under high rates of loading, $f_{ctm,St}$ is the mean value of tensile strength of concrete, and $\dot{\epsilon}_{ct0} = 1 \times 10^{-6} \text{ s}^{-1}$.

These formulations used in MC1990 and MC2010 were proposed for two domains of strains, the first ranging from low to intermediate ($\dot{\epsilon}_{ct} \leq 30 \text{ s}^{-1}$ for MC1990 and $\dot{\epsilon}_{ct} \leq 10 \text{ s}^{-1}$ for MC2010) and the other from intermediate to high rates ($\dot{\epsilon}_{ct} > 30 \text{ s}^{-1}$ for MC1990 and $\dot{\epsilon}_{ct} > 10 \text{ s}^{-1}$ for MC2010). In a log (DIF) versus log($\dot{\epsilon}$) the relationship is bilinear with a change in slope around 30 s^{-1} and 10 s^{-1} in MC1990 and MC2010, respectively.

The formulations proposed in MC1990 and MC2010 are valid for normal concrete. However, these formulations need to be updated for the case of SFRC materials due to the steel fiber effects in concrete. In order to consider the concrete steel fiber reinforcement in the formulations proposed by MC2010 (Eqs. 3–4), the alterations were conducted on the power of Eq. 3 proposed by MC2010 (k_1 in Eq. 5) for the range of $\dot{\epsilon}_{ct} \leq 10 \text{ s}^{-1}$ and on the constant coefficient of Eq. 4 proposed by MC2010 (k_2 in Eq. 6) for the strain rates beyond 10. In this regard, k_1 and k_2 parameters were derived from experimental database using Eqs. 5–6, and were adopted as output variable in the ANN-model. It should be noted that the other possibilities for the modification of the formulation of MC2010 (e.g. power of Eq. 4) was investigated by the authors, and the proposed modification strategy was adopted since it provides the best performance for predicting the tensile DIF of SFRC materials.

$$f_{ct,Dyn}/f_{ctm,St} = (\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{k_1} \Rightarrow k_1 = \ln(f_{ct,Dyn}/f_{ctm,St})/\ln(\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0}) \quad \text{for } \dot{\epsilon}_{ct} \leq 10 \text{ s}^{-1} \quad (5)$$

$$f_{ct,Dyn}/f_{ctm,St} = k_2(\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{1/3} \Rightarrow k_2 = (f_{ct,Dyn}/f_{ctm,St})/(\dot{\epsilon}_{ct}/\dot{\epsilon}_{ct0})^{1/3} \quad \text{for } \dot{\epsilon}_{ct} > 10 \text{ s}^{-1} \quad (6)$$

k_1 and k_2 parameters were considered as a function of volume fraction of steel fibers (V_f), aspect ratio of steel fibers (l_f/d_f), tensile strength of steel fibers (σ_{fu}), and concrete tensile strength (f_{ct}) for SFRC materials. Consequently, these four variables ($V_f, l_f/d_f, \sigma_{fu}, f_{ct}$) were adopted in the input layer of the ANN-model. Two neurons were introduced in the hidden layer, and k_1 and k_2 parameters were defined as the output layer.

The architecture of the ANN-model was optimized in terms of the different numbers of neurons and the different transfer functions in the hidden layer, aiming to provide the highest coefficient of correlation (R^2) with experimental data. Since the main objective of this study is to propose a closed form design formulation derived from the ANN-model for the tensile DIF of SFRC materials, the neurons number adopted in the hidden layer was minimized. The performance of the proposed ANN-model was verified against the experimental results for two ranges of lower and higher than intermediate strain rates. The plot of the experimental tensile DIF versus the corresponding ANN-model predictions for the database is shown in Figs. 3 and 4, and also, compared with the DIFs obtained from MC1990 and MC2010.

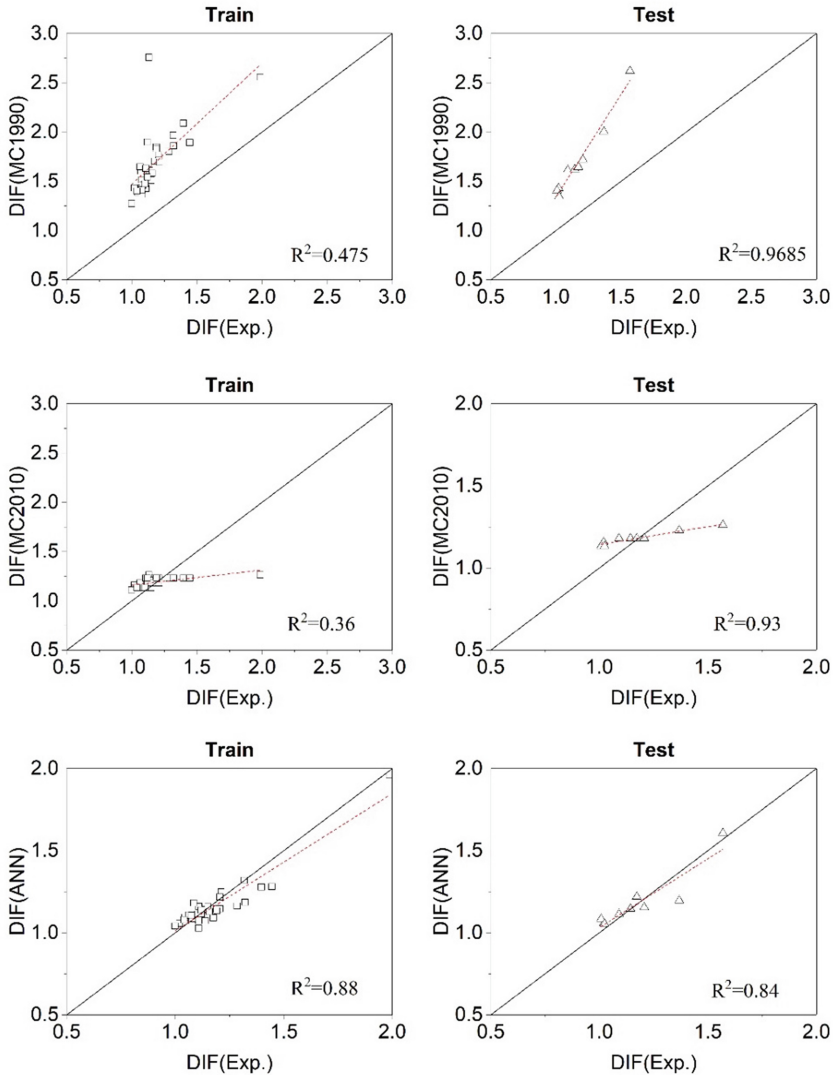


Fig. 3. Comparison of DIFs obtained from MC1990 and MC2010 and ANN-model with corresponding experimental values for strain rates lower than intermediate level

The best-fit line approximately aligns with the 45° benchmark proving a proper correlation between the experimental results and the predictions of the proposed ANN-model for the train and test data. The coefficient of correlation (R^2) of DIFs obtained from the ANN-model with the experimental results for training and test data are, respectively, $R^2 = 0.88$ and 0.84 for strain rates $\dot{\epsilon}_{ct} \leq 10 \text{ s}^{-1}$, and $R^2 = 0.65$ and 0.76 for strain rates $\dot{\epsilon}_{ct} > 10 \text{ s}^{-1}$ (Figs. 3 and 4).

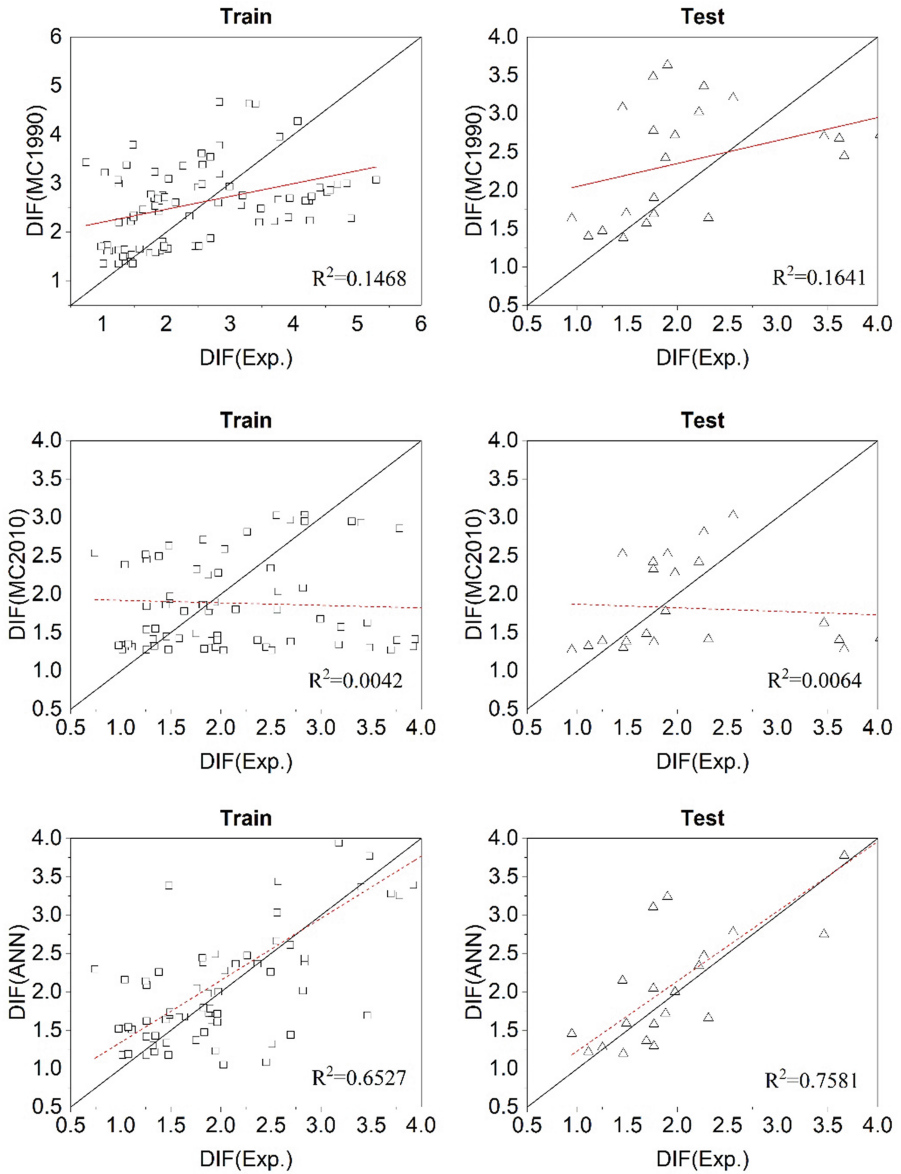


Fig. 4. Comparison of DIF obtained from MC 1990 and MC 2010 models and ANN with corresponding experimental values of strain rates higher than intermediate level.

However, the coefficient of correlation (R^2) of DIFs obtained according to MC1990 and MC2010 using Eqs. 1 and 3 for strain rates lower than intermediate level are, respectively, 0.475 and 0.36 for training data and 0.97 and 0.93 for test data. In addition, for strain rates higher than intermediate level, R^2 of DIFs of MC1990 and MC2010 (Eqs. 2 and 4) are, respectively, 0.1468 and 0.004 for training data, and 0.164 and 0.0064

for test data. This comparison evidences that the proposed ANN-model can predict the tensile DIF of SFRC materials with better accuracy compared to the models proposed in MC1990 and MC2010.

Moreover, the experimental tensile DIF versus strain rate is plotted in Fig. 5, and is compared with the tensile DIF obtained from MC1990, MC2010 and ANN-model. This figure also evidences the good predictive performance of the developed ANN-model for the tensile DIF of SFRC materials in comparison with the proposed formulations in MC1990 and MC2010.

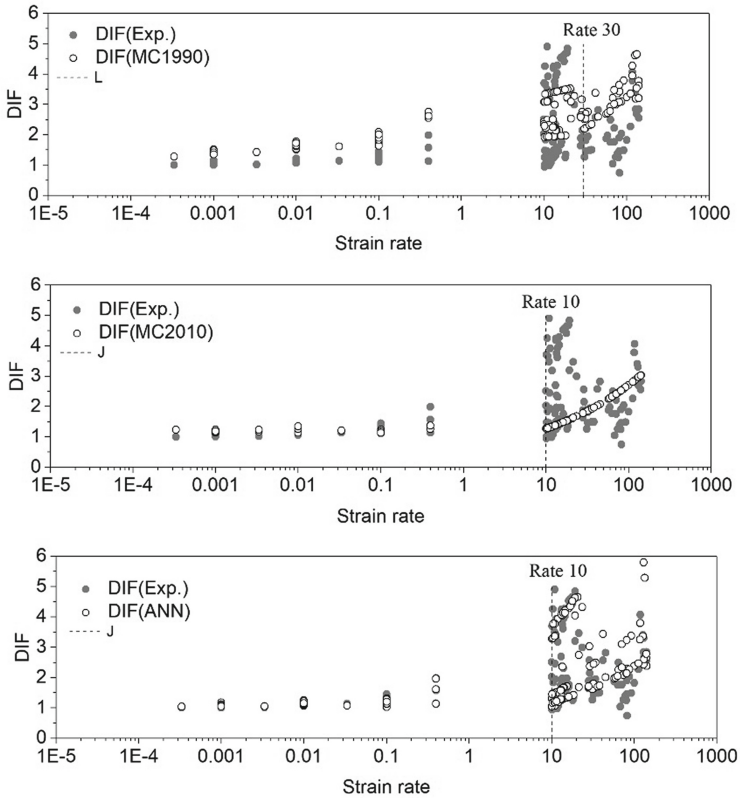


Fig. 5. Comparison of experimental DIF with DIF obtained from MC 1990, MC 2010 and proposed ANN model.

4 Design Formulation Based on the ANN-Model

In the previous section, it was confirmed that the DIF of SFRC materials under tension obtained using the ANN-Model have a good agreement with the relevant experimental data. However, it is inconvenient for engineers to use the networks for engineering design purposes, since they need to have the fundamental knowledge of ANN and Python

to be able to use the proposed model. Hence, in this section, a simplified closed form formulation derived from the developed ANN-model based on modifying the MC2010 formulation is proposed to predict the DIF of SFRC materials under tension. The simplified formulation is derived from the trained networks by using input parameters and transfer functions and combining the weight matrix and the bias matrix (Fig. 6), and more details about the adopted strategy can be found elsewhere (Pham and Hadi 2014, 2016; Yousif 2013). The sigmoid transfer function was used in the hidden layer (see Eq. 7), while the linear transfer function (see Eq. 8) was used in the output layer. The procedure to develop the user-friendly equations based on the ANN-model to determine k_1 and k_2 parameters is represented in Fig. 6.

$$f(x) = 1 / (1 + e^{-x}) \quad (7)$$

$$f'(x) = x \quad (8)$$

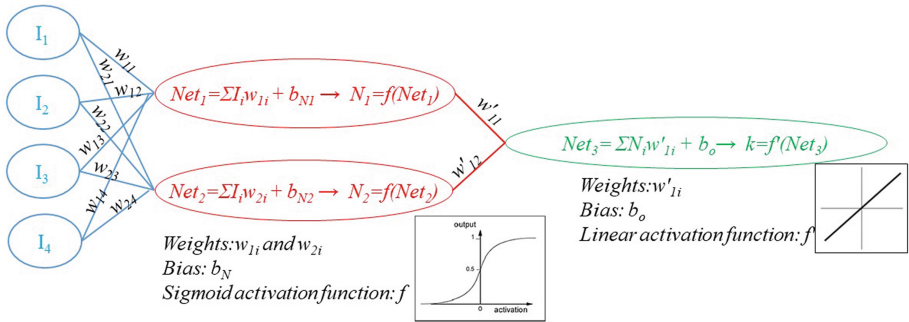


Fig. 6. Architecture of the proposed ANN equation

The equations derived from the ANN-model to determine k_1 and k_2 parameters to be used in Eqs. (5–6) for predicting the tensile DIF of SFRC composite materials are as follows:

$$k_1 = \frac{0.2231}{1 + e^{-\alpha}} - \frac{0.315}{1 + e^{-\beta}} + 0.049$$

$$\alpha = -1.1844V_f + 0.0707(l_f/d_f) + 0.0008\sigma_{fu} + 0.0433f_{ct} - 4.8253$$

$$\beta = -0.7698V_f + 0.0405(l_f/d_f) + 0.0005\sigma_{fu} + 0.0444f_{ct} - 3.1611 \quad (9)$$

$$k_2 = \frac{0.554}{1 + e^{-\alpha}} - \frac{0.217}{1 + e^{-\beta}} - 0.126$$

$$\alpha = -0.0121V_f - 0.0042(l_f/d_f) - 0.000087\sigma_{fu} - 0.0541f_{ct} + 0.7481$$

$$\beta = -0.0188V_f - 0.0099(l_f/d_f) + 0.0002\sigma_{fu} - 0.137f_{ct} + 2.58 \quad (10)$$

5 Conclusion

The current study develops a model based on artificial neural network (ANN) approach to predict the dynamic increase factor (DIF) of SFRC composite materials under high strain rate tensile loads.

The developed model is based on modifying the proposed formulation in *fib* model code 2010 (MC2010) and considers the steel fiber effects in concrete by adopting the effective parameters in the model (i.e.: volume fraction of steel fibers (V_f), aspect ratio of steel fibers (l_f/d_f), tensile strength of steel fibers (σ_{fu}), and concrete tensile strength (f_{ct})). Moreover, a simplified closed form formulation derived from the developed ANN-model is proposed with a design framework to predict the DIF of SFRC materials under tension. In addition of the evaluation of the predictive performance of the developed model by comparing with the relevant experimental data, the proposed models in the design codes of MC2010 and MC1990 were assessed for the prediction of the tensile DIF of SFRC materials. The proposed formulations in MC1990 and MC2010 for the tensile DIF of concrete cannot predict well the tensile DIF of SFRC material, due to the lack of parameters to consider the impact of steel fibers in concrete in these formulations. However, the simplified closed form formulations developed in this study can provide good estimations of SFRC strength at high strain rate tensile loads.

The models developed in this study will be used for designing the impact resistance of SFRC elements subjected to high strain rate loads such as blast and impact, representative of terrorist attacks and accidents which is an ongoing research project in the University of Minho. For the next step, the authors aims to extend the developed model to achieve a higher degree of accuracy in predicting the tensile DIF of SFRC materials by adding more important parameters in the ANN-model, i.e. shape of steel fibers, fiber orientation factor, and fiber efficiency factor.

Acknowledgements. The study reported in this paper is part of the project “PufProtec - Prefabricated Urban Furniture Made by Advanced Materials for Protecting Public Built” with the reference of (POCI-01-0145-FEDER-028256) supported by FEDER and FCT funds. The second author also acknowledges the support provided by FEDER and FCT funds within the scope of the project StreColesf (POCI-01-0145-FEDER-029485).

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