Influence of Database Size on Artificial Neural Network Results for the Prediction of Compressive Strength of Concretes Containing Reclaimed Asphalt Pavement

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ABSTRACT

The main objective of this study is to show the influence of database size on a considered architecture of multi-layer feed forward ANN results for predicting the compressive strength of concretes containing reclaimed asphalt pavement (RAP). On the basis of factorial design, polynomial models were developed for each data series reported in the literature as well as our own experimental results, in order to generate data with different increment ratios (1, 0.5, 0.2 and 0.1). The database passed from 104 data to 130, 336, 1530 and 5440 data, respectively. Training and testing the model showed the efficiency of using ANN models to predict the compressive strength of RAP concretes. The more the database size is increased, the more the results are improved. Better results were obtained when data was generated with an increment ratio of 0.5. The proposed approach proves that factorial design can be used to generate data when needed.

KEYWORDS: Compressive strength, Reclaimed asphalt pavement concrete, Artificial neural networks, Database size, Data generation, Factorial design.

INTRODUCTION

Artificial Neural Networks (ANNs) are powerful tools which can give solutions to very complex engineering problems that cannot be solved with classical techniques (Oliveira Junior et al., 2007). They have been successfully used, many years ago, to predict mechanical properties of conventional concretes (Demir, 2008; Alshihri et al., 2009 ; Kewalramani and Gupta, 2006; Ni and Wang, 2000; Pala et al., 2007), concretes containing metakaolin and silica fume (Saridemir, 2009), concretes containing rubber (Topçu and Saridemir, 2008) and, more recently, concretes containing recycled construction demolition waste aggregates (Topçu and Saridemir, 2007; Topçu and Saridemir, 2008; Duan et al., 2013; Dantas et al., 2013). The most important advantage of this method is that the model can learn through examples (Saridemir, 2009). Other advantages include that the same model can produce satisfying responses from incomplete tasks or from noisy information and thus results can be

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generalized for new cases (Saridemir, 2009).

In order to develop a model able to predict the behavior of a considered material, it must be first trained through experimental results relative to the material. Hence, the model will have learnt enough about the material to reproduce the results and above all to generate new results, thanks its property of generalization (Saridemir, 2009). Steps followed with an ANN are: a) presenting the problem and collecting data to generate the database, b) choosing the adequate architecture, c) learning step, d) training the ANN and e) testing and validating step.

ARTIFICIAL NEURAL NETWORKS

General Information

In the science of biology, neurons are the seat of intelligence; hence, artificial intelligence science was developed from biology studies' inspiration (Wira, 2008). A formal neuron is the most important unit that works with input and output parameters. It gathers information given as input, treats it in hidden layers and produces one or more parameters as output using a transfer function.

Each hidden layer neuron makes the first linear combination from the output of the previous hidden layer neuron plus a bias. The linear combination coefficients plus the bias constitute the synapse weight. A nonlinear function, most of time sigmoid, will operate in the hidden layers. Finally, neurons of the final layer will traduce the network prediction. Regarding the weight adaptation, there exist the perceptron neuron according to F. Rosenblatt (1958) and D. Hubb rule (1949), as well as the ADALINE neuron (ADAptiveLINear Element (ADALINE)) according to B. Widrow and T. Hoff rule (1960) (Wira, 2008).

All neurons are working together in a network with a considered architecture. Depending on the architecture, there are the feed forward network, the fully recurrent network, the competitive network, the Jordan network, the recurrent network with self-connections,… etc. Every architecture or structure gets its own learning algorithms. There are three types of learning algorithms; supervised learning, no supervised learning and credit-assignment problem (Wira, 2008).

Feed Forward Networks

Feed forward networks are the most popular networks for predicting the mechanical properties of materials and concretes. They offer good performance with a reasonable number of neurons in hidden layers, an input parameter layer and an output parameter layer. Besides, all neurons are arranged in lines and each neuron has connections with all neurons of the following layer. There is no definite rule for the neuron number in hidden layers. It is chosen based on experience and some tests are necessary to select the more adequate network structure (Saridemir, 2009). Most of time, problems can be solved with just one hidden layer, but if the obtained performance is not sufficient, more hidden layers can be added or the number of neurons can be increased.

Back Propagation Algorithm

As mentioned before, there are three types of learning algorithms. The most popular one, for training a multi-layer perceptron through a supervised learning, is the back propagation algorithm, because weights are adjusted at each layer from obtained errors in the network and output weight adaptation follows the gradient method (Saridemir, 2009).

PRESENTATION OF THE STUDY

Objective

The main objective of the present study is to show the influence of the database size on an ANN results, with a considered architecture, for predicting the compressive strength of concretes containing reclaimed asphalt pavement (RAP) from different sources. It is good to remember that it is just in the last years that RAP aggregates were valorized in cement concretes. Concretes obtained are usually used for the construction of rigid pavements. RAP concretes are considered as ecological and economical materials; they reduce natural aggregate demand and are low-cost materials. The main experimental results relative to RAP concretes reported in literature showed that RAP concretes are similar to conventional concretes in terms of rheology (Mathias et al., 2009).

Concerning the hardened properties, the more RAP content increase in the mix, the more decrease in mechanical properties (Mathias et al., 2009; Huang et al., 2005; Erdem and Blankson, 2014; Delwar, 1997), mainly due to the weak interface between the bituminous film surrounding the RAP aggregates and the cement paste where failure can occur (Erdem and Blankson, 2014). However, RAP concretes are more thermo-sensitive compared to conventional concretes (Mathias et al., 2009). On the other hand, RAP concretes' toughness index is increased compared to that of conventional concretes (Huang et al., 2005).

ANN Model Used

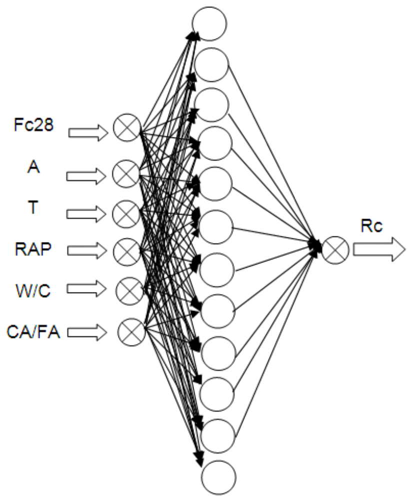

Figure (1): Architecture of the ANN model

In the present study, a multi-layered feed forward neural network with a back propagation algorithm was developed under the MATLAB interface. Sigmoid function was used. Network architecture is shown in Figure 1 with 6 input parameters, 1 output parameter, 1 hidden layer with 12 neurons chosen. Considered input parameters are: target strength (Fc28), age of concrete (A), temperature (T), RAP aggregate content (RAP), water-to-cement ratio (W/C) and coarse aggregate-to-fine aggregate ratio (CA/FA). Only one output parameter is considered: compressive strength (Rc). Errors arose when training and testing in the ANN model are expressed by the mean squared error (MSE) according to Eq. (1) (Topçu IB, Saridemir, 2008) with the regression coefficient (R) measuring the correlation between output and target.

$$\mathrm{MSE} = \frac{1}{p}\sum_i (\mathrm{ti} - \mathrm{ei})^2 \quad (1)$$

where t is the target value, e is the experimental value and p represents the patterns. Parameters used in the ANN model are reported in Table 1.

Table 1. Parameters used in the ANN model

Number of input layers	6
Number of hidden layers	1
Number of hidden layer neurons	12
Number of output layers	1
Adaptation	'trains'
Divider	'dividerand'
Gradient	'calcjx'
Initialization	'initlay'
Performance	'mse'
Train algorithm	'trainlm'

Dataset

Presentation

For training, validating and testing the ANN model, data was gathered from different literature sources (Mathias et al., 2009; Huang et al., 2005; Erdem and Blankson, 2014), taking into account the fact that researchers had used different dimensions and different specimen shapes. Therefore, a conversion from cube-specimen strength into cylinder-specimen strength was realized according to Eurocode 2 (Eurocode 2, 2004). Also, authors' own not totally published experimental results were added to the database. A total of 104 initial data were used for training, testing and validating the model, with 60% randomly taken for training, 20% randomly taken for validating and 20% randomly taken for testing.

The authors' results have not all been published yet. However, the experimental study is briefly described in the following part. CEM IIA/42.5 Portland cement from Sour El Ghozlane cement plant in Bouira (Algeria) is used to produce all mixes in the present experimental study. The chemical composition of cement is given in Table 2. Crushed calcareous 15/25 and 8/15 gravels together with sand of 3mm maximum size, from El Hachimia quarry in Bouira (Algeria), are used. The RAP is originating from the maintenance of the old national roadway N°05 (35 years old). The shape of the aggregate particles was irregular. Figure 2 shows aggregate particle size distributions of natural and recycled aggregates. The physical and mechanical properties of aggregates are reported in Table 3. In order to get a plastic concrete with a controlled slump of 90-150mm, a superplasticizer was added, the properties of which are given in Table 4.

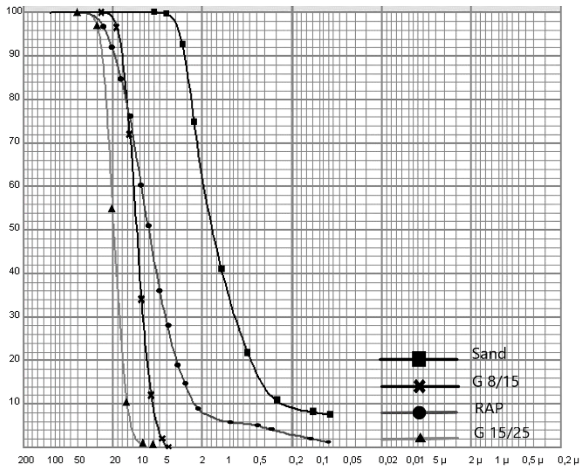

Figure (2): Grading curves of aggregates used

Table 2. Chemical composition of cement

Cement	Density (g/cm^3)	Blaine surface (cm^2/g)	SiO_2 (%)	Al_2O_3 (%)	Fe_2O_3 (%)	CaO (%)
CPJ CEM II/A 42.5	3.14	3997	19.38	4.18	3.28	60.55
Cement	MgO (%)	K_2O (%)	Na_2O (%)	CaO free (%)	C3S in clinker (%)	
CPJ CEM II/A 42.5	2.14	0.57	0.18	1.06	59.70	

Table 3. Physical and mechanical properties of aggregates used

Content	Sand	G 8/15	G 15/25	RAP
Density(t/m^3)	2.64	2.64	2.65	2.40
Fineness modulus	3.07	/	/	/
Sand equivalent (%)	80	/	/	/
Micro Deval water (%)	/	24	/	37
Los Angeles (%)	/	27	22	25
Asphalt content (%)	/	/	/	4.12

Table 4. Properties of superplasticizer used

Content	**Superplasticizer**
Color	Brown
Density (t/m^3)	1.06±0.01
pH	6±1
Na_2O Eq. (%)	≤1
Dry extract (%)	30.2±1.3
Ions Cl^-(%)	≤0.1
Recommended content (%)	0.2 to 3 % cement weight

Five series of concrete containing partial substitutions of natural aggregates with RAP aggregates at 0, 20%, 30%, 40% and 50% according to the mix proportions given in Table 5 were prepared. Concretes were respectively named RAPC 0%, RAPC 20%, RAPC 30%, RAPC 40% and RAPC 50%, where RAPC 0% are reference concretes. Each series was made using three different W/C ratios: 0.50, 0.60 and 0.70, respectively. The CA/FA ratio was 1.69. The cement content was 330 kg/m^3. It should be pointed out that with the exception of screening at 20mm, no pre-treatment was applied to the RAP used. Specimens were prepared according to NF EN 12390-2 (2001) standard. Fresh concrete was placed in 160mm diameter x 320mm high cylinder molds in three layers and consolidated by using pricking. Specimens were left in their molds for 48h and finally cured in water at 20±2°C. Three concrete specimens were prepared for every batch. Compressive strength test was conducted according to NF EN 12390-3 (2003) standard. The arithmetic mean of three values was taken. Experimental results are given in Table 6.

Table 5. Concrete mix properties

Concrete		**RAPC 0%**	**RAPC 20%**	**RAPC 30%**	**RAPC 40%**	**RAPC 50%**
Cement (kg)		330	330	330	330	330
Coarse aggregates (kg)		1192	952	832	716	596
Fine aggregates (kg)		704	564	492	424	352
RAP content (%)		0	20	30	40	50
W/C=0.50	Water (kg)	168	168	168	168	168
	Superplasticizer (kg)	5.8	9.6	10.2	11.6	14
W/C=0.60	Water (kg)	200	200	200	200	200
	Superplasticizer (kg)	2.0	2.8	3.4	4.4	7.8
W/C=0.70	Water (kg)	231	231	231	231	231
	Superplasticizer (kg)	1.2	2.0	2.0	2.4	3.4

Table 6. Authors' own experimental results

		Compressive strength (MPa)				
	W/C	**3 days**	**7 days**	**14 days**	**28 days**	**91 days**
RAPC 0%	0.50	7.13	13.64	17.32	19.19	21.64
RAPC 20%		6.05	12.10	15.73	17.19	19.21
RAPC 30%		5.43	11.28	13.75	15.68	17.56
RAPC 40%		4.20	9.12	11.79	13.03	14.73
RAPC 50%		4.05	7.63	9.55	10.38	12.12
RAPC 0%	0.60	6.05	11.78	14.45	16.60	18.06
RAPC 20%		5.71	10.12	12.85	14.66	15.85
RAPC 30%		4.97	9.37	11.15	13.53	14.34
RAPC 40%		3.55	7.71	9.66	10.66	12.92
RAPC 50%		3.65	6.64	7.92	8.94	10.03
RAPC 0%	0.70	4.83	9.12	12.94	13.54	15.24
RAPC 20%		4.19	8.13	10.67	11.91	13.10
RAPC 30%		3.56	6.47	9.45	10.87	11.78
RAPC 40%		3.00	5.47	8.12	9.07	10.03
RAPC 50%		3.27	4.96	6.89	7.15	8.31

Factorial Design

A factorial design consists of conducting tests following a systematic program leading to mathematical models according to a polynomial form, only available in studied fields and considered experimental conditions.

The factorial design matrices 2^k obtained by forming all the combinations of the two levels of each of the k factors allow calculating the mean effect, the main effects and their interactions. Among the advantages of these matrices are easy implementation and exploitation, as well as using the same unit to express the effects and the response; hence, a possible direct comparison of their values is possible. Thanks matrix orthogonality, all the effects are independently calculated, where optimal accuracy and low experimental error sensitivity can be achieved. The popularity of factorial design is mainly due to the fact that it is a formal model that can be used in various research fields (Benyoussef et al., 2000; Feki and Ayedi, 2000; Dufaud and Corbel, 2004; Amdoun et al., 2009; Kitous et al., 2016).

The experimental results obtained in different works and reported in literature, as well as those obtained in the present work, suggest that compressive strength is affected by RAP content, W/C ratio variation, temperature, as well as by the concrete's age ranging from 0 to 91 days.

Therefore, a 2^k matrix was developed for each set of data corresponding to each reference in a considered domain of RAP, according to the studied parameters. Once established, formal models obtained from factorial design have to be statistically validated through statistical tests. Compressive strength is assessed according to a polynomial model. The mean value of the studied response, in the considered domain, is represented by the coefficient a_0:

$$\mathrm{Rc} = a_0 + \sum \mathrm{a_{ij}}\,\mathrm{x_I}\,\mathrm{x_j} + \sum \mathrm{a_{ii}}\,\mathrm{x_I}^{2} + \cdots \qquad (2)$$

$$\mathrm{X} = \frac{\mathrm{P} - \frac{\mathrm{Pmin+Pmax}}{2}}{\frac{\mathrm{Pmax-Pmin}}{2}} \qquad (3)$$

where Rc is the response in terms of compressive strength.

The physical parameters considered in each study have been replaced by centered and reduced dimensionless variables X_i, where i is the number of considered physical parameters, which vary in the domain [-1, +1] according to the variable changes given by (Eq.2 and Eq.3). P_{min} and P_{max} are the minimal and maximal values of RAP content, respectively, in the considered domain. The previous part is resumed in Table 7.

Table 7. Polynomial model for each set of data

Reference	Influent parameters	Corresponding coded variable	Concrete's age	Domain RAP (%)	Polynomial model
[15]	RAP Temperature	X_1 X_2	28 days	[0-30%]	$Rc=39.05-7.1\,X_1-4.25\,X_2-0.7\,X_1\,X_2$
				[30%-100%]	$Rc=24.25-7.7\,X_1-5.55\,X_2-0.6\,X_1\,X_2$
[16]	RAP	X_1	3 days	[0-100%]	$Rc=14.49-7.51\,X_1$
			7 days	[0-100%]	$Rc=19.365-9.935\,X_1$
			28 days	[0-100%]	$Rc=24.05-13.65\,X_1$
[17]	RAP	X_1	1 day	[0-100%]	$Rc=2.16-0.88\,X_1$
			5 days	[0-100%]	$Rc=9.76-2.64\,X_1$
			7 days	[0-100%]	$Rc=11.52-3.52\,X_1$
			28 days	[0-100%]	$Rc=19.19-7.99\,X_1$
Authors'	RAP W/C	X_1 X_2	3 days	[0-30%]	$Rc=5.24-0.74\,X_1-1.04\,X_2+0.11\,X_1X_2$
				[30%-50%]	$Rc=4.08-0.42\,X_1-0.66\,X_2+0.27\,X_1X_2$
			7 days	[0-30%]	$Rc=10.13-1.25\,X_1-2.33X_2-0.07\,X_1X_2$
				[30%-50%]	$Rc=7.48-1.39\,X_1-1.97\,X_2+0.43\,X_1X_2$
			14 days	[0-30%]	$Rc=13.36-1.76\,X_1-2.17X_2+0.02\,X_1X_2$
				[30%-50%]	$Rc=9.91-1.69\,X_1-1.74\,X_2+0.41\,X_1X_2$
			28 days	[0-30%]	$Rc=15-1.36\,X_1-2.43\,X_2+0.395\,X_1X_2$
				[30%-50%]	$Rc=11.44-2.2\,X_1-1.59\,X_2+0.45\,X_1X_2$
			91 days	[0-30%]	$Rc=16.81-1.63\,X_1-2.79\,X_2+0.405\,X_1X_2$
				[30%-50%]	$Rc=12.75-2.415\,X_1-2.085\,X_2+0.305\,X_1X_2$

The proposed polynomial models can be used to generate data. Chosen increment ratios are 1, 0.5, 0.2 and 0.1, considering all possible combinations for each ratio. Then, coded results obtained have to be converted into physical results by using Eq.3 and therefore the database can be built. The initial number of data was 104. By generating new data with cited increment ratios, it passed to 130, 336, 1530 and 5440 data, respectively.

RESULTS AND DISCUSSION

Table 8 shows the results of the back propagation model with the architecture of 12-1, measured in terms of R and MSE. When the initial database was used, the coefficient R in training and in testing was respectively 0.9986 and 0.9326, whereas coefficient MSE was respectively 0.238 and 12.897 in training and testing. Both parameters were improved when generating database with the increment ratio of 1. Better results were obtained when incrementing ratio was 0.5 and 0.1; the coefficient R in training and in testing was respectively 0.9993 and 0.9966 and the coefficient MSE was respectively 0.125 and 0.509 in training and testing when the database was constituted of 336 data, whereas the coefficient R in training and testing was respectively 0.997 and 0.997 and the coefficient MSE was respectively 0.508 and 0.497in training and testing when the database was constituted of 5440 data.

Table 8. Results of compressive strength ANN with different database sizes

Number of data	Training set	R	MSE
104	62 data	0.9987	0.238
130	77 data	0.9948	0.754
336	201 data	0.9993	0.125
1530	917 data	0.9946	0.975
5440	3263 data	0.9971	0.508
Number of data	**Testing set**	**R**	**MSE**
104	21 data	0.9326	12.897
130	26 data	0.9905	7.178
336	67 data	0.9966	0.509
1530	306 data	0.9950	0.842
5440	1088 data	0.9973	0.497

Analysis results showed that the developed ANN was perfectly able to predict the compressive strength of concretes containing RAP aggregates, giving values very close to experimental values despite a reduced number of data (initial case). Results were improved when the database included a more important number of data (case of 336 data), but it was not necessary to build a pretty big database (case of 5440 data), since similar results were obtained with less data, as shown in Figure 3.

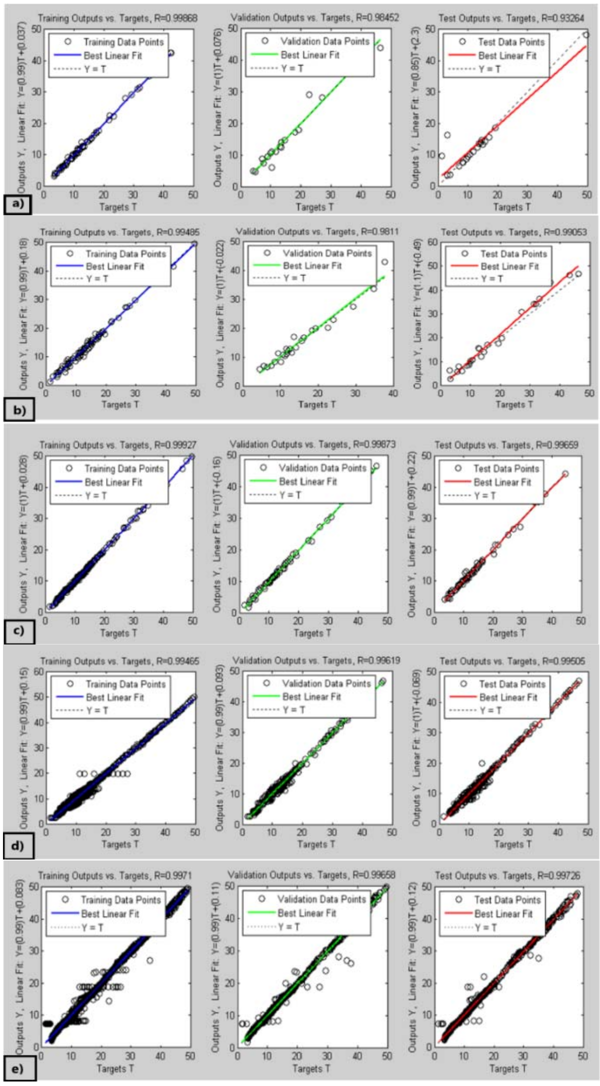

Figure (3): Performance of training, validating and testing a) Initial database with 104 data b) Database of 130 data -increment ratio of 1- c) Database of 336 data -increment ratio of 0.5- d) Database of 1530 data -increment ratio of 0.2- e) Database of 5440 data -increment ratio of 0.1-

However, some predicted values did not fit very well. This can be due to different reasons; the type of cement used in experimental studies of all the researchers was not the same and the type of cement was not introduced as input data. The conversion from cube compressive strength into cylinder compressive strength may be a source of error; hence, the database itself may contain mistaken values.

CONCLUSIONS

In the present study, a multi-layer feed forward ANN with back propagation algorithm, containing one hidden layer of 12 neurons, was developed. It was perfectly capable of predicting the compressive strength of concretes containing RAP aggregates whatever the source, just from target strength, age of concretes, temperature, RAP content, W/C ratio and CA/FA ratio, without making more investigations, thanks the capability of the ANN model to generalize and produce results for new cases, which represents a considerable gain in time. Therefore, the influence of database size used for training and testing an ANN model was established; the bigger the database size, the better the results. But, it was not necessary to use such small increment ratios (0.2 and 0.1), since, in this case, the database built from generated data with 0.5 increment ratio showed enough precision. The proposed approach showed the possibility of using factorial designs to generate data according to polynomial models with different increment ratios.

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