Predicting Fire Effects on Compressive Strength of Normal-Strength Concrete with Nanoparticles Additives using Artificial Neural Network

Alaa Ayman Mahmoud [1], Ehab Shehata Sobhy [2], Alaa Elsayed [3]

[1]B.SC faculty of engineering, Fayoum University. Teaching Assistant at October high institute OHI, Egypt
[2] Assistant Professor of Structural Engineering, Faculty of Engineering, Fayoum University, Egypt
[3] Associate Professor of Structural Engineering, Faculty of Engineering, Fayoum University, Egypt

---

Abstract - *Replacement of cement with nanoparticles additives has been confirmed that it provides a unique platform for enhancing concrete mechanical properties, especially compressive strength, after fire exposure. This conclusion, however, requires the development of effective models to predict, in a reliable manner, the Residual Compressive Strength (RCS) after burning. This study adopts Artificial Neural Network (ANN) to model the complex nonlinear behaviour of normal strength concrete. Data of 156 cubic specimens, available from a cooperative experimental work with other researchers, was chosen as a database to establish the proposed ANN model. Data includes four input parameters: 1) fire maximum temperature attained, 2) exposure time, 3) level of substituting cement with Nanosilica, and 4) level of substituting cement with Nanoclay. Only one parameter (RCS) is predicted as an output. Prediction results provided by simulation of RCS using the developed ANN model are good agreement with the available experimental results. On the other hand, the performance of ANN model is found superior compared with regression analysis.*

***Key Words*: Compressive Strength, Artificial Neural Networks, Nanosilica, Nanoclay, Prediction.**

1.INTRODUCTION

Concrete is widely used as a primary structural material in construction due to numerous advantages, such as strength, durability, and fire-resistive properties. However, concrete is a complex material and its properties can change dramatically when exposed to high temperatures. The effects of fire exposure on the mechanical properties of concrete have been investigated since 1920s [1]. The definition of concrete fire resistance can be stated as the ability of concrete to enable the structural elements to withstand fire or to give protection from it [2]. Concrete loses its compressive strength when exposed to fire due to the elevated temperature. It loses about 20 % of its compressive strength when heated up to 400°C and about 70 % when heated up to 800°C. Reduction in concrete strength due to fire and elevated temperature depends on many factors such as the type of aggregate, water/cement ratio, cement content, etc. [3].

To overcome the problem of concrete strength deterioration when exposed to fire, many researchers have traced the effect of many types of materials used as concrete additives on enhancing concrete durability characteristics. Most of these materials are categorized as Supplementary Cementitious Materials (SCMs). SCMs are finely ground solid materials which have Pozzolanic characteristics and can be used as a partial cement replacement in a concrete mix. The most common cementitious materials that are used as concrete constituents are Fly Ash (FA), Ground Granulated Blast Furnace Slag (GGBS), Silica Fume (SF), and MetaKaolin (MK) [4].

Some materials can be transformed into Pozzolanic materials when become in nano size. This transformation can be occurred by using some methods of nanotechnology. At the nanoscale (the particle dimensions are less than 100nm) [5], the nanomaterials as binders or supplementary cementitious materials in concrete mixes have a significant role in enhancing physical and mechanical properties of both fresh and hardened concrete. The improvement in mechanical properties occurs due to two actions; the reaction between the pozzolans and $Ca(OH)2$ produced by cement hydration to form Calcium Silica Hydrate (C-S-H) gel which is responsible for increasing the strength of the mix, and Nano particles act as a fine filler which reduces the porosity in concrete matrix [6]. Nanosilica, Nanoclay, and Nano carbon tubes are the most common nanomaterials for application in concrete industry.

The aim of this study is to investigate and predict the effect of Nanosilica, Nanoclay, and hybrid mix of both materials on concrete compressive strength after fire exposure.

For the conduct of reliable estimate of concrete compressive strength after fire exposure, this study adopts Artificial Neural Networks (ANNs) as powerful tools to model the non-linear cause and effect relationships inherent in complex processes. ANN, which can be defined as amulti-layered architecture composed of one or more hidden layers placed between the input and output layers, [7] is considered as one of the most important applications of artificial intelligence techniques.

The neural network modelling approach is simpler and more direct than traditional statistical methods, particularly when modelling nonlinear multivariate interrelationships [8]. Artificial Intelligent-based modelling techniques like artificial neural networks ANNs have been utilized to approximate non-linear and complex behaviour for various properties of construction materials. [9]

Recently, many researchers have applied neural networks to predict various properties of concrete [10-16]. Other researchers have applied neural networks to predict compressive strength after burning [17]. However, a few studies –adopting a reliable artificial intelligence technique- on incorporation of nanoparticles in predicting concrete strength after burning have been reported [18]. In this study, a smart modeling system utilizing Artificial Neural Network (ANN) is developed for predicting concrete compressive strength after burning.

Different conditions from temperature degree, exposure time, nanoparticles type, and replacement ratios are represented major data inputs to ANN.

2. Experimental work

The experimental work presented in this study is a result of cooperative work with other researchers (Alaa Elsayed, Islam Fathy) [19]. A Significant amount of support and funding on efforts to accomplish the experimental work was exerted. Locally available Nanoparticles (Nanosilica and Nanoclay) were the primary materials used in this research work. Besides that, for concrete mixing purposed, ordinary Portland cement, local crushed limestone (dolomite) with bulk density of 1618 Kg/m3, and fine aggregate with bulk density of 1675 Kg/m3 were used. Normal tap water was used for both concrete mixing and curing purposes. Constant contents of cement, water, and aggregate were adjusted, as listed in table (1), in all mixes to achieve comparable results that reflect the effect of adding different levels of Nanoparticles.

Table -1: Mix design

Cement content (Kg/m3)	w/c ratio	Water kg/m3	Aggregate Content (kg/m3)	
			Sand	Coarse aggregate
400	0.45	180	656	1170

182 specimens of different concrete mixes with different ratios of Nanoparticles additives were prepared. The experimental program focused on studding the effect of adding various ratios of Nanosilica, Nanoclay, and hybrid from both - as a partial replacement of cement - on some durability properties of concrete. The replacement levels of cement by Nanosilica, Nanoclay and hybrid from both were selected as (1% ,2% ,3%, and 4%), (1% ,3% ,5%,7% and 9%), and (0.5%NS + 4.5%NC), (1% NS + 4% NC) and (1.5% NS+3.5% NC) respectively. All tests were performed using cubic specimens of 100×100×100 mm. In addition to considering a diverse range of nanoparticles ratio in mix proportions, specimens at age of 28 days were tested at various elevated temperatures (200 ºC, 400 ºC, 500 ºC, 600 ºC, 700 ºC, 800 ºC) under two different fire exposure time of one hour and two hours as shown in tables (2) and (3) respectively.

Table -2: compressive strength for various mix proportions and elevated temperatures (one-hour fire exposure time).

28 days/1hr		Control mix	Nano silica (NS)%				Nano clay (NC)%					Hybrid (NS + NC)%		
Property			1	2	3	4	1	3	5	7	9	0.5+4.5	1+4	1.5+3.5
Compressive strength (kg/cm^2)	25 ºC	380	426	415	397	388	394	419	445	386	370	423	437	431
	200 ºC	371	441	455	460	456	407	438	470	456	438	440	454	448
	400 ºC	356	427	448	454	449	408	435	465	454	432	421	436	426
	500 ºC	348	400	436	445	438	370	410	451	425	402	396	413	401
	600 ºC	326	361	398	409	404	337	382	411	381	357	353	373	359
	700 ºC	252	280	304	311	307	262	288	316	298	278	280	287	281
	800 ºC	212	229	243	251	245	221	238	255	245	227	231	241	233

Table -3 compressive strength for various mix proportions and elevated temperatures (two- hours fire exposure time).

28 days/1hr		Control mix	Nano silica (NS)%				Nano clay (NC)%					Hybrid (NS + NC)%		
Property			1	2	3	4	1	3	5	7	9	0.5+4.5	1+4	1.5+3.5
Compressive strength (kg/cm^2)	25 °C	380	426	415	397	388	394	419	445	386	370	423	437	431
	200 °C	364	432	445	451	447	399	429	462	447	429	431	445	439
	400 °C	346	415	435	441	436	396	422	452	441	419	409	425	414
	500 °C	324	377	411	417	413	349	386	420	401	379	373	385	378
	600 °C	286	325	359	371	364	304	341	374	345	322	318	328	323
	700 °C	206	233	253	259	256	218	240	261	248	232	233	238	234
	800 °C	156	172	183	187	184	166	179	192	184	171	174	179	175

Artificial Neural Networks (ANNs), as the name suggests, are inspired by the biology of a brain's neuron. Even an ANN fairly simple and small in size when compared to the human brain, has some powerful characteristics in knowledge and information processing due to its similarity to the human brain. ANNs can learn from examples and able to deal with non-linear problems. One of the distinct characteristics of ANN is its ability to learn from experience and examples and then to adapt to changing situations.

The main building elements of ANNs are neurons or nodes and the links connecting between them. An artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs as showing in figure (1).

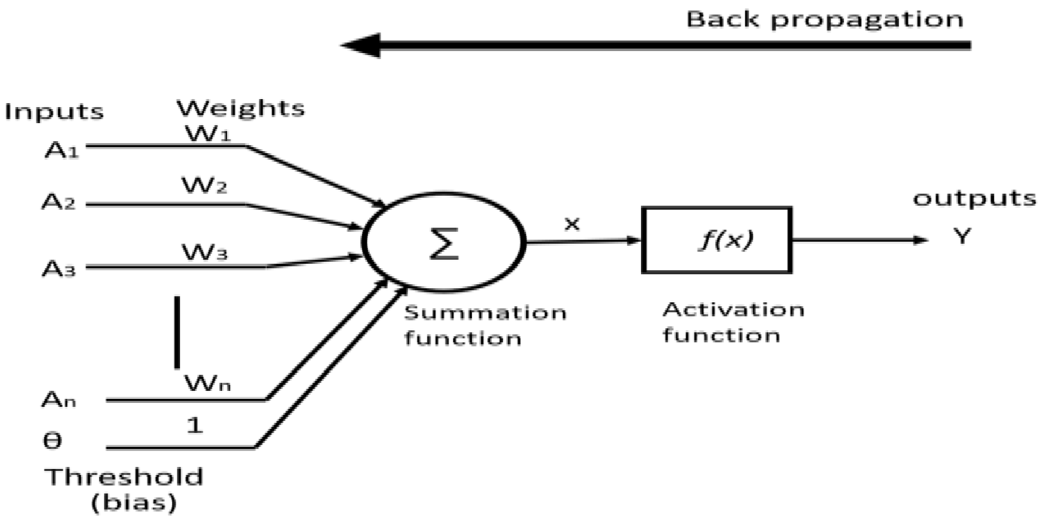

Fig -1: The architecture of the neural network model.

Inputs (A*i*)are information that enters the cell from other cells or from external world. Weights (W*i*) are values that express the effect of an input set or another process element in the previous layer on this process element. Sum function ∑ is a function that calculates the effect of inputs and weights totally on this process element. This function calculates the net input (X) that comes to a cell [20-23]. The weighted sums of the input components are calculated by using Eq. (1) as follows

$$X = \theta + \sum_i^n Ai\ Wi \quad \text{..... (1)}$$

where

(Θ): The bias which employs the result as the argument for a singular valued function
(A*i*): The value of input i.

(W*i*): the weight of input i.
(n): the number of neuron inputs.
(X): is the net input that comes to a cell.

Activation function or transfer function F(X) is a function that processes the net input obtained from sum function and determines the cell output (Y). Different choices are possible for the activation function [24]. The step and sign transfer functions are often used for classification and pattern recognition tasks. For high dimensional and non-linear-big datasets, Sigmoidal (or logistics), Tanh (hyperbolic tangent), and Relu (Rectified linear units) are most popular types of activation functions. Activation function transforms the input, which can have any value (also plus or minus infinity), into a value in the range between 0 and 1 as Log-Sigmoid transfer function or into a value in the range between -1 and 1 as Tan –Sigmoid transfer function as shown in figure (2) respectively.

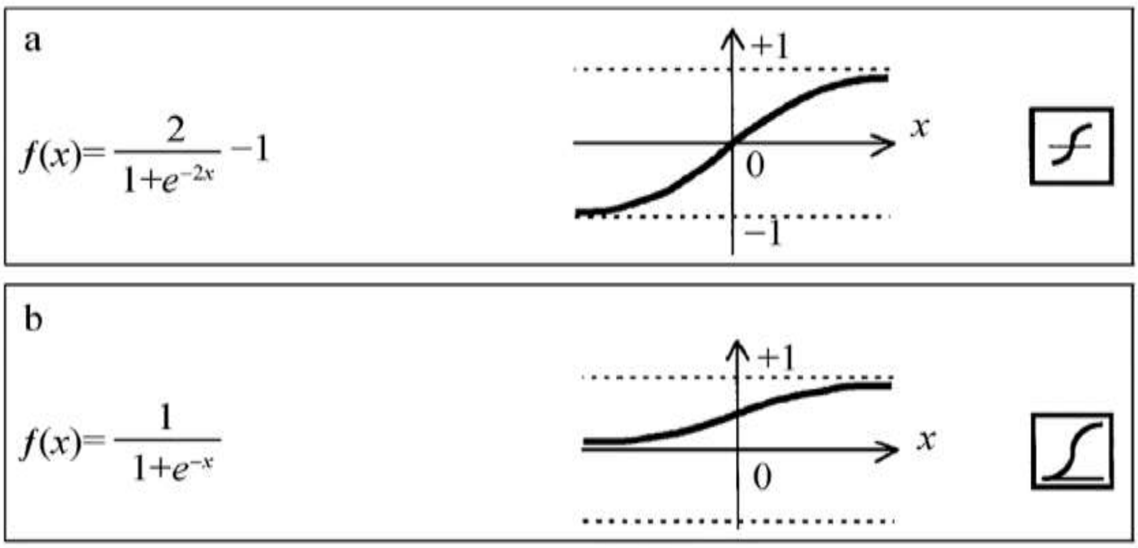

Fig -2: Transfer functions: a) Tan –Sigmoid and b) Log-Sigmoid.

In Neural Network, the term back-propagation(BP) is one of the most popular learning algorithms. It is used to solve the weight optimization problems of multilayered Artificial Neural Networks. The data sequence is principal factor in achieving a good learning process, especially, in the back-propagation pattern, as is the influence of the training data distribution on all supervised training methods. The back-propagation algorithm attempts to minimize the error function in weighted space, which leads to minimize the error function. To assess the performance of the neural network model, an error measure like mean square error (MSE) or mean absolute percentage error (MAPE) might be utilized.

4. Data normalization for ANN model

Studying the effect of nanoparticles additives and predicting compressive strength of normal strength concrete after exposure to high temperature is the main objective of this study. Based on results of experimental work provided in Tables (2) and (3), The post-fire residual compressive strength (RCS) values of 156 specimens are calculated and presented in Tables (4) and (5). On the other hand, ten of the 156 specimens were reserved for simulation of residual compressive strength prediction. Accordingly, the remaining 146 specimens were used as sample to build the proposed neural network model. It should be noted that, the ten reserved specimens were selected randomly and presented as shaded cells in Tables (4) and (5).

Table -4 Residual compressive strength (one-hour fire exposure).

28 days/1hr		Control mix	Nano silica (NS)%				Nano clay (NC)%					Hybrid (NS + NC)%		
Property			1	2	3	4	1	3	5	7	9	0.5+4.5	1+4	1.5+3.5
Residual	200 °C	97.63	103.5	109.6	115.9	117.5	103.3	104.5	105.6	118.1	118.4	104.0	103.9	103.9

Compressive strength %	400 ºC	93.68	100.2	108.0	114.4	115.7	103.6	103.8	104.5	117.6	116.8	99.5	99.8	98.8
	500 ºC	91.58	93.9	105.1	112.1	112.9	93.9	97.9	101.3	110.1	108.6	93.6	94.5	93.0
	600 ºC	85.79	84.7	95.9	103.0	104.1	85.5	91.2	92.4	98.7	96.5	83.5	85.4	83.3
	700 ºC	66.32	65.7	73.3	78.3	79.1	66.5	68.7	71.0	77.2	75.1	66.2	65.7	65.2
	800 ºC	55.79	53.8	58.6	63.2	63.1	56.1	56.8	57.3	63.5	61.4	54.6	55.1	54.1

Table -5 Residual compressive strength (two- hours fire exposure).

28 days/1hr		Control mix	Nano silica (NS)%				Nano clay (NC)%					Hybrid (NS + NC)%		
Property			1	2	3	4	1	3	5	7	9	0.5+4.5	1+4	1.5+3.5
Residual Compressive strength %	200 ºC	95.8	101.4	107.2	113.6	115.2	101.3	102.4	103.8	115.8	115.9	101.9	101.8	101.9
	400 ºC	91.1	97.4	104.8	111.1	112.4	100.5	100.7	101.6	114.2	113.2	96.7	97.3	96.1
	500 ºC	85.3	88.5	99.0	105.0	106.4	88.6	92.1	94.4	103.9	102.4	88.2	88.1	87.7
	600 ºC	101.6	76.3	86.5	93.5	93.8	77.2	81.4	84.0	89.4	87.0	75.2	75.1	74.9
	700 ºC	54.2	54.7	61.0	65.2	66.0	55.3	57.3	58.7	64.2	62.7	55.1	54.5	54.3
	800 ºC	41.1	40.4	44.1	47.1	47.4	42.1	42.7	43.1	47.7	46.2	41.1	41.0	40.6

Before building the neural network model, the 156 specimens were checked using a regression analysis with RCS as a dependent variable and 1) Temperature degree, 2) Fire exposure time, 3) Nanoclay % (as replacement of mortar cement content), and 4) Nanosilica % (as replacement of mortar cement content) as independent variables. The residual plot in figure (3) from a regression analysis of the 156 specimens shows that the residuals tend to scatter randomly around Zero line when plotted against the fitted values of RCS. The residual plot shows suitability of data for building the neural network model.

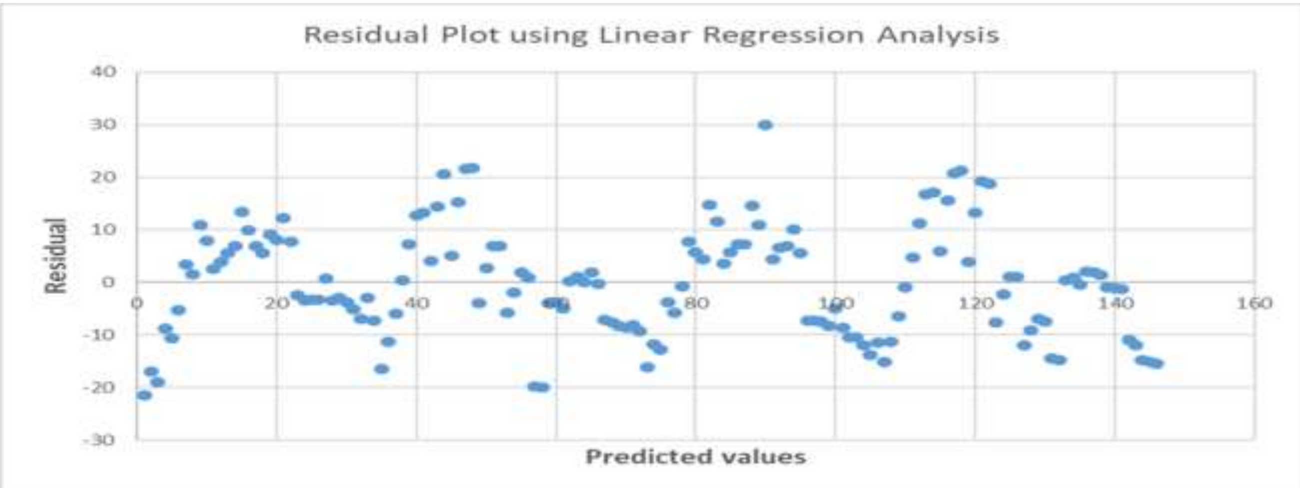

Fig -3: Residual Plot using Linear Regression Analysis.

In addition, the 146 specimens were numbered from 1 to 146. To avoid bias due to taking certain specimens for training a neural network versus other for validation or testing, the 146 specimens were divided and rotated in the manner shown in table (6) to develop six neural networks. The six neural networks represent the main constituents of the proposed model as the average of their outputs is taken as the model's output.

Table -6 Data dividing and rotating for the developing neural networks

Neural network IDs	subset for training(102 samples)	subset for validation (22 samples)	subset for testing (22 samples)
Net 1	1-102	103-124	125-146
Net 2	41-60 , 61-81 , 1-20 , 21-40 , 101-120 , 121 -122	123-140 , 141-144	145 , 146 , 81-100
Net 3	101-120 , 121-140 , 141-146 , 81-100 , 41-60 , 61-76	77-80 , 1-18	19 , 20 , 21-40
Net 4	61-80 , 81-100 , 101-120 , 1-20 , 21-40 , 121 , 122	123-144	145 , 146 , 41-60
Net 5	41-60 , 61-80 , 81-100 , 21-40 , 121-140 , 141 , 142	143-146 , 101-118	119 , 120 , 1-20
Net 6	1-20 , 21-40 , 81-100 , 101-120, 61-80 , 41 , 42	43-60 , 121-124	125-140 , 141-146

5. Neural network model and performance evaluation

As previously mentioned, neural network input vectors are composed of the following parameters:1) Temperature degree, 2) fire exposure time, 3) Nanoclay %, and 4) Nanosilica %. Target values of the corresponding residual compressive strength are the outputs of the neural networks as illustrated in Figure (4). For each of the six neural networks shown in table (6), 70% of the 146 specimens are used as a training subset, 15% as a validation subset, and the rest (15%) as a testing subset. Using MATLAB neural network fitting application, each network is trained with levenberg-Marquardt backpropagation algorithm. Two-layer feed-forward networks with Tan-sigmoid hidden neurons and linear output neurons are developed as show in figure (5). The default command 'divider and' that divides samples randomly is replaced by 'divide block' to make full use of data dividing and rotating proposed in table (6). On the other hand, for each of the six neural networks, the default number of hidden neurons (10) was replaced by two as a baseline. Number of hidden neurons were sequentially increased one by one while investigating a network performance. Several trials were performed until error was sufficiently small. Developed networks were analysed for the prediction performance in terms of mean square error (MSE), Root mean square error (RMSE), Mean absolute percentage error (MAPE) and regression values. For the best performance of each network, number of hidden neurons and performance measures are presented in table (7).

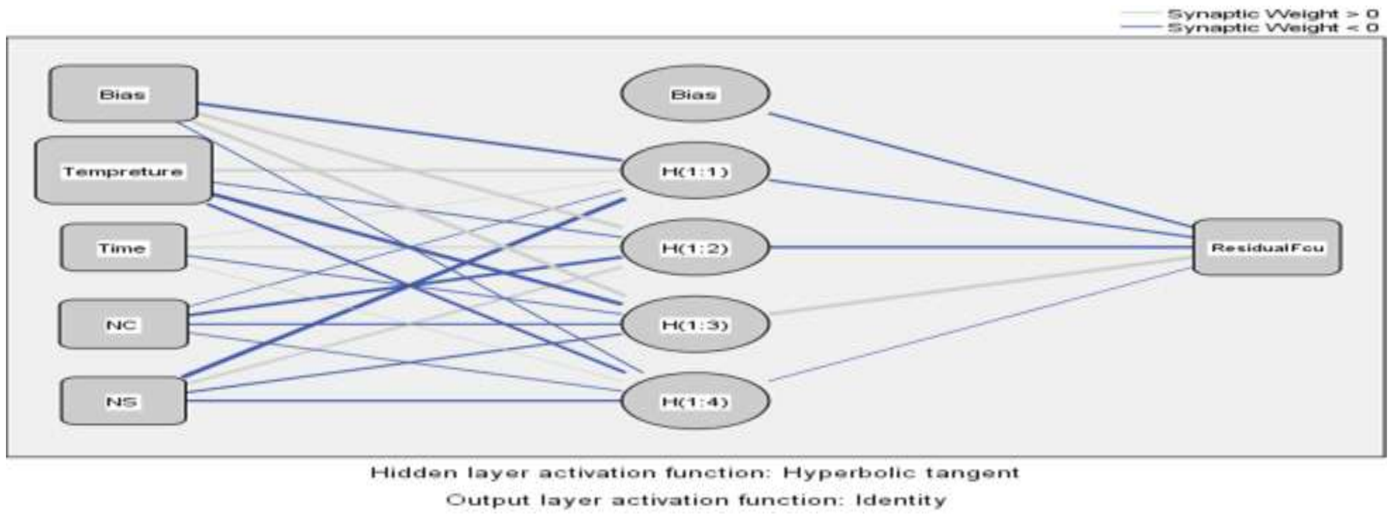

Fig -4: Structure of the neural network for prediction of RCS.

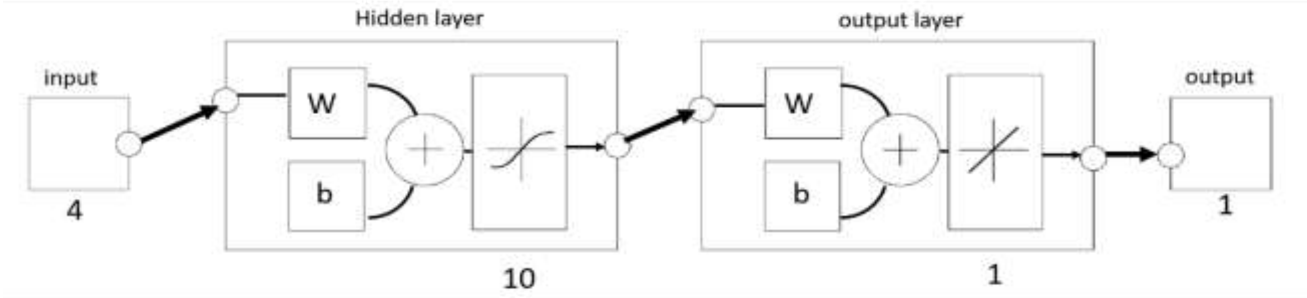

Fig -5: Two-layer feed-forward network with sigmoid hidden neurons and linear output neurons.

Table -7 Number of hidden neurons and performance measures for each of the six neural networks.

Neural network number	Number of Hidden neurons	MSE	MAPE %	Regression
Net 1	7	8.73	2.63	0.98
Net 2	8	8.2	2.22	0.97
Net 3	8	8.06	2.26	0.96
Net 4	7	8.3	2.33	0.97
Net 5	9	8.5	2.56	0.99
Net 6	9	7.6	2.24	0.96
Average	_	8.2	2.37	---

6. Prediction of RCS with Neural Network.

To reliably predict RCS after fire exposure, as previously mentioned, the six networks together comprise the proposed model and the average of their outputs is taken as the model's output. Regression value for the whole model, composed of six neural networks, can be obtained by performing a linear regression analysis between the model's output and the corresponding targets. Figure (6) shows a regression value of 0.984 (R^2 =0.969) which is sufficiently high as the proposed model is considered to describe the simulated data with enough accuracy.

On the other hand, compared to figure (3), the residual plot based on the proposed neural network model and shown in figure (7) is helpful in demonstrating the capabilities of this model to effectively predict RCS fire exposure.

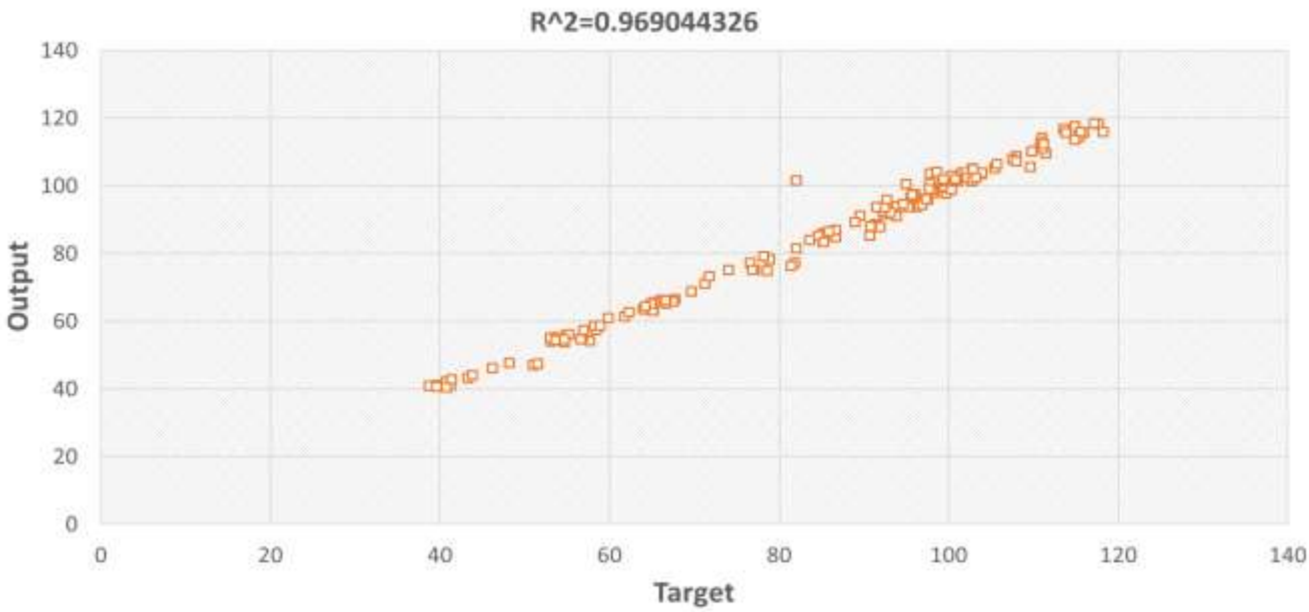

Fig -6: Regression Plot using the average of the six Network's outputs.

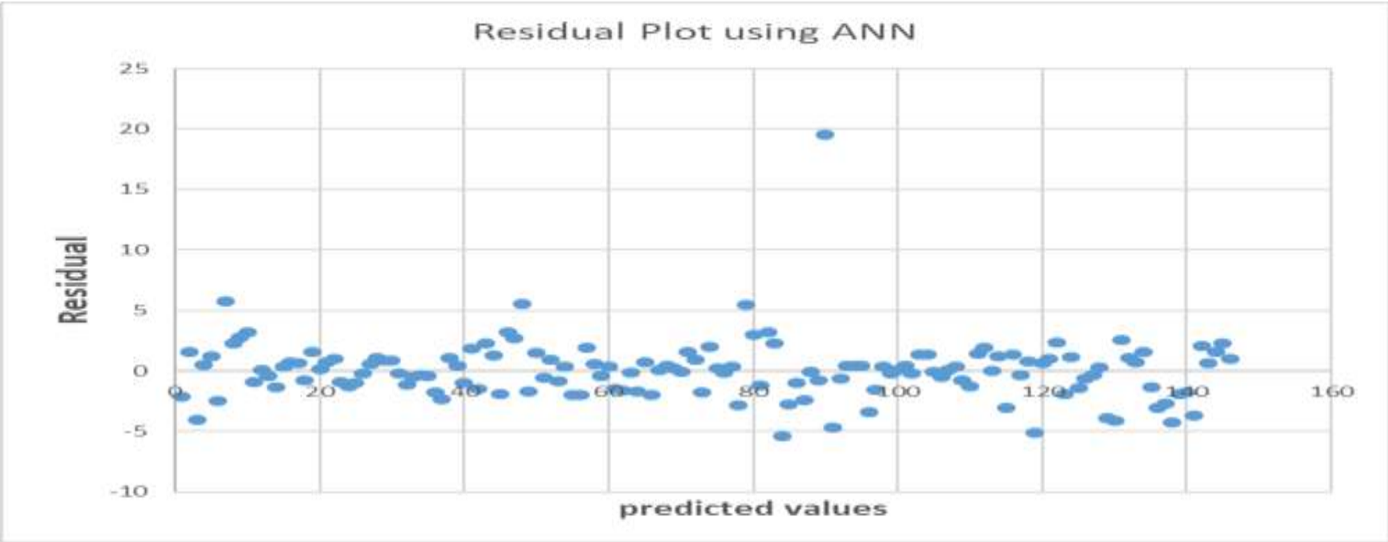

Fig -7: Residual Plot using Artificial Neural Network(ANN).

Simulation to predict RCS after fire exposure for the reserved ten specimens was then performed. Simulation results provided in table (8) show good overall accuracy and the proposed model is feasible and efficient.

Table -8 Simulation results for the reserved ten specimens.

sample	1	2	3	4	5	6	7	8	9	10
1-tempreture	200	400	200	500	200	500	200	200	200	700
2-time	1	1	1	1	1	1	2	2	2	2
3-NC(%)	3	5	0	0	0.5	1.5	5	0	1	1
4-NS(%)	0	0	4	4	4.5	3.5	0	4	4	4
%Residual Fcu Target	104.5	104.5	117.5	112.9	104.0	93.0	103.8	115.2	101.8	54.5
net1	106.5	107.1	118.2	110.6	100.5	97.5	108.3	115.6	99.2	49.3
net2	107.0	107.0	117.4	111.0	100.6	96.0	109.1	116.9	104.0	54.4
net3	107.0	106.0	120.2	108.4	102.3	93.9	108.0	116.2	99.6	54.5
net4	102.7	109.0	109.7	103.1	102.8	93.9	108.4	114.7	100.4	51.7
net5	104.6	105.8	116.0	111.0	103.2	96.3	108.5	112.9	98.9	52.0
net6	106.7	105.6	114.0	108.3	101.0	94.3	103.6	110.3	96.9	54.7
Average output	105.8	106.8	115.9	108.8	101.7	95.3	107.7	114.4	99.8	52.8

7. Regression Analysis for comparison and Sensitivity Analysis.

The prediction results of the proposed model were compared with those of the regression analysis. Regression analysis is asset of statistical processes which aims to estimate the relationships between one dependent and one or more independent variables [25]. In this study, the purposes of utilizing regression analysis were to check suitability of the available 156 specimens to build the proposed model, as previously illustrated, and then to develop an empirical equation for prediction of RCS. Statistical package for social sciences (SPSS)software was utilized to develop such equation. The technique of regression depends on making the best fitting line through a big number of results, that line can represent the overall direction of results, then the equation of the line can be concluded. Employing data of the 146 specimens, presented by Tables (4) and (5), the main deliverable of SPSS was the following empirical formula:

RCS = 146.616 - 0.10079 **X1** - 7.269 **X2** +1.096 **X3** +0.87062 **X4**

Where: X1 represents temperature degree, X2 represents exposure time, X3 represents Nano clay%, and X4 represents Nano silica%.
To assess the goodness -of-fit of the equation, the coefficient of determination (R^2) is one of the most widely used statistics. In this analysis, (R^2) associated with the equation fitted is equal to 0.787. on the other hand, the standard error of estimate for the equation is 10.42.
These values are considered acceptable in conditions of complex nonlinear behavior of concrete and the number of independent variables amounts to four.
Table (9) shows, for the ten reserved specimens, a comparison between simulation results of the developed ANN model and those predicted by regression analysis. Based on the absolute error, Table (9) clearly shows that the ANN model achieve a better fit and forecast than the equation predicted by regression.

Table -9 ANN model VS Regression Analysis.

Specimen number	Fcu before burning	Fcu after burning	RCS (Target)	RCS from ANN Model	Absolute error for ANN Model%	RCS from Regression Analysis	Absolute error for Regression Analysis %
1	419	438	104.5	105.8	1.3	122.5	18
2	445	465	104.5	106.8	2.3	104.5	0
3	388	456	117.5	115.9	-1.6	122.7	5.2
4	388	438	112.9	108.8	-4.1	92.4	-20.5
5	423	440	104	101.7	-2.3	123.7	19.7
6	431	401	93	95.3	2.3	93.6	0.6
7	445	462	103.8	107.7	3.9	117.4	13.6
8	388	447	115.2	114.4	-0.8	115.4	0.2
9	437	445	101.8	99.8	-2	116.5	14.7
10	437	238	54.5	52.8	-1.7	66	11.5

Finally, to assess the impact of each of the key four input parameters on RCS, a Sensitivity Analysis was performed.
Results of Sensitivity Analysis are summarized in figure (8) and table (10). Results show that temperature degree has the most impact on RCS. In addition, RCS is influenced by levels of Nanoclay more those of Nano silica.

Table -10 Independent Variable Importance

variable	Importance	Normalized Importance
Temperature	.706	100.0%
Time	.084	11.9%
NC	.127	18.0%
NS	.082	11.6%

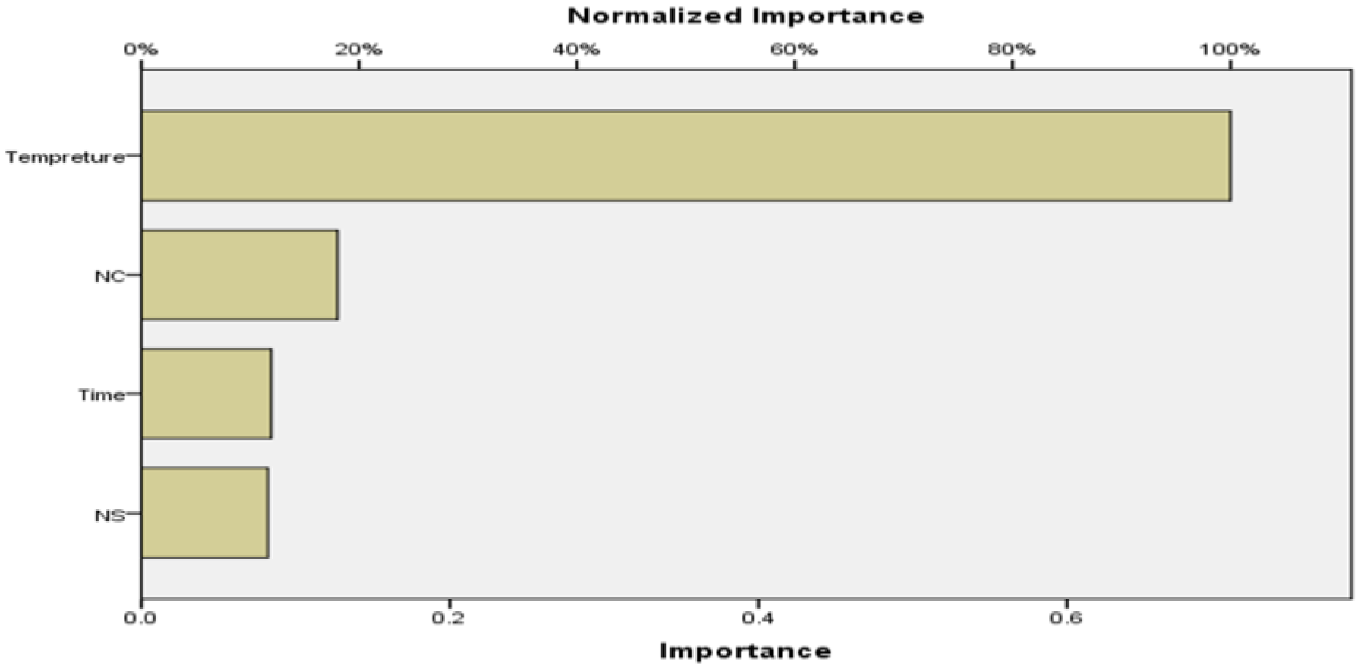

Fig -8: Relative importance of input parameters for the prediction of the residual compressive strength

8. CONCLUSIONS

Complex nonlinear behaviour of concrete can be effectively processed using neural network technique. In this study, six neural networks were developed to predict concrete residual compressive strength (RCS) after fire exposure based on four input parameters 1) fire maximum temperature attained, 2) exposure time, 3) level of substituting cement with Nanoclay, and 4) level of substituting cement with Nanosilica.

The development of six neural networks was helpful to avoid bias due to taking certain data for training a neural network versus others validation or testing.

Number of hidden neurons and performance measurements were investigated to obtain the best performance of each network.

The six neural networks represent the main constituents of the proposed model as the average of their outputs is taken as the model's output. The prediction results conclusively confirmed that the proposed model could be effectively applied to estimate RCS after burning for concrete with nanoparticles additives. Prediction results provided by simulation of RCS using the developed ANN model is found superior compared with regression analysis. On the other hand, on RCS, as dependent variable, was explored via a sensitivity analysis. Results indicated that RCS is most sensitive to temperature, followed by Nanoclay %, exposure time, and finally Nanosilica. It can be noticed that Nanoclay % has more effect on RCS than Nanosilica.

REFERENCES

[1] Khoury GA "Compressive strength of concrete at high temperatures". Mag Concr Res 1992; 61:291–308.

[2] Malhotra, H.L. (1956) "The effect of high-temperature on compressive strength ", magazine of concrete research, 8(3) pp.85 – 94.

[3] Hosny, H., and Abo Elmagd, S., "fire of Reinforced Concrete Structures", Dar Elnasher for Egyptian University, 1994.

[4] Scrivner KL. "Nanotechnology and Cementitious materials". Nanotechnology in Construction: Proceedings of the Nicom3 (3rd International Symposium on Nanotechnology in Construction), Prague, Czech Republic; 2009, PP (37-42).

[5] ASTM International E 2456: "Standard Terminology Relating to Nanotechnology", west Conshohocken, PA, 2006.

[6] Department of Nano Technology, Engineering College, Rajkot, Nano Teknika, E- Magazine Version-1, January, 2014.

[7] A. Yadollahi et al. "Application of artificial neural network for predicting the optimal mixture of radiation shielding concrete". Progress in Nuclear Energy 89 (2016) 69e77

[8] Yeh IC. "Analysis of strength of concrete using design of experiments and neural networks". J Matr Civil Eng. 2006;18(4):598–604.

[9] A. Sadrmomtazi et al. " Modeling compressive strength of EPS lightweight concrete using regression, neural network and ANFIS". Construction and Building Materials 42 (2013) 205–216

[10] Alshihri MM, Azmy AM, El-Bisy MS. " Neural networks for predicting

compressive strength of structural light weight concrete". Construction Building Materials2009; 23:2214–29.

[11] Sobhani J, Najimi M, Pourkhorshidi AR, Parhizkar T. "Prediction of the compressive strength of no-slump concrete: a comparative study of regression, neural network and ANFIS models". Construction Building Materials 2010; 24:709–18.

[12] M. Bilgehan, P. Turgut "The use of neural networks in concrete compressive strength estimation" Computers and Concrete, Vol. 7, No. 3 (2010) 271-283

[13] A.T.A. Dantas et al. "Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks". Construction and Building Materials 38 (2013) 717–722

[14] U. Atici "Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network". Expert Systems with Applications 38 (2011) 9609–9618

[15] I_. Bekir Topc¸u, M. Saridemir "Prediction of properties of waste AAC aggregate concrete using artificial neural network". Computational Materials Science 41 (2007) 117–125

[16] I_. B. Topc, u, M. Saridemir "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic" Computational Materials Science 41 (2008) 305–311

[17] Saif Salah Alquzweeni " Artificial Neural Network Model for Predicting Compressive Strength of High Strength Concrete after Burning ”. IJCEE-IJENS Vol: 15 No: 06,(2015)

[18] S.ChithraaS.R.R, SenthilKumarbK, ChinnarajucF, Alfin Ashmitad"A comparative study on the compressive strength prediction models for High Performance Concrete containing nano silica and copper slag using regression analysis and Artificial Neural Networks"Construction and Building Materials Volume 114, 1 July 2016, Pages 528-535

[19] Alaa Elsayed, Islam Fathy. "Experimental Study of fire effects on compressive strength of normal-strength concrete supported with nanomaterials additives. " IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), vol. 16, no. 1, 2019, pp. 28-37.

[20] M. Pala, E. O¨ zbay, A. O¨ ztas_, M.I. Yuce, "Construction and Building Materials" 21 (2) (2007) 384–394.

[21] A.O¨ ztas_,M. Pala, E.O¨ zbay, E. Kanca, N. C, ag˘lar, M. Asghar Bhatti, "Construction and Building Materials" 20 (9) (2006) 769–775.

[22] S. Akkurt, S. Ozdemir, G. Tayfur, B. Akyol, "Cement and Concrete" Research 33 (7) (2003) 973–979.

[23] A. Mukherjee, S.N. Biswas, "Nuclear Engineering and Design" 178 (1997) 1–11.

[24] Negnevitsky M. Artificial Intelligence: "A Guide to Intelligent Systems", vol.452. Harlow : Addison Wesley; 2002.452

[25] Laugier S, Richon D. Use of artificial neural networks for calculating derived thermodynamic quantities from volumetric property data. Fluid Phase Equili2003;2(15):247–55.