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Explicit expressions for inelastic design quantities in composite frames considering effects of nearby columns and floors

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Abstract. Explicit expressions for rapid prediction of inelastic design quantities (considering cracking of concrete) from corresponding elastic quantities, are presented for multi-storey composite frames (with steel columns and steel-concrete composite beams) subjected to service load. These expressions have been developed from weights and biases of the trained neural networks considering concrete stress, relative stiffness of beams and columns including effects of cracking in the floors below and above. Large amount of data sets required for training of neural networks have been generated using an analytical-numerical procedure developed by the authors. The neural networks have been developed for moments and deflections, for first floor, intermediate floors (second floor to ante-penultimate floor), penultimate floor and topmost floor. In the case of moments, expressions have been proposed for exterior end of exterior beam, interior end of exterior beam and both interior ends of interior beams, for each type of floor with a total of twelve expressions. Similarly, in the case of deflections, expressions have been proposed for exterior beam and interior beam of each type of floor with a total of eight expressions. The proposed expressions have been verified by comparison of the results with those obtained from the analytical-numerical procedure. This methodology helps to obtain the inelastic design quantities from the elastic quantities with simple calculations and thus would be very useful in preliminary design.

Keywords: composite frames; cracking; neural network; service load; tension stiffening

1. Introduction

In buildings, composite floors allow faster construction, due to the reduction in the extent of propping systems. When the concrete slab and the steel section are structurally connected by shear connectors, the slab provides lateral stability to the steel sections in the sagging moment regions. More importantly, the concrete slab and steel section act integrally resulting in higher structural efficiency. The composite beams help in reducing the structural depth of the floors and thus enable to increase the number of floors for the given height of a building, resulting in overall economy. Composite beams which are continuous, allow still lower depth of section, lesser deflections, etc. and hence are used in multi-storey composite frames (along with steel columns) in buildings. The use of higher grade steel and concrete results in slender and sleeker sections (Costa-Neves *et al.* 2014), for which serviceability conditions, are likely to become the governing criteria.

At service load, the hogging moments at the ends of the composite beams, cause tensile stresses in the concrete slab. Consequently, the moments result in concrete cracking when the stresses exceed the tensile strength of the concrete. This concrete cracking leads to reduction in the stiffness of the beam and thereby causes moment redistribution along the length of the beams and also to the adjacent beams and columns. The redistribution may result in an increase in curvature and deflections. The structural behavior, on account of the concrete cracking, was observed to be considerably nonlinear even at low stress levels by He *et al.* (2010). Hence, appropriate evaluation of inelastic design quantities (moments and deflections) in the composite frames at service load, considering concrete cracking, is desirable.

The inelastic analysis of composite structures can be performed by the finite element, iterative or incremental methods/procedures (Baskar *et al.* 2002, Chaudhary *et al.* 2007, Zona *et al.* 2008, Varshney *et al.* 2013, Ramnavas *et al.* 2017). However, in the preliminary stages, a numbers of trials may be required to decide the spans and sizes of the members of the composite frames. The conventional methods/procedures (finite element, iterative or incremental) may not be appropriate in such case due to requirement of a large number of degrees of freedom and consequently large computational effort. For example, the required number of degrees of freedom for the inelastic analysis of even a single storey two bay composite frame by

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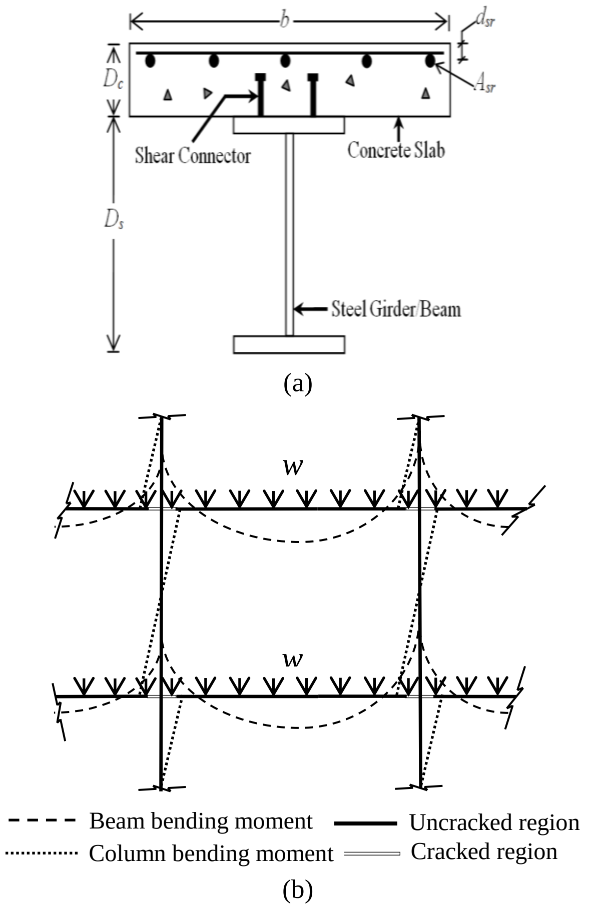

Fig. 1 (a) A Typical cross-section of a composite beam and (b) a typical segment of a composite frame with loads, bending moments, and possible cracked and uncracked regions

finite element method may be about 1500 (Chaudhary *et al.*2007). Therefore, in the preliminary stages of design, there is a need for some simple and rapid tools/methodologies. Such tools/methodologies should predict the design quantities which are acceptable for practical engineering purposes. The use of neural networks is one of the tools/methodologies which is very commonly employed in engineering analysis and design.

Neural networks have been widely used for prediction of various structural parameters (Maru and Nagpal 2004, Chandak *et al.* 2008, Panigrahi *et al.* 2008, Kim and Kim 2009, Kim *et al.* 2009, Khan 2012, Mohammadhassani *et al.* 2013a, b, c, Bigdeli *et al.* 2014, Kaloop *et al.* 2014, Kaloop and Kim 2014, Mallela and Upadhyay 2016, Bigdeli and Kim 2017). In the last decade, some researchers have proposed neural networks for predicting moments and deflections in composite beams/bridges (Pendharkar *et al.* 2010, Tadesse *et al.* 2012, Gupta *et al.* 2015) and frames (Pendharkar *et al.* 2011, 2015) subjected to service load. The support/joint moments were considered in the input parameters for assessing the inelastic redistribution.

In the present work, neural networks have been proposed for predicting the inelastic moments and deflections in composite frames, considering cracking in concrete slab at service load. The neural networks take into account: (i) the stresses produced by combined effects of axial forces and moments at the ends of the beams; (ii) the relative stiffness of beams and columns; and (iii) the relevant parameters from the floor below and the floor above. The proposed neural networks can be useful in the preliminary stages of design. It may be noted that the axial force in the members (beams and columns) and the relative stiffnesses of beams and columns at the joints, which may be significant in composite frames, were neglected in the earlier studies by Pendharkar *et al.* (2011, 2015).

The large number of data sets required for training the neural networks have been generated using a computationally efficient analytical-numerical procedure (Ramnavas *et al.* 2017), which takes into account the cracking in concrete slab and the effects of tension stiffening (Sahamitmongkol and Kishi 2011, Dai *et al.* 2012, Patel *et al.* 2016). Explicit expressions have been developed using the weights, biases and activated function of the trained neural networks. The proposed expressions have been verified by comparison of the results with that obtained from the analytical-numerical procedure developed by the authors (Ramnavas *et al.* 2017). This methodology helps to obtain the inelastic design quantities from the elastic quantities with simple calculations and thus would be very useful in preliminary design.

2. Input and output parameters for neural networks

The composite frames consist of composite beams (see Fig 1(a)) and steel columns. Fig. 1(b) shows a typical segment of a composite frame with loads, bending moments, and possible cracked and uncracked regions of concrete cracking in composite beams. The moment at any cross-section along the length of a beam can be obtained from the support moments and the loading on the span. Also, mid span deflection is the most important serviceability aspect in respect of the deformation of a beam. Hence, the support moments and the mid span deflections are the two inelastic design quantities, for which prediction models have been presented using the neural networks. These inelastic design quantities can be obtained from the non-dimensional ratios defined below which are taken as the output parameters in the neural networks.

1. Inelastic moment ratios, $R_{i,j}^{l} = \left(M^e\right)_{i,j}^{l} \Big/ \left(M^i\right)_{i,j}^{l}$ and $R_{i,j}^{r} = \left(M^e\right)_{i,j}^{r} \Big/ \left(M^i\right)_{i,j}^{r}$. Here, $\left(M^e\right)_{i,j}^{l}$ and $\left(M^e\right)_{i,j}^{r}$ are the elastic moments and $\left(M^i\right)_{i,j}^{l}$ and $\left(M^i\right)_{i,j}^{r}$ are the inelastic moments; the superscript represents the ends of the beam, left *l* or right *t* as the case may be; and the first and second subscripts represent the bay *i* and the floor *j*, respectively; and

2. Inelastic deflection ratio, $\delta_{i,j}^{d} = \left(d_{i,j}^{i} - d_{i,j}^{e}\right) \Big/ d_{i,j}^{cr}$. Here, $d_{i,j}^{e}$ is the mid-span deflection obtained from the elastic analysis and $d_{i,j}^{i}$ is the mid-span deflection obtained from the inelastic analysis, i.e., after

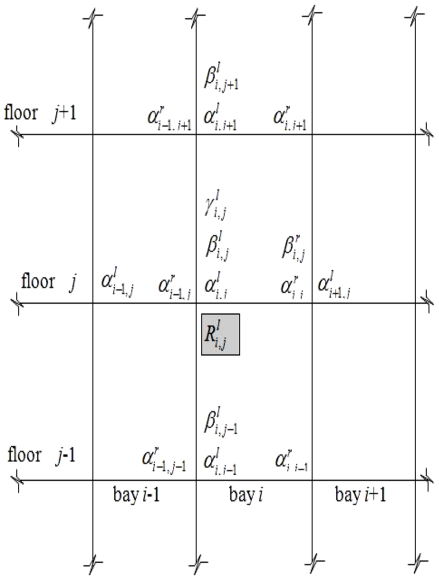

Fig. 2 Input parameters and their positions in a typical floor and bay of a frame for the output parameter $R^{l}_{i,j}$

considering the cracking. Further, $d^{cr}_{i,j}$ is the mid-span deflection of a beam with same cross-sectional properties, with fixed supports at both the ends and carrying a uniformly distributed load just sufficient to cause cracking of concrete. The subscripts *i* and *j*, refer to the bay *i* and the floor *j*.

The input parameters which significantly affect the required output parameters are to be identified. It has been reported that for establishing the inelastic effects in moment at a joint in a frame, the cracking at either sides of the joint and the adjacent joints on either sides are to be considered (Pendharkar *et al.* 2011). Similarly, the inelastic effects in the mid-span deflection of a span, are affected by the cracking in the beams at both the supports of the span (Pendharkar *et al.* 2015). Additionally, the cracking at adjacent supports is also considered for mid-span deflections, similar to the case of moments as above.

It may be noted that the cracking of concrete depends on the moments as well as axial force in case of composite frames. Compressive axial force reduces the net tensile stress and tensile axial force increases the net tensile stress. Hence, the net tensile stresses which depend on the moments as well as axial forces are to be included in the input parameters instead of the moments only in the case of frames. In addition, the relative stiffness of beams and columns at the joints, significantly affects the moment redistribution in frames, when the concrete cracks in the slab. Apart from the above, the parameters from the lower and upper floors also affect the inelastic effects in a beam in frames (apart from the parameters from the same bay and the adjacent bays of the same floor), as reported by Ramnavas (2016). Hence, it is required to consider the relative stiffnesses of beams and columns at the joints and also the parameters from lower and upper floors, as the input parameters for accurate prediction of inelastic quantities in composite frames. The input parameters considered in the present study are shown in Figs. 2, 3 and 4.

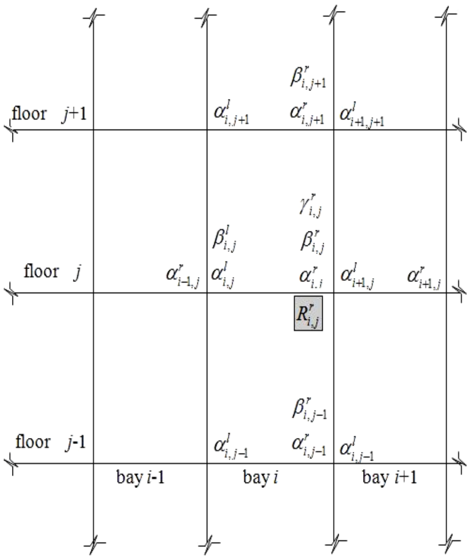

Fig. 3 Input parameters and their positions in a typical floor and bay of a frame for the output parameter $R^{r}_{i,j}$

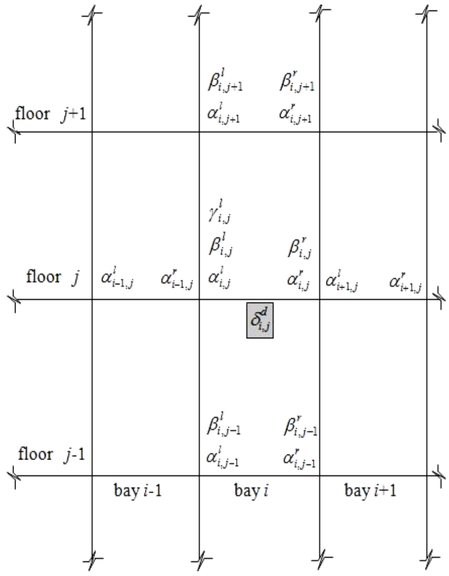

Fig. 4 Input parameters and their positions in a typical floor and bay of a frame for the output parameter $\delta^{d}_{i,j}$

1. Inertia ratio, I_{cr}/I_{un} which is the ratio of I_{cr}, the transformed second moment of area of the cracked section (consisting of steel section and reinforcement only), about its neutral axis and I_{un}, the transformed second moment of area of the uncracked composite section about its neutral axis;
2. Stiffness ratio, S_{i+1}/S_i which is the ratio of the stiffness of beams $S=E_cI_{un}/L$ in the adjacent bays (bay *i* and bay *i*+1) where *S*is the stiffness of beam, E_c is the modulus of elasticity of concrete, I_{un} is the transformed second moment of area of the uncracked composite section about its neutral axis and *L* is the span of the beam (subscripts indicate the bay numbers);
3. Load ratio, w_i/w_{i+1} which is the ratio of load *w* on the beams in the adjacent bays (bay *i* and bay *i*+1) (subscripts indicate the bay numbers);

Table 1 Input and output parameters for neural networks

Parameters	No.	Description of parameters	Neural network for Left end moment (bay i, floor j)	Right end moment (bay i, floor j)	Mid-span deflection (bay i, floor j)
Input	1	Inertia ratio	I_{cr}/I_{un}	I_{cr}/I_{un}	I_{cr}/I_{un}
	2	Stiffness ratios	S_{i+1}/S_i for end bay, S_i/S_{i-1} for interior bay	S_{i+1}/S_i for end bay, S_i/S_{i-1} for interior bay	S_i/S_{i-1}, S_{i+1}/S_i
	3	Load ratios	w_i/w_{i+1} for end bay, w_{i-1}/w_i for interior bay	$w_i/w_{i+1}$for end bay, w_{i-1}/w_i for interior bay	w_{i-1}/w_i, w_{i-1}/w_i
	4	Stress ratios (from floor j+1)	$\alpha^r_{i-1,j+1}$, $\alpha^l_{i,j+1}$, $\alpha^r_{i,j+1}$	$\alpha^l_{i,j+1}$, $\alpha^r_{i,j+1}$, $\alpha^l_{i+1,j+1}$	$\alpha^l_{i,j+1}$, $\alpha^r_{i,j+1}$
	5	Stress ratios (from floor j)	$\alpha^l_{i-1,j}$, $\alpha^r_{i-1,j}$, $\alpha^l_{i,j}$, $\alpha^r_{i,j}$, $\alpha^l_{i+1,j}$	$\alpha^r_{i-1,j}$, $\alpha^l_{i,j}$, $\alpha^r_{i,j}$, $\alpha^l_{i+1,j}$, $\alpha^r_{i+1,j}$	$\alpha^l_{i-1,j}$, $\alpha^r_{i-1,j}$, $\alpha^l_{i,j}$, $\alpha^r_{i,j}$, $\alpha^l_{i+1,j}$, $\alpha^r_{i+1,j}$
	6	Stress ratios (from floor j−1)	$\alpha^r_{i-1,j-1}$, $\alpha^l_{i,j-1}$, $\alpha^r_{i,j-1}$	$\alpha^l_{i,j-1}$, $\alpha^r_{i,j-1}$, $\alpha^l_{i+1,j-1}$	$\alpha^l_{i,j-1}$, $\alpha^r_{i,j-1}$
	7	Joint stiffness ratios (from floor j+1)	$\beta^l_{i,j+1}$	$\beta^r_{i,j+1}$	$\beta^l_{i,j+1}$, $\beta^r_{i,j+1}$
	8	Joint stiffness ratios (from floor j)	$\beta^l_{i,j}$, $\beta^r_{i,j}$	$\beta^l_{i,j}$, $\beta^r_{i,j}$	$\beta^l_{i,j}$, $\beta^r_{i,j}$
	9	Joint stiffness ratios (from floor j−1)	$\beta^l_{i,j-1}$	$\beta^r_{i,j-1}$	$\beta^l_{i,j-1}$, $\beta^r_{i,j-1}$
	10	Shortening parameter	$\gamma^l_{i,j}$	$\gamma^r_{i,j}$	$\gamma^l_{i,j}$
Output	1	Moment ratio	$R^l_{i,j}$	$R^r_{i,j}$	-
	2	Deflection ratio	-	-	$\delta^d_{i,j}$

4. Stress ratios, $\alpha^l_{i,j}$ and $\alpha^r_{i,j}$ which are the ratios of the tensile stress in the concrete (at the top fibre, obtained in the elastic analysis) to the tensile strength of the concrete, of the beam at the end considered (superscript indicate left l or right r end of a beam, whereas first and second subscripts indicate bay number and floor number respectively);

5. Joint stiffness ratios, $\beta^l_{i,j}$ and $\beta^r_{i,j}$ which are the ratios of the stiffness of a beam to the sum of the stiffnesses of the rest of the members (beams and columns) meeting at the joint (superscript indicate left l or right r end of a beam, whereas first and second subscripts indicate bay number and floor number respectively); and

6. Shortening parameters, $\gamma^l_{i,j}$ and $\gamma^r_{i,j}$ which are the ratios of the differential axial shortening of the column at the left or right end of a beam, to the span of the beam (superscript indicate left l or right r end of a beam, whereas first and second subscripts indicate bay number and floor number respectively).

The input and output parameters for the neural networks for prediction of moment and deflection in a beam in bay i and floor j are shown in Table 1 and in Figs. 2, 3 and 4. It may be noted that apart from the parameters from the bay and the floor under consideration, (i) the stress ratios from the adjacent bays and from the floors below and above; and (ii) the joint stiffness ratios from the floors below and above, are also considered.

In case of the neural networks for the end bays, some of these input parameters are non-existent and thus the number of input parameters will accordingly get reduced. Similarly, in case of the neural networks for the first floor or for the topmost floor, the input parameters are only from two floors, as detailed in the following section.

3. Designations of neural networks

As discussed above, the input parameters should consider the effects from that particular floor and from the floor below and above the particular floor. The first floor and the topmost floor are exceptions in this regard. For the neural networks for the first floor, there is no floor below it. Therefore, the input parameters are to be taken only from the first floor and the second floor. Similarly, for the neural networks for the topmost floor, there is no floor above it. Therefore, the input parameters are to be taken from the topmost floor and the penultimate floor. The ranges of the parameters are much different at the topmost floor because of the columns are terminating at the top ends. The columns have lesser translational and rotational restraints than those in other floors. Due to this uniqueness, the input parameters are different of the neural networks for the penultimate floor and the intermediate floors. Therefore, separate set of neural networks are required for the penultimate floor also.

Thus, the neural networks have been trained in four different sets, i.e., for (i) first floor; (ii) intermediate floors; (iii) penultimate floor; and (iv) topmost floor. Of these four sets, the one for intermediate floor is to be used for all the floors from the second floor to the ante-penultimate floor. Other three sets are to be used for the specific floors for which they are meant.

In the case of moments, each type of floors will have three neural networks, i.e., for (i) exterior end of exterior beam; (ii) interior end of exterior beam; and (iii) ends of interior beam. Thus, the number of neural networks for moments for all the types of floors together, is twelve. Similarly, in the case of deflections, each type of floor will have two neural networks, i.e., for (i) exterior beam; and (ii) interior beam. Thus, the number of neural networks for deflections for all the types of floors together, is eight. The different neural networks for the prediction of moments and deflections have been designated as given in Table 2 and Fig. 5.

Table 2 Description and designations of neural networks for moments and deflections

No.	Description			Designation
	Quantity	Floor	Location	
1	Bending Moment	First	Exterior end of exterior beam	NetB01
2			Interior end of exterior beam	NetB02
3			Ends of interior beam	NetB03
4		Intermediate	Exterior end of exterior beam	NetB04
5			Interior end of exterior beam	NetB05
6			Ends of interior beam	NetB06
7		Penultimate	Exterior end of exterior beam	NetB07
8			Interior end of exterior beam	NetB08
9			Ends of interior beam	NetB09
10		Topmost	Exterior end of exterior beam	NetB10
11			Interior end of exterior beam	NetB11
12			Ends of interior beam	NetB12
13	Deflection	First	Exterior beam	NetD01
14			Interior beam	NetD02
15		Intermediate	Exterior beam	NetD03
16			Interior beam	NetD04
17		Penultimate	Exterior beam	NetD05
18			Interior beam	NetD06
19		Topmost	Exterior beam	NetD07
20			Interior beam	NetD08

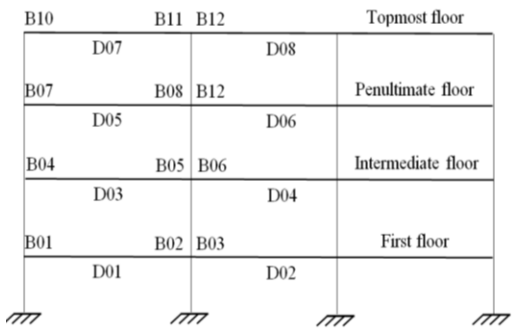

Fig. 5 Representative three bay four storey frame for data generation showing the designations of neural networks (only significant characters in the designations of neural networks are shown e.g. B01 for NetB01 and D01 for NetD01)

4. Analytical-numerical procedure

As mentioned in section 1, a computationally efficient analytical-numerical procedure (Ramnavas *et al.* 2017) is used for generating the large number of data sets required for the neural networks, in an automated manner.

The procedure uses a cracked span length beam element (see Fig. 6) comprising two cracked regions (at the ends of beam) and one uncracked region (at the middle), with six degrees of freedom, for the beams in the frame. Use of a single beam element for a span, reduces the computational effort. The tension stiffening effect in the cracked concrete is accounted in the cracked span length beam element. Average values over the cracked regions are used for the tension stiffening characteristics, which help in retaining the analytical nature of the procedure at the element level. The flexibility matrix coefficients, stiffness matrix coefficients, end displacements, cracked region lengths and mid-span deflection of the beam element, are obtained analytically. The procedure (Ramnavas *et al.* 2017) uses an iterative technique for establishing the cracked region lengths and distribution coefficients (for tension stiffening), and yields the inelastic deflections and redistributed moments. The procedure had also been validated by comparing the results with finite element analysis results as well as with the experimental results reported in literature.

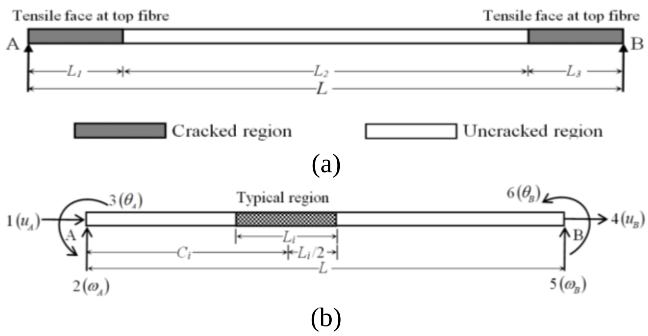

Fig. 6 A cracked span length beam element with (a) cracked and uncracked regions; and (b) degrees of freedom

Table 3 Ranges of input parameters for moments and deflections

Value	Inertia Ratio	Stiffness Ratios	Load Ratios	Stress Ratios	Joint Stiffness Ratios	Shortening Parameters
Minimum	0.36	0.50	0.50	0.40	0.15*	0.000003**
Maximum	0.57	2.00	2.00	3.20	0.50 *	0.000404**

Note : (i) The values marked * are the joint stiffness ratios for the left end of left extreme bay in the topmost floor. The joint stiffness ratios for other joints and ends of beams vary, according to the number of columns and beams meeting at the joint. (ii) The values marked ** are the shortening parameters obtained for the combinations considered and accepted as the practical ones.

5. Generation of data sets

From the discussions in the section 3 on various neural networks required to be trained, it can be seen that the minimum number of storeys required for a representative frame for generating the data sets, is four. Also, as stated in

Table 4 Sampling points for the input parameters for moments and deflections

Inertia Ratio	Stiffness Ratios	Load Ratios	Stress Ratios	Joint Stiffness Ratios	Shortening Parameters
0.36, 0.46, 0.57	0.50, 0.75, 1.00, 1.50, 2.00	0.50, 0.75, 1.00, 1.50, 2.00	0.40, 0.60, 0.80, 0.90, 0.99, 1.01, 1.11, 1.25, 1.60, 2.00, 2.50, 3.20	0.15*, 0.25*, 0.50*	As obtained

Note : (i) In each data set, one of the stress ratios is controlled to the values shown as sampling points and for other stress ratios, the values as obtained from the analysis are adopted. (ii) While targeting the stress ratios at various locations as explained in section 4.6, the values other than the sampling points are also obtained in the data sets generated. (iii) The values marked * are the joint stiffness ratios for the left end of left extreme bay in the topmost floor. The joint stiffness ratios for other joints and ends of beams vary according to the number of columns and beams meeting at the joint.

section 1, the inelastic effects in a beam are affected by the cracking in the adjacent bays and hence as mentioned in section 2, the input parameters are to be taken from the adjacent bays too. This necessitates a minimum of three bays for the representative frame for generating data sets. Hence, the configuration of frame used for the generation of data sets, is a three bay four storey frame (see Fig. 5). The cross-sectional properties of beams and columns, spans and loads, are changed to get various combinations of input parameters as desired, and data sets have been generated.

The ranges for the input parameters to be considered in the data generation have been arrived at, from the commonly used dimensions of the frame configuration (bay dimensions and storey heights), beam and column sections, loading, etc. for composite frames in the practical cases of buildings and are furnished in Table 3. Columns of the frame are assumed to have same cross-sectional properties.

The sampling points for each of the input parameters have been selected such that they are well distributed over their respective ranges and are furnished in Table 4.

The practice generally followed for generating data sets is to make combinations of all the input parameters with the sampling points. In this way, all the input parameters are to be maintained at their respective values (sampling points) for each of the combinations considered. Maintaining the values of all the input parameters to the predetermined values by the trial and error method is not feasible in this case where the number of input parameters is significantly large. It is also possible that by defining some of the input parameters, the whole structural system (including loading) may get defined and achieving the desired values for other parameters may not be possible. This necessitates an alternative way for generating the data sets which will cover the range of all the input parameters.

It can be seen that all the combinations have a number of stress ratios like $\alpha^{l}_{i,j}$, $\alpha^{r}_{i,j}$, etc. in the input parameters. In the alternative way followed here for generation of data set for a particular combination, initially an analysis is carried out with assumed values of loads considering all the input parameters except the stress ratios. Now, one of the stress ratios in this combination is selected and the value of the same obtained in the analysis is compared with the value required to be obtained in this combination (sampling point). If these obtained value of the selected stress ratio is not equal to the required value (which is the situation in almost all the cases), the values of all the loads are modified duly maintaining the load ratios intact, so as to get the value of the selected stress ratio equal to the required value. Other stress ratios are not controlled and are accepted, as obtained from the analysis. However, it is ensured that these stress ratios, are also within the desired ranges, for accepting a particular data set (In order to include those data sets in which the values of uncontrolled stress ratios are marginally falling outside the desired ranges (i.e., 0.40 to 3.20), such ranges are slightly expanded (i.e., 0.39 to 3.21) while accepting the data sets). The above steps are followed for the other stress ratios in the same combination. Other combinations are also dealt with, in the same way.

6. Training of neural networks and explicit expressions

As stated in the previous section, twelve and eight neural networks have been trained for prediction of moments and deflections, respectively.

For better training of neural networks, the input and output parameters of the data sets need to be normalized for bringing the values within the range 0.0 to 1.0, which has been done using the following expression

$$y_{norm} = \left(y_{act} - y_{\min}\right) / \left(y_{\max} - y_{\min}\right) \tag{1}$$

where y_{act} is the actual value, $y_{\min}$ is the minimum value, $y_{\max}$ is the maximum value and y_{norm} is the normalized value, of the respective parameters. The $y_{\min}$ and $y_{\max}$ for the input and output parameters for a typical neural network NetB06 are given in Appendix A. It can be seen that though the values of $y_{\min}$ and $y_{\max}$ are within the respective ranges (or the expanded ranges as mentioned in section 4 for stress ratios), but not exactly the lower and upper limits in the case of some of the parameters. This is due to the reason that when the sampling points are the lower or upper limits of the ranges for such parameters, some other parameters do not fall within their ranges and the data set becomes unacceptable.

Training of the neural networks has been carried out using the MATLAB (2009). In this work, Levenberg-Marquardt back propagation algorithm is used for supervised multilayered feed forward networks along with log-sigmoid transfer function. Single hidden layer has been chosen and the numbers of neurons in the hidden layer have

Table 5 Statistical parameters for training of neural networks for NetB06 having configuration (19-27-1)

Parameters	Set		
	Training	Testing	Validation
MSE	0.00005	0.00005	0.00005
RMSE	0.0072	0.0071	0.0071
R	0.9993	0.9993	0.9993
AAD	1.7629	1.7656	1.7361
COV	2.4024	2.3856	2.3567
SSE	0.4692	0.5174	0.5203

been decided by trial and error, in the learning process so as to get optimum results. The data sets have been divided into 70%, 15% and 15% for training, validation and testing respectively (Gedam *et al.* 2014, Joshi *et al.* 2014). The division of data sets has also been done with different random states. Various trials of training have been carried out with different number of hidden neurons and also with different random states.

A goal has been set for a mean square error (MSE) of 0.0001 and the number of epochs depends on the attainment of goal. The statistical parameters like mean square error (MSE), root mean square error (RMSE), correlation coefficient (R), average absolute deviation (AAD), coefficient of variation (COV) and sum of squared errors (SSE) have been calculated for the training, validation and testing of each trial. Of the various trials performed for each neural network, the one which gives the best statistical parameters for training, validation and testing has been selected. The statistical parameters for typical neural network NetB06 are given in Table 5, along with the network configuration (number of input neurons-hidden neurons-output neurons).

Simplified explicit expressions can be derived from the trained neural networks, for use in preliminary design by the practicing engineers. These expressions require the values of inputs, the weights of the links between the neurons in different layers and the biases of output neurons. Since the sigmoid functions have been used as the activation functions in the hidden and output layer neurons, the output P_O is given as below (Tadesse *et al.* 2012, Gupta *et al.* 2015)

$$P_O = \frac{1}{1+e^{-z}} \tag{2}$$

where $z = \left(\sum_{h=1}^{q} \frac{w_h}{1+e^{-(X_h+b_h)}} \right) + b_{out}$ and $X_h = \sum_{g=1}^{r} w_{hg} I_g$.

where, P_O is the value of output parameter, w_h is the weight between hidden and output layers for hidden neuron *h*, w_{hg} is the weights between input neuron *g* and hidden neuron *h*, I_g is the value of input neuron *g*, b_h is the bias between input layer and hidden layer for the hidden neuron *h*, b_{out} is the bias of output neuron, *q* is the number of hidden neurons and *r* is the number of input neurons.

The inelastic moment at the left end (*l*) and right end (*r*) of beam in bay *i* and floor *j* can be obtained as $\left(M^i\right)_{i,j}^l = \left(M^e\right)_{i,j}^l \Big/ \left(P_O\right)_{i,j}^l$ and $\left(M^i\right)_{i,j}^r = \left(M^e\right)_{i,j}^r \Big/ \left(P_O\right)_{i,j}^r$ respectively. Similarly, the inelastic deflection at the mid span of the beam in bay *i* and floor *j* can be obtained as $d_{i,j}^i = \left(P_O\right)_{i,j} d_{i,j}^{cr} + d_{i,j}^e$. The value of P_O can be obtained using the weights and biases of the respective developed

Table 6 Input parameters for three bay four storey example frame EF1: (a) Inertia ratio, stiffness ratios and load ratios; and (b) Stress ratios, joint stiffness ratios and shortening parameters

(a)

I_{cr}/I_{un}	S_2/S_1	S_3/S_1	w_1/w_2	w_2/w_3
0.41	0.80	1.25	1.07	0.93

(b)

Bay 1				Bay 2				Bay 3			
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
$\alpha_{1,1}^l$	1.9013	$\alpha_{1,1}^r$	2.2651	$\alpha_{2,1}^l$	3.0531	$\alpha_{2,1}^r$	3.0531	$\alpha_{3,1}^l$	2.2651	$\alpha_{3,1}^r$	1.9013
$\alpha_{1,2}^l$	1.9465	$\alpha_{1,2}^r$	2.1429	$\alpha_{2,2}^l$	2.9984	$\alpha_{2,2}^r$	2.9984	$\alpha_{3,2}^l$	2.1429	$\alpha_{3,2}^r$	1.9465
$\alpha_{1,3}^l$	2.0709	$\alpha_{1,3}^r$	2.1397	$\alpha_{2,3}^l$	3.0604	$\alpha_{2,3}^r$	3.0604	$\alpha_{3,3}^l$	2.1397	$\alpha_{3,3}^r$	2.0709
$\alpha_{1,4}^l$	1.5417	$\alpha_{1,4}^r$	2.2074	$\alpha_{2,4}^l$	2.7880	$\alpha_{2,4}^r$	2.7880	$\alpha_{3,4}^l$	2.2074	$\alpha_{3,4}^r$	1.5417
$\beta_{1,1}^l$	0.150253	$\beta_{1,1}^r$	0.1341302	$\beta_{2,1}^l$	0.1045008	$\beta_{2,1}^r$	0.1045008	$\beta_{3,1}^l$	0.13413	$\beta_{3,1}^r$	0.15025
$\beta_{1,2}^l$	0.150253	$\beta_{1,2}^r$	0.1341302	$\beta_{2,2}^l$	0.1045008	$\beta_{2,2}^r$	0.1045008	$\beta_{3,2}^l$	0.13413	$\beta_{3,2}^r$	0.15025
$\beta_{1,3}^l$	0.150253	$\beta_{1,3}^r$	0.1341302	$\beta_{2,3}^l$	0.1045008	$\beta_{2,3}^r$	0.1045008	$\beta_{3,3}^l$	0.13413	$\beta_{3,3}^r$	0.15025
$\beta_{1,4}^l$	0.300506	$\beta_{1,4}^r$	0.2422645	$\beta_{2,4}^l$	0.1848548	$\beta_{2,4}^r$	0.1848548	$\beta_{3,4}^l$	0.242264	$\beta_{3,4}^r$	0.30051
$\gamma_{1,1}^l$	0.000050	$\gamma_{1,1}^r$	-0.000050	$\gamma_{2,1}^l$	0.000000	$\gamma_{2,1}^r$	0.000000	$\gamma_{3,1}^l$	-0.000050	$\gamma_{3,1}^r$	0.000050
$\gamma_{1,2}^l$	0.000088	$\gamma_{1,2}^r$	-0.000088	$\gamma_{2,2}^l$	0.000000	$\gamma_{2,2}^r$	0.000000	$\gamma_{3,2}^l$	-0.000088	$\gamma_{3,2}^r$	0.000088
$\gamma_{1,3}^l$	0.000113	$\gamma_{1,3}^r$	-0.000113	$\gamma_{2,3}^l$	0.000000	$\gamma_{2,3}^r$	0.000000	$\gamma_{3,3}^l$	-0.000113	$\gamma_{3,3}^r$	0.000113
$\gamma_{1,4}^l$	0.000126	$\gamma_{1,4}^r$	-0.000126	$\gamma_{2,4}^l$	0.000000	$\gamma_{2,4}^r$	0.000000	$\gamma_{3,4}^l$	-0.000126	$\gamma_{3,4}^r$	0.000126

Table 7 Elastic and inelastic moments in example frame EF1

Bay and Floor	Elastic moment (kN/m)	Inelastic moment (kNm)		
		Analytical-numerical procedure	Explicit expressions	Error (%)
Interior joint of end bay - First floor	93.57	82.40	82.20	-0.2
Interior bay Left end - First floor	125.93	113.80	112.28	-1.3
Exterior joint of end bay - Intermediate floor (2nd floor)	83.19	78.10	77.38	-0.9
Interior joint of end bay - Intermediate floor (2nd floor)	91.52	82.17	82.57	0.5
Interior bay left end - Intermediate floor (2nd floor)	127.77	112.35	112.29	0.0
Exterior joint of end bay - Penultimate floor (3rd floor)	84.87	78.61	79.38	1.0
Interior joint of end bay - Penultimate floor (3rd floor)	87.79	79.36	79.25	-0.1
Interior bay left end - Penultimate floor (3rd floor)	126.11	110.76	110.97	0.2
Interior joint of end bay - Topmost floor (4th floor)	102.80	92.67	92.70	0.0
Interior bay left end - Topmost floor (4th floor)	131.04	118.54	118.73	0.2

neural networks (Eq. (2)). The weights and biases for a typical neural network NetB06 are given in Appendix A.

7. Verification of explicit expressions

The explicit expressions are verified for two example frames of 4 storey-3 bay (EF1) and 4 storey-5 bay (EF2) with a wide variation of input parameters. The frames have been chosen in such a way that the set of input parameters for each of the network, has not been used as a combination

Table 8 Elastic and inelastic deflections in example frame EF1

Bay and Floor	Elastic mid-span deflection (mm)	Inelastic mid-span deflection (mm)		
		Analytical-numerical procedure	Explicit expression	Error (%)
End bay - First floor	1.564	1.928	1.932	0.2
Interior bay - First floor	3.518	4.705	4.766	1.3
End bay - Intermediate floor (2nd floor)	1.546	1.941	1.931	-0.5
Interior bay - Intermediate floor (2nd floor)	3.497	4.778	4.790	0.2
End bay - Penultimate floor (3rd floor)	1.520	1.943	1.933	-0.5
Interior - Penultimate floor (3rd floor)	3.493	4.816	4.759	-1.2
End bay - Topmost floor (4th floor)	1.684	1.993	2.020	1.3
Interior bay - Topmost floor (4th floor)	3.659	4.729	4.700	-0.6

in the data sets for training of the same network.

First, consider the 4 storey-3 bay example frame EF1. The spans of bay 1, 2 and 3 have been taken as 4.80 m, 6.00 m and 4.80 m respectively and the height of all the storeys has been taken as 3.00 m. The uniformly distributed load (udl) on beams of bay 1, 2 and 3 has been taken as 46.0 kN/m, 43.0 kN/m and 46.0 kN/m respectively, on each floor. The beams and columns of all bays and storeys have been assumed to be of same cross-sections. The cross-sectional properties of the beams are: depth of steel section, D_s=305 mm; width of concrete slab, b=1000 mm; depth of concrete slab, D_c=70 mm; area of steel reinforcements, A_{sr}=113 mm^2; depth of steel reinforcements from top fibre, d_{sr}=15 mm; area of steel section, A_{ss}=5132 mm^2 (UB

Table 9 Input parameters for five bay four storey example frame EF2 (a) Inertia ratio, stiffness ratios and load ratios; (b) Stress ratios, joint stiffness ratios and shortening parameters

(a)

I_{cr}/I_{un}	S_2/S_1	S_3/S_2	S_4/S_3	S_5/S_4	w_1/w_2	w_2/w_3	w_3/w_4	w_4/w_5
0.41	0.80	1.00	1.00	1.25	1.07	1.00	1.00	0.93

(b)

Input para-meters	Floor (j)	Bay 1 (i=1)		Bay 2 (i=2)		Bay 3 (i=3)		Bay 4 (i=4)		Bay 5 (i=5)	
		Left (l)	Right (r)	Left (l)	Right (r)	Left (l)	Right (r)	Left (l)	Right (r)	Left (l)	Right (r)
$\alpha_{i,j}^{l}$ *and $\alpha_{i,j}^{r}$	1	1.9003	2.2569	3.0159	3.1106	3.0806	3.0806	3.1106	3.0159	2.2569	1.9003
	2	1.9525	2.1445	2.9880	3.0636	3.0478	3.0478	3.0636	2.9880	2.1445	1.9525
	3	2.0478	2.1493	3.0114	3.1050	3.0666	3.0666	3.1050	3.0114	2.1493	2.0478
	4	1.5149	2.2345	2.7346	2.9323	2.8756	2.8756	2.9323	2.7346	2.2345	1.5149
$\beta_{i,j}^{l}$ and $\beta_{i,j}^{r}$	1	0.1503	0.1341	0.1045	0.1073	0.1073	0.1073	0.1073	0.1045	0.1341	0.1503
	2	0.1503	0.1341	0.1045	0.1073	0.1073	0.1073	0.1073	0.1045	0.1341	0.1503
	3	0.1503	0.1341	0.1045	0.1073	0.1073	0.1073	0.1073	0.1045	0.1341	0.1503
	4	0.3005	0.2423	0.1849	0.1938	0.1938	0.1938	0.1938	0.1849	0.2423	0.3005
$\gamma_{i,j}^{l}$ and $\gamma_{i,j}^{r}$	1	0.000050	-0.000050	0.000005	-0.000005	0.000000	0.000000	-0.000005	0.000005	-0.000050	0.000050
	2	0.000087	-0.000087	0.000009	-0.000009	0.000000	0.000000	-0.000009	0.000009	-0.000087	0.000087
	3	0.000112	-0.000112	0.000012	-0.000012	0.000000	0.000000	-0.000012	0.000012	-0.000112	0.000112
	4	0.000125	-0.000125	0.000013	-0.000013	0.000000	0.000000	-0.000013	0.000013	-0.000125	0.000125

Table 10 Elastic and inelastic moments in example frame EF2

Description			Elastic moment (kNm)	Inelastic moment (kNm)		
Floor No.	Bay No.	End		Analytical-numerical procedure	Explicit expressions	Error (%)
First floor (1st floor)	End bay (1st bay)	Right	93.49	80.57	82.24	2.1
	First interior bay (2nd bay)	Left	124.98	118.03	112.41	-4.8
	First interior bay (2nd bay)	Right	129.00	115.58	115.60	0.0
	Middle bay (3rd bay)	Left	127.95	118.14	115.58	-2.2
Intermediate floor (2nd floor)	End bay (1st bay)	Left	83.13	78.36	77.35	-1.3
	End bay (1st bay)	Right	91.28	81.60	82.53	1.1
	First interior bay (2nd bay)	Left	126.58	111.84	111.63	-0.2
	First interior bay (2nd bay)	Right	129.79	112.91	112.66	-0.2
	Middle bay (3rd bay)	Left	128.84	112.59	112.18	-0.4
Penultimate floor (3rd floor)	End bay (1st bay)	Left	84.36	77.93	79.05	1.4
	End bay (1st bay)	Right	88.66	80.51	79.93	-0.7
	First interior bay (2nd bay)	Left	125.26	110.65	110.58	-0.1
	First interior bay (2nd bay)	Right	129.24	112.89	112.76	-0.1
	Middle bay (3rd bay)	Left	128.08	112.37	112.03	-0.3
Topmost floor (4th floor)	End bay (1st bay)	Right	103.67	93.79	93.15	-0.7
	First interior bay (2nd bay)	Left	127.92	116.08	116.95	0.7
	First interior bay (2nd bay)	Right	136.31	122.06	121.31	-0.6
	Middle bay (3rd bay)	Left	133.53	119.97	119.54	-0.4

Table 11 Elastic and inelastic deflections in example frame EF2

Description		Elastic mid-span deflection (mm)	Inelastic mid-span deflection (mm)		
Floor No.	Bay No.		Analytical-numerical procedure	Explicit expressions	Error (%)
First floor (1st floor)	End bay (1st bay)	1.566	1.906	1.938	1.7
	First interior bay (2nd bay)	3.433	4.577	4.713	3.0
	Middle bay (3rd bay)	3.343	4.492	4.617	2.8
Intermediate floor (2nd floor)	End bay (1st bay)	1.548	1.943	1.938	-0.3
	First interior bay (2nd bay)	3.423	4.735	4.763	0.6
	Middle bay (3rd bay)	3.344	4.689	4.685	-0.1
Penultimate floor (3rd floor)	End bay (1st bay)	1.520	1.940	1.932	-0.4
	First interior bay (2nd bay)	3.426	4.759	4.734	-0.5
	Middle bay (3rd bay)	3.359	4.715	4.676	-0.8
Topmost floor (4th floor)	End bay (1st bay)	1.695	2.003	2.036	1.6
	First interior bay (2nd bay)	3.513	4.623	4.514	-2.4
	Middle bay (3rd bay)	3.350	4.505	4.487	-0.4

305×165×40); and moment of inertia of steel section, I_{ss}=85.03×10^6 mm^4 (see Fig. 1(a)). The cross-sectional area of the steel column section, A_{col}=33620 mm^2 (2×UC 254×254×132); and the moment of inertia of the steel section, I_{col}=450.60×10^6 mm^4. The material properties are: the modulus of the elasticity of the steel, E_s=2×10^5 N/mm^2; the modulus of elasticity of concrete, E_c=34129 N/mm^2; cylindrical compressive strength of the concrete, f_c'=32 N/mm^2; and the tensile strength of concrete, f_t=3.04 N/mm^2.

The values of the input parameters of the frame EF1 are given in Table 6 for prediction of inelastic moments and deflections. As stated earlier, these parameters are in different combinations than those used in training. The values of the inelastic end moments and the inelastic mid-span deflections, obtained from the proposed explicit expressions and from the analytical-numerical procedure are reported in Tables 7 and 8 respectively (Quantities which vary from elastic to inelastic states by more than 5% are only reported, for brevity). The root mean square percentage errors are 0.63% and 0.86% for prediction of moments and deflections respectively. It can be seen that the errors in the predicted values of inelastic moments and deflections are small and are acceptable for engineering applications.

Next, consider 4 storey-5 bay example frame EF2. The spans of bay 1-5 have been taken as 4.80 m, 6.00 m, 6.00 m, 6.00 m and 4.80 m respectively and the height of all the storeys has been taken as 3.00 m. The udl on beams of bay 1-5 have been taken as 46.0 kN/m, 43.0 kN/m, 43.0 kN/m, 43.0 kN/m and 46.0 kN/m respectively, on each floor. The cross-sections and material properties of the beams and columns are same as that of the beams and columns considered for the frame EF1 above. The values of the input parameters of the frame EF2 are given in Table 9 for prediction of inelastic moments and deflections. The values of the inelastic end moments and the inelastic mid-span deflections obtained from the proposed explicit expressions and from the analytical-numerical procedure are reported in Tables 10 and 11 respectively (Quantities which vary from elastic to inelastic states by more than 5% are only reported, for brevity). The root mean square percentage errors are 1.47% and 1.56% for prediction of moments and deflections respectively. It can be seen that the errors in the predicted values of inelastic moments and deflections are small and are acceptable for engineering applications. From the above, it is found that the proposed explicit expressions are applicable to frames with any number of bays.

8. Conclusions

Explicit expressions for rapid prediction of the inelastic design quantities (considering cracking of concrete) from the corresponding elastic quantities (uncracked structure), are presented for multi-storey composite frames (with steel columns and steel-concrete composite beams) subjected to service load. These explicit expressions have been derived from the weights and biases of the neural networks developed for the purpose. The expressions take into account concrete stress, relative stiffness of beams and columns along with effects of cracking in the floors below and above. Accordingly, the input parameters considered are inertia ratio, stiffness ratios, load ratios, stress ratios and joint stiffness ratios. The large numbers of data sets required for training of neural networks have been generated using the analytical-numerical procedure developed by the authors. The expressions have been presented in four different sets, i.e., for (i) first floor; (ii) intermediate floors (second floor to ante-penultimate floor); (c) penultimate floor; and (d) topmost floor. Twelve expressions have been presented for prediction of the inelastic moments and eight expressions for prediction of the inelastic deflections. The proposed expressions for prediction of moments and deflections have been verified for two example frames, both having all the input parameters different from that used in training, and the error in the predicted values are found to be small for engineering applications and are acceptable.

The methodology presented herein can be extended for tall building frames, with change in column sections between the storeys and also with significant effect of differential axial shortening, where large saving in computational efforts will be resulted.

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Appendix A: $y_{\min}$, $y_{\max}$, weights and biases for a neural network NetB06

Table A1 $y_{\min}$ and $y_{\max}$

Parameters	I_{cr}/I_{un}	S_i/S_{i-1}	w_{i-1}/w_i	$\beta^l_{i,j-1}$	$\alpha^r_{i-1,j-1}$	$\alpha^l_{i,j-1}$	$\alpha^r_{i,j-1}$	$\beta^l_{i,j}$	$\beta^r_{i,j}$	$\alpha^l_{i-1,j}$	$\alpha^r_{i-1,j}$	$\alpha^l_{i,j}$	$\alpha^r_{i,j}$	$\alpha^l_{i+1,j}$	$\beta^l_{i,j+1}$	$\alpha^r_{i-1,j+1}$	$\alpha^l_{i,j+1}$	$\alpha^r_{i,j+1}$	$\gamma^l_{i,j}$	$R^l_{i,j}$
$y_{\min}$	0.36	0.50	0.50	0.04	0.44	0.39	0.39	0.04	0.04	0.44	0.41	0.39	0.39	0.41	0.04	0.39	0.39	0.39	-0.0003	0.97
$y_{\max}$	0.56	2.00	2.00	0.39	3.21	3.21	3.21	0.39	0.39	3.08	3.15	3.16	3.17	3.15	0.39	3.21	3.21	3.21	0.0002	1.18

Table A2 Weights and biases

h	$w_{h,1}$	$w_{h,2}$	$w_{h,3}$	$w_{h,4}$	$w_{h,5}$	$w_{h,6}$	$w_{h,7}$	$w_{h,8}$	$w_{h,9}$	$w_{h,10}$	$w_{h,11}$	$w_{h,12}$	$w_{h,13}$	$w_{h,14}$	$w_{h,15}$	$w_{h,16}$	$w_{h,17}$	$w_{h,18}$	$w_{h,19}$	b_h	w_h
1	-0.41	0.86	-0.08	-0.89	3.35	1.66	-1.88	1.10	-0.71	-1.44	-1.16	-0.79	0.10	-1.40	-1.27	1.38	2.99	-1.13	1.03	6.93	0.15
2	0.08	-0.65	-0.34	-1.72	1.99	-2.69	-4.95	0.51	2.79	-2.69	1.06	-0.93	-0.57	0.64	-1.25	0.05	-5.08	-2.91	-0.85	3.53	2.57
3	3.26	0.29	-0.59	1.13	-0.31	2.38	1.98	-0.43	-1.21	0.73	1.19	-1.68	0.65	0.62	-1.93	-1.87	-0.73	0.11	4.98	-1.24	0.09
4	-1.34	-0.15	0.05	0.96	-1.84	-0.43	2.89	1.56	1.09	0.29	2.96	-0.03	-1.31	-1.24	-1.15	0.83	0.18	0.74	2.55	-5.46	1.79
5	-3.54	1.98	-1.84	2.18	2.02	-1.91	-1.80	0.98	1.82	-1.20	0.73	0.17	1.47	-1.04	1.86	-1.77	-0.93	0.82	-0.73	2.46	-0.05
6	0.58	-2.59	0.49	1.95	-1.15	-0.04	-0.26	-2.45	-1.16	0.56	-1.05	-0.97	-0.28	-0.06	-3.09	-2.19	-2.12	3.09	1.79	4.68	-0.03
7	-0.27	3.75	2.00	0.82	0.73	0.96	-1.08	0.92	-1.82	0.77	0.84	-3.87	-0.15	1.09	0.87	-1.75	-0.57	-3.67	-3.71	-4.21	0.67
8	1.16	3.27	-1.81	0.26	-0.28	1.10	0.60	-1.69	0.54	2.39	1.65	1.55	2.44	0.72	-0.92	-1.58	-0.85	0.88	-0.57	-4.08	-0.07
9	-1.28	1.07	0.71	-0.73	-1.19	2.13	-1.29	-1.47	0.36	-1.16	1.88	-1.90	-2.04	0.09	0.70	-0.73	-3.27	-1.12	-1.20	5.15	-0.42
10	-0.39	-0.23	-0.11	-1.55	1.24	-3.72	-1.52	2.00	0.81	0.32	-0.26	-1.27	0.35	0.16	-1.55	-1.04	-4.28	-3.21	-0.37	3.67	-2.58
11	-0.26	-0.38	-0.07	3.39	-0.28	-4.32	2.17	-1.83	-1.54	-0.47	-2.87	-3.46	2.05	0.88	0.11	0.68	-0.63	1.61	-2.37	1.96	-2.42
12	-1.00	-0.26	-0.93	2.55	1.14	-0.98	-0.73	0.38	-2.54	2.29	-3.77	2.68	-2.37	-0.96	1.05	-1.31	0.13	-1.12	-0.42	-0.65	-1.98
13	-1.85	3.46	0.89	1.01	-0.87	0.72	-0.17	-0.16	1.17	-0.59	3.41	-0.25	2.47	-3.89	0.24	-0.84	0.35	2.15	-2.28	-0.64	0.10
14	-2.10	1.37	0.71	1.48	1.17	0.69	2.25	-1.44	2.74	-0.47	2.39	-1.15	2.30	0.02	1.31	0.36	3.38	-0.30	2.73	-2.71	-0.24
15	-4.94	-1.73	-0.78	0.31	2.95	0.44	1.14	-0.92	-0.43	1.77	1.60	0.95	-1.00	-2.10	3.21	1.73	1.46	-0.58	0.27	5.39	-0.26
16	-4.49	-0.11	-0.05	0.31	-1.40	1.56	0.92	0.71	-0.85	-0.56	1.00	2.91	1.74	-0.19	-2.62	1.81	-0.86	-0.20	-0.53	-5.90	2.93
17	0.82	0.30	0.08	0.18	3.59	-1.47	1.97	-0.21	-4.25	0.10	5.09	0.87	0.01	-0.10	1.09	2.58	-1.99	-0.09	0.81	-0.81	-0.52
18	-0.87	-1.36	-0.37	1.35	-0.33	1.59	1.81	-0.78	-1.78	0.93	-0.39	1.87	2.39	1.21	-1.01	-0.92	-0.52	-1.54	0.02	-2.29	0.36
19	-0.15	2.39	0.81	-2.93	-0.17	-1.92	1.95	-2.35	-2.16	0.09	-1.36	0.04	-1.52	2.74	-1.97	-1.80	-1.14	1.70	-1.03	2.25	-0.22
20	3.26	-0.01	-0.18	0.87	1.36	-0.31	2.30	2.10	-2.15	-0.36	-0.28	0.71	-2.11	-1.03	1.30	-1.47	2.89	2.05	-0.04	-0.67	0.59
21	3.58	1.66	-0.33	-1.60	1.69	-0.43	0.27	0.80	-1.92	-2.21	2.59	0.41	2.09	2.65	-3.09	0.24	1.95	-0.75	4.08	2.08	2.11
22	1.83	1.65	3.48	2.53	2.13	-0.30	0.59	-1.51	1.52	-0.21	1.24	0.73	2.12	0.47	-1.94	-0.03	1.62	-1.28	-1.33	1.79	-0.01
23	1.19	2.54	0.38	-2.50	0.67	3.96	-1.65	0.08	-2.10	1.85	3.56	0.64	-1.04	5.17	-1.62	2.27	0.56	0.88	1.45	0.33	-0.78
24	2.03	-0.84	-0.58	1.97	-2.08	-0.05	0.23	-0.33	-0.96	1.68	-1.62	2.08	0.43	-0.81	-0.57	0.13	-0.92	2.08	-0.32	0.03	0.43
25	-1.18	0.41	0.13	-3.07	-1.67	3.58	-1.26	-0.15	1.21	0.21	-0.05	1.79	-1.59	0.45	1.07	0.87	-0.32	-2.02	-0.60	0.41	3.46
26	0.43	5.53	2.84	-0.64	1.70	-0.72	-0.03	-1.46	0.56	3.91	0.17	1.17	-0.77	2.38	-1.11	2.53	-1.27	-2.09	-1.15	-3.84	-0.07
27	1.32	-0.24	0.06	1.47	-0.39	-0.56	-0.79	1.65	-1.95	1.75	-0.40	0.56	1.06	-4.30	1.35	0.39	-1.00	2.16	1.75	1.87	-0.89
b_{out}											-1.56										