Global Journal of Computer Sciences: Theory and Research

Volume 13, Issue 2, (2023) 75-91 www.gjcs.eu

Applying developed genetic algorithm operators to knapsack problems

Mustafa Kaya [a*], Aksaray University, Faculty of Engineering, Aksaray, Turkey

Suggested Citation:

Kaya, M. (2023). Applying developed genetic algorithm operators to knapsack problems. Global Journal of Computer Sciences: Theory and Research *13*(2), 75-91.

Received from; July 31, 2022, revised from; August 24, 2022, and accepted from September 07.

Selection and peer review under the responsibility of Assoc. Prof. Dr. Ezgi Pelin YILDIZ, Kafkas University, Turkey.

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Abstract

The increasing phenomenon of information overload is a direct result of the ongoing trend to reduce the cost of data. This study investigated the effect of the previously developed random mixed crossover (RMC), back controlled selection (BCSO), double directions sensitive mutation operators (DDSM), and backward controlled termination criteria (BCTC) on the performance of a genetic algorithm (GA). In the first study, the following three benchmark 0-1, bounded, and unbounded knapsack problems problems were analyzed. In the first stage, the existing were applied to the benchmark problems. In the second stage of the study, the analysis was conducted by separately applying the previously developed operators, RMC, BCSO, DDSM, and BCTC to the same benchmark problems. In the third stage of the study, the previously developed RMC, BCSO DDSM operators, and BCTC were applied to the same benchmark problems in the same analysis, and the results were compared with those obtained from the first stage. The results of the analysis showed that when the developed operators (crossover, selection, and mutation) and termination criteria were collectively used, they were more successful than the existing operators and the developed operators that were separately applied to the benchmark problems.

Keywords: back controlled selection; Genetic algorithm; random mixed crossover; sensitive mutation; termination criteria

* ADDRESS FOR CORRESPONDENCE: Kaya Mustafa, Aksaray University, Faculty of Engineering, Aksaray, Turkey.

E-mail address: kaya261174@hotmail.com

1. INTRODUCTION

In the literature, there are a substantial number of studies on Genetic Algorithms (GAs), investigating the effect of different GA operators, particularly crossover, selection, and mutation operators and termination criteria, on the performance of GAs. Examples of these studies are given below.

Fairbairn et al. [1] suggested a procedure to optimize the construction of mass concrete structures using GAs. Castilho et al [2] described the use of a modified GA as an optimization operator in structural engineering to minimize the production costs of slabs using precast pre-stressed concrete joists. Govindaraj and Ramasamy [3]. presented an application of GAs for the optimum detailed design of reinforced concrete continuous beams based on Indian Standard specifications. Atabay [4] investigated the cost optimization of an r/c structural system using a GA operator. Rafiq and Southcombe [5] introduced a new approach to the optimal design and detailing of reinforced concrete biaxial columns using GAs. Coello et al [6] presented an operator to optimize the design of reinforced concrete beams subject to a specified set of constraints. Sahab et al [7] examined the cost optimization of reinforced concrete flat slab buildings, according to the British Code of Practice (BS8110).

Atabay and Gülay [8] investigated the cost optimization of the three-dimensional shear-wall reinforced concrete structure using a GA operator. Bagui & Stanley [9] researched concept drift using frequent itemsets for mining streaming data using a genetic algorithm. Brighenti [10] researched the optimal distribution of fibers in fiber-reinforced composites (FRC) using a GA. Qin et al., [11] researched the use of a genetic algorithm to explore the optimization method of transmission line planning in energy distribution. Huang et al., [12] researched an Automatic design system of optimal sunlight-guiding micro prism based on a genetic algorithm. Ansary and Nassef [13] proposed a nonlinear finite element model and a GA optimization technique developed specifically for the analysis and design of steel conical tanks. Mota et al. [14], Motuzienė et al. [15], and Elgohary et al. [16] researched using genetic algorithms to enhance intelligent energy management systems in designing buildings. Maheri et al [17] recommended that the topology optimization of steel braces in two-dimensional steel frames was carried out using a GA. Kradinov and Madenci [18] analyzed the design variables of; laminate thickness, laminate lay-up, bolt location, bolt flexibility, and bolt size. Mezzommo et al [19] recommended the best alternatives for trapezoidal-shaped cross-sections of steel sheets, subjected to bending moments.

Jenkins, Rajeev, and Krishnamoorty [20-23]. investigated the effect of crossover operators on the behavior of GAs and found that the crossover operator is as important as coding, selection, and mutation in GAs. Adeli and Cheng [24-26] applied dimension optimization problems to three trusses, and beams to numerically compare one-point, two-point, and uniform crossover operators and obtained the best result from the two-point crossover operator. Wu and Chow [27] compared the one-point, two-point, three-point, and four-point crossover operators and showed that two-point, three-point, and four-point crossover operators are better than the one-point crossover. Jenkins [28] argued that the multi-point crossover operator fastened the progress whereas the use of a single-point crossover slowed it down. Syswerda [29] showed that the uniform crossover operator is more efficient when compared with two-point crossover. Erbatur and Hasancebi [30] proposed a new mixed and direct design variable exchange crossover operator in their study to investigate the effect of crossover operators on the behavior of GAs. Stern et al. [31] compared three popular selection operators; proportional selection, ranking selection, and tournament selection.

1.1. Purpose of study

In the current study, the following four benchmark problems were analyzed namely; high strength concrete mix design, traveling salesman, 0-1, and bounded knapsack problems. In the first stage; existing operators namely; the multi-point crossover operator and tournament selection operator, 1% mutation ratio, and fitness convergence termination criteria were applied to the problems.

In the second stage of the study, previously developed operators, randomly mixed crossover (RMC), back controlled selection (BCSO), double directions sensitive mutation operators (DDSM), and backward controlled termination criteria (BCTC) were applied to the benchmark problems conducting a separate analysis for each criterion, and the results obtained from this stage were compared with those obtained from the first stage.

In the third stage of the study, previously developed RMC, BCSO, DDSM, and BCTC were applied to the same benchmark problems conducting only one analysis, and the results obtained from this stage were compared with those obtained from the first and second stages.

2. METHODS AND MATERIALS

2.1. Population

A GA realizes the search within a population formed by points. When this population is being formed, ensuring the dissimilarity of the individuals is important; thus, the individuals should be formed randomly. In this study, the initial population consisted of 100 dissimilar individuals.

2.2. Coding

For the high-strength concrete mix design, reinforced concrete beam, and bounded knapsack problems, a permutation coding type was used since the design variables consisted of more than one variable group. For the 0-1 knapsack problem, a binary coding type was chosen and the variables were changed to 0 or 1.

2.3. Evaluation

A GA finds the maximum of an unconstrained objective function. To solve a constrained objective minimization function, two transformations are needed in this operator; transforming the original objective constrained function into an unconstrained objective function using the concept of the penalty function and transforming the unconstrained objective function into the fitness function. In this study, different constrained objective functions occurred for the four problems. After these functions occurred, this function was transformed into the unconstrained objective function. Finally, the unconstrained objective function was transformed into the fitness function.

2.4. Selection operator

Individuals of new populations in each generation were selected from the individuals of the existing population using a selection operator after creating the initial population. This operator artificially performed the natural selection. In this study previously developed back-controlled selection operator was applied to the problems [32].

2.5. Crossover operator

A GA can rapidly identify discrete zones within a large search space area to concentrate the search for an optimum solution. This technique changes mutually defined parts of the two selected members and obtains different members that produce new points in the search space. In this study previously developed random mixed crossover operator was applied to the problems [33].

2.6. Mutation operator

When examining a limited population, some of the genetic information will likely be lost over time. In the later generations, all the genes forming a chromosome can be the same, and it is not possible to change this chromosome via the crossover operator. In such circumstances, for the individuals forming the population externally in a certain ratio, the code of these individuals can be changed. In this study previously developed double directions sensitive mutation operator was applied to the problems [34].

2.6. Termination criteria

Termination is the criterion by which a GA decides whether to continue or stop searching. Each enabled termination criterion is checked after each generation to determine whether it is time to stop. In this study previously developed backward controlled termination criteria applied to the problems [35].

3. RESULTS

The application is captured in this section.

The four benchmark problems used in this study are; high strength concrete mix design, traveling salesman, 0-1, and bounded knapsack problems. The study was carried out in three stages. In the first stage, the existing operators namely; the multi-point crossover operator, tournament selection operator 1% mutation ratio, and fitness convergence termination criteria were applied to the benchmark problems. In the second stage of the study, the analysis was conducted by applying the previously developed operators, RMC, BCSO, DDSM, and BCTC, separately to the same benchmark problems, and the results obtained from the analysis in this stage were compared with those obtained from the first stage. In the third stage, RMC, BCSO, DDSM, and BCTC were collectively applied to the same benchmark problems, and the results were compared with those obtained from the first and second stages.

3.1. The knapsack problems (KP)

The KP is a combinatorial optimization problem. The objective of the KP is to maximize the total value (profit) without exceeding the maximum weight. It is modeled as a situation analogous to filling a backpack, unable to bear more than a certain weight and value (profit).

The most commonly solved KP problem is the 0-1 KP, which restricts the number x_i of copies of each kind of item to zero or one. Let there be n items, z_1 to z_n where z_i has a value w_i and weight w_i. x_i is the number of copies of the item z_i, which, as mentioned above, must be 0 or 1. The maximum weight that can be carried in the bag is w. It is common to assume that all values and weights are non-negative. To simplify the representation, it is also assumed that the items are listed in an increasing order of weight. Mathematically, the 0-1-KP can be formulated using Eq. 1.

$$\text{Maximize } \sum_{i=1}^{n} v_i . x_i \qquad \text{Restraints: } \sum_{i=1}^{n} w_i . x_i \leq W \qquad x_i \in \{0,1\} \tag{1}$$

The sum of the values of the items in the knapsack is maximized so that the sum of weights is less than or equal to the capacity of the knapsack.

3.1.1. The "0-1" knapsack problem

In this problem, a 0-1 knapsack was analyzed. In the first stage of the study, the existing operators, multi-point crossover operator, and tournament selection operator were applied to the BKP problem using a 1% mutation ratio and fitness convergence termination criteria. In the second stage, the developed operators (RMC, BCSO, DDCM, and BCTC) were separately applied to the BKP. In the third stage of the study, the developed operators (RMC, BCSO, DDSM, and BCTC) were collectively applied to the BKP.

The BKP removes the restriction of having only one of each item but restricts the number x_i of copies of each kind of item to an integer value c_i. Mathematically the BKP can be formulated using Eq. 18.

For example, a tourist wants to take a trip with his friends at the weekend. He has a knapsack for carrying things but knows that he can carry a maximum of 3 kg. He creates a list of what he wants to take for the trip, but the total weight of all items is too much. He then decides to add columns to his initial list detailing their weights and a numerical value representing how important each item is for the trip (Table I). In this problem, the total weight of the tourist's knapsack cannot exceed 3 kg and his total value should be maximized.

TABLE I
ITEMS WILL BE PUT IN THE 0-1 KNAPSACK PROBLEM

Code	Item	Weight (kN)	Value ($)	Number
1	Map	2,5	4,55	1
2	Compass	3,0	6,82	1
3	Water	15,0	1,36	1
4	Sandwich	5,0	1,36	1
5	Glucose	5,0	4,55	1
6	Tin	1,0	3,41	1
7	Banana	5,0	2,05	1
8	Apple	5,0	1,59	1
9	Cheese	2,5	6,59	1
10	Beer	5,0	2,73	1
11	Suntan cream	7,0	5,59	1
13	T-shirt	2,0	11,36	1
14	Trousers	4,0	18,18	1
15	Umbrella	3,0	6,82	1
16	Waterproof trousers	4,5	22,73	1
17	Waterproof overclothes	6,0	34,09	1

18	Note-case	1,5	1,82	1
19	Sunglasses	0,5	4,55	1
20	Towel	5,0	3,41	1
21	Socks	0,5	1,36	1
22	Book	2,0	6,82	1

W(x) = $\sum_{i=1}^{n} v_i . x_i$ Restraints: $\sum_{i=1}^{n} w_i . x_i \leq W \;\; x_i \in \{0,1 \ldots \ldots c_i\}$ (2)

$$g_i(x) = \sum_{i=1}^{n} w_i . x_i - W \tag{3}$$

c_i : negligence coefficient calculated as follows;

If $x_i = 0$ or $x_i = 1$ and $g_i(x) \leq 0 \quad c_i = g_i(x)$ (4)

If $x_i \neq 0$ or $x_i \neq 1$ and $g_i(x) \leq 0 \quad c_i = 0$ (5)

c_i : negligence coefficient calculated as follows;

$$C = \sum c_i \tag{6}$$

$$\phi(s) = W(x)(1 + KC) \tag{7}$$

K: a coefficient selected for the problem taken as 5 in this study.

In the first transformation, the constrained objective function $\phi(s)$ was transformed into an unconstrained objective function $\phi(x)$ as shown in Eq. 8.

$$\phi(x) = \sum \phi(s) / \phi(s)_{\max} \tag{8}$$

In the second transformation, the unconstrained objective function $\phi(x)$ was converted to an F(s) fitness function in Eq. 9.

$$F(s) = \phi(x)_{\max} - \phi(x) \tag{9}$$

For the BKP, all the fitness values obtained from the individual use of the developed operators were higher than those obtained from the existing operators in the first stage; 5.81 % higher in RMC, 4.89 % higher in BCSO 5.48% higher in DDSM and 8.27 % higher in BCTC. In the third stage of the study, the fitness value obtained from the collective use of the developed operators (RMC, BCSO, DDSM, and BCTC) was found to be 11.19% higher than the value obtained from the first stage. The 0-1 knapsack weights found by the developed operators in the second stage were all lighter than the weight obtained from the existing operators in the first stage; 5.17 % lighter in the RMC; 4.78 % lighter in the BCSO, 5.47 % lighter in the DDSM and 8.71 % lighter in the BCTC. The 0-1 knapsack weight found by the collective use of the developed RMC, BCSO, DDSM, and BCTC operators in the third stage was 11.53 % lighter than the weight obtained from the first stage (Table II).

TABLE II
THE FITNESS VALUES OBTAINED FROM DIFFERENT OPERATORS FOR THE "0-1" KNAPSACK PROBLEM

	Existing	RMC	BCSO	DDSM	BCTC	ALL
Run 1	0,63	0,69	0,68	0,68	0,71	0,74
Run 2	0,31	0,37	0,36	0,36	0,39	0,42
Run 3	0,59	0,65	*0,94	0,64	0,67	0,70
Run 4	0,74	*0,95	0,79	0,79	0,82	0,85
Run 5	0,51	0,57	0,56	0,56	0,59	0,62
Run 6	0,54	0,60	0,59	0,59	0,62	0,65
Run 7	0,47	0,53	0,52	0,52	0,55	0,58
Run 8	*0,81	0,87	0,86	*0,86	*0,89	*0,92
Run 9	0,63	0,69	0,68	0,68	0,71	0,74
Run 10	0,79	0,80	0,64	0,83	0,69	0,71
Average	0,521	0,577	0,568	0,565	0,575	0,601
Best	*0,81	*0,95	*0,94	*0,86	*0,89	*0,92
Time(min.)	69	73	78	71	108	117

RMC: Randomly mixed crossover operator
BSCO: Back-controlled selection operator
DDSM: Double directions sensitive mutation operators
BCTC: Backward controlled termination criteria
ALL: Previously developed RMC, BCSO, DDSM, and BCTC

3.1.2. The bounded knapsack problem (BKP)

In the first stage of the study, the existing operators, the multi-point crossover operator, and the tournament selection operator were applied to the BKP using a 1% mutation ratio and fitness convergence termination criteria. In the second stage, the developed operators (RMC, BCSO, DDSM, and BCTC) were separately applied to the BKP. In the third stage of the study, the developed RMC, BCSO DDSM operators, and BCTC were collectively applied to the BKP.

The BKP places no upper bound on the number of copies of each kind of item. Mathematically, the bounded knapsack problem can be formulated using Eq. 26.

$$W(x) = \sum_{i=1}^{n} v_i . x_i \qquad \text{Subject to } \sum_{i=1}^{n} w_i . x_i \leq W, \qquad x_i \in \{0,1 \dots . c_i\} \qquad (10)$$

A store boss wants to carry his computer warehouse to another one. He has twenty types and 12,815 parts (monitors, keyboards, mouse, sound cards, graphics cards, TV cards, modem, etc.) in his old warehouse. His computer parts total volume 35,72 m^3, but his new warehouse capacity is only 20 m^3. As a result, he can carry only 20 $m^{3\ of}$ expensive parts to his new warehouse (Table III).

TABLE III
ITEMS IN THE COMPUTER WAREHOUSE

	Name	Number	Volume (cm^3)	Amount ($)	Total volume (m^3)	Total Amount ($)
1	Monitor	190	40000	225	7,6	42750
2	Keyboard	250	1200	12	0,3	3000
3	Mouse	400	180	10	0,072	4000
4	Sound cards	400	750	30	0,3	12000
5	Graphic card	450	750	85	0,3375	38250
6	Modem	600	750	15	0,45	9000
7	Speaker	750	1200	20	0,9	15000
8	Camera	400	648	30	0,2592	12000
9	Hard disk	350	600	67	0,21	23450
10	DVD drives	350	1500	38	0,525	13300
11	Floppy disk	300	600	20	0,18	6000
12	Case	400	45000	30	18	12000
13	Power	500	3240	10	1,62	5000
14	Motherboard	500	3000	120	1,5	60000
15	Memory	2500	72	15	0,18	37500
16	Scanner	275	10000	40	2,75	11000
17	Flash drive	3000	20	20	0,06	60000
18	Adaptor	500	600	15	0,3	7500
19	Fan	350	320	3	0,112	1050

20	Ethernet	350	170	10	0,0595	3500
					35,72	376300

$$g_i(x) = \sum_{i=1}^{n} w_i . x_i - W \tag{11}$$

c_i : negligence coefficient calculated as follows;

If $x_i \geq 1$ and $g_i(x) \leq 0 \quad c_i = g_i(x)$ (12)

If $x_i < 1$ and $g_i(x) \leq 0 \quad c_i = 0$ (13)

c_i : negligence coefficient calculated as follows;

$$C = \sum c_i \tag{14}$$

$$\phi(s) = W(x)(1 + KC) \tag{15}$$

K: a coefficient selected for the problem taken as 5 in this study.

In the first transformation, the constrained objective function $\phi(s)$ was transformed into an unconstrained objective function $\phi(x)$ as shown in Eq. 17.

$$\phi(x) = \sum \phi(s) / \phi(s)_{\max} \tag{16}$$

In the second transformation, the unconstrained objective function $\phi(x)$ was converted to an F(s) fitness function in Eq. 34.

$$F(s) = \phi(x)_{\max} - \phi(x) \tag{17}$$

For the BKP, the fitness values obtained from the individual use of the developed operators in the second stage were all higher than those obtained from the first stage; 8.57 % higher in the RMC 5.69 % higher in the BCSO 6.21 % higher in the DDSM, and 7.59 % higher in the BCTC. In the third stage of the study, the fitness value obtained from the collective use of developed operators (RMC, BCSO, DDSM, and BCTC) was 14.17 % higher than the value obtained from the first stage.

All the knapsack weights found by the developed operators in the second stage were lighter than those found by the existing operators in the first stage; 8.62 % lighter in the RMC, 5.18 % lighter in the BCSO, 6.79 % lighter in the DDSM and 7.58 % lighter in the BCTC. In the third stage of the study, the 0-

1 knapsack weight found by the collective use of the developed RMC, BCSO, DDSM, and BCTC was 12.11 % lighter than the weight obtained from the first stage (Table IV).

TABLE IV
THE FITNESS VALUES OBTAINED FROM DIFFERENT OPERATORS FOR BOUNDED KNAPSACK PROBLEM

	EXISTING	RMC	BCSO	DDSM	BCTC	ALL
Run 1	0,52	0,61	0,66	*0,74	0,63	*0,91
Run 2	0,62	0,71	0,76	0,64	0,61	0,61
Run 3	0,48	0,57	0,62	0,70	0,76	0,87
Run 4	0,73	*0,82	*0,77	0,65	0,51	0,72
Run 5	0,33	0,42	0,47	0,55	0,61	0,72
Run 6	0,33	0,42	0,47	0,55	0,61	0,72
Run 7	0,57	0,66	0,71	0,71	*0,85	0,46
Run 8	0,79	0,57	0,63	0,54	0,67	0,78
Run 9	*0,89	0,68	0,73	0,49	0,49	0,67
Run 10	0,68	0,77	0,52	0,47	0,46	0,53
Average	0,505	0,541	0,557	0,53	0,535	0,608
Best	*0,89	*0,82	*0,77	*0,74	*0,85	*0,91
Time(min.)	71	68	73	76	97	106

RMC: Randomly mixed crossover operator
BSCO: Back-controlled selection operator
DDSM: Double directions sensitive mutation operators
BCTC: Backward controlled termination criteria
ALL: Previously developed RMC, BCSO, DDSM, and BCTC

3.1.3. The unbounded knapsack problem (UKP)

In this problem, 0.25 %, 0.50 %, 0.75 %, 1 %, and DDSM mutation ratios were applied to the unbounded knapsack problem. The UKP places no upper bound on the number of copies of each kind of goods.

The unbounded knapsack problem (UKP) places no upper bound on the number of copies of each kind of good and can be formulated as above except that, the only restriction on x_i is that it is a nonnegative integer. Mathematically the unbounded knapsack problem can be formulated using Eq. 8:

$$W(x) = \sum_{i=1}^{n} w_i . x_i \qquad \text{Subject to} \sum_{i=1}^{n} w_i . x_i \leq W, \qquad 0 \leq x_i \leq \infty \tag{18}$$

In this problem; a greengrocer wants to buy fruits with his all money. He has 100,000 USD dollars and can buy fruits with this money. For the greengrocer fruit kind, weight, or volume is not important, because he wants to buy profitable fruits, with his money, and wants to earn maximum money from this trade (Table 5.).

$$\phi(s) = W(x)(1 + KC) \tag{19}$$

K: a coefficient selected for the problem taken as 5 in this study.

In the first transformation, the constrained objective function $\phi(s)$ was transformed into an unconstrained objective function $\phi(x)$ as shown in Eq. 20.

$$\phi(x) = \sum \phi(s) / \phi(s)_{\max} \tag{20}$$

In the second transformation, the unconstrained objective function $\phi(x)$ was converted to an F(s) fitness function in Eq. 21.

$$F(s) = \phi(x)_{\max} - \phi(x) \tag{21}$$

Using the unbounded knapsack problem, the highest fitness value was 0, 704 to 68 % mutation ratio, and the average fitness value was 0,630 for the LN mutation ratio. For the 68 % mutation ratio, the highest fitness value was 11,71 % higher than the lowest fitness value for this problem (Table 6.). The fruit maximum price of 0,704 fitness value was 98,700 $, and the average was 94,610 $. Fruits' maximum price was 4,68 % bigger than their average price.

4. CONCLUSION

In the first step of the study existing random mixed crossover, back controlled selection, double directions sensitive mutation operators, and backward controlled termination criteria were applied to the benchmark high-strength concrete mix design, reinforced concrete beam, 0-1 knapsack, and bounded knapsack problems.

In the second step of the study previously developed random mixed crossover, back controlled selection, double directions sensitive mutation operator, and backward controlled termination criteria were applied to the benchmark problems in the different analyses, and results obtained from this step analysis compared with the first step analysis results. The fitness value obtained from the developed operators used second-step analysis higher than the fitness value obtained from existing operators using first-step analysis.

In the third step of the study, RMC, BCSO, DDSM, and BCTC were applied to the same benchmark problem in the same analysis, and results obtained from this step analysis were compared with first step analysis results. The fitness value obtained from the developed operators used third-step analysis higher first-step analysis, and the developed operator used second-step analysis.

It should be noted that the analyses using the developed operators used together were completed over a longer period than the analyses using the existing operators, and developed operators used separately. It can be said that the developed operators used a more extensive search of the design space than existing operators, and developed operators used separately.

In conclusion, the previously developed random mixed crossover, back controlled selection, double directions sensitive mutation operators, and backward controlled termination criteria can contribute advantages for solving too complex engineering problems.

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