Cost Optimization of No-Slump Concrete Using Genetic Algorithm and Particle Swarm Optimization

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Abstract—**Overall cost optimization of no-slump concrete (NSC) is investigated in this study. In this investigation, some restriction for the amount of compressive strength is considered and overall cost of concrete is minimized by designing mixture proportion. Cement, silica fume, water, fine aggregate, coarse aggregate and filler are the materials that are used in mentioned concrete. In this study, the purpose is to find the cheapest concrete that its compressive strength is 65 MPa. Genetic algorithm (GA) and particle swarm optimization algorithm (PSO) are used to find the best solutions. The results indicate that PSO introduced mixture proportion is 2% cheaper than that of GA. Also, running GA takes two times as much time as running PSO.**

Index Terms—**Compressive strength, cost, genetic algorithm (GA), optimization, particle swarm optimization (PSO).**

I. Introduction

The terms zero-slump concrete, no-slump concrete, and dry mix concrete generally refer to concrete of stiff or extremely dry consistency showing no measurable slump after removal of a conventional slump cone. In fact, so little water is used that the mixture of sand, gravel, and Portland cement does not fall down or "slump" at all. This condition is contrasted with the much higher water contents of normal concrete mixes, which usually range in slump from 75 to 200 mm (3 to 8 in.) [1]. this zero-slump concrete is widely used in impact-placed piles. A variation of zero-slump concrete is also used in precast concrete plants to form concrete pipes, culverts, hollow floor slabs, and concrete building blocks. In these precast applications the concrete placement technique often includes some form of vibratory compaction, a condition not usually associated with the placing of zero-slump piling concrete [1].

Compressive strength of concrete is a major and perhaps the most important mechanical property, which is usually measured after a standard curing of 28 days. Concrete strength is influenced by lots of factors like concrete ingredients, age, ratio of water to cementitious materials, etc [2]. So in designing concrete structures and concrete elements, minimum amount of compressive strength is defined and concretes have to achieve the suitable compressive strength after a standard curing of 28 days.

According to ACI 318, the compressive strength is usually determined based on a standard uniaxial compression test performed 28 day after casting the concrete [3]. If the test results do not satisfy the required strength, costly remediation efforts must be undertaken. Therefore, an accurate estimation of the compressive strength before the placement of concrete is very important. In recent years, prediction of the compressive strength of concrete has been an active area of research and different approaches have been proposed to estimate the compressive strength based on the mix proportions of different ingredients [4].

On the other hand, the cost is one of the most important criterion in projects and to improve the efficiency, cost of projects should be minimized and the quality should be maintained. Qualified structural design must satisfy required safety and minimum cost. Cost minimization is especially important for large-scale structures. Portland concrete girder bridges are generally large-scale constructions. In fact, all bridge and structures projects are designed as minimum-cost in application. But, trial and error method is generally used to design the mixture proportion of minimum-cost bridge and build in application. Trial and error method requires preliminary study and experience. On the other hand, optimization methods give minimum-cost design exactly and directly in one step. This paper considers the economic profitability in the premise of ensuring the concrete's compressive strength [5], [6].

II. Literature Review

Many research works can be found in the literature that focused on the prediction of compressive strength and the optimization of cost. Jafar Sobhani predicted compressive strength of no-slump concrete by regression, neural network and ANFIS models [2]. Behrouz Ahmadi-Nedushan set An optimized instance based learning algorithm for estimation of compressive strength of concrete [4]. J.KARNI used regression model to predict compressive strength of concrete [7]. Zhe Yuan predicted the concrete compressive strength by Research on hybrid models genetic based algorithms and ANFIS [8]. Xiansong Xie designed a genetic algorithm optimization model to minimize cost of High-Performance Concrete [5]. Zekeriya Aydin minimized the Overall Cost of Pre-stressed Concrete Bridge and Genetic Algorithm was used in his investigation [6]. Kamal C. Sarma optimized the cost of concrete structures [9].

As it can be seen from the references above, the populity of cost and compressive strength optimization is dramatically increased.

III. Optimization Model

The data and regression model are extracted from Jafar Sobhani article (2010). The initial mixture proportions are

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presented on that article [2]. In this study, we investigate on the cost of no-slump concrete and the aim is to find optimal mixture design. Optimal mixture design refers to the most economical mixture that has enough compressive strength. In other words, the algorithms try to find the cheapest grade 65 concrete. To improve the efficiency and to provide the model based on the real conditions, some constraints are added to this model. Compressive strength should be 65 MPa. To make the model feasible, 1MPa error is considered in compressive strength prediction, so compressive strength should be between 64 and 66 MPa. The volume of the mixture proportions are limited to $1m^3$. However, all the spaces in the concrete cannot be fill with materials because of small pores. Approximately pores are composed 2% of volume in concretes and volume of materials is considered $0.98m^3$ [10].

In order to change the model closer to data real situation, the amount of silica fume is considered between 4% and 8% of binder (cement and silica fume) weight. So, silica fume should be used more than 4% of binder weight, if it is used.

The materials have various ranges. The weight of some materials in concrete are much greater than the others. The ranges of materials are presented in Table I. To unify the value of all materials in compressive strength prediction, all the inputs (materials) and output (compressive strength) are scaled between 0.1 and 0.9. So according to the equation (1) data are scaled [2].

$$V_s=0.1 + 0.8 \times (V_r - V_{min}) / (V_{max} - V_{min}) \quad (1)$$

where V_s is the scaled data, V_r is the rough data, V_{max} and V_{min} are the maximum and minimum rough data values respectively.

The purpose of this investigation is to find the most economical grade 65 concrete. The cost function is calculated with the weight of ingredients and the unit cost them for $1m^3$. Sobhani [2] investigated on Prediction of the compressive strength based on regression models. He compared different types of regression models with R^2 and RMSE coefficients and 2th polynomial regression was opted as the best model. His introduced function is used in this study to find the most economical grade 65 mixture proportion. The compressive strength function and cost functions are presented in equation (2) and equation (3) respectively. Also, the unit cost and specific gravity of materials for $1m^3$ can be seen in the Table II.

$$V_{f'c} = a_0 + a_1 V_C + a_2 V_{SF} + a_3 V_W + a_4 V_{FA} + a_5 V_{CA} + a_6 V_{FI} + a_7 {V_C}^2 + a_8 {V_{SF}}^2 + a_9 {V_W}^2 + a_{10} {V_{FA}}^2 + a_{11} {V_{CA}}^2 + a_{12} {V_{FI}}^2 \quad (2)$$

where $V_{f'c}$, V_C, V_{SF}, V_W, V_{FA}, V_{CA}, and V_{FI} are the scaled value of compressive strength, cement, silica fume, water, fine aggregate, coarse aggregate, and filler respectively. And a_0, a_1, …, a_{12} are the constant coefficients which represent on Table III.

Minimize:

$$Cost = P_C C + P_{SF} SF + P_W W + P_{FA} FA + P_{CA} CA + P_{FI} FI \quad (3)$$

where P_C, P_{SF}, P_W, P_{FA}, P_{CA}, and P_{FI} are the unit price of cement, silica fume, water, fine aggregate, coarse aggregate, and filler in the order named; and C, SF, W, FA, CA, FI are the weight (Kg) of the cement, silica fume, water, fine aggregate, coarse aggregate, and filler in $1m^3$ concrete. The unit price of materials are presented in Table II. All the prices are announced in IRR which is Islamic Republic of Iran Rial (Iran currency).

The optimal mixture compressive strength have to be 65MPa. So, to find better mixtures and to improve the efficiency a small range [64], [66] is considered for compressive strength. In other words, the compressive strength has to be between 64 and 66 MPa.

To compare two specific algorithms (GA and PSO), the population size and the number of iterations should be the same. So population size and number of iterations are considered 20 and 500 respectively.

TABLE I: BOUNDARY RANGE OF INPUTS AND OUTPUT OF RECORDS [2]

Inputs		Range	
		Minimum	Maximum
Cement (kg/m^3)	C	252.6	410
Silica fume (kg/m^3)	SF	0	27.3
Water (kg/m^3)	W	95	139.7
Fine aggregate (kg/m^3)	FA	354.2	1300
Coarse aggregate (kg/m^3)	CA	600	1440.6
Filler (kg/m^3)	FI	0	188
Output		Range	
		Minimum	Maximum
28 days-Compressive Strength of no-slump concrete (MPa)		50	78

TABLE II: THE UNIT COST AND SPECIFIC GRAVITY OF MATERIALS

Materials	Unit Cost (IRR/Kg)	Specific gravity (Kg/m^3)
Cement	1200	3150
Silica fume	7000	2250
Water	150	1000
Fine aggregate	200	2560
Coarse aggregate	120	2530

Filler	280	2320

TABLE III: THE CONSTANT COEFFICIENTS IN EQUATION (2) [2]

Coefficient	Amount
a_0	-3.665
a_1	1.563
a_2	-0.292
a_3	0.662
a_4	-1.72
a_5	8.627
a_6	-0.446
a_7	-1.013
a_8	0.736
a_9	-0.787
a_{10}	5.337
a_{11}	-5.198
a_{12}	0.703

IV. GENETIC ALGORITHM (GA)

Genetic algorithm is a heuristic algorithm based on Darwin's natural selection theory [11]. It is an evolutionary algorithms which mimics the principles of biological evolution in nature. Variables of problem are encoded as chromosomes. According to the object function, chromosomes are firstly selected, then they overlap and mutate in an evolutionary process. After many times of evolution, the best individual will be found. Compared to other optimization method, GA has a good convergence and robustness. Under the same calculation accuracy, GA method takes much less time to find the optimal solution [12].

Genetic Algorithms has three operators namely selection, crossover, and mutation. In each iteration or generation, these operators are used on a population of all possible solutions, in order to develop their fitness function. Every solution is described by a string, and these strings are very much of the original chromosomes, hence it is named genetic algorithms. Initially, the population is randomly generated, and it continues until a terminating criterion is attained, e.g. the exceeding of a given limit of generations [13].

In this study, the real-coded genetic algorithm in MATLAB software 2016 was applied to find optimal mixture proportions of no-slump concrete. In this study, uniform crossover is used and for selecting genes are selected by Random selection, Tournament selection and Roulette wheel selection. In every selection, one of the selection processes above is selected randomly.

Implementing the GA technique for the problem at hand involved five primary steps: (1) Setting the gene structure; (2) deciding the gene evaluation criteria (objective function); (3) generating an initial population of genes; (4) selecting an offspring generation mechanism; and (5) coding the procedure in a computer program [14]. Flowchart of GA can be seen in Fig. 1.

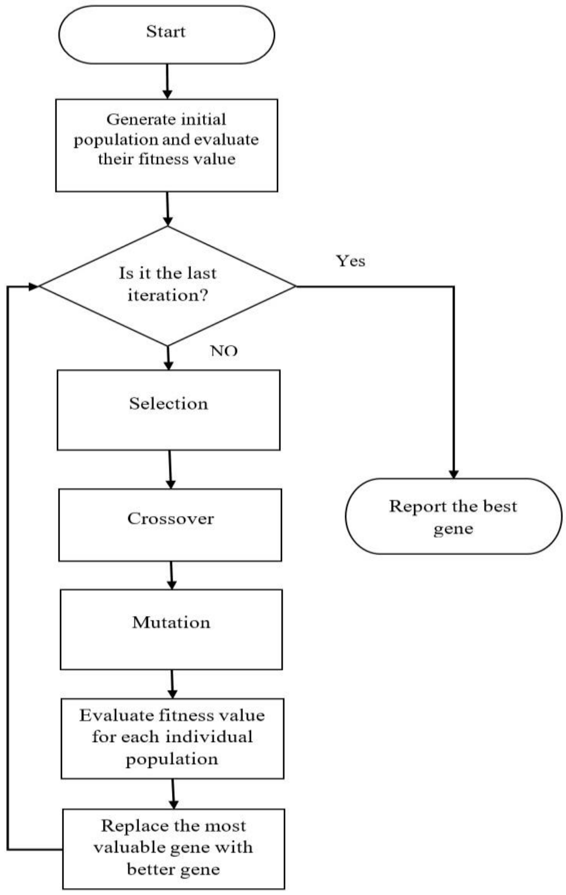

Fig. 1. Flowchart of genetic algorithm.

V. PARTICLE SWARM OPTIMIZATION (PSO)

In PSO, a number of simple entities (the particles) are placed in the search space of some problem or function, and each evaluates the objective function at its current location. Each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function. Each individual in the particle swarm is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position x_i, the previous best position p_i, and the velocity V_i.

The current position X_i can be considered as a set of coordinates describing a point in space. On each iteration of the algorithm, the current position is evaluated as a problem solution. If that position is better than any that has been found so far, then the coordinates are stored in the second vector, P_i. The value of the best function result so far is stored in a variable that can be called $P\text{best}_i$ (for "previous best"), for comparison on later iterations. The objective, of course, is to keep finding better positions and updating P_i and $P\text{best}_i$. New points are chosen by adding V_i coordinates to X_i, and the algorithm operates by adjusting V_i, which can effectively be seen as a step size.

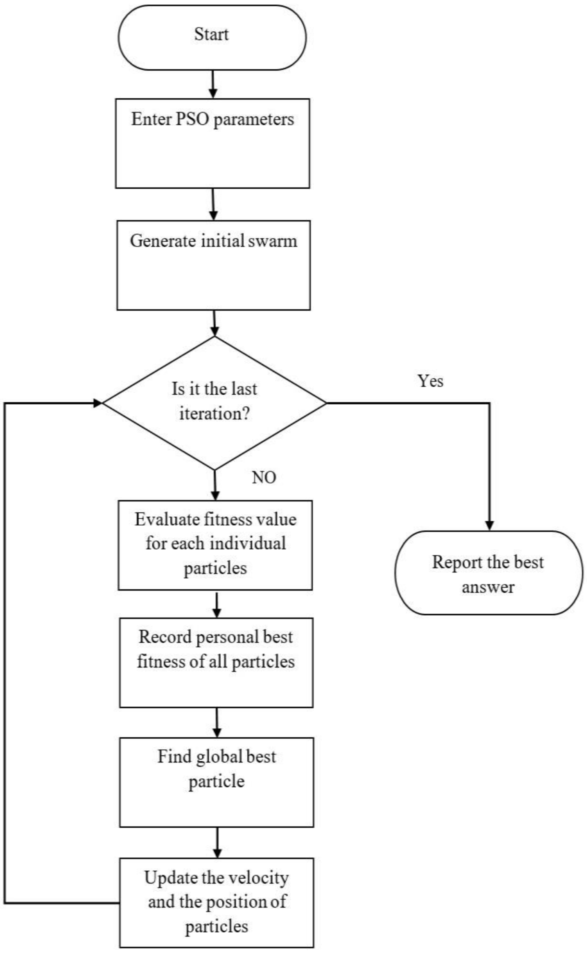

Fig. 2. Flowchart of particle swarm optimization

In this paper, first a population array of particles with random positions are initialized and velocities on D dimensions in the search space. Then desired optimization fitness functions (Cost and Compressive strength) are evaluated for each particle in D variables. In the next step, the fitness value of particles are compared with their $P\text{best}_i$. If current value is better than $P\text{best}_i$, algorithm sets the $P\text{best}_i$ equal to the current value, and P_i equal to the current location X_i in D-dimensional space. Afterward, the particle in the neighborhood with the best success so far is identified, and its index is assigned to the variable G. Then the velocity and position of the particle are changed according to the (4) and (5) equations. This loop continues until the maximum number of iterations is happened [16].

$$V_i(t+1) = WV_i(t) + c_1r_1[P_i(t)-X_i(t)] + c_2r_2[G_i(t)-X_i(t)] \quad (4)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (5)$$

The index of the particle is represented by i. Thus $V_i(t)$ is the velocity of particle i at any time t and $Xi(t)$ is the position of particle i at time t. c_1 and c_2 are two positive constants [17]. r_1 and r_2 are two random functions in the range [0, 1]. W is a positive coefficient and it is gradually reducing. By reducing the amount of W, the effect of initial point is decreased steadily and algorithm concentrates on the better points.

VI. Results and Discussions

TABLE IV: The Optimal Mixture Proportions

Optimal mixture proportions	Unit	GA	PSO
Cement	Kg/m^3	255.3	252.6
Silica fume	Kg/m^3	0	0
Water	Kg/m^3	103.55	108.01
Fine aggregate	Kg/m^3	1249.74	1156.32
Coarse aggregate	Kg/m^3	811.61	858.58
Filler	Kg/m^3	0	0

Is this study, mixture proportion of no-slump concrete is designed. The purpose is to find the cheapest mixture proportion which has 65MPa [64-66] compressive strength. GA and PSO are used in this optimization. To compare GA and PSO, the situations for two algorithms ought to be the same. So for both algorithms, the number of population and number of iterations are considered 20 and 500 respectively. Each algorithm runs 50times, and the cheapest mixture proportions grade 65 no-slump concrete are reported in Table IV.

For comparison of two algorithms running time is one of the most important criteria. Because faster algorithm let us to achieve the best solutions in fewer time. Hence, the average running time of two algorithms for each run, and cost of optimal mixtures are presented in Table V.

Also convergence history of cost according to the iterations is presented in Fig. 3.

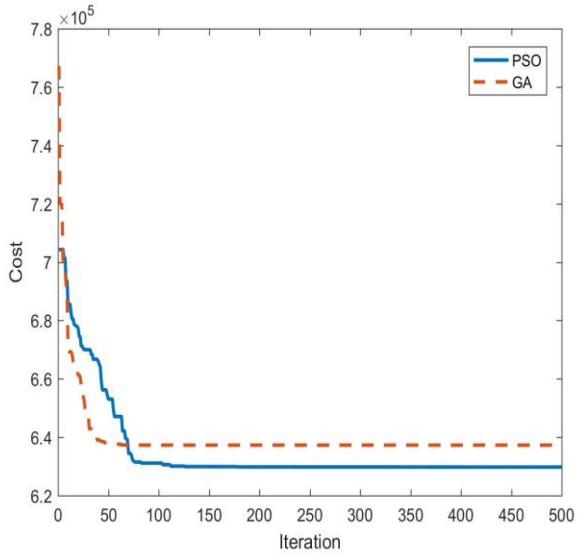

Fig. 3. Convergence history of cost.

TABLE V: COST OF OPTIMAL MIXTURES AND AVERAGE RUN TIME OF ALGORITHMS

Optimal mixture proportions	Unit	GA	PSO
Average run time	Second	0.8013	0.4081
Cost	Iran Rial (IRR)	637292.4864	629793.6887

VII. CONCLUSION

In this paper, Genetic algorithm and Particle swarm optimization are used to design the most economical mixture proportion of no-slump concrete. The compressive strength is considered 65MPa and the algorithms minimized the cost by finding the ideal amount of material in $1m^3$ concrete.

The following conclusions can be drawn from the results of this study:

- In this model, PSO is better than GA, because it finds better solution. PSO introduced mixture proportion is cheaper than GA introduced mixture. According to equations which were introduced in Sobhani [2] investigation, both mixtures compressive strength is 65MPa.
- PSO is a faster algorithm in this optimization. GA average running time takes about 0.8 second. However PSO average running time is 0.4 second. So, approximately running GA takes two times more than running PSO.
- Using heuristic algorithms can help to find optimal or near optimal solutions. In this case by virtue of these algorithms, cost of making concrete is dramatically reduced. However, finding the most economical mixture proportions with experimental work needs lots of money, time, and energy.

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