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Prediction of mechanical and fresh properties of self-consolidating concrete (SCC) using multi-objective genetic algorithm (MOGA)

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Abstract

Compressive strength and concrete slump are the most important required parameters for design, depending on many factors such as concrete mix design, concrete material, experimental cases, tester skills, experimental errors etc. Since many of these factors are unknown, and no specific and relatively accurate formulation can be found for strength and slump, therefore, the concrete properties can be improved to an acceptable level using the neural networks and genetic algorithm. In this research, having results of experimental specimens including soil classification parameters, water to cement ratio, cement content, super-lubricant content, compressive strength, and slump flow, using the MATLAB software, the perceptron neural network training, general regression neural network, and radial base function neural network are considered, and then, with regard to coefficient of determination (R2) criteria and mean absolute error, the above networks are compared, and the proper neural network was identified, and finally, using the multi-layer perceptron neural network as the chosen network as well as multi-objective genetic algorithm fitting function, the 28-day compression strength and slump flow of self-compacting concrete are simultaneously optimized.

Keywords: *Neural networks, Genetic Algorithm, Self-Compacting Concrete, Strength, Slump*

1. Introduction

Concrete consists of two pulp and aggregate parts, the pulp contains cement and water, and chemical reaction between two substances, which is called hydration, leads to aggregates conjunction. There are many factors affecting concrete mixing design, including water to cement ratio, cement content, lubricant content, and types of aggregates and suitable granulation range of aggregates, which are obtained using the soil mechanic functional equations (coefficient of uniformity and coefficient of curvature). Self-compacting concrete is a new branch of medium to high strength concrete, and a new technology in the construction, filling the template without vibrations undergoing its own weight among the massive structural flowing components, not separating the aggregates from mortar [1-3]. Many numeral methods such as neural networks are used increasingly in civil engineering [4-8]. The concrete modeling is complex, due to its composite nature, however, many regression equations are obtained using experimental results, but these equations have many errors for data that has not experienced it earlier. The artificial neural networks (ANN) have been highly effective in predicting the compressive strength of concrete in cases where the relationship between input and output data are nonlinear [9, 10]. However, many studies have been performed in estimating compressive strength of concrete using neural networks [8, 9, 11-19]. The genetic algorithm is a statistical method for optimization and search. The genetic algorithm is a part of evolutionary calculations, which is a part of the artificial intelligence. The specific properties of this algorithm make it impossible to consider it as a simple random explorer. In fact, the idea of this method was first introduced by Netherlands in the optimization field. The genetic algorithm is a global technique of optimization for complex, nonlinear, and multi-dimensional problems, which is performed based on the natural selection, transplantation and mutation mechanism that is inspired by the nature [20]. In civil engineering,

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many studies have been conducted using the genetic algorithm in the field of concrete [21-24]. In this research, using 38 experimental data with input results including water to cement ratio, cement content, lubricant content, and soil granulation parameters, and output results are 28-day compressive strength and slump of self-compacting concrete, which focus on single-layer and multi-layer perceptron neural networks training, general regression, and radial base function neural network, and then, the neural networks are compared with respect to R2 and MAE¸ and an appropriate neural network was selected, and finally, using the selected neural network as the multi-objective genetic algorithm fitness function, the compressive strength and self-compacting slump were simultaneously optimized using the genetic algorithm.

2. Neural network

Artificial neural networks are among the methods that can estimate numerous nonlinear cases in the data as a flexible computational framework for a wide range of nonlinear problems. In fact, the neural networks are educational systems that are often trained from a dataset to solve complicated problems, and use the acquired knowledge to solve the unobserved data, therefore, they are called self-organizing systems. In fact, the artificial neural network is a data processing system, by obtaining the idea from human brain, giving the data processes to many small processors that are interconnected in a network in parallel to solve a problem. In these networks, with the help of programming knowledge, a data structure is designed that can act like the neural neurons.

In the neural network, in the input data layer, the input data is given to the network, and in the output layer, the results of network are calculated. The number of input and output network neurons are obtained with respect to number of input and output data, and the number of network layers and neurons are obtained using trial and error. In order to access the relationship between input and output data, the network must be trained. First, the network inputs enter the input layer neurons and transferred to the output layer through the connections (synaptic weights), and the output is calculated, then, the network compares the calculated output and objective output, and with regard to the differences, the network weights (inter-neuron relationship) are adjusted. The accuracy of the neural network is calculated using coefficient of determination (R2) and mean absolute error (MAE).

$$R^2 = 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y-\hat{y}| \quad (2)$$

In equations (1) and (2), y is the real value of the objective, $\hat{y}$ is the output value of the neural network, and $\bar{y}$ is the mean value of the objective function. The closer value of R2 to the number one, the value predicted by the network is closer to reality, and the network has less error.

3. Genetic algorithm

Genetic algorithm is an algorithm based on the natural selection and natural genetic mechanism. This algorithm chooses the most appropriate strings among randomly organized information[22]. In each generation, a new group of strings are created using the best parts of previous sequences and new random section to achieve a proper solution. At the time of event simulation, the genetic algorithms don't pass the simple event simulation, but also mix the previous data with thought of choosing the new search points to achieve the desired progress. In the genetic algorithm, a series of design variables are encoded by strings that are called chromosomes in the biological system. In the simple genetic algorithm, the design variables are defined with strings containing 0 and 1, each of the numbers 0 and 1 in each variable is called a gene, and value of 0 and 1 for each gene is called allele. For example, if an optimization problem has three design variables, and each design variable contains five genes, in general, the chromosome used in the genetic algorithm will contain 15 bits. Each string and chromosome contain design variables, representing a point in the problem search space. The genetic algorithms are a duplicate process, calling the repetitive step and a series of chromosomes in each generation as generation and population, respectively. The genetic algorithm performs the main search in the response space, which began with start of generation, which is responsible for creating a series of initial points and determined randomly. Since the genetic algorithm uses statistical methods to direct search operations toward the optimal point, in a process that depends on natural selection, the existing population is selected for the next generation with regard to the fitness of individuals. The genetic operators include selection, transplantation, and mutation, after applying these operators to the initial population, a new population replaces the previous population and the cycle continues. Often, a new population has more fitness, which means that the population is improved based on statistical relationships from a generation to another generation. The search will be effective when the convergence is obtained, or the stopping criteria for genetic algorithms are achieved. For the production of the concrete mixtures a rotating planetary type cylindrical mixer with two blades was used. (Fig. 1)

3. 1. Multi-objective genetic algorithm with non-dominated sorting

This algorithm is turned into a multi-objective algorithm by adding two essential operators to a normal single-objective genetic algorithm, which finds a series of best solutions instead of the best solution, which are known as Pareto front[22]. These two operators including 1. An operator that gives a rank superior criteria to the population based on non-dominated sorting, 2. An operator that maintains the variety of solution among solutions with crowding distance.

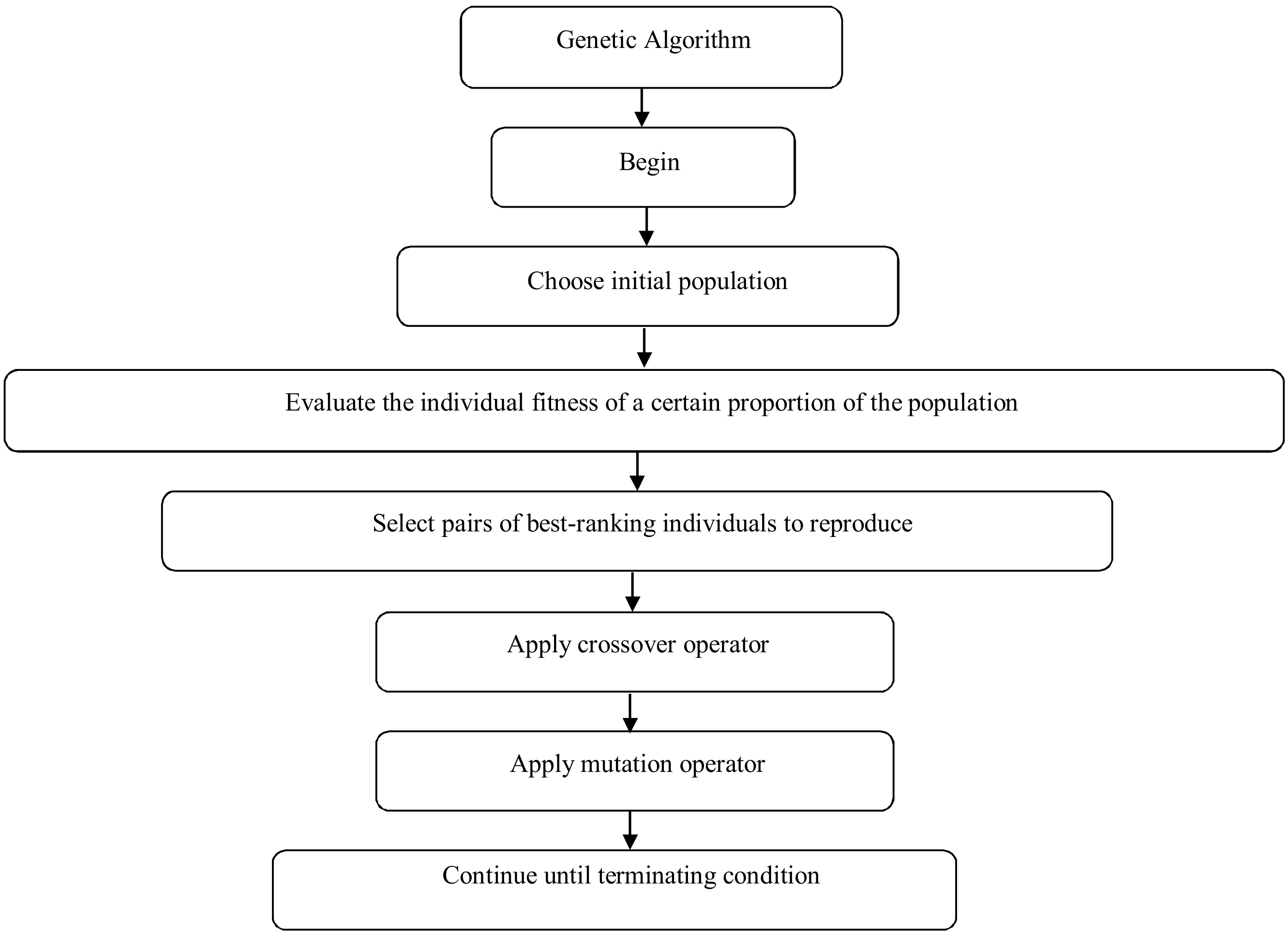


Figure.1, General schematic of genetic algorithm

4. Experimental data

Experimental data consists of 38 self-compacting mixing designs such as input parameters including cement, water to cement ratio, super lubricant, coefficient of curvature (cc), coefficient of uniformity (cu), and output parameters such as 28-day self-compacting compressive strength of concrete and slump flow. For the purposes of the current study, Portland cement (type II) was used to build the concrete. The fine aggregate used was natural sand with the bulk specific gravity of 2640 kg/m3 ranging from 0.075 mm to 4.75 mm. The coarse aggregate was the natural crushed gravels passed through 19 mm, retained on 4.75 mm with a specific gravity of 2580 kg/m3. In Table 1, the mixing designs, corresponding values of compressive strength, and slump flow have been shown[25].

Table 1. Mixing design[25]

No.	c_u	c_c	W/C	Cement Content (Kg/m3)	Super-plasticizer (%)	Slump flow (mm)	Compressive Strength 28-days (MPa)
1	10	0.45	0.4	500	10	725	18.3
2	9.06	0.49	0.4	500	7.5	790	22
3	9.95	0.99	0.4	500	4.5	760	24.5
4	9.31	1.06	0.35	450	1.5	735	32.2
5	9.31	1.06	0.45	450	1.4	700	33
6	9.31	1.06	0.4	550	1.8	700	50.8
7	9.95	0.99	0.35	450	16	763	10.8
8	9.95	0.99	0.4	450	6	670	28
9	9.95	0.99	0.45	500	0.25	630	39.6
10	9.95	0.99	0.4	550	0.5	810	44.9
11	9.95	0.99	0.45	550	0.35	795	48.8
12	11.64	0.96	0.4	500	1.3	725	38.3
13	12.36	0.92	0.4	500	0.6	725	38.6
14	14.36	0.78	0.4	500	0.6	740	34.4
15	15.27	0.74	0.4	500	1	730	47
16	15.27	0.73	0.4	500	1.1	710	48.7
17	7.2	1.09	0.35	450	2.5	450	40.1
18	7.2	1.09	0.4	500	0.5	697	44.3
19	7.2	1.09	0.45	550	0.1	695	43
20	8.4	1.01	0.4	450	0.45	605	31.4
21	8.4	1.01	0.45	450	0.25	610	48.8
22	8.4	1.01	0.45	500	0.25	630	39
23	8.4	1.01	0.35	550	1.3	780	45.5
24	8.4	1.01	0.45	550	0.25	550	59.9
25	9.31	1.06	0.4	450	1.5	685	28
26	9.31	1.06	0.35	500	1.4	720	31
27	9.31	1.06	0.4	500	0.5	710	34.8
28	9.31	1.06	0.45	500	0.4	650	39.9
29	9.31	1.06	0.35	550	2.1	785	44.5
30	9.95	0.99	0.35	550	1.25	780	50.7
31	8.4	1.01	0.35	500	1.4	525	45.1
32	9.31	1.06	0.45	550	1	800	48.7
33	9.95	0.99	0.45	450	2	666	29.3
34	9.95	0.99	0.35	500	4.5	733	45.4
35	9.95	0.99	0.4	500	0.6	785	59.8
36	8.4	1.01	0.35	450	1.6	500	34.7
37	8.4	1.01	0.4	500	0.35	530	34.6
38	8.4	1.01	0.4	550	0.55	680	45.9

4. 1. Coefficient of uniformity (Cu)

This parameter is selected to express the distribution of particles based on their size, and expresses the quality of seed distribution, in other words, Cu expresses the degree of uniformity and granulation of particles and aggregates. The larger the Cu, the greater is the distribution of aggregates.

$$Cu = \frac{D_{60}}{D_{10}} \quad (3)$$

where D_{60} is the sieve size that 60% of the aggregates can pass through it, and D_{10} is the sieve size that 10% of the aggregates can pass through it.

4. 2. Coefficient of curvature (Cc)

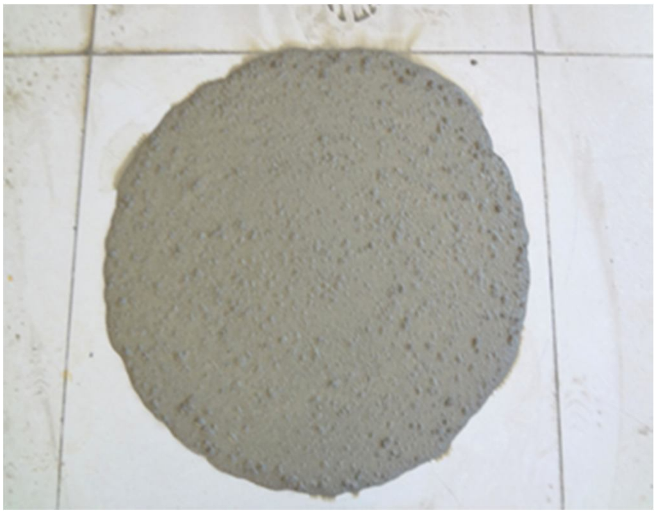
Since the coefficient of uniformity cannot precisely determine the certain size of the seeds at a distance of D_{60} and D_{10}, the coefficient of curvature is used. The value of Cc shows the granulation curved shape between D_{60} and D_{10}. The farther Cc from the unit suggests no grain size between D_{60} and D_{10}. This parameter can also be used to detect the granulation that lacks a part of particles with specific size.
where D30 is the sieve size that 30% of the aggregates have passed through it, D60 is the sieve size that 60% of the aggregates have passed through it, and D10 is the sieve size that 10% of the aggregates have passed through it.

$$Cc = \frac{{D_{30}}^2}{D_{10} \times D_{60}} \quad (4)$$

4. 3. Slump flow test

Slump flow test is performed to determine the freedom of self-compacting concrete motion on the horizon when there is no obstruction. The test is based on the principles, which is the basis of typical slump test. The diameter of circle that concrete makes after dispersion will be the concrete impregnation criteria. (Fig. 2)

(a)



(b)
Figure. 2, A and B Slump flow test[25]

5. Neural network training

5. 1. Perceptron neural network training

In order to achieve the desirable neural network, the single-layer perceptron neural network and multi-layer perceptron neural network (MLP) were studied. Determining the structure of ANNs in perceptron networks means to determine the number of the hidden layers and number of neurons per layer. In all networks, 60% of the data were considered and randomly selected as the training set, 20% as validation set, and 20% as testing set. In Table 2, for selecting the proper numbers of the hidden layer neurons for modeling, using the perceptron neural network, number of 100 replications were performed. Thus, in each replication, from the number of 1 to 20 neurons in the hidden layer, the number of neurons with better performance of the model based on the R2 criterion was selected. A number of 100 of replications were considered for a decrease in effectiveness of results of the perceptron neural network models to the initial weights as well as recognizable the number of neurons with greater chance of better performance of the model.

5. 2. GRNN and RBFNN Neural network training

In Table 3, in the GRNN and RBFNN neural networks, the dispersion of networks parameter is obtained using trial and error (in order to determine the appropriate dispersion of models) with mutual accreditation approach (to prevent the exact fitting of the models).

Table 2. Suitable number of neurons for neural network

Number of best neuron	Neural network	Number of best neuron	Neural network
12	perceptron neural network with one hidden layer in prediction of slump	16	perceptron neural network with two hidden layer in prediction of slump for the second layer
1	perceptron neural network with one hidden layer in prediction of compressive strength	18	Perceptron neural network with two hidden layer in prediction of compressive strength for the second layer
10	Perceptron neural network with one hidden layer in prediction of compressive strength and slump	5	Perceptron neural network with two hidden layer in prediction of compressive strength and slump for the first layer
12	Perceptron neural network with two hidden layer in prediction of slump for the first layer	8	Perceptron neural network with two hidden layer in prediction of compressive strength and slump for the second layer

Table 3. Dispersion parameter for RBFNN and GRNN neural networks

GRNN neural network		RBFNN neural network	
out put	spread parameter	out put	spread parameter
slump flow	1.1	slump flow	0.5
compressive strength	1.5	compressive strength	0.2
Slump flow and compressive strength	1.1	Slump flow and compressive strength	0.5

6. Statement and analysis of results

In Table 4, the values of R2 and MAE have been shown for the perceptron neural network as a single-objective and multi -objective network. In single-objective networks, the values of R2 are higher than the multi-objective networks, and in general, for both network cases, the value of R2 in the training data is greater than validation and testing data. It can also be seen that the accuracy of perceptron network in predicting the slump flow is higher than 28-day compressive strength of self-compacting concrete.

In Table 5, the values of R2 and MAE have been shown for the GRNN and RBFNN neural networks as single-objective and multi-objective networks. In general, in single-objective networks, the values of R2 is higher than the multi-objective networks, in the RBFNN network, the values of R2 in the validation and testing data are very low and close to zero. Also, the value of R2 in GRNN network is also low for validation and testing data.

Table 4. Values of R^2 and MAE for the perceptron neural network

neural network type	out put		R^2			MAE		
			train	validation	test	train	validation	test
Perceptron neural network with one hidden layer	slump flow		0.90	0.78	0.77	17.59	29.33	57.47
	28- day compressive strength		0.77	0.73	0.64	4.1	4.24	11.64
	together	slump flow	0.67	0.55	0.30	33.79	44.86	76.91
		28- day compressive strength	0.64	0.61	0.55	5.94	4.27	6.46
Perceptron neural network with two hidden layer	slump flow		1.00	0.88	0.78	0	48.94	40.89
	28- day compressive strength		0.68	0.83	0.66	4.57	6.14	7.75
	together	slump flow	0.76	0.89	0.73	27.53	26.74	61.48
		28- day compressive strength	0.53	0.57	0.43	5.56	3.41	4.12

Table 5. Values of R^2 and MAE for the RBFNN and GRNN neural networks

neural network type	out put		R^2			MAE		
			train	validation	test	train	validation	test
GRNN neural network	slump flow		0.83	0.37	0.31	22.8	53.65	77.89
	28- day compressive strength		0.86	0.69	0.06	2.92	4.52	8.32
	together	slump flow	0.83	0.37	0.31	22.8	53.65	77.89
		28- day compressive strength	0.88	0.70	0.08	2.52	4.43	8.2
RBFNN neural network	slump flow		1.00	0.01	0.03	0	59.17	98.97
	28- day compressive strength		1.00	0.39	0.00	0	5.56	10.29
	together	slump flow	1.00	0.01	0.03	0	59.17	98.97
		28- day compressive strength	1.00	0.27	0.02	0	5.6	10.52

According to the results shown in Tables 4 and 5, and evaluating the values of MAE and R2 in the neural networks, it was determined that the multi-layer single-objective perceptron neural network and 28-day compressive strength show better results. The suitable number of neurons in this network is 4 for the first layer and 18 for the second layer, which is selected as the proper neural network for modeling. Fig. 3 compares the Experimental and predicted results by multi-layer perceptron neural network for slump flow, the data of 1 to 38 are classified as training, validation and testing data, respectively. The data of 1 to 22 belong to training data, the data of 22 to 30 belong to validation data, and data of 30 to 38 belong to testing data. First, in the training data, the deviation had been close to zero, indicating that the network training was highly ideal with respect to the training data, and the network has been very effective in this regard. However, in the validation and testing data, the deviation is increased since the network has not been trained undergoing these data. Fig. 4 shows the Experimental results predicted by the multi-layer perceptron neural network for 28-day compressive strength of self-compacting concrete. In this figure, the data of 1 to 38 have been classified as training, validation, and testing data. At the beginning of the figure, which is belonged to the training data, a small amount of deviation can be seen, however, moving towards validation and testing data, the deviation is increased.

Fig. 5 shows dispersion of the predicted data by the multi-layer perceptron neural network and experimental data compared to the ideal status for 28-day compressive strength of self-compacting concrete. Due to the higher frequency of experimental data in the compressive strength of 30 MPa. to 50 MPa., the data dispersion is in desirable status, also the majority of points are located in ± 20% tolerance range of ideal status. In Fig. 6, the dispersion of predicted data using the multi-layer perceptron neural network and the experimental data can be seen by the ideal status for slump flow of self-compacting concrete. The majority of points for slump data are in range of ± 10% of ideal status, having a better status compared to the compressive strength data.

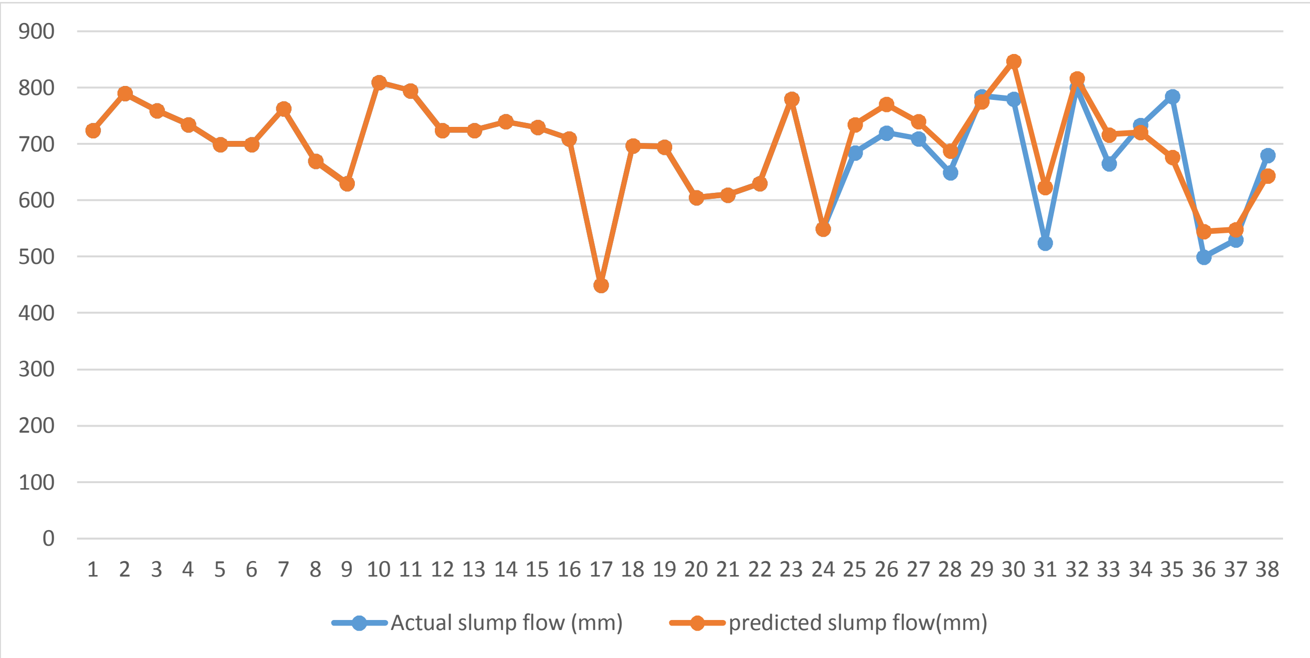


Figure. 3. Comparing the results of perceptron neural network data with experimental data for slump flow of self-compacting concrete

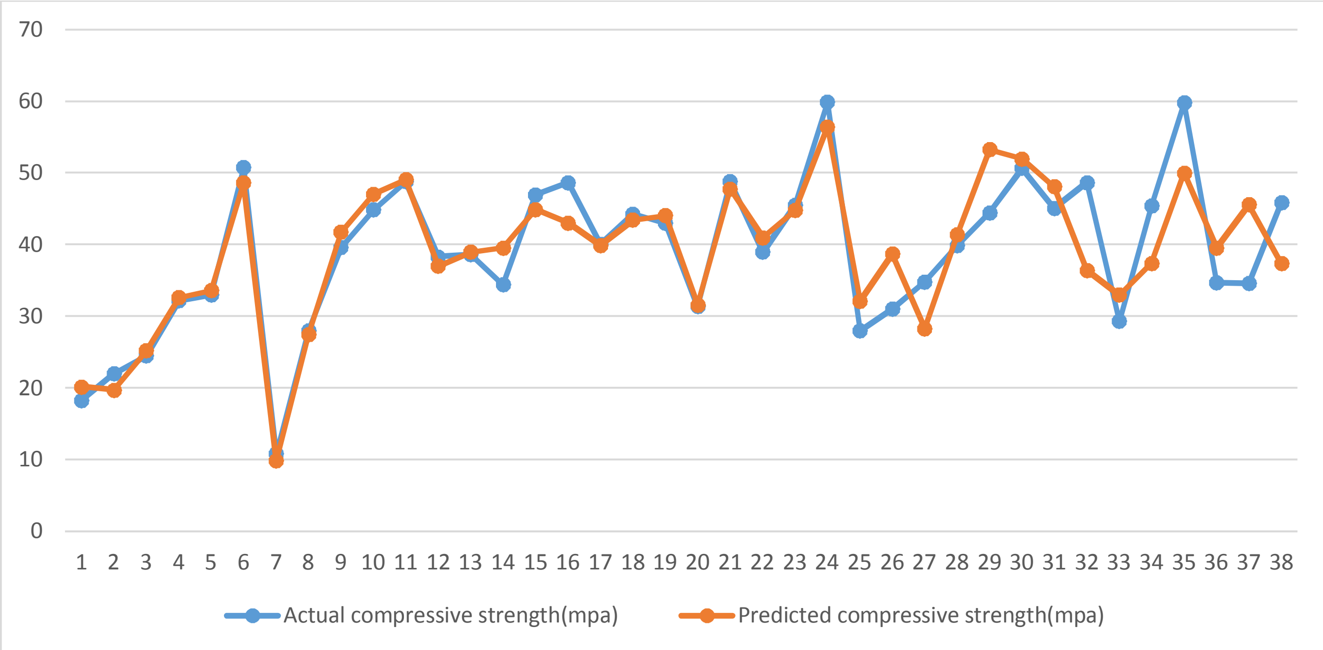
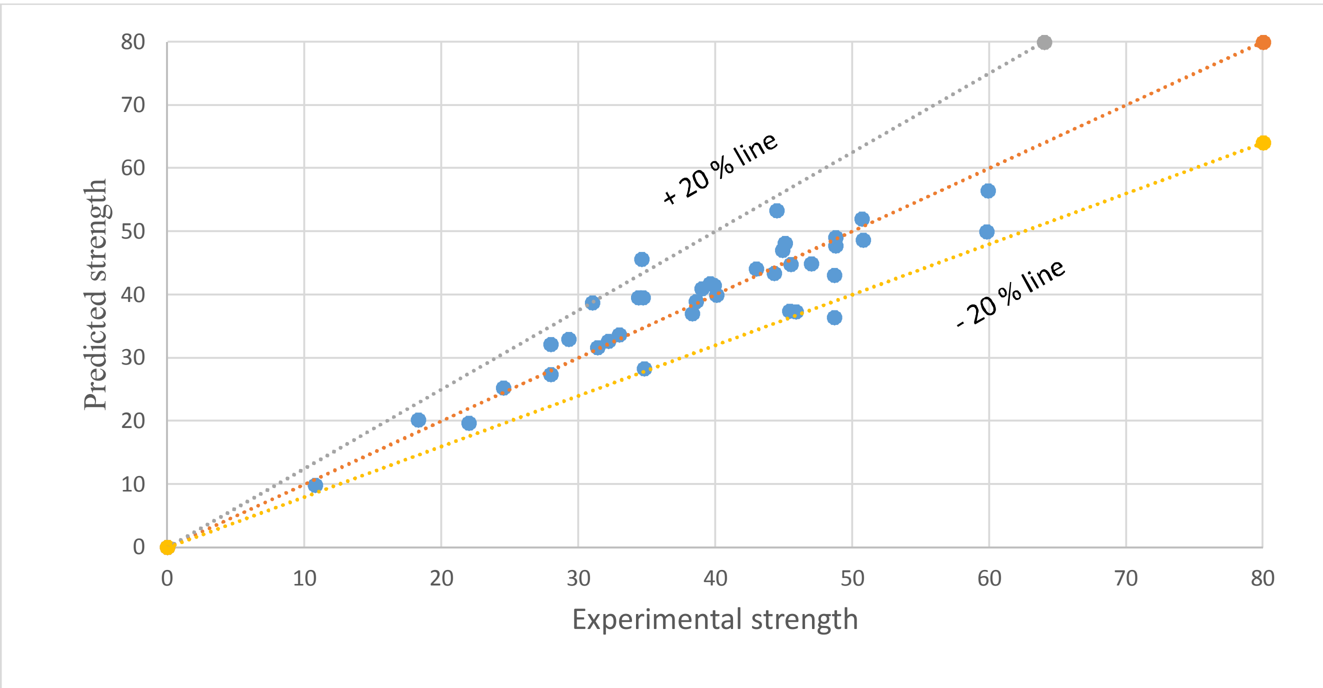


Figure.4. Comparing the results of perceptron neural network data with experimental data for compressive strength of self-compacting concrete



Figure, 5. Dispersion of results of the neural network for compressive strength (MPa) compared to experimental data

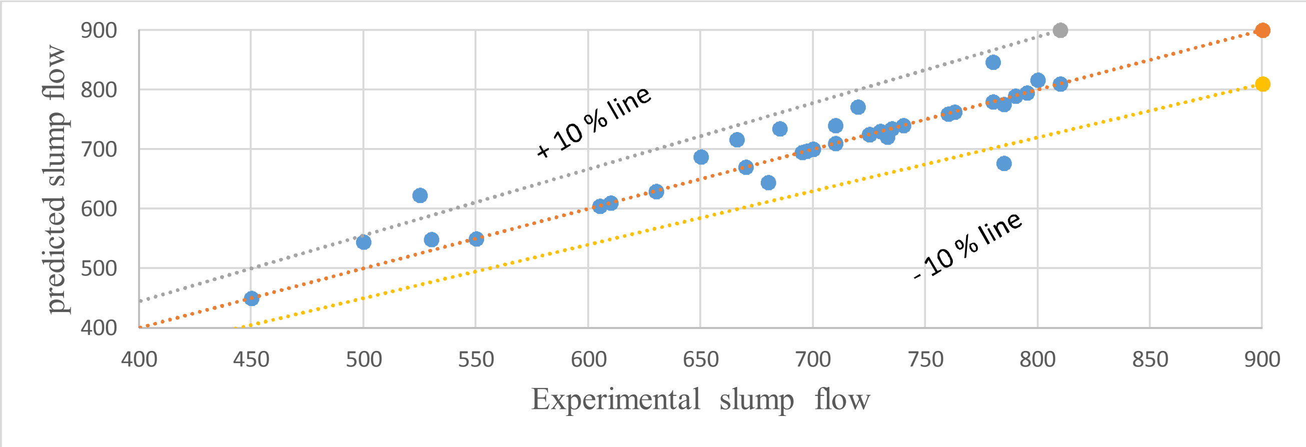


Figure. 6. Dispersion of results of the neural network for slump flow (mm) compared to the experimental data

Table 6 shows the variables of multi -objective genetic algorithm with the number of its cases. The number of variables of genetic algorithm is considered 4, including lubricant content, cement content, water to cement ratio, and soil mechanical parameters (coefficient of uniformity and coefficient of granulation). In order to determine the suitable genes for the multi-objective genetic algorithm, first, the frequency of input variables were determined, and then, for equal probability between variables, the number of the genetic algorithm was considered 6. In Table 7, a sample of the input chromosome to a multi-objective genetic algorithm shows that it is consisted of 4 variables, and each variable contains 6 genes as 0 and 1. For simultaneous optimization of the compressive strength and slump flow of self-compacting concrete using genetic algorithm, the numbers of 1000 generations were used, and for selecting the best mixing design, for simultaneous increase in 28-day compressive strength and slump flow using trial and error, the different values of intersection, population, mutation, migration parameters of the genetic algorithm were used. In Table 8, values of the desirable parameters obtained from trial and the errors have been shown for multi-objective genetic algorithm. The maximum accumulation of solutions is limited to the range containing slump of 1050 to 1150 mm and compressive strength of 75 to 80 MPa. It can be seen that in the results with decrease in slump, the compressive strength is increased.

Table 6. Number of input variables cases

Cu	Cc	W/C	Cement Content (Kg/m3)	Super-plasticizer (%)	
10	0.45	0.35	450	0.1	1.4
9.06	0.49			0.25	1.5
15.27	0.73			0.35	1.6
15.27	0.74	0.4	500	0.4	1.8
14.36	0.78			0.45	2
12.36	0.92			0.5	2.1
11.64	0.96			0.55	2.5
9.95	0.99			0.6	4.5
8.4	1.01	0.45	550	1	6
9.31	1.06			1.1	7.5
7.2	1.09			1.25	10
				1.3	16
11 case	11 case	3 case	3 case	24 case	

Table 7. A sample of input chromosome to multi-objective genetic algorithm as 0 and 1 data

1	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	0	1	0	1	0	1	0	1
C_U , C_C						W/C						cement content						super plasticizer					

Table 8. Parameters obtained from multi-objective genetic algorithm

cross over	population size	mutation	migration	selection
0.85	50	3	2	2

Table 9. Results obtained from the genetic algorithm

No.	Slump flow (mm)	Compressive Strength 28-days (MPa)	c_u	c_c	W/C	Cement Content (Kg/m3)	Super-plasticizer (%)
1	1094.8	78.34	15.27	0.73	0.4	550	2.5
2	1073.1	80.02	15.27	0.73	0.4	550	4.5
3	1108.5	62.7	15.27	0.74	0.45	550	4.5
4	721.6	104.01	10	0.45	0.45	550	16
5	1095.2	77.42	15.27	0.73	0.4	550	2.1
6	1105.3	76.43	15.27	0.74	0.4	550	2.1
7	1105	77.1	15.25	0.74	0.4	550	2.5
8	809.9	95.03	10	0.45	0.45	550	10

In Table 9, a series of solution obtained from the genetic algorithm, including eight solutions with different values of slump flow and 28-day compressive strength of self-compacting concrete along with input variables. The multi-objective genetic algorithm has simultaneously increased two output objectives, with regard to the input with increase in coefficient of uniformity, causing the separation of aggregates. Also, in the results that the compressive strength is increased, the coefficient of uniformity and coefficient of granulation are decreased, and lubricant content is increased.

7. Conclusions

Neural networks are a powerful tool to find a relationship between input and output data for the non-linear and complex problems. This methods are mixed with metaheuristic algorithms, which are not
problem-oriented algorithms and used for a variety of problems. The benefit of the proposed approach are listed as follows

1. It was observed that the perceptron neural network is more accurate than other neural networks in estimating the compressive strength of concrete, and superiority of all statistical indicators of this neural network to other neural networks indicated this fact.
2. In order to obtain a more accurate solution of the neural networks approach, the number of cases and frequency of training variables are increased.
3. Use of the multi-layer perceptron neural network as the fitness function of multi-objective genetic algorithm had a desirable result for the simultaneous

optimization of the slump flow and the compressive strength of self-compacting concrete, however, in order to prevent the excessive increase of slump by the multi-objective genetic algorithm, the penalty rate should be written on the code of genetic algorithm.

4. The advantage of using the multi-objective genetic algorithm is that instead of proposing an optimal response as the final solution of problem, a number of points are provided known as Pareto front as problem responses. This method also totally covered the weak points of solving multi-objective problems using the classic methods such as weighted sum.
5. Dispersion of slump flow data is lower than the compressive strength, leading to higher accuracy of results of the neural network for predicting the slump flow compared to 28-day compressive strength of the self-compacting concrete.

8. References

[1] Sonebi, M., Medium strength self-compacting concrete containing fly ash: Modelling using factorial experimental plans. Cement and Concrete research, 34(7): p. 1199-1208, 2004.

[2] Farokhzad, R., Yaseri, S., Entezarian, M. H., & Yavari, A. , Investigating Effects of Sulfates on Compressive Strength of Different Types of Pozzolan Concrete and Measuring Penetration Rate by Ultrasound Tests at Different Ages, 2016.

[3] Siddique, R. and G. Kaur, Strength and permeation properties of self-compacting concrete containing fly ash and hooked steel fibres. Construction and Building Materials, 103: p. 15-22, 2016.

[4] Topçu, İ.B., A.R. Boğa, and F.O. Hocaoğlu, Modeling corrosion currents of reinforced concrete using ANN. Automation in Construction, 18 (2): p. 145-152, 2009.

[5] Orejarena, L. and M. Fall, The use of artificial neural networks to predict the effect of sulphate attack on the strength of cemented paste backfill. Bulletin of engineering geology and the environment, 69 (4): p. 659-670, 2010.

[6] Sarıdemir, M., Predicting the compressive strength of mortars containing metakaolin by artificial neural networks and fuzzy logic. Advances in Engineering Software, 40 (9): p. 920-927, 2009.

[7] Mashhadban, H., S.S. Kutanaei, and M.A. Sayarinejad, Prediction and modeling of mechanical properties in fiber reinforced self-compacting concrete using particle swarm optimization algorithm and artificial neural network. Construction and Building Materials, 119: p. 277-287, 2016.

[8] Chithra, S., Kumar, S. S., Chinnaraju, K., & Ashmita, F. A., 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, 114: p. 528-535, 2016.

[9] Yeh, I.-C., Modeling of strength of high-performance concrete using artificial neural networks. Cement and Concrete research, 28 (12): p. 1797-1808, 1998.

[10] Bagheri, A., Farrokhi, F., Mahdikhani, M., Farokhzad, R., & Baghdadi, J., REPRESENTING APPROPRIATE AGGREGATES GRADING ZONE FOR SELF-CONSOLIDATING CONCRETE BY USING SOIL CLASSIFYING PARAMETERS.

[11] Lai, S. and M. Serra, Concrete strength prediction by means of neural network. Construction and Building Materials, 11 (2): p. 93-98, 1997.

[12] Yeh, I.-C., Modeling concrete strength with augment-neuron networks. Journal of Materials in Civil Engineering, 10 (4): p. 263-268, 1998.

[13] Yeh, I.-C., Design of high-performance concrete mixture using neural networks and nonlinear programming. Journal of Computing in Civil Engineering, 13 (1): p. 36-42, 1999.

[14] Sebastia, M., I.F. Olmo, and A. Irabien, Neural network prediction of unconfined compressive strength of coal fly ash–cement mixtures. Cement and Concrete Research, 33 (8): p. 1137-1146, 2003.

[15] Kim, J. I., Kim, D. K., Feng, M. Q., & Yazdani, F., Application of neural networks for estimation of concrete strength. Journal of Materials in Civil Engineering, 16 (3): p. 257-264, 2004.

[16] Dias, W. and S. Pooliyadda, Neural networks for predicting properties of concretes with admixtures. Construction and Building Materials, 15 (7): p. 371-379, 2001.

[17] Ni, H.-G. and J.-Z. Wang, Prediction of compressive strength of concrete by neural networks. Cement and Concrete Research, 30 (8): p. 1245-1250, 2000.

[18] Ren, L. and Z. Zhao, An optimal neural network and concrete strength modeling. Advances in Engineering Software, 33 (3): p. 117-130, 2002.

[19] Lee, S.-C., Prediction of concrete strength using artificial neural networks. Engineering Structures, 25 (7): p. 849-857,2003.

[20] Holland, J., A d aptation in nat u ral an d artifi cial s y s tem s. U niversity of Michigan Press. Ann Arbor, 1 (975): p. 1, 1975.

[21] Yeh, I.-C. and L.-C. Lien, Knowledge discovery of concrete material using genetic operation trees.

Expert Systems with Applications, 36 (3): p. 5807-5812, 2009.

[22] Farokhzad, R., Mohebi, B., Amiri, G.G. and Ashtiany, M.G., Detecting structural damage in Timoshenko beams based on optimization via simulation (OVS). Journal of Vibroengineering, 18 (8) , 2016.

[23] Farokhzad, R., Ghodrati Amiri, G., Mohebi, B., & Ghafory-Ashtiany, M., Multi-Damage Detection for Steel Beam Structure. Journal of Rehabilitation in Civil Engineering, 4 (2): p. 25-44, 2016.

[24] Eskandari-Naddaf, H. and R. Kazemi, ANN prediction of cement mortar compressive strength, influence of cement strength class. Construction and Building Materials, 138: p. 1-11, 2017.

[25] Farokhzad, R., Mahdikhani, M., Bagheri, A. and Baghdadi, J., Representing a logical grading zone for self-consolidating concrete. Construction and Building Materials, 115: p. 735-745, 2016.