A Combined Genetic Algorithm-Artificial Neural Network Optimization Method for Mix Design of Self Consolidating Concrete

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Abstract— **The use of intelligent optimization and modeling methods is rapidly increasing in many fields including concrete technology. In recent years, concrete mix design has been studied using intelligent models in which the artificial neural networks are among the most popular and widely utilized method. However, this modeling depends on an optimization process, and the structured model should be tuned by implementing optimization techniques. Additionally, finding the most appropriate neural network structure for solving the concrete mix design problem was proven to be an important challenge in the state-of-the art. Therefore, this paper introduces a novel strategy in which an evolutionary algorithm and a structure of artificial neural network were fused to find the best network for modeling the compressive strength of Self Consolidating Concrete (SCC) and to extract the most optimal mix design. The novel strategy is tested using 169 data-sets with each set containing 11 concrete constituent properties. The proposed GA-ANN-GA strategy not only finds the best model but also presents the most optimal mix design of concrete to mitigate the challenges reported in recent studies.**

Index Terms—**optimization, modeling, artificial neural network, concrete mix design, evolutionary algorithm**

I. INTRODUCTION

Concrete is one the most important achievements in the human era and has been used in construction industry for many years. Concrete production is a multi – stage process whereby different parameters influence its properties considerably. Generally, workability, strength, and durability are the three main features of concrete. The strength and durability are related to hardened concrete and workability is relevant to fresh concrete; furthermore, hardened properties are directly related to the concrete mix design [1].

The purpose of concrete mix design is to determine the most suitable proportions of its constituent materials such as cement, water, fine aggregate, coarse aggregate in a way that the concrete offers desirable and required features. Concrete mix design is dependent on a variety of parameters that play a vital role in concrete performance and cost. Recently, much effort has been made to present new methods for determining the mixing ratios of concrete and obtaining a suitable mix design [1-3]. Therefore, in order to achieve the desired strength of concrete, the optimal mix design and the ratio of each component should be determined accordingly.

The strength of concrete is influenced by many factors, such as water-cement ratio and consolidation degree [4]. One of the most important factors in controlling concrete quality is its 28-day compressive strength [5]. Concrete mix design and achieving optimal strength by using traditional methods has limitations. As such, intelligent modeling techniques with higher efficiency can be utilized for predicting material behavior [6]. Artificial neural network, fuzzy logic systems, and neuro fuzzy are among the most widely methods of intelligent modeling [5, 7]. Finding the best model among all the optimal models has always been one of the existing challenges [8]. Generally, optimization is the procedure of finding the best answer among all the existing solutions for a given problem. Optimization methods are divided into two categories, i.e. exact and approximate. Meta-heuristic methods are among the most effective intelligent methods that determine an approximate solution [9-11].

Ni Hong-Guang and Wang Ji-Zong used neural network and presented a method for predicting 28-day compressive strength of concrete. Their model determined the non-linear complex relation between the inputs (concrete components) and the output (concrete strength) of their study [5]. Young et al. used neural network to analyze more than 10,000 samples and presented an approximate model for predicting 28-day compressive strength of concrete [12].

Dac-Khuong Bui et al. obtained a model for determining the tensile strength of High-Strength Concrete. They selected neural network for their research due to the nonlinear relation between concrete strength and its components. They also chose firewall algorithm in order to train their neural network [13]. Guohua Liu and Jian Zheng used intelligent modelling to predict the

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Green Concrete Compressive Strength Development over Time (GCCSDOT) based on the required inputs. In this study, the authors focused on 3,7 and 28-day compressive strength of concrete [14].

Khosravani et al. investigated the implementation of an artificial intelligence system in order to estimate the dynamic properties of Ultra-High-Performance Concrete (UPHC). By studying the database of implemented systems from different research projects, they proposed an intelligence system that reduced the time-consuming tests and the need for technicians [15]. Anh-Duc Pham et al. introduced a machine learning approach in which the compressive strength of High-Performance Concrete (HPC) was predicted. In this regard, firefly algorithm (FA) and a class of Support Vector Machine (SVM), which were used for regression, were applied in order to optimize the parameters of regression model [16]. Moreover, Leonardo Vanneschi et al. recommended a contribution on Genetic Programming (GP), which is another computational intelligence technique, to predict HPC compressive strength. On this subject, they defined a prediction model base on GP with 7 variables, which were described as HPC components [17].

Nowadays, various kinds of concrete with different properties and range of applications are produced. Self-Consolidating Concrete (SCC) is one of the most important class of concrete that has a high level of consistency, and it does not require mechanical vibration for forming [18]. SCC has more fine particles, higher dosage of additives and more optimal consolidation compared with Plain Concrete (PC). These features provide desirable fluidity and viscosity [19]. It is well-known that the mechanical and physical properties of concrete will be improved when reforming it by some fine particles. In addition, adding fly ash into concrete components has some positive effects on the flexural and compressive strength of concrete [19].

Asteris et al. presented nonlinear modeling for predicting SCC strength by utilizing artificial neural network. They selected 20 top networks through trade-off process, developing 21,760 BPNN models, and considering MSE error. The comparison of the proposed method with the experimental finding showed the capability of the selected neural network [8]. Among different models for predicting compressive strength of concrete, Artificial Neural Network (ANN) and ANFIS are more reliable than other similar ones [20-22].

Mahmoud Abu Yaman et al. investigated two different approaches of neural network in order to obtain six components of SCC. In the first approach, compressive strength and slump flow diameter were considered as inputs and six components of concrete were considered as outputs. In the second approach, six neural networks with unique outputs were considered. These six neural networks were six components of SCC. The results of comparing these two approaches showed that their second approach was the most appropriate method [18]. Artificial Neural Networks are quite popular in modeling compressive strength of concrete, due to their high accuracy and reliability [23-26]. Moreover, it has been demonstrated that ANN is a more accurate technique than regression analysis or Genetic Programming [27-29].

In the above-mentioned studies, an optimal intelligent model with an appropriate pattern has not been presented, and finding the most appropriate mix design had several challenges. As such, this paper presents a novel intelligent optimization method by combining optimization algorithms and neural network. In this novel approach, first the best model is searched. Then, the optimal mix design of concrete with maximum compressive strength and the most economical cost is obtained using the GA-ANN-GA strategy. Such a novel approach is important in helping designers achieve goals that incorporate economy, sustainability, and safety [30]

II. GA-ANN-GA

In recent years, the computational intelligence toolbox has a massive number of tools in order to model and optimize different problems in engineering. Additionally, intelligent modeling methods that are based on machine learning have been used to simulate the non-linear and complex behavior of various building materials. In this regard, Artificial Neural Network (ANN) is a non-linear framework, which are strong tools for modeling particularly when the relations between data are unknown to construct an intelligent prediction tool [31]. ANN is used in a variety of engineering systems especially civil engineering cases for modeling processes [32]. MLP (Multi-Layer Perceptron) is one of the most well-known neural network structures. In order to have an efficient MLP model, weights and biases must be optimized with a training algorithm. The most well-known gradient training algorithm is the Levenberg-Marquardt (LM). Moreover, LM is the fastest algorithm, and is highly recommended as a first-choice supervised one [33]. Also, an activation function is the most important unit in the ANN structure, and the most well-known activation function used in MLP is Hyperbolic Tangent (tansig), and this function performs better results [34]. However, it is noteworthy to mention that finding the most appropriate activation function for each particular problem has always been a challenge [35].

Since one of this study's aims is to find the most optimal model for modeling the SCC compressive strength based on SCC components, Genetic Algorithm (GA) is utilized in this regard. Therefore, GA is the next tool, which is selected from the soft computing toolbox. Moreover, GA is a class of metaheuristic global optimization algorithms, which is applied to a wide range of optimization problems, these methods are utilized in case of searching the most optimum answer for engineering problems (29). Also, when the fitness function is highly complex and indistinguishable, GA can solve the problem efficiently [36]. In the next step, GA is implemented once more in order to achieve the second aim of this study, which is finding the most optimum concrete mix design.

III. METHODOLOGY

The ANN in class of MLP has been used in order to predict and model the compressive strength of SCC. To achieve this purpose, a suitable experimental data-set is required to model the compressive strength of SCC based on its components. In this study, for providing suitable data-set, the data-set presented by Asteris et al. [8] was utilized. The network's inputs were the SCC component proportions and its output was the compressive strength of SCC. These data-set has 169 samples with each data-set containing 11 inputs. Moreover, these SCC input components were Cement (C), Limestone Powder (LP), Fly Ash (FA), GGBS, Silica Fume (SF), RHA, Coarse Aggregate (CA), Fine Aggregate (FA), Water (W), SP and VMA, which are show in table 1 with details.

TABLE I. INPUT AND OUTPUT PARAMETERS FOR MODELING [8]

Number	Variable	Data used in ANN models		
		Minimum	Average	Maximum
1	Cement *(kg)*	150.00	345.32	570.00
2	Limestone powder *(kg)*	0.00	29.83	272.00
3	Fly ASH *(kg)*	0.00	106.77	350.00
4	GGBS *(kg)*	0.00	18.64	330.00
5	Silica fume *(kg)*	0.00	16.56	250.00
6	RHA *(kg)*	0.00	5.24	200.00
7	Coarse aggregate *(kg)*	500.00	745.37	927.00
8	Fine aggregate *(kg)*	478.00	862.67	1135.00
9	Water *(kg)*	94.5	178.40	250.00
10	SP *(kg)*	0.00	6.93	22.50
11	VMA *(kg)*	0.00	0.16	1.23
12	Compressive strength *(MPa or N/mm²)*	10.20	55.37	117.03

Additionally, input and output variables were normalized between 0 and 1 in order to prevent situations in which features with higher magnitudes influence those with lower magnitudes [37]. The function utilizes to normalize data set is shown in (1).

$$X_n^{nomilize} = \frac{X_n - X_n^{min}}{X_n^{max} - X_n^{min}} \quad (1)$$

In MLP, the best model should be chosen among all constructed ones including the trade-off process. At first, weights and biases are randomly selected and then optimization algorithm search the most suitable weights and biases. Moreover, the most appropriate network is the one which has the lowest error in its modeling, and here the error criterion is Mean Square Error (MSE), which is expressed in the (2). Also, constructed nets are trained with LM, and the activation function for all neurons is Tansig, which is demonstrated by (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

$$Tansig(n) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (3)$$

Searching the best network in terms of structure and lowest MSE can be considered as an optimization problem. Hence, in the first step of GA-ANN-GA strategy, LM and GA accomplish this task together, and then in the next step, GA searched the most optimum mix design of SCC from the excerpted model. Furthermore, the GA parameters are set as follows, number of generations = 100 - 150, population size = 50, crossover rate = 0.8, mutation rate = 0.15, and the algorithm runs five times to have higher range of assurance. Indeed, the best MLP model is searched and selected among 75000 constructed nets. The proposed GA-ANN-GA strategy flowchart is shown in Fig. 1, and the procedure of this strategy is described in the following.

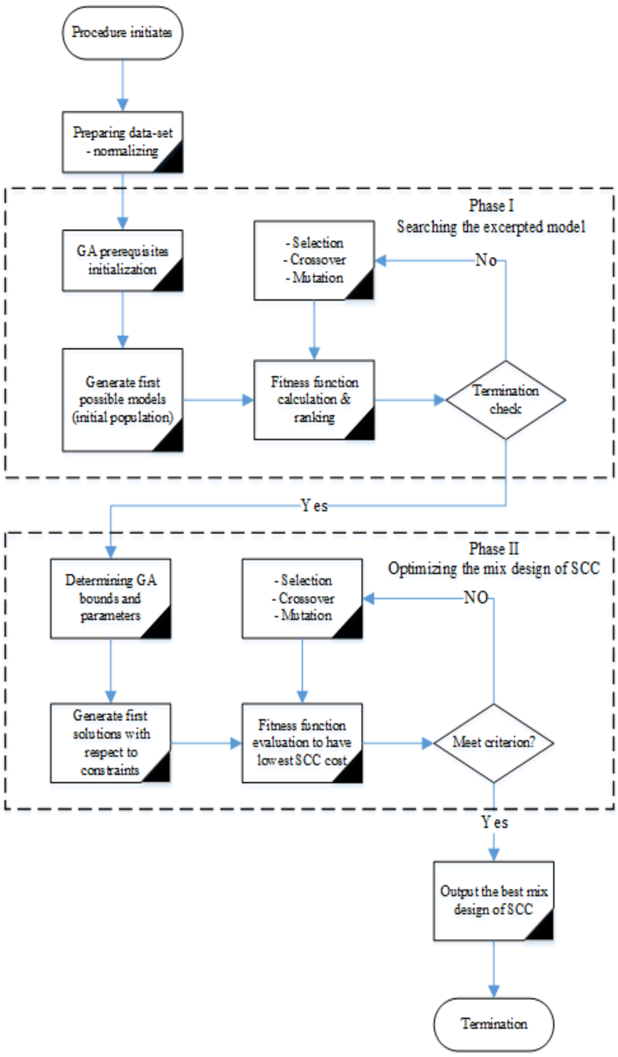

Figure 1. Procedure of GA-ANN-GA

A. First Phase: Finding the Excerpted MLP Model for the Problem

Step 1: Preparing input data for modeling the compressive strength of SCC.

Step 2: Considering GA requirements and parameters for this specific optimization problem.

Step 3: Designing a suitable and efficient fitness function to determine the most optimum MLP structure, which is trained with LM algorithm, and has the lowest test MSE.

Step 4: Running GA initiates until the stopping criterion is achieved.

B. Second Phase: Syncing GA with Selected Model from Phase 1.

Step 1: Defining GA bounds and parameters.

Step 2: Constructing the fitness function based on the SCC compressive strength model with respect to the SCC components costs.

Step 3: Formulate the required constraints.

Step 4: Running GA to extract and search the most optimum mix design of SCC form the model for maximum compressive strength, or a suitable mix design for specified compressive strength.

In the GA-ANN-GA process, in the first part, networks are made, and then the GA is used in order to find the most optimal network structure. In addition, in this part, two optimization algorithms work in parallel to find the most suitable network, and the second part is related to finding the most optimal mix design, which is implemented in MATLAB.

IV. Results and Discussions

The LM algorithm is used to optimize the network's weights and biases. Besides, the GA has been run totally five times with the parameters discussed in order to deplete the random process of the initial weights and biases. In this study, 75,000 networks are investigated and tested during first GA implementation, and then the excerpted model is selected. The best searched MLP model, which is a three-layer net with 6, 12 and 4 neurons for each layer respectively, and its performance for three types of data (validation 10%, test 15% and train 75%) is shown in Fig. 2. The regression diagram for the divided-up data is demonstrated in Fig. 3.

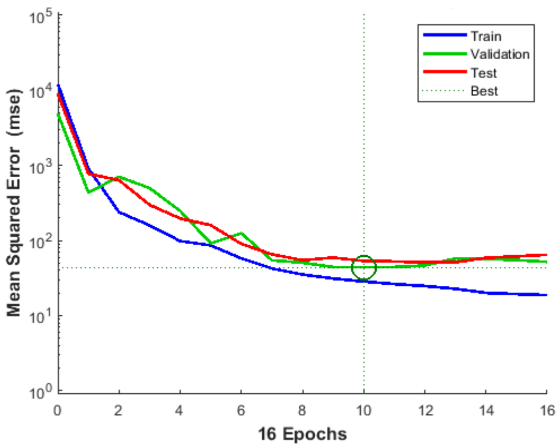

Figure 2. The performance of selected network (3 layers with [[6,12,4]] neurons)

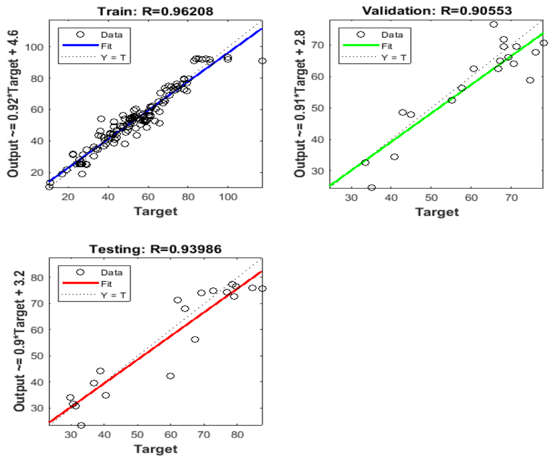

Figure 3. Regression diagram of selected network for train, test and validation data

This excerpted model, which is constructed on SSC compressive strength is identified by cooperating GA and LM algorithms. After this, the most optimal one to three-layer networks are compared with each other in terms of their regression, relative mean error and structure. This comparison is given in Table II.

TABLE II. The Most Optimal Searched Networks among over Than 75000 Neural Networks (1, 2, 3 Layers)

Best Network	Number of Layers	Number of neurons	R	Error
1	3	[[6,12,4]]	0.951	0.084
2	2	[[2,4]]	0.923	0.126
3	1	[[2]]	0.921	0.13

According to Table II, the three-layer network with identified number of neurons is the most suitable network for predicting the compressive strength of SCC. The prediction model's details for all 169 SCC samples is shown in Fig. 4.

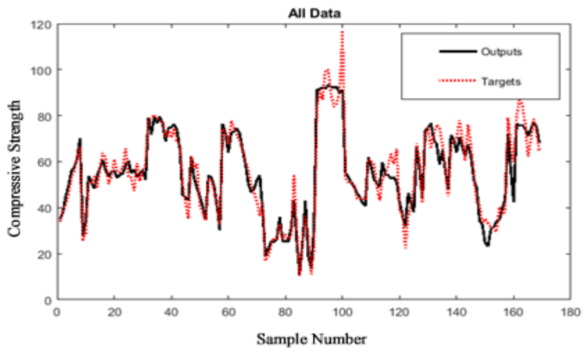

Figure 4. Comparision of predicted values and experimaetal data for SCC compressive strength via three-layer [[6,12,4]] network

In the last part of the GA-ANN-GA methodology, the optimum network is synced with the GA in order to derive the most optimal mix design for achieving the highest compressive strength of SCC considering the concrete components' cost. If the unit price of each SCC component is denoted by C1 to C11, the total cost of SCC can be calculated with (4).

$$\text{Total Cost of SCC (TCSCC)} = C_1 \times X_1 + C_2 \times X_2 + \ldots\ldots + C_{11} \times X_{11} \quad (4)$$

Since the TCSCC/CS ratio should be minimized, the value of these 11 parameters should be calculated so as to maximize the compressive strength. It should be noted that the price of each SCC components was determined in advance. The interpolating process of mix-design model is done by GA, which means that the lowest ratio of the Fitness Value is searched.

As it is shown in Fig. 5, in the 150th generation, the TCSCC/CS ratio reaches its minimum value (demonstrated as a negative value). To achieve this goal, the compressive strength is maximized based on the total cost of SCC, and then GA determines the most suitable mix design as an output (the amount of each SCC components). This robust GA-ANN-GA method also has enough ability to extract the best mix design in specific compressive strength of SSC with respect to the defined constraints, which are formulated precisely in the second phase of this strategy. The final outputs of the optimum mix design for some level of compressive strength are listed in Table III.

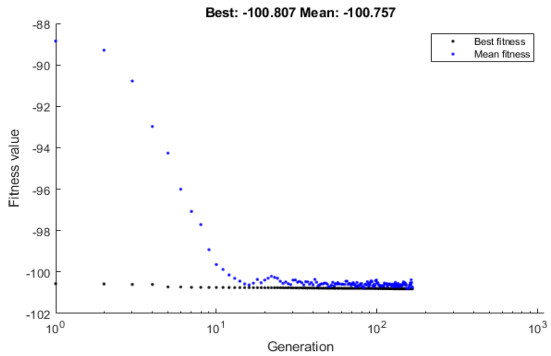

Figure 5. Convergence graph of the selected three-layer network for finding the most suitable mix design

Traditional methods for finding optimum mix design have low speed and accuracy. Therefore, creating and searching an efficient model and also finding mix design of SCC through interpolation process by utilizing intelligent algorithms such as GA-ANN-GA, is a new approach in this domain. In this study, the most suitable mix design of SCC is extracted from the most optimal network by utilizing an innovative strategy, which is a unique method in compressive strength modeling.

TABLE III- OPTIMIZED SCC MIXTURE COMPONENTS FOR SOME TARGETED COMPRESSIVE STRENGTH

	Predicted components for CSS by GA-ANN-AG										
Targeted f/c *(Mpa)*	**Cement**	**Limestone powder**	**Fly ash**	**GGBS**	**Silica fume**	**RHA**	**Coarse aggregate**	**Fine aggregate**	**Water**	**SP**	**VMA**
25	151.07	1.79	2.84	74.64	0.26	3.21	500.37	481.80	97.30	1.97	1.05
30	151.25	6.044	1.6	9.95	0.83	9.7	505.93	485.34	95.48	8.14	0.95
45	152.30	77.65	35.20	252.28	78.91	1.31	501.69	480.15	109.49	20.38	0.861
55	308.33	136.56	84.96	93.1	23.78	162.7	512.30	756.29	243.17	14.35	0.75
60	523.69	3.88	3.51	201.69	3.01	1.91	504.30	543.11	96.84	13.08	0.49

V. CONCLUSION

This study presented an innovative approach for intelligent modeling of concrete mix designs by augmenting two different computational intelligence solutions. The two-step strategy of intelligent modeling was developed using the MLP class of artificial neural network. Firstly, in order to make this model as the most appropriate and optimal one in terms of structure and accuracy, the chosen model was searched and selected from the possible models by using the evolutionary algorithm. To achieve this goal, the evolutionary and gradient algorithm performed the modeling process in parallel.

Consequently, the most optimal network for predicting the compressive strength of SCC was structured with respects to its components. Since the relation between the compressive strength of concrete and its components is unknown and non-linear, using a novel approach, which is capable to predict the compressive strength of concrete based on its components, can be highly beneficial in the concrete industry. At first, finding the best SCC compressive strength model is an optimization issue. Hence, this was delegated to a search algorithm (GA) in order to perform the search process and identify the most optimal model. Then, in the second step, for extracting the most suitable mix design of SCC based on the concrete cost and obtaining the aimed compressive strength with respect to constraints, the optimization algorithm was synced and implemented.

In GA-ANN-GA strategy, the best neural network model for the compressive strength of SCC is searched and introduced via GA, and then GA has extracted the optimal mix design with respect to identified fitness function and constraints. Utilization of this strategy's steps can improve the process of using artificial neural network and facilitate the creation of better models as well as extract the most appropriate network inputs from the model according to the optimization problem.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Author Contributions

AT performed the analysis; HH designed the research methodology; HH and GU drafted the manuscript; AT and AR reviewed the manuscript; HH revised the final manuscript. All authors read and approved the final manuscript.

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