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Minimization of differential column shortening and sequential analysis of RC 3D-frames using ANN

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Abstract. In the preliminary design stage of an RC 3D-frame, repeated sequential analyses to determine optimal members' sizes and the investigation of the parameters required to minimize the differential column shortening are computational effort consuming, especially when considering various types of loads such as dead load, temperature action, time dependent effects, construction and live loads. Because the desired accuracy at this stage does not justify such luxury, two backpropagation feedforward artificial neural networks have been proposed in order to approximate this information. Instead of using a commercial software package, many references providing advanced principles have been considered to code a program and generate these neural networks. The first one predicts the typical amount of time between two phases, needed to achieve the minimum maximorum differential column shortening. The other network aims to prognosticate sequential analysis results from those of the simultaneous analysis. After the training stages, testing procedures have been carried out in order to ensure the generalization ability of these respective systems. Numerical cases are studied in order to find out how good these ANN match with the sequential finite element analysis. Comparison reveals an acceptable fit, enabling these systems to be safely used in the preliminary design stage.

Keywords: sequential analysis; differential column shortening; optimization; minimization; finite element analysis; 3D-frame; artificial neural network

1. Introduction

The erection of a building is a gradual process. The setting up of all individual parts draws a sequence from which the structural analysis must be calqued (Choi and Kim 1985, Kim and Shin 2011, Kwak and Kim 2006, Fu *et al.* 2008, Njomo and Ozay 2014). Although many researchers address the importance of the sequential analysis over the simultaneous analysis especially for middle and high-rise buildings, the latter analysis is still unfortunately applied for diverse reasons. Differences between the two analyses are due to the: (1) differential column shortening (Choi and Kim 1985); (2) sequential application of dead load (Choi and Kim 1985, Fu *et al.* 2008, Njomo and Ozay 2014), and temperature actions (Fu *et al.* 2008, Njomo and Ozay 2014, Azkune *et al.*

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2007); (3) aging, creep, and shrinkage of the concrete (Fu *et al.* 2008, Njomo and Ozay 2014, Kwak and Kim 2006); and (4) consideration of the coming and going of construction loads (Fu *et al.* 2008, Njomo and Ozay 2014).

The differential column shortening may affect non structural elements (Fintel *et al.* 1986), aesthetic appearance, and the normal use of edifices. It is, therefore, imperative to be minimized in order to reduce its consequences. Given a structure destined to some use, made in a definite-characteristic material and located in a particular environment, the structural response depends on the timing of the construction sequence. Thus, the amount of the differential shortening is a function of the interphase, the common duration between two consecutive stages.

On the other hand, performing sequential analysis calls for much more computational effort than performing simultaneous analysis, since the former requires many intermediate computations in addition to the final stage analysis that corresponds to the simultaneous analysis. But regarding the accuracy and the features carried by this strategy, it can be said that this excess demand is duly justified though it needs to be lowered. Some research works tried to accomplish this purpose keeping full or partial accuracy (Choi and Kim 1985, Kim and Shin 2011, Njomo and Ozay 2014, Choi *et al.* 1992).

Choi *et al.* (1992) proposed the so-called correction factor method (CFM) based on regression analysis aiming to obtain sequential analysis results from those of simultaneous. They succeeded to well approximate sequential analysis results considering only dead loads. Gupta and Sharma (2001) reported that Khan developed a neural network which simulates results of sequential analysis from those of one stage analysis. They accounted that the said neural network had not taken into account the time dependent effect. These two models may be merged to a unique one submitted under many other actions, and accounting the tri-dimensional properties of buildings. This new model is expected to be more realistic as it does depict the actual situation of edifices.

Although, the seriousness of these studies has been recognized among the scientific community, the gap as presented above is still present. Moreover, the regression analysis used by Choi *et al.* (1992) may suffer from constraints such as linear or curvilinear relationship of the data with heteroscedatic error (Walczak and Cerpa 1999). Khan tried to overcome this limitation with a multilayer feedforward neural network. He took profit to the fact that this system is a universal function approximator that can interpolate between vectors (Gupta and Sharma 2011, Walczak and Cerpa 1999, Belic 2012, Leondes 1998, Iliadis and Jayne 2011, Fausett 1994, Haykin 2005).

Nevertheless, two actions arose to be capital. The first concerns the reduction of the computational effort needed to obtain results of acceptable accuracy. The second is related to the determination of the sequence interphase with the intention of being able to make good decision at the earlier stage of preliminary study (Gupta and Sharma 2001), since the project phase is the most influential in the total cost (Haroglu *et al.* 2009, Ballal and Sher 2003). In the present paper, the soft computing tool of artificial neural network is utilized in order to reduce the computational effort and the differential column shortening on RC 3D frames. Various loads are considered. These include dead loads, time dependent effects, temperature actions, construction forces and live load. Seismic loads are not considered herewith since they induce similar structural response whether considering sequential analysis or simultaneous analysis (Njomo and Ozay 2014).

Various heuristic principles are considered herein with the intention of developing a home-made routine that implements artificial neural network training modules. Based on this routine, two neural networks are designed. The first aims to predict the optimal interphase yielding to minimal maximorum differential column shortening. Meanwhile, the second one prognosticates both erroneous differential shortening and erroneous internal forces between simultaneous and sequential analyses.

2. Sequential analysis strategy

Sequential analysis of a given building consists of successive analyses at different dates throughout the construction processes. The typical schedule considered herein is to set each of the story erections as a phase. At the beginning, the formwork is put over and the first story is erected. The new cast structure is put to wait for a definite period, termed as interphase, while getting hard. During this elapsing period, it undergoes temperature stresses and time dependent effects. An analysis is carried out in order to determine the structural response at the end of this stage. It shows that this part of the structure has undergone deformations, and presents internal forces across its members.

After that, the story is stricken and the second floor is constructed over shores supported by the existing slab. Instead of keeping the idealized length of column at this new floor, the top is leveled at its designed position. From this moment on and during the second interphase, the first floor supports its own dead load, the construction loads coming from the second floor's erection, temperature action and time dependent effects; and the second floor is submitted under temperature stresses and time dependent effects. Once more, a second analysis is completed considering the deformed shape of the existing structure as reference. This new analysis regards the first story as being weightless because its weight has already been considered in the first analysis. However, it takes into account the temperature action and the time dependent effect occurred during the last interphase. The analysis reveals a new structural response which is cumulated to the previous one.

At the end of the second period, the third floor comes; and the part of the structure, constituted by the first and second stories serves altogether as the first one, while the third serving as the second of the preceding phase. Here, the construction loads formerly applied on the first slab is removed. Operations are repeated till the last floor which is not subjected to any construction load, but to all the remaining load types. After an appropriate analysis is performed and structural response summed up, the live load is applied along with the temperature action and time dependent effect considering the deformed geometry as reference.

3. Minimization of differential column shortening

Choi and Kim (1985), and Choi *et al.* (1992) remarked that the different tributary areas which exterior and interior column support, generate different loads upon these columns, approximately the double for internal columns. Since external columns are also robustly designed to withstand lateral forces, their shortening is relatively moderate compared to those of internal ones. This causes differential column shortenings in buildings. According to Fintel *et al.* (1986), the immediate consequence results in damages on non structural elements such as partitions especially the light ones, architectural finishes and built-in furnishings, mechanical equipments and cladding. Also, the functionality and the visual aspect may be concerned. Wherefore, it is important to reduce this differential settlement.

3.1 Overview

A particular project is characterized by many factors, which determine the structural response whose displacements. Impacting on these displacements necessarily passes through the judicious adjustment of the relevant factors, such as environment, structure geometry and materials, and construction process. Environmental factors are mainly concerned with the temperature and relative humidity which are difficult to influence on. The general geometry of the edifice and members' sizes are dictated by the architectural and structural design. Generally, the material specifications to be used, say cement type and concrete grade, are specified in the tender documents or guided by the availability in the project location. The construction process, especially the interphase period between two typical stages, has a great impact on the total duration of the project, thereby on the total cost (Haroglu *et al.* 2009, Ballal and Sher 2003). Haroglu *et al.* (2009) claimed that it is the structural engineer who is the most influential in selecting the correct structural frame for a project's feasibility and success. Therefore, he should propose a typical duration characterizing the construction timing. In short, it is convenient to minimize the differential shortening by choosing an elementary duration since the other factors are awkward to be imposed or modified.

By considering a very short period of time between two stages, the concrete is still weak when receiving loads, and, thus, is more subjected to instantaneous deformations. On the other hand, if one waits too much between two stages, he allows temperature to change a lot and induces more stresses across the members. Here, the daily variations on temperature are considered negligible because they are generally small and do not have enough time to penetrate across the member's sections (Fintel *et al.* 1986). Also, a high amount of temperature change may cause more shrinkage effects. By increasing the internal forces and keeping the construction loads applied on story below, for a long period of time, one will result in more instantaneous deformations and more creep effects over the lengthy phase. Obviously, there is an optimal interphase between these two extreme cases that leads to a minimum maximorum differential shortening, because it is suitable to minimize the differential shortening at the member location it is more critical.

3.2 Illustrative example

An L-shaped 15-story office building already considered by Njomo and Ozay (2014), is chosen to illustrate the aforementioned phenomenon. Fig. 1 depicts the plan layout of the building. All the slabs are 120 mm thick and the other members' dimensions are recapitulated in Table 1. The concrete properties are f_{c28}=20 MPa; E_{28}=27 050 MPa, and the concrete is made of a normal hardening cement. Time effects are studied along CEB-FIB 90 code. The yielding strength of reinforcement bars is f_y=415 MPa. The environmental factors are 61.6% for relative humidity and -15°C for temperature change. The shrinkage starts at t_s=0 day. A distributed force of 2.0 kN/m^2 is applied onto slabs as office live load plus light partition walls weight (AFNOR 2000). The weight

Table 1 Dimensions of 3D-frame members in reinforced concrete

Floor	Member	Width × Depth (cm)	Cross sectional area of concrete (cm^2)
1-15	Beam	25 × 60	1500
10-15	Column	30 × 60	1800
7-10		40 × 60	2400
1-6		60 × 60	3600

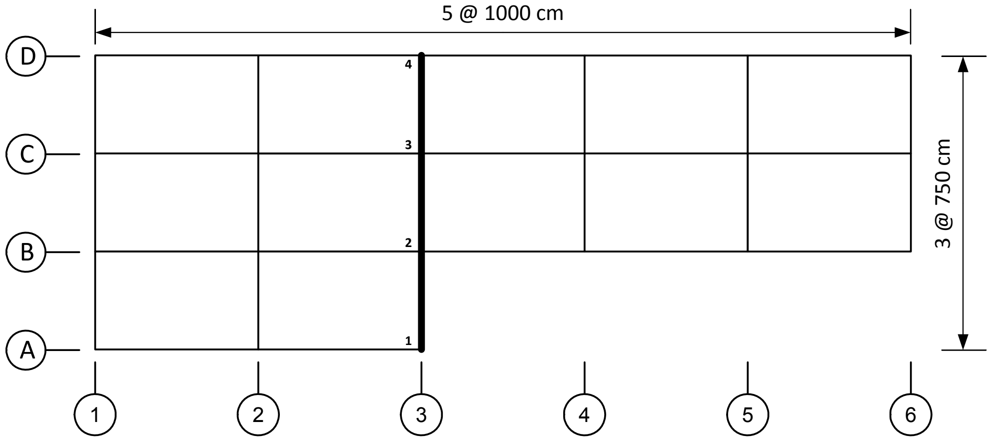


Fig. 1 Plan configuration of the 15-story building

Table 2 Construction sequence

Stage	Duration (in days)	Added Structure	Operations
1	variable	Story 1	
2	variable	Story 2	Striking story 1
3	variable	Story 3	Striking story 2
4	variable	Story 4	Striking story 3
5	variable	Story 5	Striking story 4
6	variable	Story 6	Striking story 5
7	variable	Story 7	Striking story 6
8	variable	Story 8	Striking story 7
9	variable	Story 9	Striking story 8
10	variable	Story 10	Striking story 9
11	variable	Story 11	Striking story 10
12	variable	Story 12	Striking story 11
13	variable	Story 13	Striking story 12
14	variable	Story 14	Striking story 13
15	variable	Story 15	Striking story 14
16	variable		Striking story 15; partition and furnishing; service phase

of the shored floor is increased by 20% to account the construction loads. The construction process is presented in Table 2.

Different analyses have been carried out along with the commercial structural analysis software package *SAP*2000 *version* 15.1.0. The interphase has been varied from 1 to 28 days. That is, for a given interphase, the analysis has been conducted and the maximum differential column shortening has been noted as result. The graph in Fig. 2 represents the evolution of the maximum differential shortening versus the interphase. It readily appears that the minimum occurs for the critical interphase of 10 days.

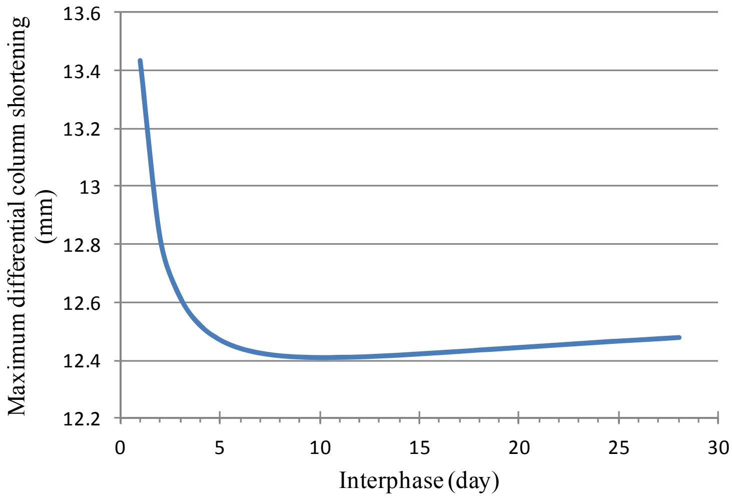


Fig. 2 Evolution of the maximum differential shortening versus the interphase

4. Overview on Artificial Neural Network (ANN)

Human brain is able to complete highly sophisticated tasks. To achieve all these, it is made of about one hundred of billions of neurons (Wikipedia 2012), nerve cells connected together through a large network. With the intention of mimicking such a system, scientists developed an artificial neural network comprised by processing units. The final result can mainly perform two specific tasks: pattern recognition and function approximation (Belic 2012). This last task is evidently for our concern.

ANN presents several units to the external world arranged in two layers: one for data input, and the other for data output. The input nodes do not process. Sandwiched between the two external world related layers, there are hidden layers whose connections to the other hidden layers or input/output units are strengthened or weakened by weights. The actual output of a given processing unit is the image of the sum of weighted inputs minus the unit threshold through the activation function. Herein, output units received zero-value thresholds. Several functions may act as activation function but they need to be continuous, differentiable, monotonically non-decreasing and easy to derivate (Fausett 1994). A typical function complying with these requirements is the bipolar sigmoid function *tanh*(·) which will be used for the current problems.

The weights as well as thresholds have to be s*et along* an operation called training or learning. There are many types of ANN learning algorithm. Walcsak and Cerpa (1999) claimed that feedforward back propagation algorithm is superior to the others because of its robustness and its easy accessibility. This algorithm consists of progressively adjusting the weights and thresholds in order to minimize the system energy based on gradient descent method.

After having presented an arbitrary pattern, the energy may be estimated from

$$E_p = \frac{1}{2}\sum_{k=1}^{m}(t_k - y_k)^2 \tag{1}$$

where m is the number of output units, t is the target output value and y is the actual output. The minimization of this energy with respect to the network parameters, say the connection weights and unit thresholds, leads to the updating factors as described by Rumelhart *et al.* (1986). Plus, it is

Table 3 Input data for modeling

#		Parameters	Range	Sensitivity results
1	Environment	Relative humidity (%)	[0, 100]	sensitive
2		Temperature (°C)	[-110, +110]	sensitive
3	Material properties	Cement type	{0.20, 0.25, 0.38}	sensitive
4		Concrete grade (MPa)	[15, 50]	sensitive
5	Building geometry	Building height (number of stories)	[2, 20]	sensitive
6		Width of beam (mm)	[100, 350]	sensitive
7		Depth of beam (mm)	[150, 700]	sensitive
8		Length of beam (mm)	[500, 15000]	sensitive
9		Position of beam	{intermediate, middle, exterior}	sensitive
10		Story of beam	[1, 20]	sensitive
11	Construction process	Interphase (days)	[1, 28]	sensitive
12		Date of shrinkage start		non sensitive

involved a momentum term used to smooth out the learning parameter changes. At this step, a given parameter is obtained from

$$v_m\,(\tau+1) = v_m(\tau) - \eta\,\frac{\partial E_p}{\partial v_m} + \alpha\,\Delta v_m(\tau) \tag{2}$$

in which v_m is the parameter under optimization, τ is the counter of the learning process, η is the gain fraction, α is the momentum term, and $\Delta v_m(\tau) = v_m(\tau) - v_m(\tau-1)$.

As a supervised paradigm, all the input/output patterns should be presented to the network during the learning phase. One epoch designates a complete passage through all the training set. The number of epoch may be used to characterize the learning process. It is necessary to precondition the patterns to have good performance. The input variables are scaled between [-1, 1] so that their respective mean values should be close to zero or else small compared to their respective standard deviation (Haykin 2005) and the output are preprocessed to be within the range of the activation function avoiding saturation (Belic 2012, Haykin 2005).

5. Implementation and results

One hundred of different buildings have been analyzed using *SAP*2000 *version* 15.1.0. The various determinant parameters that characterized these buildings have been chosen within practical ranges. 389 patterns have been obtained from these analyses. 273 of them were used as training set, 58 as validation set and 58 as testing set. To implement backpropagation feedforward ANN, routines have been written by using the computer algebra system *Wolfram Mathematica version* 7.0.

5.1 Input data

As the first approach, parameters from the environment, material properties, building geometry and construction process have all been chosen to model the problem, as presented in Table 3.

Results from sensitivity analysis are also reported. Note should be made that from CEB-FIB 90 code, there is a relationship between the concrete grade and the elastic modulus; therefore, only one of them must be considered. Since the concrete grade is more accessible than the elastic modulus, it is the one held here. Also, it is noteworthy to precise that relative humidity and temperature are not related because one can find some geographical areas with the same temperature average but different humidity values, and vice versa (Wikipedia 2012, Mherrera 2012).

The sensitivity analysis reveals that the age of concrete at the beginning of the shrinkage is not sensitive, so this parameter has not been considered in this study. The cement type here is denoted by its characteristic coefficient as presented by CEB-FIP Model 90. Ali and Moon (2007) argued that for cost-efficiency the maximum number of stories of R/C frame building is 20 stories, and it is not relevant in this study to deal with mono-story buildings. http://www.mherrera.org/temp.htm recapitulates the extreme temperatures around the world. It presented the extreme temperature change of ±104.9℃ as occurring in Verkhojansk, Russia. But, as Anderson *et al.* concluded in 1997, this range has been little enlarged with the intention to allow the network to handle the edge of data space, and to foresee special cases (potentially due to uncertainties of measures or global warming). However, the interphase has been restricted under 28 days due to the symbolism carried by this age of concrete.

Since, it is necessary to normalize them, all of the input variables have been scaled between [-1, 1]. Two variables experienced a specific preprocessing treatment. By convention specific to this study, the position of the beam has been coded -1 for intermediate, 0 for middle and +1 for exterior. Apart from the cement type which has directly been scaled such that 0.2 corresponds to -1, 0.25 to -4/9, and 0.38 to +1, the remaining parameter ranges have been size into [-1, 1] using the log/antilog strategy because of the wide range (several decades) of their natural collections (Belic 2012). With such wide ranges taken into [-1, 1], some variables will be confined within subparts and will not differ enough to be efficiently handled by the network; thus, they need to be redistributed along the entire bipolar interval. As the decimal logarithm tends to separate small but close numbers, and, also, tends to bunch greater ones, Eq. (3) has been developed to propose in this study a bijective function which keeps both signs and order of variables as well as it achieves the required equal distribution. Therefore, preconditioned values are obtained from

$$x' = \frac{2(lg\,x - lg\,x_{min})}{lg\,x_{max} - lg\,x_{min}} - 1 \tag{3}$$

where x is the natural value, and x_{max} and x_{min} are the maximum and minimum natural values of the corresponding input, respectively. $lg(\cdot)$, which involves the decimal logarithm $log_{10}(\cdot)$, is defined as

$$lg(z) = \begin{cases} -\,log_{10}(|z-1|)\,, & z < 0 \\ \quad log_{10}(z+1)\,, & z \geq 0 \end{cases}. \tag{4}$$

5.2 Output data

Based on the targeted objectives, Table 4 displays the possible final output. The output data are scaled into [-1+S_m, +1-S_m]. S_m is the saturation margin at each bound of the interval and is taken as S_m=0.01. Therefore, the preprocessed values are given as

$$y' = \frac{2(1-S_m)(lg\,y - lg\,y_{min})}{lg\,y_{max} - lg\,y_{min}} - (1 - S_m) \tag{5}$$

Table 4 Output data for modeling

#	Parameters	Range
a	Optimal interphase (day)	[4, 28]
b	Erroneous diff. col. shortening (mm)	[-6, 3]
c	Erroneous moment at node 1 (kNm)	[-100, 165]
d	Erroneous moment at node 2 (kNm)	[-135, 75]
e	Erroneous shear force at node 1 (kN)	[-60, 40]
f	Erroneous shear force at node 2 (kN)	[-30, 195]

and the postprocessed or natural values as

$$y = gl(\frac{(\lg y_{max} - \lg y_{min})(y' + 1 - S_m)}{2(1 - S_m)} + \lg y_{min}). \tag{6}$$

$$gl(t) = \begin{cases} 1 - 10^{-t}, & t < 0 \\ -1 + 10^{t}, & t \geq 0 \end{cases}. \tag{7}$$

In Eqs. (3), (5) and (6), $lg(\cdot)$ is the function as defined in Eq. (4), $gl(\cdot)$ is the inverse function of $lg(\cdot)$, and y_{max} and y_{min} are the maximum and minimum natural values of the corresponding output, respectively.

5.3 The training process

For each (sub-) problem, the numbers of exterior nodes are fixed by the problem itself. But there is neither any deterministic method to set the number of hidden layers, nor any one for the number of nodes within each hidden layer. Although theoretically a unique hidden layer with sufficient nodes can be efficient (Walczak and Cerpa 1999, Belic 2012, Fausett 1994), it may be convenient to have more hidden layers in order to handle more complexities in the hyperspace (Walczak and Cerpa 1999, Fausett 1994).

However, there are some heuristic principles, which have been reported by authors, that guide the setting up of the interior ANN size. For instance, Walczak and Cerpa (1999) proposed to use 75% of the quantity of input nodes; or to use 50% of the quantity of input and output nodes; or to use 2*n*+1 hidden layer nodes where n is the number of nodes in the input layer. Fausett (1994) suggested to utilize as the number of weights to be trained *P*×*e*, where *P* is the number of training patterns, and *e*, the accuracy of classification expected.

Anyway, different trials are necessary to obtain the most efficient architecture. Some authors suggest starting with a small number of nodes, and increase them in number till the network performs well. Others recommend, on contrary, to select a huge number, and prune the network as its performance get better. This last solution can also be reached by adopting the so-called weight elimination technique which aims at pushing to zero the connection weights related to useless nodes, thus to prevent them from any participation. It consists of modification of the network energy from Eq. (1) to $W = \sum_p E_p + 0.5\,\lambda \sum_m \frac{(\frac{v_m}{v^*})^2}{1 + (\frac{v_m}{v^*})^2}$, thus Eq. (2) becomes, for connection weights only (thresholds are not concerned)

$$v_m\,(\tau + 1) = v_m(\tau) - \eta\,\frac{\partial E_p}{\partial v_m} + \alpha\,\Delta v_m(\tau) - \eta\,\frac{\lambda}{v^*}\frac{\frac{v_m}{v^*}}{\left[1 + (\frac{v_m}{v^*})^2\right]^2} \tag{8}$$

where λ and v^* are constants.

Also, it is a tremendous task to choose the initial values of weights and thresholds in order to start the training process. However, to avoid saturation, they should be small enough (Haykin 2005). Fausset (1994) recommended setting them randomly between -0.5 and 0.5. Then, a simple modification as developed by Nguyen and Widrow in 1990 is accounted. If n and h are the numbers of input and hidden units, respectively, then the scale factor $\beta = 0.7\sqrt[n]{h}$ and the column norm into the input-hidden weight matrix would be as $\|w_j\| = \sqrt{\sum_{i=1}^{n} w_{ij}^2}$, where w_{ij} is the weight from input unit i to hidden unit j. Then, the reinitialized weights will be $w_{ij} \leftarrow w_{ij} \times \beta/\|w_j\|$ and the unchanging thresholds for hidden units would remain as randomly chosen between $-\beta$ and β. Weights to output units and thresholds are not subjected to this modification.

Finally, the optimal learning rate η and momentum α are, as well, the result from many tentative trials although Anderson *et al.* (1997) suggested to take $\eta = 1/n$ and $\alpha = 3/(2n)$ where n is the number of input nodes.

Once launched, the training has been stopped for one of these three reasons arranged in order of priority: (1) the validation energy starts to increase; (2) the training energy drops under an arbitrary tolerance, say 10^{-6}; (3) a given number of epochs, 10^8, is reached.

Along the energy defined in Eq. (1), the error at each output, following the presentation of the last epoch corresponding to the end of the training phase, is calculated through

$$error = \frac{0.5}{P \times m} \sqrt{\sum_{j=1}^{P} \sum_{k=1}^{m} (t_k - y_k)^2} \tag{9}$$

where *m*, *t* and *y* are defined as in Eq. (1), and *P* is the number of patterns.

5.4 Minimization of differential shortening

For the differential shortening minimization, a network with a single architecture has obviously been held. As input data, the parameters that describe the project in hand as a whole are used: items 1-5 from Table 3. The expected output is the optimal interphase yielding to minimum maximorum of differential column shortening. Since this optimal has been ceiled at 28 days, the ANN tends to reduce a bit the actual output but it still performs with a good accuracy. Table 5

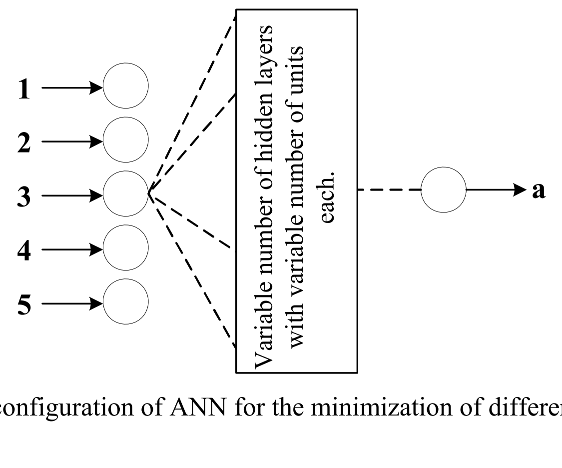


Fig. 3 Typical configuration of ANN for the minimization of differential shortening

Table 5 Differential shortening minimization ANN's training results

Configuration	Number of epochs	Training error	Validation error	Generalization error
5-15-1	28	0.00418	0.00912	0.01095
5-15-1-1-1	**1294**	**0.00279**	**0.00728**	**0.00636**
5-5-20-4-1	2137	0.00266	0.00744	0.00658
$\boldsymbol{\eta} = 0.100$; $\boldsymbol{\alpha} = 0.020$; $\boldsymbol{\lambda} = 0.00$ or 0.01; $\boldsymbol{v}^* = 3.00$				

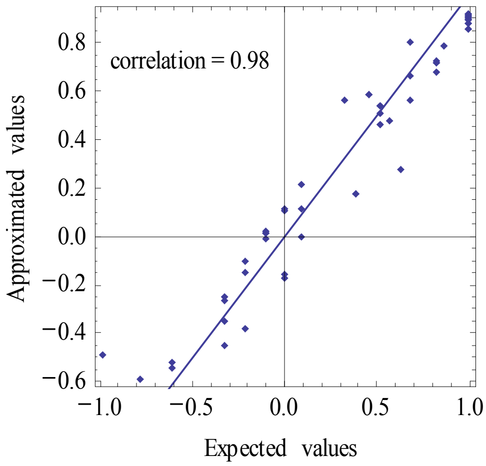


Fig. 4 ANN 1: mapping of the expected values versus ANN results

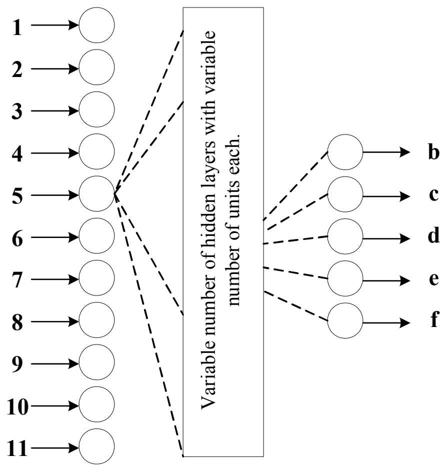


Fig. 5 Typical configuration of structural response ANN

points out the results obtained. Using the highlighted network in this Table 5, Fig. 4 has been drawn up. The relative position of each point with respect to the 45° line shows how well the approximated prediction fits with the expected perfect value.

Numerical example

The case study described above is recalled here to serve as the checking case of the ANN

Table 6 Structural response ANN's training results

Configuration	Number of epochs	Training error	Validation error	Generalization error
11-50-50-50-5	468	0.00171	0.00360	0.00431
11-20-20-20-5	915	0.00175	0.00338	0.00460
11-35-45-35-5	**1198**	**0.00138**	**0.00329**	**0.00431**
$\boldsymbol{\eta} = 0.100$; $\boldsymbol{\alpha} = 0.020$; $\boldsymbol{\lambda} = 0.00$; $\boldsymbol{v}^* = 3.00$				

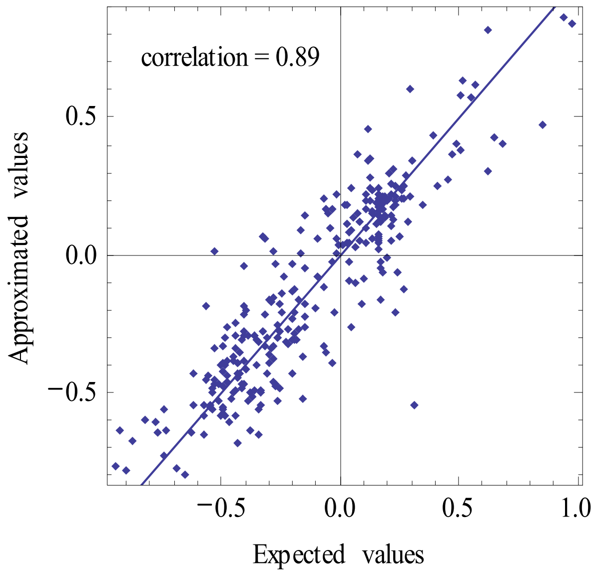


Fig. 6 ANN 2: mapping expected values versus ANN results

designed above. As depicted in Fig. 1, the optimum interphase is 10 days. The prediction obtained is 9.95 days. Considering the aforementioned fact about the capping of interphase, this result is definitely considered acceptable.

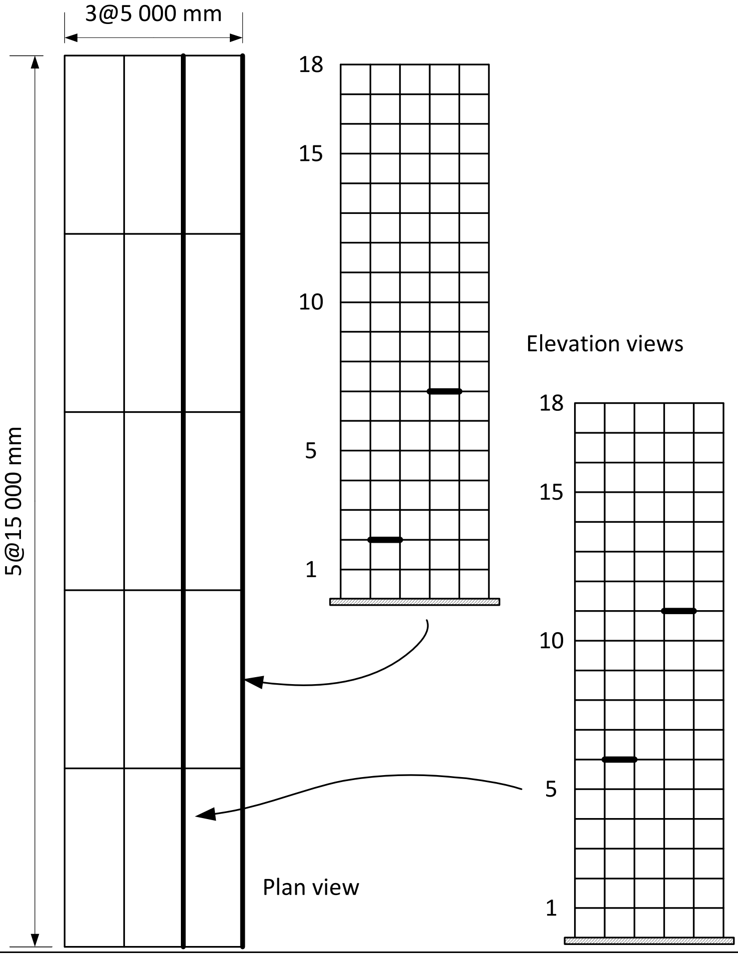
5.5 Structural response prediction

This neural network (Fig. 5) aims at predicting all the data required, *b-f* from Table 4, using input data 1-11 in Table 3. The analysis results are reported as in Table 6. As in the first problem, Fig. 6 has been produced from the network in the boldface of Table 6. The correlation between the ANN prognostics and the FEM results is 0.89.

Numerical example

A numerical case is taken, herewith, to show the prediction performance of the second neural network. Table 7 illustrates and describes the building in hand, Table 8 reports the different results obtained from various methods herein considered, and Table 9 states the errors observed in ANN predictions compared to finite element analysis. These errors, expressed in percent (%), vary from -2.34 to 5.69, values which are acceptable regarding the simplicity of this method.

Table 7 Illustration and description of the numerical case S2



Relative Humidity = 59%	Concrete grade = 28 MPa	Position: intermediate
Temperature change = 23°C	Building height = 18 stories	Holder story = 2, 6, 7 or 11
Cement type = 0.38	Beam 250×650×15 000 mm^3	Interphase = 23 days

Table 8 Result report for numerical case #2

		Story 2		Story 6		Story 7		Story 11	
		Node 1	Node 2	Node 1	Node 2	Node 1	Node 2	Node 1	Node 2
Differential settlement (mm)	SM-FEA	2.729		7.162		8.067		10.906	
	SQ-FEA	3.688		9.205		10.118		11.987	
	SQ-ANN	3.898		8.963		9.794		12.147	
Moment (kNm)	SM-FEA	-394.85	-436.85	-418.96	-412.05	-422.42	-408.09	-433.36	-395.74
	SQ-FEA	-377.26	-412.81	-397.29	-393.19	-400.07	-390.65	-406.53	-386.67
	SQ-ANN	-383.78	-403.82	-399.27	-383.98	-399.21	-386.28	-397.89	-389.56
Shear force (kN)	SM-FEA	-133.38	138.98	-136.23	135.41	-136.66	134.87	-138.03	133.19
	SQ-FEA	-123.93	128.30	-126.56	126.01	-127.00	125.78	-128.28	125.76
	SQ-ANN	-126.08	131.94	-129.55	123.42	-129.46	123.85	-128.62	126.10

Table 9 Percentage errors in the results for numerical case #2

	Story 2		Story 6		Story 7		Story 11	
	Node 1	Node 2	Node 1	Node 2	Node 1	Node 2	Node 1	Node 2
Differential settlement	5.69		-2.63		-3.20		1.33	
Moment	1.73	-2.18	0.50	-2.34	-0.21	-1.12	-2.13	0.75
Shear force	1.73	2.84	2.36	-2.06	1.94	-1.53	0.27	0.27

6. Conclusions

One hundred RC 3D-frames with various characteristics within the common practical ranges have been analyzed both sequentially and simultaneously, by considering various types of loads as dead load, temperature action, time dependent effects, construction and live loads. A huge database of 389 input/output vectors has been drawn from these studies in order to design each of the two backpropagation feedforward artificial neural networks. They have been designed based on a home-made routine developed after considering various heuristic principles. The first network aimed at simulating the optimal interphase from the determinant parameters. The second was to portray the relationship between the simultaneous analysis results and those obtained from sequential analysis. Many attempts have been made through the use of different possible configurations and parameters in order to detect a good performing combination.

Acceptable energies have been found out and held under 0.01. Numerical cases have sequentially been studied both with the finite element method and with the ANN procedure. Results have shown a good matching with the maximum error of about 5%.

The preliminary design stage requires repeated FEM sequential analyses to determine the optimal member sizes, and investigate the parameters required to minimize the differential column shortening. This phase is laborious, computational effort consuming, but does not requires much precision. It is expected that these soft computing tools will be utilized in the preliminary design stage because the desired accuracy does not justify such luxury.

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