Advances in Computational Design, *Vol. 3, No. 3 (2018) 289-302*
DOI: https://doi.org/10.12989/acd.2018.3.3.289

Compressive strength prediction of limestone filler concrete using artificial neural networks

Hocine Ayat[1a], Yasmina Kellouche[1b], Mohamed Ghrici[*1] and Bakhta Boukhatem[1,2c]

[1]*Geomaterials Laboratory, Hassiba Benbouali University of Chlef, P.O. Box 151, Chlef 02000, Algeria*
[2]*Department of Civil Engineering, University of Sherbrooke, Sherbrooke, Canada*

(Received April 6, 2018, Revised July 3, 2018, Accepted July 10, 2018)

Abstract. The use of optimum content of supplementary cementing materials (SCMs) such as limestone filler (LF) to blend with Portland cement has been resulted in many environmental and technical advantages, such as increase in physical properties, enhancement of sustainability in concrete industry and reducing CO_2 emission are well known. Artificial neural networks (ANNs) have been already applied in civil engineering to solve a wide variety of problems such as the prediction of concrete compressive strength. The feed forward back propagation (FFBP) algorithm and Tan-sigmoid transfer function were used for the ANNs training in this study. The training, testing and validation of data during the backpropagation training process yielded good correlations exceeding 97%. A parametric study was conducted to study the sensitivity of the developed model to certain essential parameters affecting the compressive strength of concrete. The effects and benefits of limestone filler on hardened properties of the concrete such as compressive strength were well established endorsing previous results in the literature. The results of this study revealed that the proposed ANNs model showed a high performance as a feasible and highly efficient tool for simulating the LF concrete compressive strength prediction.

Keywords: concrete, limestone filler, compressive strength, prediction, artificial neural networks

1. Introduction

Concrete is the most used material in civil engineering because of its strong ability to resist compression. Mechanical properties, such as compressive strength, require selection of blend ratios, blend design specifications and economics of the cementitious materials used (Khan 2012). The compressive strength is one of the most important mechanical properties in mix design of concrete, which is defined as the capacity of concrete sample to withstand the momentum of a pivotal strength. The sample concrete is crushed when the compressive strength limit is reached, which is usually measured after a standard curing of 28 days (Neville 1996). This property is one of the major factors for controlling the strength of cementitious materials. It can be improved by

*Corresponding author, Professor, E-mail: m.ghrici@univ-chlef.dz
[a]Ph.D. Candidate, E-mail: hocineayat@yahoo.fr
[b]Ph.D. Student, E-mail: yasmina.kellouche@yahoo.fr
[c]Associate Professor, E-mail: Bakhta.Boukhatem2@usherbrooke.ca

http://www.techno-press.org/?journal=acd&subpage=7 ISSN: 2383-8477 (Print), 2466-0523 (Online)

using a partial replacement of Portland cement in concrete through the use of alternative cementitious materials (Ramezanianpour 2014).

The supplementary cementitious materials (SCM's) are now commonly used to reduce the clinker factor of cement and reduce its environnemental impact (Ergun 2011, Antoni *et al.* 2012, Habert 2013). Binders are usually composed of binary, ternary and quaternary combination of supplementary cementitious materials (SCM's), such as pozzolanic materials (fly ash, ground granulated blast furnace slag, silica fume, metakaolin, …etc.) or filler materials (quartzite filler, limestone filler), with Portland cement. Therefore, SCM's can be used in Portland cement replacement for these reasons: (1) their cost is significantly lower than that of Portland cement; (2) some of SCM's increases the early-age mechanical properties and reduces the aggressive environmental impacts of concrete; (3) improve the long-term performances of concrete (Bouasker *et al*. 2014).The main issues which have been gained much attention in recent years toward of design and enhancement properties of concrete is the use of the optimum content of non-reactive SCM's such as limestone filler (LF) to partial replacement the OPC (Ramezanianpour 2014). Moreover, the use of limestone blended cement in concrete has several environmental and technical benefits, such as the reduce of CO_2 emission and improves the workability, the strength and the durability of concrete. The term fillers refer to rock particles obtained by crushing or milling added to a binder. The use of fillers is intended to enhance the particle distribution of the powder skeleton, reducing inter-particle friction and ensuring greater packing density (Elyamany *et al*. 2014). The limestone is calcareous sedimentary rock mainly consisting of calcium carbonate ($CaCO_3$) commonly so-called calcite (Thongsanitgarn *et al*. 2011). According to the European standard EN 197-1, the minimum amount of $CaCO_3$ is specified to be 75% by mass of limestone used as a filler material in cement (EN 197-1 2012). In recent decades, many countries around the world have focused in research the use of this material as replacement materials for ordinary Portland cement (OPC) in concrete due to the technical, economic and ecological importance of limestone filler, as part of the sustainability movement (Bentz *et al*. 2015).

Artificial Neural Networks (ANNs) are soft computing techniques developed to mimic the neural system of human being in learning from training patterns or data. They are capable to solve very complex problems, such as highly non-linear problems with the help of interconnected computing elements by approximating the nonlinear input-output relationship for a wide range of applications (Haykin 1994, Pratt 1994, Munakata 1998). The technique of neural networks is increasingly used in the field of civil engineering to predict or optimize more or less complicated phenomena, such as the efficiency factor of slag concretes and fly ash concrete (Boukhatem *et al*. 2010, 2011), the concrete mix design incorporating natural pozzolans (Boukhatem *et al*. 2012), properties of self-compacting concrete containing fly ash (Douma *et al*. 2016), carbonation depth of fly ash concrete (Kellouche *et al*. 2017). Several researchers have applied this technique for the prediction of the compressive strength of concrete and have proved her performance compared to other classical techniques (Yeh 1999, Rafat Siddique *et al*. 2011, Ferhat Bingol *et al*. 2013, Adriana Trocoli *et al*. 2013, Chou and Pham 2013, Muhd Fadhil *et al*. 2015). Some have optimized the compressive strength of concrete containing cement additions; The silica fume concrete (Özcan *et al*. 2009), concrete with siliceous filler and silica fume addition (Sobhani *et al*. 2010), fly ash concrete (Topçu and Sarıdemir 2008), self-compacting and high performance concrete with high volume fly ash (Prasad *et al*. 2009).

The aim of this investigation is to develop an ANNs model with easy handling for predicting the compressive strength of concrete incorporating limestone filler. The training of the ANN model was carried out on a set of experimental data considering several parameters such as the binder content (B), limestone filler percentage (LF), Gravel content (G), Sand content (S), water/binder ratio (W/B), superplasticiser (Sp) and curing age (A).These parameters were used as experimental input variables while the experimental compressive strength (CS) property was used as an output. Furthermore, a parametric analysis and a comparison study were carried out between the experimental and the ANNs predicted results for evaluating the performance of developed ANNs model.

2. Brief overview of ANNs

ANNs is a soft computing technique, which works on the principle of neural networks inspired by biological nervous systems of living organisms. It can learn by examples of data, such as each the intelligence models. Typically, the architecture of ANNs is composed by a set of interconnected many simple computational nodes operating in parallel so-called the neurons, that are usually arranged into groups systematically, for forming layers in network, which provide a response so-called output from a series of inputs (Shahin *et al*. 2009). Thus, the neural networks might be single layer or multilayer, which is consisted by an input layer which have no computation activities, while it was distributing the information from the environment to one or more hidden layers of network, which process the information to provide into the desired output. The number of neurons in the input and the output layers is equal to the variable in the model and the hidden and output layers make the activation function except for input layers. For that, all processing of information in the neural network is happening in the hidden and output layers. The connection strength between the layers is represented by links channels carrying numeric values so-called weights, which are initially set to a random value and adjustable during the training process. The use of nonlinear activation functions in hidden layers improve the ability of ANNs to learn nonlinear relationships between sets of inputs and outputs data; as shown in Fig. 1. The modeling with ANNs required five main stages: (a) acquisition and analysis the data, (b) determining the architecture of model, (c) learning process determination, (d) training of the networks and (e) testing and validation of the model proposed for generalization evaluation. Therefore, an artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. The weighted sums of the input component $(net)_j$ are calculated by using Eq. (1) as follows:

$$(net)_j = \sum w_{ij}\, x_i + b \tag{1}$$

where x_i is the input data; w_{ij} is the weight of the neural model; b is the bias. The FFBP is the effective learning and the most commonly algorithm used for training the ANNs (Freeman and Skapura 1991). The FFBP algorithm is a gradient descent technique used to determine the appropriate weights adjustments necessary from output layer back to input layer and to minimize the squared error of a particular training pattern by a small amount at a time. The training phase of this algorithm consists: The forward pass computes for the network output for a given set of connection weights and input data. The backward pass computes for the error of the network with respect to the target outputs and this error is passing backward to the network and is used to modify the connection weights. In testing phase, another input data can be used in testing of the ANNs, while they are used the final values of the weights obtained in the training phase. A typical FFBP neural network is shown in Fig. 1. The FFBP is reinforced with an advanced training

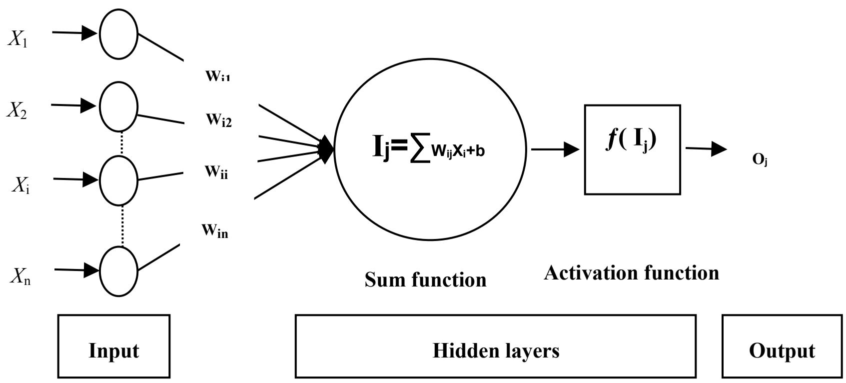


Fig. 1 Typical neural network architecture

supervised learning algorithm named as Levenberg-Marquardt (LM), which is considered to be the fastest method for training moderate-sized of FFBP algorithm, through to reduce the time required for training and simplify the learning process. Thus, the Levenberg-Marquardt is highly recommended as a first choice supervised algorithm, although it requires more memory compared to other algorithms, which in turn makes it ideal for learning the networks (Suratgar *et al*. 2005).

3. Experimental database collections and normalization

In this study, the main objective is to develop an ANNs model based on a comprehensive database to predict the compressive strength of concrete. For this aim, the first step needs to collect and select a large variety of pre-existing experimental data and construct a database reliable for training and testing samples and modeling with ANNs. A large number of databases with 360 cases, were collected and selected from six different distinct sources in literature (Meddah *et al*. 2014, Lollini *et al*. 2014, Ramezanianpour *et al*. 2009, Cam and Neithalath 2010, Tsivilis *et al*. 2003, Marques *et al*. 2013), were used to construct the ANNs model. The complete list of the database is summarized in Table 1. In order to measure the performance of the optimal model obtained by ANNs, it is necessary to use the testing data. The network needs to use the validation data in order to improve the construct network generalization after the training and testing phases were completed and to specify the generalization ability of the model chosen on data which they did not used in training in them (Boukhatem *et al*. 2011). To obtain a consistent division, the data sets are divided randomly into three subsets: 252 data sets were allocated for the stages of training, approximately 70% of the database and remaining data sets were allocated about 108 data sets for the stages of testing and validation, approximately 30% of the database. The range of the different input and output variables of total data sets used for building of ANNs model are summarized in Table 2.

The pre-process of data is very necessary in order to improve the accuracy of prediction and increase the speed in the training process, because the data will not be entered directly in ANNs by real values. Therefore, the data are scaled asymptotic in the range of [-1, 1], according to the hyperbolic tangential sigmoid transfer function which varies between -1 and +1; as given in Figure 2. A “Tansig” sigmoid type activation function is used for hidden and output layers. The hyperbolic tangent sigmoid transfer function is defined by Eq. (2) in the following:

$$Y = \left(\frac{e^{2x} - 1}{e^{2x} + 1}\right) \tag{2}$$

The normalized value is calculated by using Equation (3) in the following:

$$X_n = 2\left(\frac{X - X_{min}}{X_{max} - X_{min}} - 1\right) \tag{3}$$

where X_n is the normalized value, X is the raw data value to be normalized from the dataset and X_{min} and X_{max} are the minimum and maximum raw values from the dataset, respectively. Therefore, after the training process is evident that must be remapped the corresponding real values for the calculating any prediction. The output values were post processed and calculated to convert the data from unnormalized units in the end process by using Equation (4) in the following:

$$Y = 0.5\left(\frac{Y_i + 1}{Y_{max} - Y_{min}}\right) + Y_{min} \tag{4}$$

where Y and Y_i are the ***i***-th components of the output vector before and after translation, respectively and Y_{max} and Y_{min} are the maximum and minimum values of the real data of all components of the output vector.

Table 1 Summary of data used

Reference	Years	fc range (MPa)	Binder range (Kg/m^3)	Limestone filler range (%)	Water to binder ratio range	Age (days)	Number of data set
Meddah *et al*.	2014	0.8-56.8	235-410	0-45	0.45-0.79	1-365	175
Lollini *et al*.	2014	15.4-69.6	250-400	0-30	0.42-0.61	1-180	59
Ramezaniapour *et al*.	2009	9.2-53.6	350	0-20	0.37-0.55	3-180	75
Cam *et al*.	2010	32.8-60.9	416	0-15	0.34-0.40	7-56	15
Tsivilis *et al*.	2003	21.6-31.9	270-330	0-35	0.62-0.70	7-28	12
Marques *et al*.	2013	32.1-57.0	330-390	0-35	0.55	28-365	24

Table 2 Boundary range of inputs and output of model (records)

Inputs variables		Minimum	Maximum
Binder (Kg/m^3)	*B*	235	416
Limestone filler (%)	LF	0	45
Gravel (Kg/m^3)	G	733	1289
Sand (Kg/m^3)	S	650	1050
Water to binder ratio	W/B	0.34	0.79
Superplasticizer (%)	Sp	0	2.6
Age of specimen (days)	A	1	365
Output variable Compressive Strength (MPa)	CS	1	70

4. ANNs model Development

4.1 Neural Network Architecture

In this research, the ANNs model employs the FFBP network; it was trained through a learning rule based on Levenberg-Marquardt algorithm. The computer software was performed to design the network using neural network toolbox -*NNTOOL*- available in MATLAB. It was trained using the *"TRAINLM"* training function with the "LEARNGDM" adoption of learning function. The ANNs model selected consists of four layers: seven neurons in the input layer correspond to variables, two hidden layers with three neurons in the first hidden layer and eight neurons in the second hidden layer and an output layer with one neuron corresponding to compressive strength (CS). The neuron numbers in each the two hidden layers were selected after several attempts in order to achieve the desired result since there is no any theory until now for determining the number of hidden layers in to construct the network. Consequently, the optimum network architecture is 7-3-8-1, which contains two hidden layers. The following variables were used as input parameters to build and train the model namely: amount of Binder (B), Limestone filler percentage replacement (LF), amount of Gravel (G), amount of Sand (S), Water to binder ratio (W/B), Superplasticizer percentage (Sp) and Age of curing (A). The corresponding model illustration is given graphically in Fig. 3.

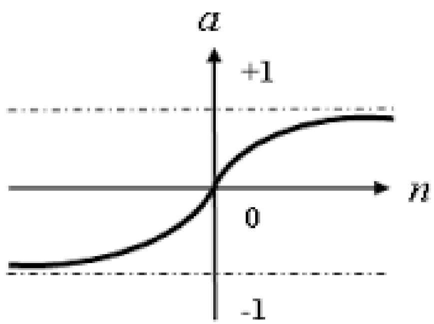


Fig. 2 Tan-Sigmoid Transfer function

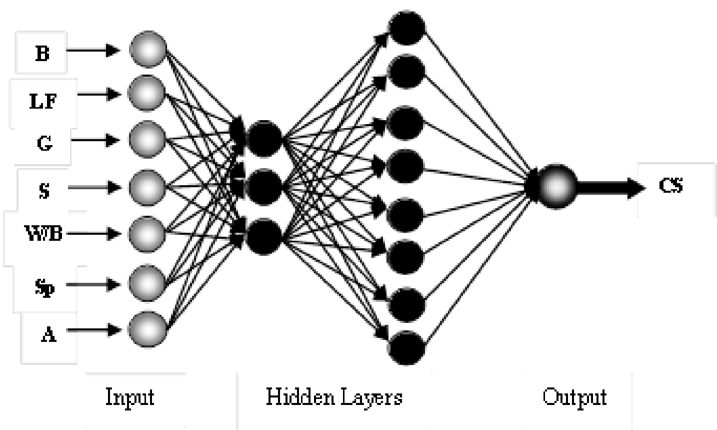
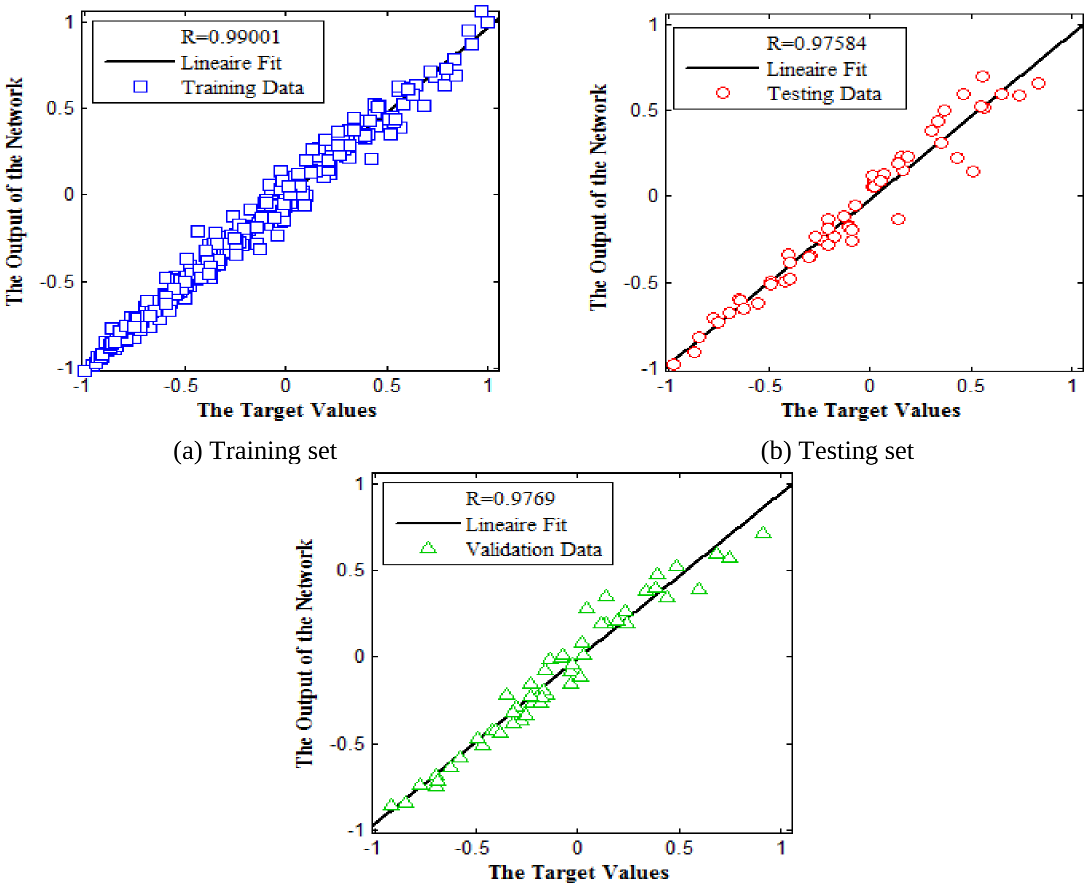


Fig. 3 Architecture of neural network model



(a) Training set

(b) Testing set

(c) Validation set

Fig. 4 Classes evaluation of system error: (a) training set; (b) testing set and (c) validation set

Table 3 ANN model Learning Parameters

Parameters	Values assigned
Training data set	252
Testing data set	54
number of epochs	1000
Learning rate	0.1
Momentum rate	0.001
Goal	1e-3
Show	5

4.2 Model training, testing and validation

In order to compare the compressive strength results predicted by ANNs model and those of the experimental data, with different LF replacements (0% - 45%) and W/B ratios (0.34 - 0.79). A simple statistical analysis was performed through the scatter plot by determining the correlation coefficient (R). This analysis was carried out after selecting the neural network paradigm subject to several training parameters; such as the number of iterations (Epochs=1000), desired minimum

Table 4 Validation of the ANNs model

References	Experimental fc (MPa)	ANN fc model (MPa)	Deviation (MPa)
Skaropoulou *et al*. 2013	45.6	42.7	2.9
	37.1	37.6	0.5
	33.5	32.4	1.1
Githachuri *et al*. 2013	46.7	46.3	0.4
	34.7	32.2	2.5
	51.9	50.1	1.8
Guemmadi *et al*. 2009	39.6	35.4	4.2
	33.3	31.0	2.3
	29.5	31.0	1.5
	25.8	28.0	2.2
	22.2	23.0	0.8
	18.7	18.0	0.7
	15.4	14.0	0.6
ABS[(Exp-ANN)/Exp] ×100	5.6		

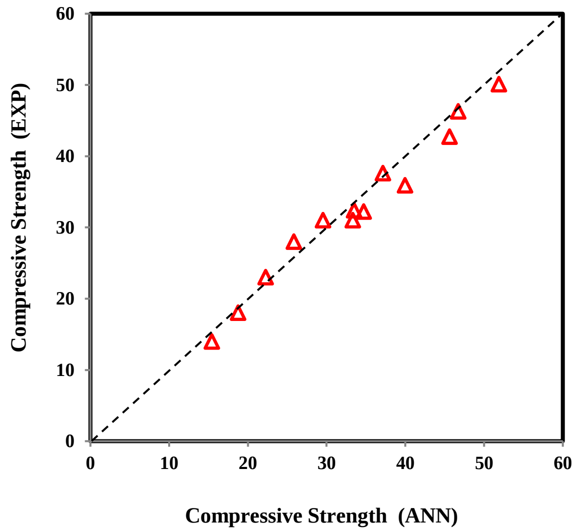


Fig. 5 Comparison between the ANN results and experimental results

error (Goal=0.001) and frequency of progress displays (Show=5). The model was trained through number of iterations, learning rate and momentum rate values were determined. The details of network architecture chosen are shown in table 3. The R values are shown in figures 4a, b and c that were 0.990, 0.995 and 0.976 for training, testing and validation, respectively. According to R values obtained, the proposed ANNs model is very close and suitable to that of the experimental results, indicating that it is reliable for predicting the compressive strength of limestone concrete.

5. Checking validity of model

Unfortunately, available previous studies on the prediction of compressive strength of limestone concrete by ANNs are unknown and, thus, a comparison cannot be made (Öztaş *et al*. 2006). For this aim, to validate any results is to consider earlier studies and compared with these results obtained from this model. In this study, a comparative validation was carried out between the experimental results obtained from several studies from the literature (Skaropoulou *et al*. 2013, Githachuri *et al*. 2013, Guemmadi *et al*. 2009) and the predicted results obtained from the ANNs model. Table 4 presents the validation of the ANNs model by using the experimental results of compressive strength. Figure 5 shows the curve fitting between the ANN predicted values and the expected values. Obviously, in figure 5 and approved by findings of Table 4, the results obtained from the ANNs model are in agreement with those of the experimental values.

6. Parametrical analysis of ANN proposed model

Previous studies in the literature confirmed that many factors are affecting in compressive strength of concrete such as SCM's used for partial replacement of Portland cement, water content and Superplasticizer. Therefore, a parametric analysis was carried out to study the influence of some essential parameters affecting concrete compressive strength using the ANN model previously developed through a sensitivity analysis. The sensitivity of the ANNs model to some main parameters was evaluated by examining its behavior with respect to the variation of single parameter. As a result of that, this analysis was performed by keeping fixed parameters values, whereas the desired parameter was varied (Madandoust *et al*. 2010). This parametric analysis was performed for further verification of the ANNs model performance. Therefore, this analysis through the simulation per network is required to validate the model selected. Accordingly, the main influencing parameters on compressive strength was analyzed separately in the following sections (the water to binder ratio, percentage replacement of limestone filler, cement content, age and Superplasticizer content). The parametric analysis results as shown in Figs. 6 to 8, are generally consistent with previous results in concrete technology.

6.1 Influence of water-binder ratio (w/b)

According to the viewpoint of civil Engineering, it has been reported that water to binder ratio (w/b) is the first parameter significantly affects the concrete compressive strength (Yılmaz *et al*. 2014). The effect of the water to binder ratio (w/b) on compressive strength of concrete containing different LF percentages replacement (from 0 to 30%) at various ages is shown in Figure 6.

It could be clearly seen that the compressive strength is continuously decreasing due to the increase of w/b ratio and vice versa, as to be expected. On the other hand, the compressive strength decreases with increasing the percentage replacement of LF. Moreover, the third observation is pertinent to note that the CS is increased with increasing the age. The effect of w/b ratio can be explained by the fact that an increase in the ratio will increase the volume of capillary pores which will also lead to a reduction in compressive strength of concrete (Madandoust *et al*. 2010).

6.2 Influence of LF replacement

Figure 7 shows the effect of percentage replacement of LF for different binder dosages at

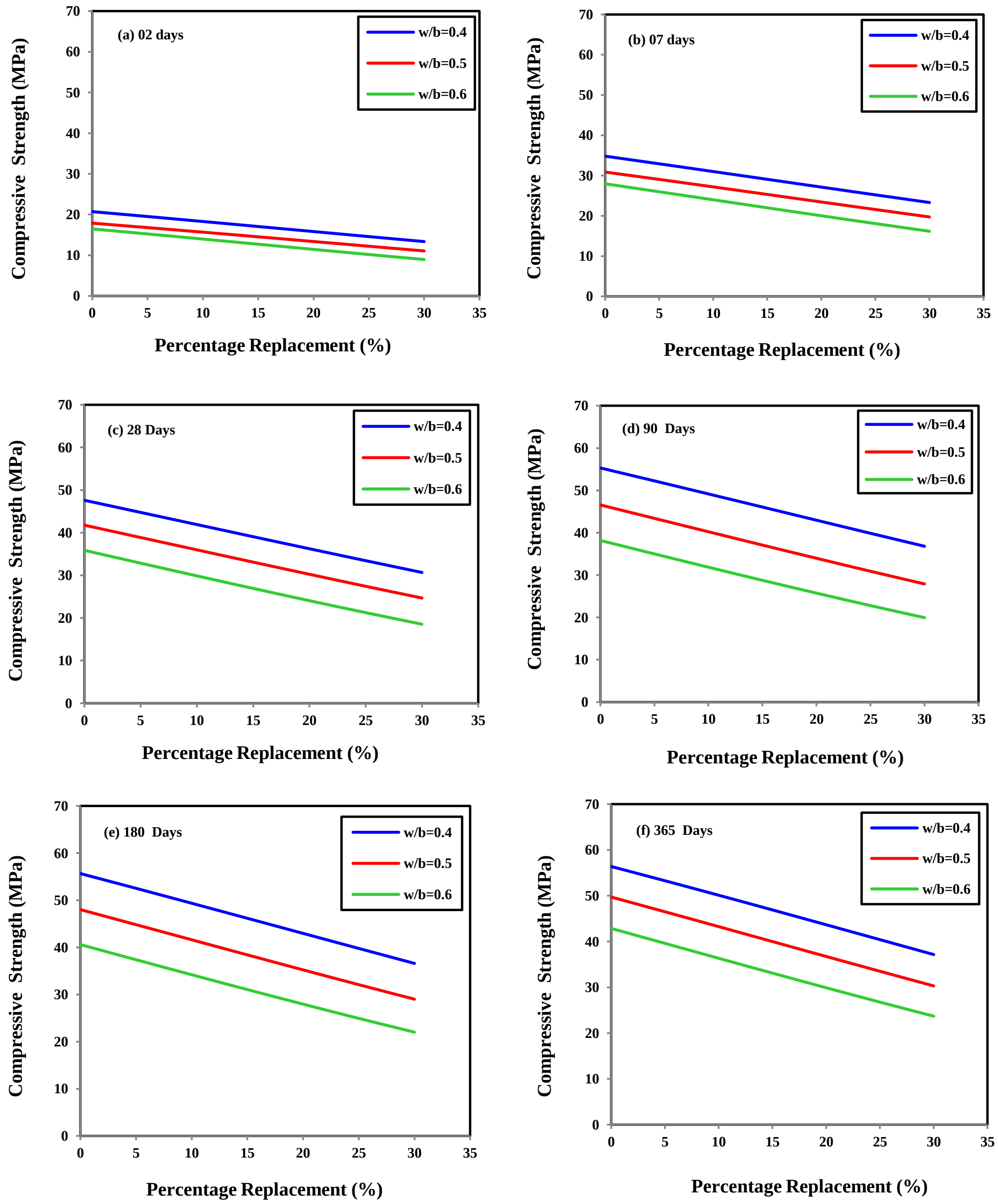


Fig. 6 Effect of w/b on compressive strength of concrete at various ages

various ages on the compressive strength of concrete. It is clear to see that the compressive strength decreases proportionally to the LF levels increase. On the other hand, it should be noted

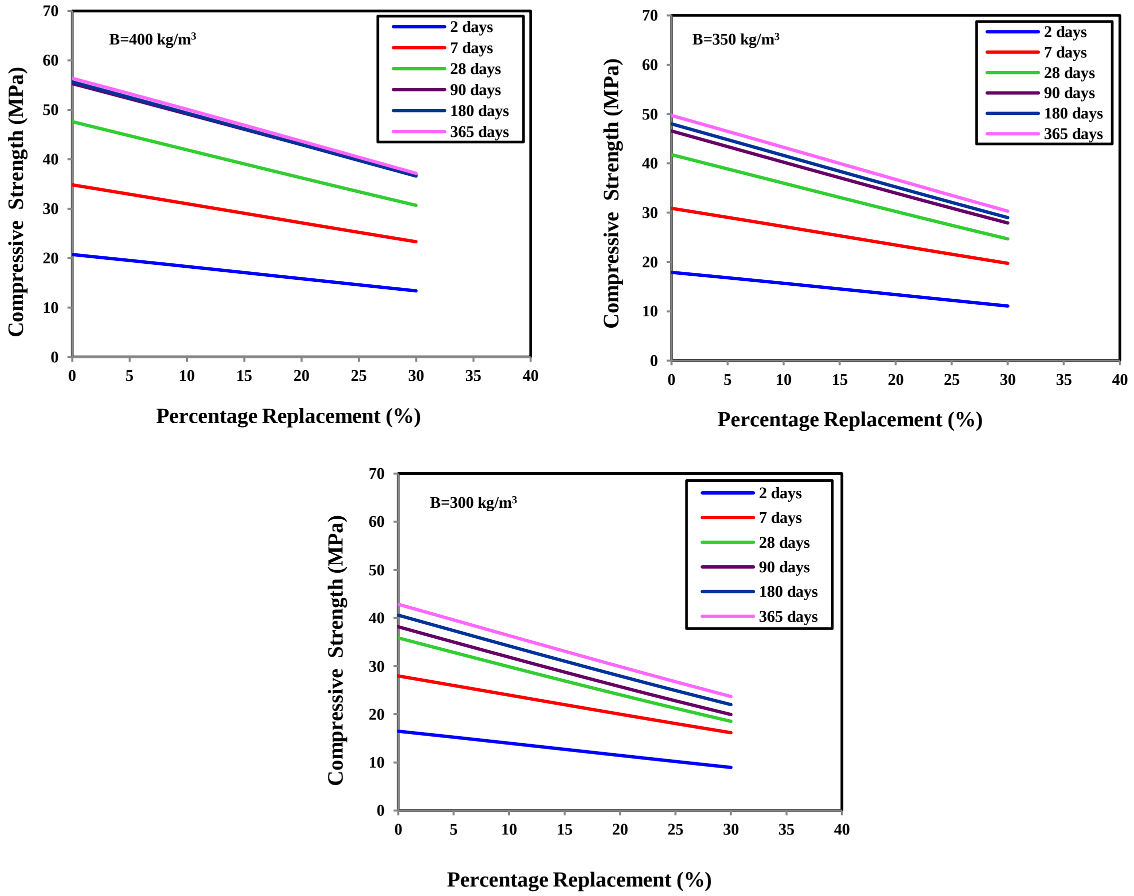


Fig. 7 Effect of LF replacement on concrete compressive strength at different cement content

that the increase in CS values is due to the increase of cement content (Binder); the strength of mix prepared with 400 kg/m^3 binder content is higher than that of the mix prepared with 300 and 350 kg/m^3 binder content. The decrease of the compressive strength can be explained by the effect of the clinker dilution, consequence of substitution replacement of a quantity of cement by the same quantity of limestone (Ramezanianpour *et al*. 2009).

6.3 Influence of Superplasticizer content

A chemical admixture such as a Superplasticizer can be added to the concrete for the purpose of enhancing and achieving a specific modification the overall properties of concrete such as compressive strength. The effect of the Superplasticizer with the variation percentage content (0%, 1%, 2%) by mass of cement on CS of control concrete, at 1, 2, 7 and 28-days is plotted in Figure 8. This figure illustrates the ANNs simulation of CS associated with the dosage of binder kept fixed at (B=400 kg/m^3). Considering this figure, it was observed that the CS increased proportionally with increasing the content of Superplasticizer and age, as expected according to the literature (Neville 1996).

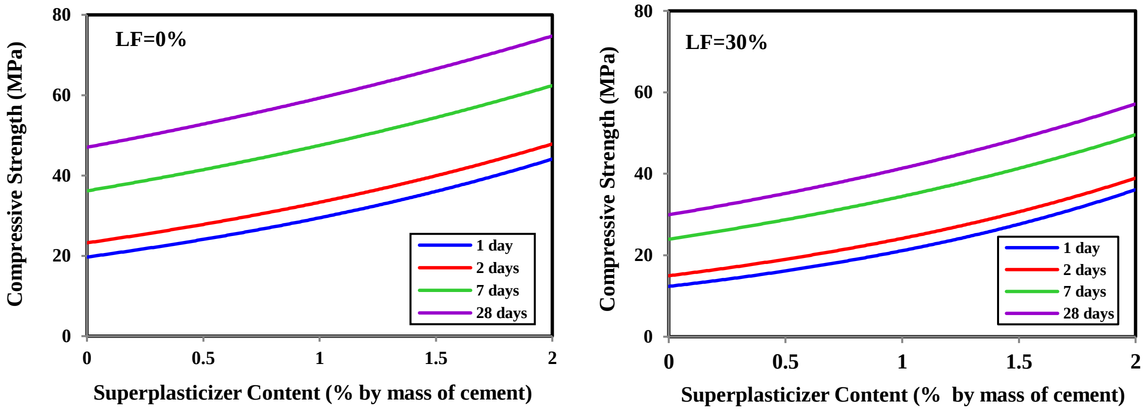


Fig. 8 Effect of Superplasticizer content on concrete compressive strength at various ages

7. Conclusions

In this research, a soft computing approach such as ANNs is used to predict the compressive strength of limestone filler concrete. The results obtained from this paper lead us to the following conclusions:

- The ANNs model proposed in this current study showed its ability to predict the compressive strength of limestone filler concrete and the best ANN's architecture of the proposed model is 7-3-8-1.
- A back-propagation ANNs model can be trained to predict the compressive strength of concrete while relating the mix design of concrete and age of curing.
- The modeling results are very good coinciding well with the experimental values in all phases of training, testing and validation clarifying the accuracy of the proposed ANNs model. Thus, the ANNs model is a powerful tool for predicting the compressive strength of concrete
- A parametric study was carried out to see the effect of each parameter taken into account in the proposed model on compressive strength. The results were in agreement with the literature.
- The compressive strength continuously decreasing with increasing the w/b ratios at all ages and different LF replacement.
- Any replacement of limestone filler in the concrete mixes decreases the strength in all ages, that's mean that the limestone filler contributes less to concrete strength than cement Portland.
- The superplasticizer tends to increase the concrete compressive strength at all ages.
- There are a lot of potential avenues for further works. In the future, the work can be extended by applying the ANN's for predicting several proprieties of concrete with limestone filler such as the workability, elasticity module, durability etc.

Acknowledgments

The authors wish to express their gratitude and sincere appreciation to Professor Federica Lollini from Milan University of Italy and Dr. Pedro Faustino Marques from Instituto Politécnico de Setúbal University of Portugal, for the data collection.

References

Antoni, M., Rossen, J., Martirena, F. and Scrivener, K. (2012), "Cement substitution by a combination of metakaolin and limestone", *Cement Concrete Res*., **42**(12), 1579-1589.

Bentz, D.P., Ardani, A., Barrett, T., Jones, S.Z., Lootens, D., Peltz, M.A., Sato, T., Stutzman, P.E., Tanesi, J. and Weiss, W.J. (2015), "Multi-scale investigation of the performance of limestone in concrete", *Construct*. *Build*. *Mater*., **75**, 1-10.

Bingol, A.F., Tortum, A. and Gul, R. (2013), "Neural networks analysis of compressive strength of lightweight concrete after high temperatures", *Mater*. *Design*, **52**, 258-264.

Bouasker, M., Khalifa, N.E.H., Mounanga, P. and Kahla, N.B. (2014), "Early-age deformation and autogenous cracking risk of slag–limestone filler-cement blended binders", *Construct*. *Build*. *Mater*., **55**,158-167.

Boukhatem, B., Ghrici, M., Kenai, S. and Hamou, A.T. (2011), "Prediction of efficiency factor of ground-granulated blast-furnace slag of concrete using artificial neural network", *ACI Mater*. *J*., **108**(1), 55-63.

Boukhatem, B., Kenai, S., Ghrici, M. and Hamou, A.T. (2010), "Prévision de l'efficacité des cendres volantes dans le béton par l'utilisation d'un réseau de neurones artificiel", XXVIIIèmes Rencontres Universitaires de Génie Civil, La Bourboule, Juin, France.

Boukhatem, B., Kenai, S., Hamou, A.T., Ziou, D. and Ghrici, M. (2012), "Optimizing a concrete mix design incorporating natural pozzolans using artificial neural networks", *Comput*. *Concrete*, **10**(6), 557-573.

Cam, H.T. and Neithalath, N. (2010), "Moisture and ionic transport in concretes containing coarse limestone powder", *Cement Concrete Composites*, **32**(7), 486-496.

Chou, J.S. and Pham, A.D. (2013), "Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength", *Construct*. *Build*. *Mater*., **49**, 554-563.

Douma, O.B., Boukhatem, B., Ghrici, M. and Hamou, A.T. (2017), "Prediction of properties of self-compacting concrete containing fly ash using artificial neural network", *Neural Comput*. *Appl*., **28**(1), 707-718.

Elyamany, H.E., Elmoaty, A.M.A. and Mohamed, B. (2014), "Effect of filler types on physical, mechanical and microstructure of self compacting concrete and Flow-able concrete", *Alexandria Eng*. *J*., **53**(2), 295-307.

EN 197-1 (2012), Cement. Composition, specifications and conformity criteria for common cements, British Standards Institution; London, United Kingdom.

Ergün, A. (2011), "Effects of the usage of diatomite and waste marble powder as partial replacement of cement on the mechanical properties of concrete", *Construct*. *Build*. *Mater*., **25**(2), 806-812.

Freeman, J.A. and Skapura, D.M. (1991), *Neural networks: Algorithms*, *Applications and Programming Technique*, Addison-Wesley Publishing Company, U.S.A.

Githachuri, K. and Alexander, M.G. (2013) "Durability performance potential and strength of blended Portland limestone cement concrete", *Cement Concrete Composites*, **39**, 115-121.

Guemmadi, Z., Resheidat, M., Chabil, H. and Toumi, B. (2009), "Modeling the influence of limestone filler on concrete: a novel approach for strength and cost", *Jordan J. Civil Eng*., **3**(2), 158-171.

Habert, G. (2013), "A method for allocation according to the economic behavior in the EU-ETS for by-products used in cement industry", *J. Life Cycle Assess*., **18**(1), 113-126.

Haykin, S. (1994), *Neural Networks: A Comprehensive Foundation*, MacMillan, New York, U.S.A.

Kellouche, Y., Boukhatem, B., Ghrici, M. and Hamou, A.T. (2017), "Exploring the major factors affecting fly-ash concrete carbonation using artificial neural network", *Neural Comput*. *Appl*., **2017**, 1-20.

Lollini, F., Redaelli, E. and Bertolini, L. (2014), "Effects of Portland cement replacement with limestone on the properties of hardened concrete", *Cement Concrete Composites*, **46**, 32-40.

Madandoust, R., Ghavidel, R. and Zadeh, N.N. (2010), "Evolutionary design of generalized GMDH-type neural network for prediction of concrete compressive strength using UPV", *Comput*. *Mater*. *Sci*., **49**(3), 556-567.

Marques, P.F., Chastre, C. and Nunes, Â. (2013), "Carbonation service life modeling of RC structures for concrete with Portland and blended cements", *Cement Concrete Composites*, **37**, 171-184.

Meddah, M.S., Lmbachiya, M.C. and Dhir, R.K. (2014), "Potential use of binary and composite limestone cements in concrete production", *Construct. Build. Mater.*, **58**, 193-205.

Munakata, T. (1998), *Fundamentals of the New Artificial Intelligence: Beyond Traditional Paradigms*, Springer, New York, U.S.A.

Nakhaei, F., Mosavi, M.R. and Sam, A. (2013), "Recovery and grade prediction of pilot plant flotation column concentrate by a hybrid neural genetic algorithm", *J. Mining Sci. Technol.*, **23**(1), 69-77.

Neville, A.M. (1996), *Properties of Concrete*, 4th Ed., Wiley and Sons, New York, U.S.A

Nuruddin, M.F., Khan, S.U., Shafiq, N. and Ayub, T. (2015), "Strength prediction models for PVA fiber – reinforced high-strength concrete", *J. Mater. Civil Eng.*, **27**(12), 2-16.

Özcan, F., Atiş, C.D., Karahan, O., Uncuoğlu, E. and Tanyildizi, H. (2009), "Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete", *Adv. Eng. Software*, **40**(9), 856-863.

Öztaş, A., Pala, M., Özbay, E., Kanca, E., Çağlar, N. and Bhatti, M.A. (2006), "Application of Artificial Neural Network to Predict Compressive Strength of High Strength Concrete", *Construct. Build. Mater.*, **20**, 769-775.

Prasad, B.K.R., Eskandari, H. and Reddy, B.V.V. (2009), "Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN", *Construct. Build. Mater.*, **23**,117-128.

Pratt, I. (1994), *Artificial Intelligence*, McMillan, New York, U.S.A.

Ramezanianpour, A.A. (2014), *Cement Replacement Materials: Properties, Durability and Sustainability*, Springer, Berlin, Germany.

Ramezanianpour, A.A., Ghiasvand, E., Nickseresht, I., Mahdikhani, M. and Moodi, F. (2009), "Influence of various amounts of limestone powder on performance of Portland limestone cement concretes", *Cement Concrete Composites*, **31**, 715-720.

Shahin, M.A., Jaksa, M.B. and Maier, H.R. (2009), "Recent advances and future challenges for artificial neural systems in geotechnical engineering applications", *Adv. Artif. Neural Syst.*, **2009**, 1-9.

Siddique, R., Aggarwal, P. and Aggarwal, Y. (2011), "Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks", *Adv. Eng. Software*, **42**(10), 780-786.

Skaropoulou, A., Sotiriadis, K., Kakali, G. and Tsivilis, S. (2013), "Use of mineral admixtures to improve the resistance of limestone cement concrete against thaumasite form of sulfate attack", *Cement Concrete Composites*, **37**, 267-275.

Sobhani, J., Najimi, M., Pourkhorshidi, A.R. and Parhizkar, T. (2010), "Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models", *Construct. Build. Mater.*, **24**, 709-718.

Suratgar, A.A., Tavakoli, M.B. and Hoseinabadi, A. (2005), "Modified Levenberg-Marquardt method for neural networks training", *J. Comput. Inform. Eng.*, **1**(6), 1745-1747.

Thongsanitgarn, P., Wongkeo, W., Sinthupinyo, S. and Chaipanich, A. (2011), "Effect of limestone powders on compressive strength and setting time of portland-limestone cement pastes", *Proceedings of the TIChE International Conference*, Songkhla, Thailand, November.

Topçu, İ.B. and Sarıdemir, M. (2008), "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic", *Comput. Mater. Sci.*, **41**(3), 305-311.

Tsivilis, S., Tsantilas, J., Kakali, G., Chaniotaki, E. and Sakellariou, A. (2003), "The permeability of Portland limestone cement concrete", *Cement Concrete Res.*, **33**(9), 1465-1471.

Yeh, I.C. (1999), "Design of high-performance concrete mixture using neural networks and nonlinear programming", *J. Comput. Civil Eng.*, **13**(1), 36-42.

TK