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Artificial Neural Networks for Evaluating the Compressive Strength of Self Compacting Concrete

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ABSTRACT

This research work focuses on artificial neural networks (ANNs) for evaluating compressive strength of self compacting concrete (SCC) at 28 days. To evaluate the compressive strength of SCC six input parameters that are the weigth of cement, coarse and fine aggregate, fly ash, chemical admixture and water cement ratio are identified. A detail research of hidden layer for the architecture of ANNs was considered only one. A total of 250 different data sets of SCC was collected from the ready-mix factory and concrete laboratory in Surabaya. Training data sets comprises 120 data entries, and the remaining data entries are divided between the testing and validation sets. Different number of neurons in hidden layer and different coefficient for learning rate were considered and the results were validated using an independent validation data set. The performance of the 6-5-1 architecture, with the value of learning rate = 0.1 and momentum = 0.01, was the best possible architecture. The error for the training set was 1.74 percent for the 120 training data sets, at running time 43.890 seconds, 3.57 percent for the 80 testing data sets, and 2.02 percent for the 50 verification data sets. The results of the present investigation indicate that ANNs have strong potential as a powerful tool for evaluating the compressive strength of SCC at 28 days.

KEY WORDS: compressive strength, self-compacting concrete, architecture of artificial neural network, learning rate.

INTRODUCTION

Self compacting concrete (SCC) is a mixture of new concrete technologies used in developed countries, such as Japan, Europe and the United States of America (Ouchi Masahiro, 2003). SCC first developed and used in Japan since 1989 (Okumura Hajime and Ouchi Masahiro, 2003), in order to obtain concrete structure which has high durability and easy to pour the concrete mix into every corner of the mold, eliminating the noise pollution generated by the vibrator, produce smooth concrete surface without any additional finishing work, and need less manpower. The hardened concrete of SCC is dense, homogeneous and has the same properties and durability as conventional concrete.

The mix design principles of SCC, compared to conventional concrete, contains: lower coarse aggregate content, increased paste content, low water-powder ratio, increased superplasticiser, and sometimes a viscosity modifying admixture. There is no standard method for SCC mix design and many academic institutions, ready-mixed industries; precast and contracting companies have developed their own mix proportioning methods (Efca, 2005). Mix designs often use volume as a key parameter because of the importance of the need to over fill the voids between the aggregate particles. Some methods try to fit available constituents to an optimised grading envelope. Another method is to evaluate and optimise the flow and stability of first the paste and then the mortar fractions before the coarse aggregate is added and the whole SCC mix tested. So in doing trial and error technique requires a long time and needs more concrete material.

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To overcome the problems, need a tool for evaluating concrete mix composition of SCC. This study uses ANNs as a tool to evaluate the compressive strength of SCC at 28 days.

METHODS

An ANN is a computer model whose architecture essentially mimics the knowledge-acquisition of the human brain. It consists of a number of interconnected processing elements, commonly referred to as neurons. The neurons are logically arranged into two or more layers and interact with each other via weighted connections. These scalar weights determine the nature and strength of the influence between the interconnected neurons. Each neuron is connected to all the neurons in the next layer. There is an input layer where data are presented to the neural network and an output layer that holds the response of the network to the input. It is the intermediate layers, also known as hidden layers, which enable these networks to represent and compute complicated associations between patterns (Kim, *et al.,* 2004). Every hidden and output layer processes its inputs by multiplying each input by its weight, summing the product, and passing the sum through a nonlinear transfer function to produce a result. The sigmoid curve as known as activation function is commonly used as a transfer function.

Evaluating the compressive strength of SCC using ANNs is the aim of this research. The program in this research was written in Microsoft Visual C#. Using this program, an ANN model can be constructed, trained, tested, and validated using the available test data of 250 different concrete mix-designs collected from the ready-mix industry in Surabaya and concrete laboratory of Sepuluh November Institute of Technology (ITS) Surabaya. The proposed ANN model evaluates the compressive strength of SCC.

Architecture of ANN uses six neurons in the input layer (X_1–X_6), one hidden layer with several neurons (Z_1–Z_{12}) , and one unit output layer (Y_1). While the input layer consists of six neurons that are the amount of cement (kg/m3), coarse aggregate (kg/m3), sand (kg/m3), fly ash (kg/m3), admixture (lt/m3), and water cement ratio (%). The hidden layer uses sigmoid activation, and the output layer consists of one neuron that is compressive strength of SCC at 28 days. That is, the ANNs developed in the investigation has six units in the input layer and one unit in the output layer. The ANN architecture is illustrated in Figure 1, and comprises many simple processing neurons organized in a sequence of layers: input, hidden and output layers. The simulation problem consists of finding a satisfactory relationship between a set of neurons representing the input data and associated known output.

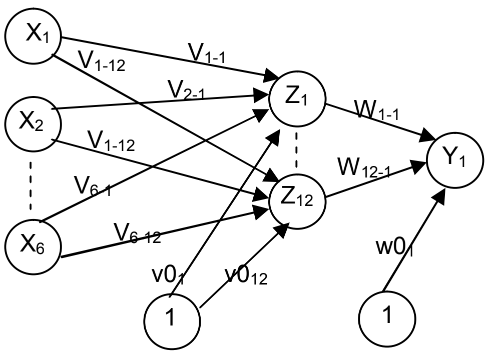

Fig. 1. Architecture of ANNs model

RESULTS AND DISCUSSION

ANN for Evaluating the Compressive Strength of SCC

The result of experimental data include 250 data sets, which was collected from the ready-mix factory and concrete laboratory in Surabaya. The compressive strength of SCC at 28 days was determined by the compressive strength machines. The data were randomly divided into a training phase (120 data sets), testing phase (80 data sets), and validation phase (50 data sets). For this compressive strength of SCC at 28 days modeling problem the obvious inputs are the component contents of concrete, including cement, coarse aggregate, fine aggregate, fly ash, chemical admixture, and water cement ratio. That is, the ANN investigated in the developing has six units in the input layer and one unit in the output layer. The values of ANN parameters considered in this approach are as follows: number of hidden layers = 1; number of hidden neurons = 1, 2, 3, … and 12; learning rate = 0.01, 0.05, 0.1, 0.25 and 0.5; momentum factor = 0.01; and learning cycles (epochs) = 10000 which each cycle covers the entire database available for training. After a number of trials, the best network parameters are as follows: number of hidden layers = 1; number of hidden units = 9; learning rate = 0.1; momentum factor = 0.01; and learning cycles = 10000. Training time on a personal computer was 43.890 seconds. The error was 1.74 percent for training phase. The best architecture ANN, in predicting the compressive strength of SCC that minimize the error and running time, for training data sets, is 6-5-1, shown in Table 1.

Table 1: Result of Training ANN with 1 output (compressive strength) in 10000 iteration

Architecture of ANN	Running of Training									
	LR=0,01 & M=0,01		LR=0,05 & M=0,01		LR=0,1 & M=0,01		LR=0,25 & M=0,01		LR=0,5 & M=0,01	
	Error (%)	Run Time (s)	Error (%)	Run Time (s)	Error (%)	Run Time (s)	Error (%)	Run Time (s)	Error (%)	Run Time (s)
6-1-1	2.47	39.844	2.08	39.953	2.07	39.594	2.03	40.109	42.98	43.125
6-2-1	2.74	41.188	2.07	40.454	2.11	40.328	1.95	44.078	57.87	43.843
6-3-1	2.52	42.125	2.08	41.766	1.86	41.765	1.95	44.953	46.74	45.031
6-4-1	2.84	43.047	2.31	42.985	1.76	43.562	1.97	47.140	41.67	46.546
6-5-1	2.75	44.390	2.06	43.922	1.74	43.890	1.96	47.297	45.02	47.719
6-6-1	2.61	44.734	2.26	45.109	1.84	44.734	1.95	46.547	44.52	50.172
6-7-1	2.95	46.047	2.17	46.266	1.84	45.875	1.95	47.218	48.18	50.312
6-8-1	2.84	47.406	2.23	47.250	1.94	47.515	2.25	48.828	47.17	51.250
6-9-1	3.05	48.016	2.31	48.234	1.79	50.781	2.19	49.891	44.50	52.204
6-10-1	2.84	49.046	2.16	49.531	1.83	51.095	2.09	51.171	44.96	53.234
6-11-1	3.00	50.203	2.82	50.218	1.87	51.937	2.10	52.204	47.74	54.235
6-12-1	2.75	51.188	2.46	51.625	1.94	53.266	2.22	52.750	47.25	55.547

Note : ANN = Artificial Neural Networt; HL = Hidden Layer; LR = Learning Rate; M = Momentum

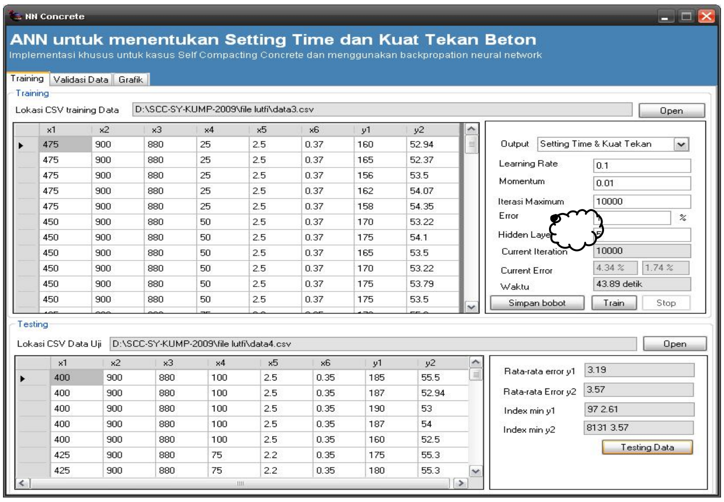

Fig. 1. The error of training phase with 6-5-1 architecture of ANNs

Training Phases of ANN

Training phase of the ANNs is carried out using 120 data sets. It is worth mentioning that in this study, the training process was terminated when any of the following conditions are satisfied:

1. The maximum number of iterations (epoch) is reached to 10,000.
2. The error of the training set is reached to 1 percent.

Two variables in neural network design are the learning rate and momentum coefficient . Each time a pattern is presented to the network, the weights leading to a neuron are modified slightly during learning in the direction required to produce a smaller error at the outputs the next time the same pattern is presented. The amount of weight modification is proportional to the learning rate and momentum. The value of learning rate and momentum ranges between 0.001 and 0.1. However, the learning rate in a parameter that determines the size of the weights adjustment each time the weights are changed during training. Small values for the learning rate cause small weight changes and large values cause large changes. The best learning rate is not obvious. If the learning rate is zero coefficient, the ANN will not learn. The learning rate is very important in identifying over-learning and when to stop training (Al-khaleefi, *et al.,* (2002).

For preventing unstable and oscillation network, is added in back propagation algorithm of ANN a value that is called momentum. The momentum term adds inertia to the training procedure, and helps avoid oscillatory entrapment in local minima (Al-khaleefi, *et al.,* (2002). In this study, the ANN checked for range of value 0.01. Variations of error versus the number of iterations with value 0.01 of momentum, is illustrated in Figure 2. Based on the results, value for momentum rate is selected 0.01. It can be seen in this Figure 2 the value of error of training phase (red line) and testing phase (blue line).

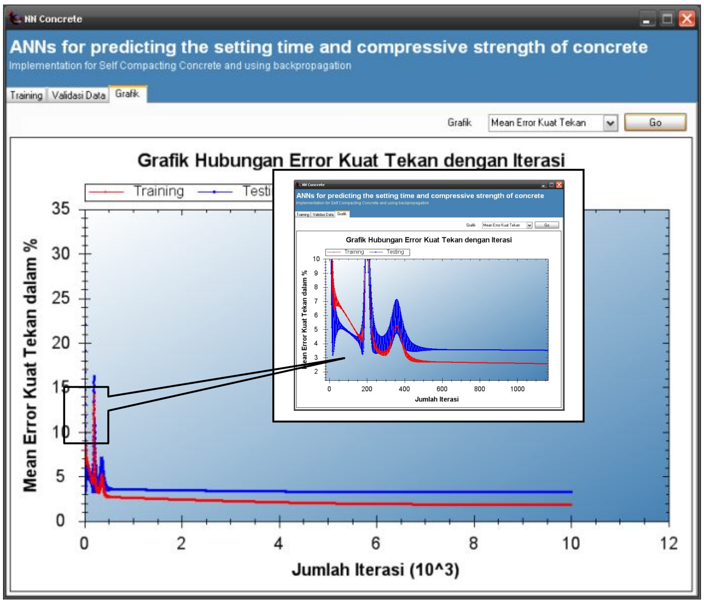

Fig. 2. The result of training and testing phase with 6-5-1 architecture of ANNs

Testing Phase of ANN

After training process in the development of the ANN completed, next step is to test the developed ANN model. After ANN was trained in the 120 training cases, is used the testing set to avoid over-training and to evaluate the confidence in the performance of the trained network with a training set for a 10,000 number of iterations (epoch). The testing process has been carried out for a total 80 data sets. Figure 2 shows that the ANN was very successful in predicting of compressive strength of SCC with error 3.57 percent at the end and 3.57 percent at the lowest point of iteration. Also the ANN predicts the compressive strength of SCC in testing phase reasonably well the 6-5-1 architecture of ANN in general performs better than the others and it is able to give accurate prediction of compressive strength of SCC.

Table 2 : Result of Testing ANN with 1 output (compressive strength) in 10000 epoch

Architecture of ANN	Running of Testing														
	LR=0,01 & M=0,01			LR=0,05 & M=0,01			LR=0,1 & M=0,01			LR=0,25 & M=0,01			LR=0,1 & M=0,1		
	Error (%)		Epc	Error (%)		Epc	Error (%)		Epc	Error (%)		Epc	Error (%)		Epc
	At the end	Lowest		At the end	Lowest		At the end	Lowest		At the end	Lowest		At the end	Lowest	
6-1-1	3.68	3.68	9571	3.62	3.62	6027	3.60	3.60	3024	3.59	3.57	2167	47.62	28.15	3490
6-2-1	3.80	3.80	9580	3.61	3.61	9593	3.63	3.63	7714	3.89	3.57	67	48.00	34.76	3
6-3-1	3.71	3.65	1	3.60	3.60	8096	3.57	3.57	9328	3.92	3.58	77	51.15	12.15	2
6-4-1	3.84	3.65	13	3.66	3.66	9048	3.57	3.56	6035	3.90	3.55	1203	37.22	28.00	2763
6-5-1	3.82	3.82	9511	3.60	3.66	8756	3.57	3.57	8131	3.91	3.62	69	39.13	9.69	4
6-6-1	3.80	3.65	13	3.65	3.65	9446	3.56	3.56	9679	3.72	3.55	2319	39.03	28.77	3
6-7-1	3.88	3.65	7	3.60	3.60	9904	3.56	3.56	9507	3.73	3.55	2216	42.12	22.17	4
6-8-1	3.89	3.70	5	3.66	3.66	9313	3.58	3.58	116	4.00	3.55	3290	49.15	13.14	5
6-9-1	4.01	3.58	9	3.64	3.64	9683	3.55	3.55	8956	3.97	3.55	3498	39.01	38.73	7
6-10-1	3.89	3.89	9798	3.62	3.62	9358	3.56	3.55	62	3.94	3.55	5294	39.44	39.44	9973
6-11-1	3.91	3.72	8	3.83	3.67	0	3.56	3.56	9277	3.97	3.55	2110	43.07	27.88	2873
6-12-1	3.79	3.79	9346	3.75	3.75	9950	3.58	3.58	9943	3.96	3.56	3119	49.23	27.01	2

Note : ANN = Artificial Neural Networt; HL = Hidden Layer; LR = Learning Rate; M = Momentum; Epc = Epoch

Validation Phase of ANN

The validation set is used to as a further check for the generalization of the Neural Network, but do not have any effect on the training and testing phase. In the validation phase, the ANN accuracy is examined using the validation set. The plot of experimental data and predicted compressive strength of SCC in validation sets (50) is shown in Figure 8. It is obvious from this plot that is reasonably good agreement between the results predicted and target results. These results show that the ANN was successful in training the relationship between the input and output data with the error of 3.12 percent (error for validation set).

Table 3. The result of vadation phase of 6-5-1 architecture of ANN

No	X1	X2	X3	x4	x5	x6	CS of ANN	CS of Lab	Error
1	400	900	880	100	2.50	0.35	56.00	53.36	4.71
2	400	900	880	100	2.50	0.35	55.50	53.36	3.86
3	400	900	880	100	2.50	0.35	52.94	53.36	0.79
4	400	900	880	100	2.50	0.35	53.00	53.36	0.68
5	400	900	880	100	2.50	0.35	54.00	53.36	1.19
6	400	900	880	100	2.50	0.35	52.50	53.36	1.64
7	425	900	880	75	2.20	0.35	55.30	53.54	3.18
8	425	900	880	75	2.20	0.35	55.30	53.54	3.18
9	425	900	880	75	2.20	0.35	54.00	53.54	0.85
10	425	900	880	75	2.20	0.35	52.50	53.54	1.98
11	425	900	880	75	2.20	0.35	53.50	53.54	0.07
12	425	900	880	75	2.20	0.35	54.30	53.54	1.40
13	400	900	880	100	2.20	0.35	52.50	53.34	1.60
14	400	900	880	100	2.20	0.35	56.80	53.34	6.09
15	400	900	880	100	2.20	0.35	52.50	53.34	1.60
16	400	900	880	100	2.20	0.35	53.50	53.34	0.30
17	400	900	880	100	2.20	0.35	51.50	53.34	3.57
18	400	900	880	100	2.20	0.35	52.50	53.34	1.60
19	425	900	880	75	1.65	0.35	54.00	53.51	0.91
20	425	900	880	75	1.65	0.35	52.50	53.51	1.92
21	425	900	880	75	1.65	0.35	54.00	53.51	0.91
22	425	900	880	75	1.65	0.35	55.50	53.51	3.59
23	425	900	880	75	1.65	0.35	52.50	53.51	1.92
24	425	900	880	75	1.65	0.35	54.00	53.51	0.91
25	400	900	880	100	1.65	0.35	53.00	53.31	0.58
26	400	900	880	100	1.65	0.35	54.00	53.31	1.28
27	400	900	880	100	1.65	0.35	52.00	53.31	2.52
28	400	900	880	100	1.65	0.35	51.50	53.31	3.51
29	400	900	880	100	1.65	0.35	54.40	53.31	2.00
30	400	900	880	100	1.65	0.35	52.30	53.31	1.93

Note : X1:cement, X2=coarse agg, X3=fine agg, X4=FA, X5=admix, X6=w/c ratio, CS=compressive strength

Conclusion

In this research, ANNs model for evaluating the compressive strength of SCC was developed. The study suggests that the use of ANNs has several significant advantages over other conventional methods. The following summarizes are:

1. The performance of the 6-5-1 architecture was better than other architectures. That means, there are six neurons in the input layer corresponding to the six neurons, one hidden layers with five neurons and one neuron in the output layer corresponding to compressive strength of SCC at 28 days
2. The learning rate coeficient as 0.1 and momentum parameter as 0.01 gave a best possible results for training phase of ANN.
3. The error for the training set was 1.74 percent for the 120 training data sets, at running time 43.890 seconds, 3.57 percent for the 80 testing data sets, and 2.02 percent for the 50 verification data sets.
4. The results of compressive strength of SCC at 28 days obtained from the developed computer program were compared with results from experimental studies. The comparisons of results indicate good agreements.

Acknoledgements

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