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OPTIMIZATION OF AERATED CELLULAR CONCRETE (ACC) RECYCLING ALUMINUM WASTE USING GENETIC ALGORITHM

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Abstract

Eight experiments were performed on five samples of Aerated Cellular Concrete (ACC) with varying aluminum powder particle sizes [A1 (95 μ m), A2 (30-70 μ m), A3 (10-30 μ m), A4&A5 (96.96nm)]. which are ready at the Thermiston Najaf factory. Based on statistical data from testing findings, an ideal composite material was discovered utilizing the hybrid approach represented by genetic algorithms by carrying out three methods of crossover (1X, 2X, & multi). To characterize the composite, the fundamental data were constructed based on their characteristics. In order to prevent clusters from overlapping with one another, the evolution algorithm then creates a strategy for the genetic clustering process and offers a number of necessary clusters. One of the clustering validity measures termed "Davies-Bouldin index" as fitness function of the method that employed. Then, the two categories of qualities for each cluster: mechanical features (hardness, compression strength and impact strength, physical features (density, porosity, thermal conductivity, Total absorption ratio (%), Depth of water

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absorption). This article indicates that composite (37, 45 & 45) represented optimal sample by employing one point, two-point crossover and multi crossover operators (1X, 2X & multi) accordingly.

Keyword: Recycling, aluminum waste, concrete, Nano, micro powder, ACC.

Introduction

Natural selection and genetics are the foundations of the adaptive heuristic known as the genetic algorithm (GA). One of the most well-known types of evolutionary algorithms is the GA. The mechanics of biological evolution, which were first studied by John Holland University of Michigan in the 1970s and later expanded by De Jong and Goldberg [1], are the foundation of the GA. Due to the many benefits of GAs and their hybrids, including their parallel search nature, easy optimization model creation, and free derivative features, they have been used to solve a variety of optimization issues. A population, or collection of solutions represented by chromosomes, is the first prerequisite for a GA [2].

GA is a population based evolutionary optimization approach for finding the best or near-optimal solution to a given objective function in a specified search area. The optimization process starts by generating an initial population, which is a collection of possible solutions, generally referred to as chromosomes. Each chromosome is a string of genes, each gene being a distinct decision variable or issue parameter. The GA develops the population repeatedly to successively higher generations by the sequential use of three basic genetic operators: selection, crossover and mutation according to the principles of natural selection and biological evolution. The selection operator is used to select high quality individuals preferentially on the basis of their fitness values, the crossover recombines the genetic information of parent chromosomes to generate better offspring, and the mutation introduces random genetic variations to maintain the diversity of the population and improve the global search capability. This

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evolutionary process is repeated until a predetermined termination criterion (including maximum number of generations or convergence to an acceptable fitness value) is reached, at which point the best performing chromosome in the final population is considered to be the optimal solution to the optimization problem [3].

Basics of Genetic Algorithms (GA)

According to Goldberg (1994), the GA approach is a significant and solid study topic. Additionally, Deb (1998) offered it as a possible search and optimization technique to address a variety of intricate issues. The GA was initially conceptualized by Professor J. Holland of University of Michigan, Ann Arbor in 1965 [3].

Overview of the Genetic Algorithms (GA) and Operators

GA is a powerful evolutionary search and optimization tool based on the principles of natural selection and processes of biological genetics. It is meant to tackle difficult optimization problems by evolving a population of candidate solutions towards an optimum or near-optimal solution repeatedly. The optimization process starts with a randomly generated population of individuals, where each possible solution is represented as a chromosome, which is typically a binary string, but other encoding schemes, including real-valued representations, can be used, depending on the problem. For each chromosome, a fitness function is created in order to quantify the quality of the candidate solution with regard to the optimization goal. Chromosomes with higher fitness values have a larger possibility of being selected to become part of the next generation, and hence guide the search towards better areas of the solution space. The evolutionary process is driven by physiologically inspired processes including selection, crossover (recombination), mutation, and inheritance which together encourage the retention of beneficial genetic information while

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maintaining sufficient variety to prevent premature convergence. By repeatedly using these operators on generations, the population is gradually evolved towards better solutions with better objective function values. A typical GA usually comprises five basic operators for population initialization, fitness evaluation, parent selection, genetic recombination, and mutation, which offer an efficient and flexible optimization framework for a wide variety of complex engineering and scientific optimization problems [4]:

Reproduction

Reproduction is a two-step process. First, a single S-expression is picked from the population according to some selection procedure based on fitness. Secondly, the chosen individual is replicated, unaltered, from the present population (i.e., the next generation) [5].

Fitness Function

The fitness function is the main component of the genetic algorithm. It assesses the quality of each potential solution quantitatively and drives the evolutionary search to the global optimum. In the current work, the fitness of each chromosome was evaluated using the Davies-Bouldin (DB) index, a well-known internal cluster validity measure that considers simultaneously both intra-cluster compactness and inter-cluster separation. The DB index is computed as a ratio of the within-cluster dispersion to the between-cluster centroid separation. A low index value indicates good clustering results, with clusters being compact and well separated. The optimization target was therefore to reduce the Davies–Bouldin index that improves the overall clustering quality. The within-cluster dispersion related to the i -th cluster was calculated as:

$$S_{i,q} = \left(\frac{1}{|C_i|} \sum_{x \in C_i} \|X - Z_i\|_2^q \right)^{\frac{1}{q}} \quad (1)$$

and the distance between cluster C_i and C_j is described as

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$$d_{ij,t} = \| Z_i - Z_j \|_t \quad (2)$$

The term $S_i(q)$ denotes the q -th root of the q -th central moment of the $|C_i|$ data points belonging to cluster C_i with respect to its centroid z_i , thereby providing a quantitative measure of the intra-cluster dispersion. In the present study, $S_i(q)$ is described as the mean Euclidean distance between all data vectors assigned to cluster C_i and the corresponding cluster centroid z_i , thereby reflecting the compactness of the cluster. Conversely, $d_{ij}(t)$ represents the Minkowski distance of order t between the centroids z_i and z_j of clusters C_i and C_j , respectively, and serves as a measure of inter-cluster separation. The combined assessment of intra-cluster compactness and inter-cluster separation provides a robust criterion for evaluating clustering quality. Accordingly, the clustering validity index was subsequently computed using the following expression [6]:

$$R_{i,qt} = \max_{j, j \neq i} \left\{ \frac{S_{i,q} + S_{j,q}}{d_{ij,t}} \right\} \quad (3)$$

The Davies–Bouldin DB index is then described as:

$$DB = \frac{1}{K} \sum_{i=1}^K R_{i,qt} \quad (4)$$

In order to achieve appropriate clustering, the goal is to reduce the DB index. The fitness function for chromosome j is described as $1/DB_j$, where DB_j is the Davies–Bouldin index derived for this chromosome, where the maximizing of the fitness function will assure reduction of the DB index [7].

Crossover

The crossover operator is one of the most significant evolutionary processes in GA that enables the exchange of genetic information across parent chromosomes, generating new offspring that may possess better features. Crossover improves the algorithm's exploitation potential by recombining good genetic material of

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high-quality solutions and at the same time increases the chance of finding better candidate solutions in the search space.

In the current research, many crossover procedures were investigated to assess the efficiency of maintaining and pooling useful genetic characteristics. The typical one-point crossover is that one crossover site is picked along the chromosome and the genetic segments beyond the designated place are swapped between two parent chromosomes to generate two offsprings. Moreover, two-point crossover was performed by picking two crossing places, and just the chromosomal section between these points was transferred, retaining the rest of the genetic material from each parent. Additionally, the uniform crossover operator was also investigated, in which each gene was inherited separately according to a certain probability, which enabled a more varied and uniform recombination of parental genetic material. Together, the crossover processes provide a better tradeoff between exploration and exploitation, increase the variety of the population and improve the chances to converge to globally optimum solutions.

•Single Point Crossover

11001011+11011111 = 11001111



Figure 1. Single point crossover [7].

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• Two Points Crossover

11001011 + 11011111 = 11011111



Figure 2. Two Points Crossover [7].

• Uniform Crossover

11001011 + 11011101 = 11011111



Figure 3. Uniform crossover [7].

Mutation

The offspring chromosomes were mutated after the crossover operation to improve the exploration capabilities of the GA. Mutation is a basic evolutionary operator that randomly changes chosen genes, therefore ensuring genetic variety of the population and lowering the risk of early convergence to local optima. Mutation helps to avoid the possible loss of vital genetic information during the selection and crossover operations by disturbing the genetic structure of candidate solutions and provides a possibility to generate new patterns of solutions, which have not been studied before. Mutation is an exploration method, which spreads the search to uncharted parts of the solution space. Contrary to crossover, that

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mainly leverages the information stored in high quality parent chromosomes to enhance existing solutions. This trade-off between exploitation and exploration allows the algorithm to escape local minima and improve its capacity to find global optimum solutions. Furthermore, the constant infusion of fresh genetic material maintains the variety of the population, avoids genetic stagnation and keeps the evolutionary quest going across generations. Hence, the mutation operator is very important to improve the resilience, convergence reliability and global optimization ability of the GA.

11001001 => 10001001

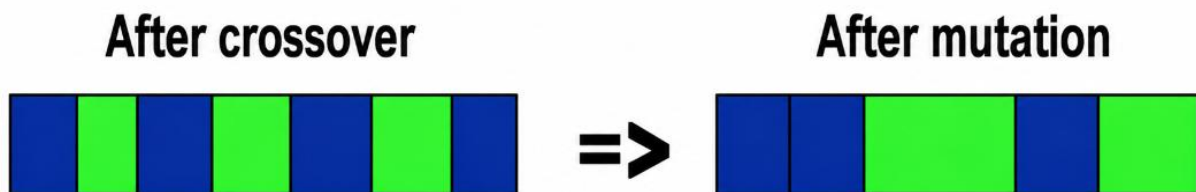


Figure 4. Mutation process [7].

Elitism

In order to maintain the best quality solution throughout the evolutionary process, it has been included an elitism approach into GA. Conventional selection, crossover and mutation operators may accidentally delete better chromosomes during the production of a new population due of the fact that the selection of parents is stochastic in nature [8]. In order to solve this problem, the elitism process copies the best chromosome(s) or a set number of elite chromosomes from the current generation to the next generation without any change. This guarantees that the most promising solution found throughout the search is maintained, limiting the loss of people with high-fitness. In the current work, elitism was applied at each generation by keeping the best chromosome found so far in a special memory location outside of the developing population and inserting it into each new generation [9]. Therefore, the suggested elitist

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technique made the GA converge faster, search more stably, and perform better overall by exploiting the best candidate solution continuously, while retaining population variety.

Representation of solution

The chromosomes were encoded with real-magnitude representations of the material qualities empirically evaluated in laboratory tests, as detailed in Table 1. Visual Basic programming language was used to build the GA to ease the implementation of chromosomal encoding, population creation and evolutionary operations. The length of the chromosome was equal to the number of material qualities included in the optimization process, and each chromosome consisted of N genes. Gene lengths were dynamically allocated based on the features of the encoded data (Figure 1). The first gene (length = 1) was the density; the second gene (length = 1) was the total water absorption ratio (%); the third gene (length = 420) was the water absorption depth; the fourth gene (length = 1) was the porosity ratio (%); the fifth gene (length = 1) was the thermal conductivity; the sixth gene (length = 1) was the compressive strength; the seventh gene (length = 1) was the hardness; and the eighth gene (length = 1) was the mechanical impact strength. The use of real- magnitude chromosomal structure allowed the evolutionary algorithm to effectively maintain the continuous character of the empirical data, and also to enhance the efficiency and robustness of the optimization process.

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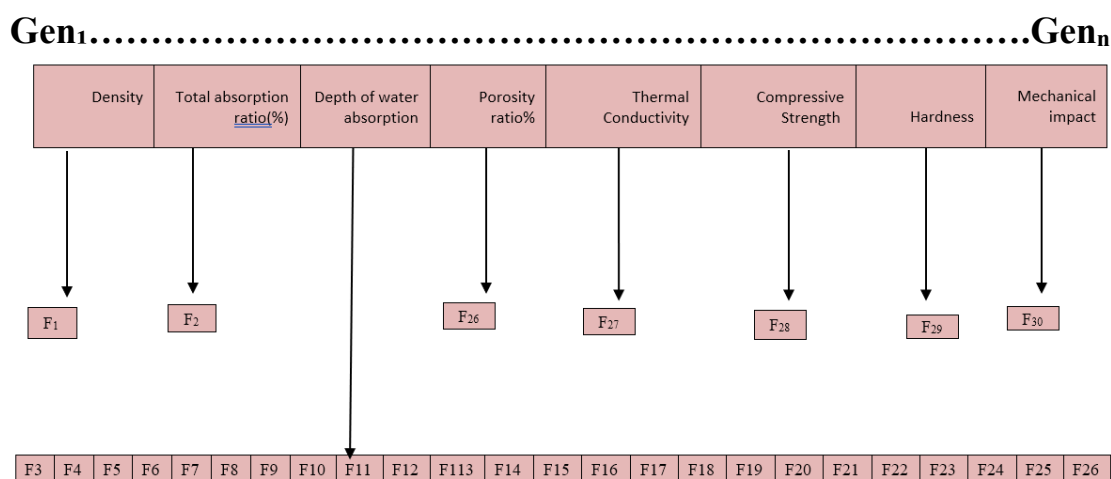


Figure 5. The representation of chromosome.

Implementation

The genetic operators are utilized in the GA optimization technique accordance to the flowchart presented in Fig. 6 It is not required to utilize all of these operators in a GA since each actions independent of the other, the choice or design of operators relies on the problem in question and the illustration scheme chosen. For example, operators built for binary strings cannot be utilized directly on string coding with integers or real number.

Table 1: Features of tests results.

Features	Meaning of features	Features	Meaning of features
F ₁	Drying density value at drying temperature 105 °C	F ₁₇	Depth of water capillary absorption After 15hour
F ₂	Total absorption ratio (%) value at drying temperature 105 °C	F ₁₈	Depth of water capillary absorption After 16hour
F ₃	Depth of water capillary absorption After 1hour	F ₁₉	Depth of water capillary absorption After 17hour

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F ₄	Depth of water capillary absorption After 2hour	F ₂₀	Depth of water capillary absorption After 18hour
F ₅	Depth of water capillary absorption After 3hour	F ₂₁	Depth of water capillary absorption After 19hour
F ₆	Depth of water capillary absorption After 4hour	F ₂₂	Depth of water capillary absorption After 20 hour
F ₇	Depth of water capillary absorption After 5hour	F ₂₃	Depth of water capillary absorption After 21hour
F ₈	Depth of water capillary absorption After 6hour	F ₂₄	Depth of water capillary absorption After 22hour
F ₉	Depth of water capillary absorption After 7hour	F ₂₅	Depth of water capillary absorption After 23hour
F ₁₀	Depth of water capillary absorption After 8hour	F ₂₆	Depth of water capillary absorption After 24 hour
F ₁₁	Depth of water capillary absorption After 9hour	F ₂₇	porosity ratio % value at drying temperature 150 °C
F ₁₂	Depth of water capillary absorption After 10hour	F ₂₈	Thermal conductivity value at temperature 100 °C
F ₁₃	Depth of water capillary absorption After 11hour	F ₂₉	compressive strength value at rate 0.1
F ₁₄	Depth of water capillary absorption After 12hour	F ₃₀	Vickers hardness value at load 9.4N and dwelling time 20 s
F ₁₅	Depth of water capillary absorption After 13hour	F ₃₁	Charpy mechanical impact value in joules/m ² unit
F ₁₆	Depth of water capillary absorption After 14hour		

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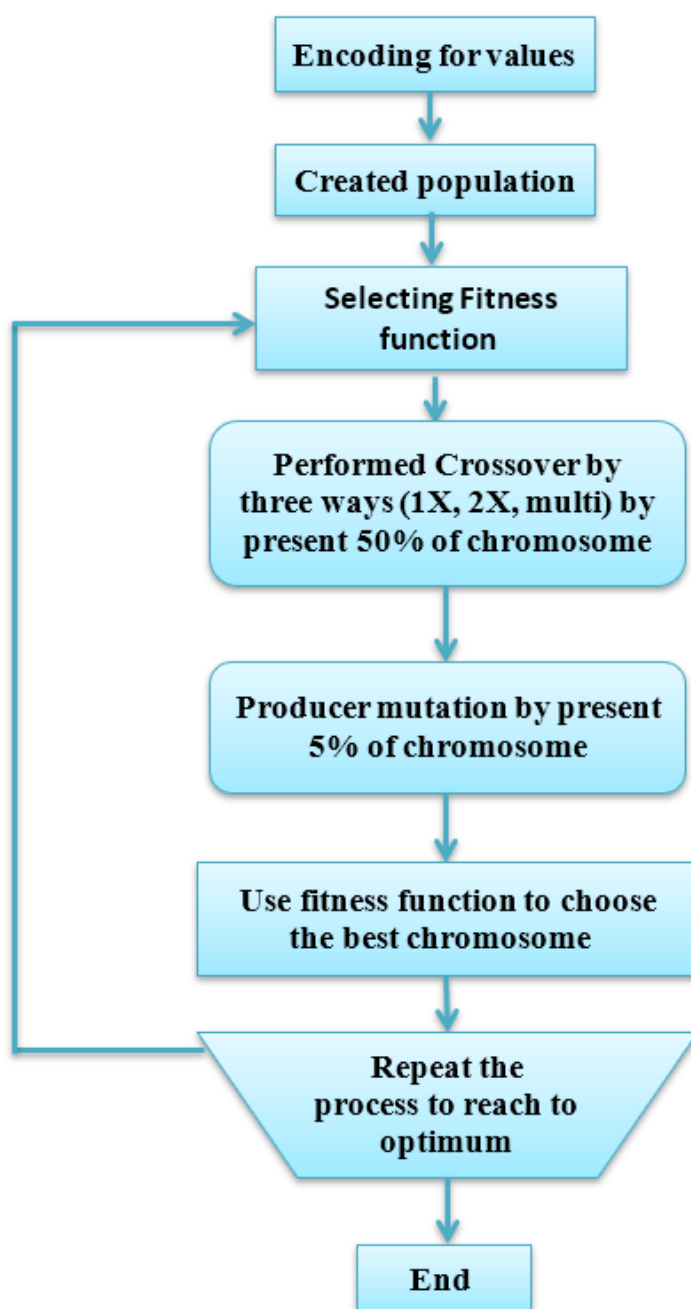


Figure 6. Flowchart of a simple GA.

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Results and Discussion

The hybrid technique, which is expressed by statistical variables and GAs, is used in this investigation to reach the optimal specimen. Data from experiments are used to identify the optimal features of samples (i.e., in this research, eight of the features of samples have been identified); consequently, a database was constructed to characterize samples based on their features. Based on Table 2 findings, chromosome (37) is the ideal specimen for the 1X-crossover operator that provides the best characteristics; Table 3 findings indicate that chromosome (45) is the ideal alloy for the 2X-crossover operator; and Table 4's results indicate that chromosome (45) is the ideal alloy for the multi-crossover operator that provides the most desirable features.

Step1 load the alloys database that contain the (100) alloys and (31) features (described) mechanical characteristics) including a density test, Total absorption proportion test, Depth of water absorption test, Thermal Conductivity test, Compressive Strength, hardness test and mechanical impact test with (F1, F2, F3-F10, F11-F18, F19-F26 and F27-F31) respectively as illustrated in Fig. 7.

Step 2: As shown in Fig. 8, transform the magnitudes from the database above to magnitudes in the range [0,1].

In the third step of our study, it has been used the GA to choose the best sample utilizing the three crossover methods (1X, 2X, and multi), as seen in Fig. (9, 10). To identify the optimal magnitudes of the final alloy feature findings, a GA is used. Prior to this, it must ascertain a few GA-related characteristics, including population size (100 people), likelihood of crossover (50%), probability of mutation (5%), and number of generations (100).

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Next
Create Population

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
545	44	5.27	7.14	4.24	6.38	5.39	5.15	5.47	7.67	
521	45	6.74	3.97	7.27	6.93	5	4.65	4.89	7.75	
531	43	7.56	4.31	6.63	4.14	5.9	5.48	4.57	3.93	
558	44	5.74	4.08	5.07	6.23	5.2	4.87	5.98	4.65	
547	43	4.2	3.89	5.02	7.6	7.84	5.89	6.53	5.59	
541	43	6.12	5.03	7.81	6.38	4.81	5.36	6.16	7.39	
546	44	5.61	4.58	5.46	7.34	7.5	6.18	4.37	5.99	
526	44	6.53	4.33	7.09	7.53	5.98	6.78	7.38	4.18	
547	45	4.39	7.28	6.16	7.65	7.31	7.02	7.85	6.14	
563	43	5.06	5.6	6.84	7.39	7.63	4.99	5.53	7.34	
564	44	4.65	3.99	5.97	5.26	6.18	3.87	6.45	6.4	
531	43	4.03	5.11	4.02	7.79	6.10	5.21	6.33	7.68	

Figure 7. Load the specimen's database.

Next to GA

Population Size:

Chromosome Size:

Probability of mutation:

Probability of crossover:

Number of generation:

Type of crossover:

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
1	81846502.9	94384330.2	92031178.7	75087732.7	52936573.6	60079562.8	50330888.9	91874589.8	99071274.6	50795476.5	88163575.5	606.985
2	74460168.5	52965252.5	53001666.1	80642494.5	61254554.5	68189736.7	72945106.8	56371256.7	88991022.4	97312071.5	72982088.4	865
3	63723289.8	81872919.1	54251398.7	85060614.4	65945705.6	80895702.6	88613914.9	62629497.0	94448898.6	54271001.1	68313838.1	674
4	58334944.7	71152562.4	97452300.7	93549135.1	52506897.5	88253311.9	90023668.7	77077713.2	80854255.7	58978580.1	99035831.4	605
5	56233230.7	74648540.5	58752933.9	88250632.2	78636532.2	51572968.5	57877891.1	60700947.1	86393825.8	7887394.3	97792862.2	884
6	52704650.1	56783788.2	83323946.5	71715757.2	53380450.6	67384988.6	52260470.1	55131706.5	70390143.5	53937394.3	58220756.1	546
7	78012898.7	45897847.5	59688268.6	56735932.5	55329307.9	83814128.6	57556668.2	61134006.9	60832746.5	59256457.1	68838131.0	706
8	67245721.6	53162028.6	73191291.6	83269176.1	84037840.5	55099888.7	72684615.4	68332815.1	64758069.2	53777678.7	66653866.1	975
9	67624268.1	71880637.5	60466346.1	87578830.8	88229039.0	69193071.6	66416032.1	50033956.4	83479556.7	79888192.1	59475748.6	801
10	53935248.6	72248070.3	564									
11	95444150.6	88252757.1	566									
12	83246075.1	91630456.5	858									

100%

Start Genetic Algorithm

Figure 8. Database of alloys transformation.

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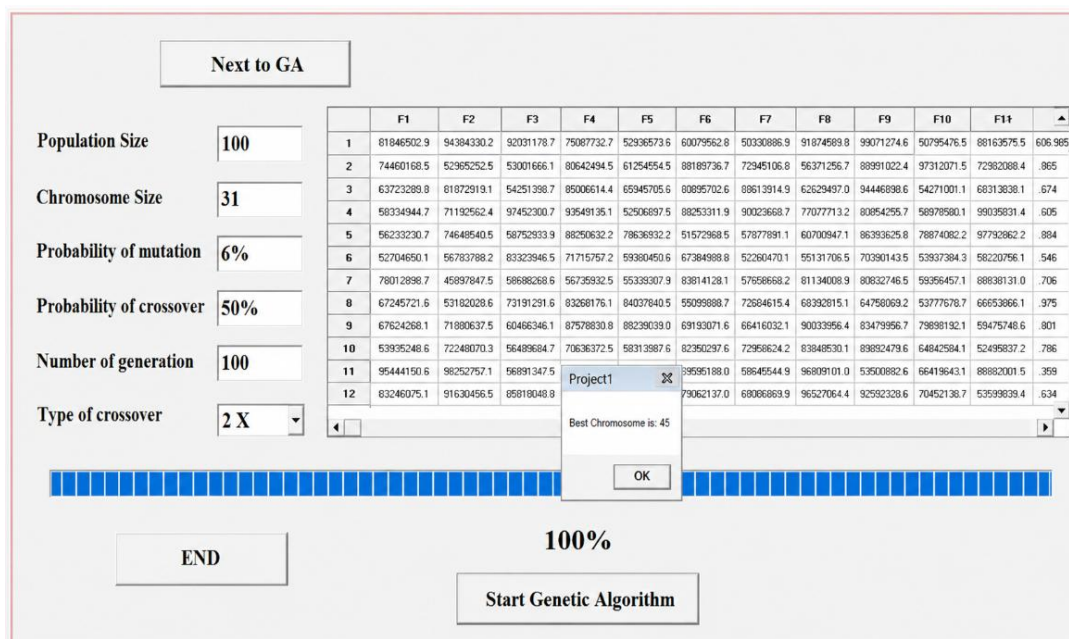
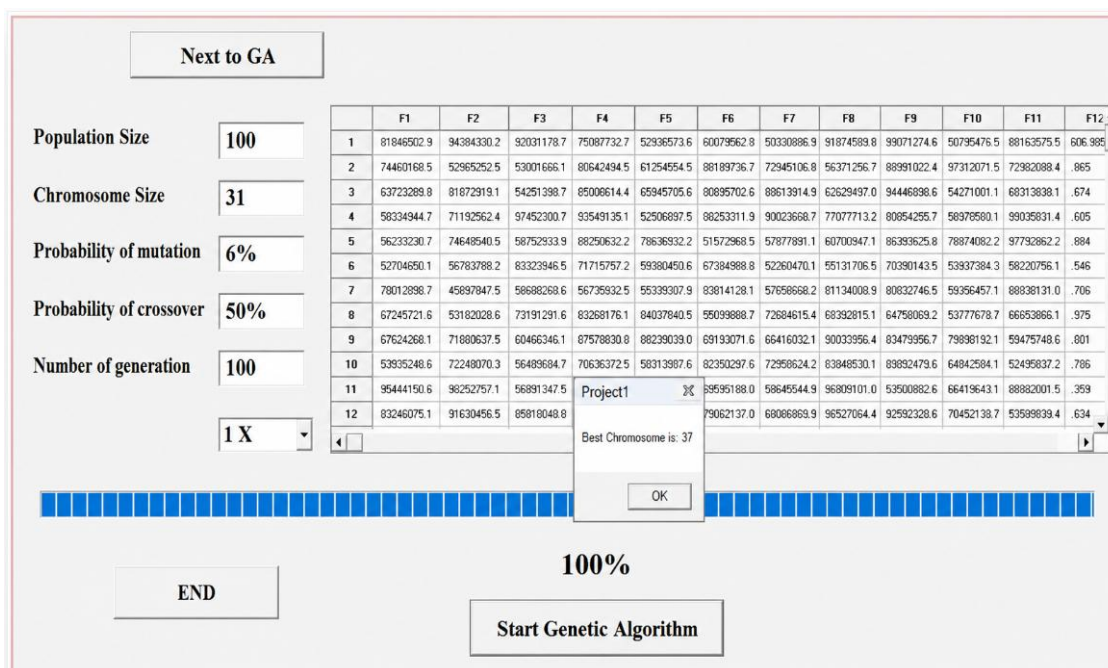


Figure 9. GA findings for two crossover methods (1X, 2X).

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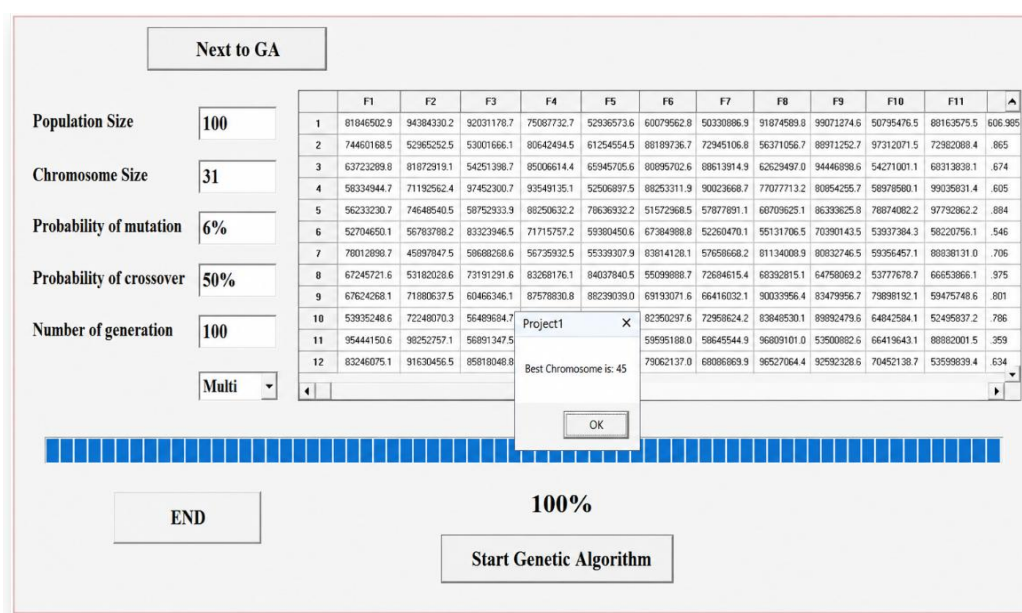


Figure 10. GA results for two crossover methods.

Table 2: Findings of the optimization method representing GA for 1X-crossover operator comparison with the empirical findings.

Features	Empirical	Optimization Algorithm	Features	Empirical	Optimization Algorithm
F ₁	530	520	F ₁₇	6.5	7.1
F ₂	43	45	F ₁₈	6.55	7.2
F ₃	4.5	3.8	F ₁₉	6.6	7.3
F ₄	4.8	4	F ₂₀	6.67	7.4
F ₅	5	4.8	F ₂₁	6.7	7.5
F ₆	5.2	5	F ₂₂	6.8	7.6
F ₇	5.3	5.3	F ₂₃	6.85	7.7
F ₈	5.5	5.7	F ₂₄	6.9	7.8
F ₉	5.6	5.9	F ₂₅	6.98	7.9
F ₁₀	5.7	6.2	F ₂₆	7	8
F ₁₁	5.8	6.3	F ₂₇	75.681	72.05
F ₁₂	5.9	6.5	F ₂₈	0.130	0.14
F ₁₃	6	6.7	F ₂₉	2.577	2.93
F ₁₄	6.1	6.8	F ₃₀	71.907	73.4
F ₁₅	6.2	6.9	F ₃₁	0.0156	0.0154
F ₁₆	6.3	7			

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Table 3: The differences between the empirical and optimization algorithm results for the GA for the 2X-crossover operator.

Features	Empirical	Optimization Algorithm	Features	Empirical	Optimization Algorithm
F ₁	530	517	F ₁₇	6.5	7.1
F ₂	43	44	F ₁₈	6.55	7.2
F ₃	4.5	3.8	F ₁₉	6.6	7.3
F ₄	4.8	4	F ₂₀	6.67	7.4
F ₅	5	4.8	F ₂₁	6.7	7.5
F ₆	5.2	5	F ₂₂	6.8	7.6
F ₇	5.3	5.3	F ₂₃	6.85	7.7
F ₈	5.5	5.7	F ₂₄	6.9	7.8
F ₉	5.6	5.9	F ₂₅	6.98	7.9
F ₁₀	5.7	6.2	F ₂₆	7	8
F ₁₁	5.8	6.3	F ₂₇	75.681	73.66
F ₁₂	5.9	6.5	F ₂₈	0.130	0.145
F ₁₃	6	6.7	F ₂₉	2.577	2.93
F ₁₄	6.1	6.8	F ₃₀	71.907	73.4
F ₁₅	6.2	6.9	F ₃₁	0.0156	0.0156
F ₁₆	6.3	7			

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Table 4: The differences between the empirical findings and the optimization algorithm's GA for the multi-crossover operator.

Features	Empirical	Optimization Algorithm	Features	Empirical	Optimization Algorithm
F ₁	530	528	F ₁₇	6.5	6.6
F ₂	43	43	F ₁₈	6.55	6.7
F ₃	4.5	4.3	F ₁₉	6.6	6.8
F ₄	4.8	4.5	F ₂₀	6.67	6.82
F ₅	5	4.9	F ₂₁	6.7	6.93
F ₆	5.2	5	F ₂₂	6.8	6.97
F ₇	5.3	5.1	F ₂₃	6.85	7
F ₈	5.5	5.3	F ₂₄	6.9	7.05
F ₉	5.6	5.5	F ₂₅	6.98	7.15
F ₁₀	5.7	5.7	F ₂₆	7	7.2
F ₁₁	5.8	5.9	F ₂₇	75.681	73.66
F ₁₂	5.9	6.1	F ₂₈	0.130	0.122
F ₁₃	6	6.2	F ₂₉	2.577	2.601
F ₁₄	6.1	6.3	F ₃₀	71.907	70.05
F ₁₅	6.2	6.4	F ₃₁	0.0156	0.0139
F ₁₆	6.3	6.5			

Conclusions

According to the result of the present work, the following can be concluded.

1. The GA is provided already the ideal solution of many problems by generating an integrated population individual as well as allowing to identify the attributes with higher precision and generality.
2. Alloy (37) is the ideal alloy for utilizing the one-point crossover operator, meaning it provides the greatest characteristics that are comparable to the sample magnitudes of (A3).

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3. Alloy (45) is the ideal alloy when using the two-point crossover operator, meaning it provides the greatest qualities that are comparable to the specimen magnitudes of (A3).
4. Alloy (45) is the best alloy utilizing the multi-point crossover operator, meaning it has the greatest characteristics comparable to those of the (A3) sample.
5. As opposed to the laboratory findings, which take longer time and more expense. The findings were acquired by applying GA in a quicker period and less expense.

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