ADDRESSING THE KNAPSACK CHALLENGE THROUGH CULTURAL ALGORITHM OPTIMIZATION

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ABSTRACT

The "0-1 knapsack problem" stands as a classical combinatorial optimization conundrum, necessitating the selection of a subset of items from a given set. Each item possesses inherent values and weights, and the primary objective is to formulate a selection strategy that maximizes the total value while adhering to a predefined capacity constraint. In this research paper, we introduce a novel variant of Cultural Algorithms tailored specifically for solving 0-1 knapsack problems, a well-known combinatorial optimization challenge. Our proposed algorithm incorporates a belief space to refine the population and introduces two vital functions for dynamically adjusting the crossover and mutation rates during the evolutionary process. Through extensive experimentation, we provide compelling evidence of the algorithm's remarkable efficiency in consistently locating the global optimum, even in knapsack problems characterized by high dimensions and intricate constraints.

KEYWORDS

knapsack problem, cultural algorithm, genetic algorithm.

1. INTRODUCTION

The 0-1 knapsack problem is one of the most studied combinatorial optimization problems. It contains a knapsack with a limited capacity and a set of N items, each with a weight (w) and a value (v) [30]. Solving this problem means finding a collection of items that the total weight of them is less than or equal to the knapsack capacity and the total value is as large as possible [1,11].

Suppose, W is the capacity of the knapsack ($W>0$), vector $w = (w_1, w_2, \ldots, w_N)$ and $v=(v_1,v_2,\ldots,v_N)$ stand for the weight and the value of items, where $w_i > 0$, $v_i > 0$, $1 \leq i \leq N$.
Our aim is to find a set of x_i where x_i ($0 < i < N$) is equal to 0 or 1 which satisfies the constraints of Eq. (1) and Eq. (2) [2]:

$$\sum_{i=1}^{N} x_i w_i \leq W \qquad (1)$$

$$max \sum_{i=1}^{N} x_i v_i \qquad (2)$$

If the i-th item is put into the knapsack then xi =1; otherwise xi =0.

Knapsack problem has numerous applications in theory and real world such as capital budgeting problems [3], loading problems [5], resource allocation [4] and project selection problems [6], also it can be found as a sub problem of the other general models.

Many methods have been developed to solve the knapsack problem: such as dynamic programming [7, 12], branch-and-bound approach [8], ant colony optimization [9, 13], particle swarm optimization [10, 14], simulated annealing [15], harmony search algorithm [16], amoeboid organism algorithm [17], schema-guiding evolutionary algorithm [20], soccer league algorithm [18] and so on.

In the real world, 0-1 knapsack problems usually have high dimension. Available algorithms lose their efficiency in solving such high dimensional 0-1 knapsack problems [2]. Hence, these algorithms are not suitable enough for real world scenarios. More research on this topic in required exploring more efficient and optimized solutions [2].

A Genetic Algorithm (GA) is a metaheuristic method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution [28]. The algorithm repeatedly modifies a population of individual solutions.

Cultural Algorithms (CAs) are a population-based optimization technique inspired by the way societies preserve and share knowledge. In a CA, individuals within a population interact and adapt their knowledge through social learning, guided by a belief space. This belief space represents the shared knowledge of the population and plays a crucial role in shaping the algorithm's behavior. A cultural algorithm is a branch of evolutionary computation where in addition to the population component, there is a knowledge component that is called belief space [27]. Cultural algorithm can be seen as an extension of a conventional genetic algorithm.

In this paper, we propose a new approach for solving 0-1 knapsack problem based on CA. Our focus is to select items for belief space that result the best solution in minimum time. For this purpose, we introduce our situational and normative components. In addition, we employ GA for this purpose. In genetic algorithm, we tune parameters and fitness function for having the best solution.

The rest of the paper is organized as of the following: Section 2 reviews genetic algorithms and cultural algorithms. In Section 3 we introduce the proposed method for solving knapsack problem with cultural algorithms. We demonstrate the efficiency and accuracy of our method by comparing it to the existing methods in Section 4. Finally, Section 5 concludes the paper.

2. Related works & Background

In this section, we briefly review genetic and cultural algorithms

2.1. Genetic algorithm

Genetic Algorithm is a heuristic algorithm that mimics the process of natural selection [10]. This heuristic (aka, Meta heuristic) is used to generate useful solutions in optimization and search problems. Genetic algorithms are a subset of Evolutionary Algorithms (EA), which solve optimization problems using techniques inspired by natural evolution (e.g inheritance, mutation, selection, and crossover) [8].

In a genetic algorithm, a population of candidate solutions in an optimization problem evolves toward better solutions. This evolution happens through alteration and mutations in candidate solution’s set of properties (usually called chromosomes or genotype). Binary or real vectors can represent candidate solutions (genotypes). Based on the problem, other representations can be employed.

Usually the iterative evolution process starts from a population includes individuals those are generated randomly. We will call the population in each iteration “a generation”. The finesses of individuals are evaluated in each generation [13]. Fitness is usually defined by assessing the optimization the objective function of a problem. Regarding the results of this evaluation, the fittest individuals are selected stochastically, and individuals are altered by recombination and mutation functions to form a new generation. The new generation of candidate solutions is then evaluated and altered in the next iteration of the algorithm. The algorithm terminates when a satisfactory fitness value is achieved (optimization problem solved) or if a maximum number of generations have been produced.

The fitness function definition depends to the problem measures the excellence of a candidate solution. For instance, in the knapsack problem the objective is to maximize the total value of objects that can be put in a knapsack with a fixed capacity [29]. A representation of a solution can be a bit array, where each bit represents a different object and the value of the bit (0 or 1) shows whether or not the object is chosen to be in the knapsack [30]. Many of such representations are invalid, as the total size of objects may exceed the capacity of the knapsack. We can define the fitness of the solution to be the sum of values of all objects in the knapsack, if the representation is valid or 0 otherwise.

2.2. Cultural Algorithm

Cultural algorithms are a branch of evolutionary computation where in addition to the population component, there is a knowledge component called belief space. Cultural algorithms can be considered as an extension of a conventional genetic algorithm.

The best individuals of the population update the belief space after each iteration. Here, similar to genetic algorithms, the best individuals are selected using a fitness function that assesses the performance of each individual in population [19]. The belief space of a cultural algorithm can be separated to different categories. These categories represent different domains of knowledge that the population has about the search space. Normative and situational are example sub categories of belief space. Normative knowledge is a collection of desirable value ranges for the individuals in the population component. e.g., acceptable behavior for the agents in the population [14]. Situational knowledge includes specific examples of important events - e.g. successful/unsuccessful solutions. Figure. 1. shows the block diagram of a Cultural Algorithm.

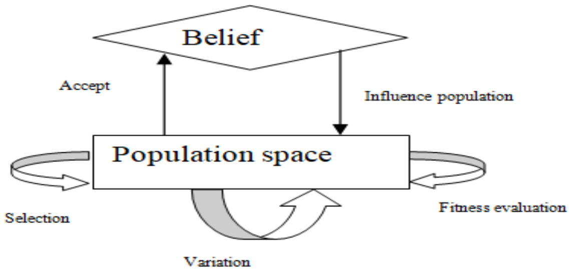

Figure 1. Block diagram of Cultural Algorithm

3. PROPOSED METHOD

In this section, we introduce our Cultural Algorithm and the procedure of building the belief space. The following sub sections describe each component separately. In formulating the Knapsack problem for our CA method, we make several key assumptions. Firstly, we assume a discrete representation of items, where each item is represented as a binary variable, indicating whether it is included (1) or not included (0) in the knapsack. Secondly, we assume a predefined capacity constraint for the knapsack. These assumptions are fundamental to the problem formulation in the context of our CA.

3.1. Fitness function

In Section 1, Eq. (1) and Eq. (2) formulate the fitness of a normal knapsack problem. In this paper, we propose a new approach for formulating the knapsack problem.

The cultural algorithm builds a chromosome of items for solving the knapsack problem. The procedure of chromosome building is described in the following:

Assume that the solution of the knapsack problem is represented by a binary sequence, where ith element is 1 if item i is put in the knapsack. The length of chromosome depends on the dimension of the problem. For example, for the problem called p5 (in Table 2), its chromosome represents the knapsack with 15 items [33].

Our new fitness function verifies the chromosome in construction process. When an item is unsuitable for the solution, its violation is calculated using Eq. (3) and a penalty is assigned to the old fitness. Our proposed fitness considers enough penalties for all the problems; in other words, we have an adaptive penalty for each situation. We indicate this with Eq. (4)

$$\mathrm{C} = \max\left(\sum_{0}^{N}(x.*w) - W,\ 0\right) \qquad (3)$$

$$\mathrm{Z} = \mathrm{Z} - \left(\frac{100}{d}\right) * C \qquad (4)$$

Where variable Z in Eq. (3) and Eq. (4) is the value of fitness used in previous researches. The way of calculating Z is explained in Eq. (5). Variable d is used in Eq. (4) to address the high dimensionality problem. Value of variable d depends on the number of selected items, meaning higher dimension knapsack problem results in decreased penalty d.

$$d = 1 + \log\log N \qquad (5)$$

Using this parameter capacitates fitness in high dimensional problems and ensures the approach does not lose efficiency.

3.2. Parameters Setting

Two important parameters of cultural algorithm are crossover rate (Pc) and mutation rate (Pm). We proposed a new formula to adjust the crossover rate. The focus of this formula is on iteration of the algorithm. At the beginning of the algorithm (means in initial iterations) exploration must be maximized and exploitation is in minimum value. In the middle iterations, rate of crossover and mutation can be equal for searching entirety of solution space. At the end, maximum exploitation is required for converging the algorithm to a solution. In this respect, in each iteration, the rate or probability for cross over and mutation operations is calculated by Eq. (6) and Eq. (7).

$$p_c = \min(\frac{p_c}{d} + \left[\frac{iter}{1000}\right] * 0.1\,, 1) \qquad (6)$$

$$p_m = 1 - p_c \qquad (7)$$

This formulation has been obtained by trial and error approach based on executing different experimentations.

3.3. Crossover and Mutation

Crossover and mutation are two basic operators of GA. Our crossover is a single-point crossover. A single crossover point is selected on both parents' chromosome strings. All data beyond that point in either chromosome string is swapped between the parent chromosomes [28]. The resulted chromosomes are the children. The parent selection mechanism is described in the next subsection.

The employed mutation in our algorithm is bit string mutation. Bit string mutation is the mutation of bit strings ensue through bit flips at random positions.

3.4. Belief Space

Belief space is an advantage of cultural algorithm compared to the genetic algorithm. In the following, we describe how we consider two functions, Accept, and Influence population [32], in Figure. 1.

1) Accept: At the first iteration, 10 percent of the best individuals in the population are selected for belief space creation. At other iterations, when an individual has a better fitness than the individuals in the belief space and up the 50 percent of thing selected for knapsack are different from individuals in belief space, belief space is updated with a new individual. Efficacy of belief space is in cross over.
2) Influence population: One of the parents for crossover is selected from belief space and the other parent is randomly selected from population. This change is like society. In society when an important people change the way of life other people of society accept this change without any question and efficacy of important people is very high.

4. EXPERIMENTAL RESULTS

In this section, we expand our comparison of the CA method with a broader range of optimization algorithms, including Genetic Algorithms, Particle Swarm Optimization, and Simulated Annealing. We present a comprehensive analysis of their performance on various benchmark problems, highlighting the strengths and weaknesses of each approach.

Previously, we focused on comparing our CA method with a specific set of algorithms. However, to provide a more holistic view of its performance, we have now included these additional algorithms in our comparative analysis.

Here, the performance of the GA and CA are studied by different experiments. All the computational experiments are conducted with Matlab R2013a in Intel® Core™i3 CPU M 350 @ 2.27GHz with 4 GB RAM system.

In order to comprehensively evaluate the performance of the proposed algorithm, we employ a combination of benchmark datasets and custom-generated problem instances. This approach allows us to assess the algorithm's effectiveness across a diverse range of problem scenarios, encompassing both synthetic instances designed to vary in complexity and dimensions, as well as real-world problem instances when applicable and available.

In all experiments, max iteration is set to 50 and the size of population is 100. The initial probability of crossover and mutation are set to Pc=0. 9 and Pm=0.1. the parameter setting has been shown in Table 1.

Table 1. Parameter settings

Description of parameter	Parameter name	Value
Cross over rate	P_c	0.1 to 0.9
Mutation rate	P_m	$1-P_c$
Iteration	iter	50 to 2000
Population size	Pop	100
Dimension	D	5 to 1500

At first, we consider ten small 0-1 Knapsack problems which their details (contain weight of item w, value of item v, capacity of knapsack W and optimum solution) have been presented in Table 2 [2]. It should be noted that some studies have used these test cases for evaluating their methods. In [9], problems P1 and P2 are solved by an improved ant colony algorithm. P3 is used with a sequential combination tree algorithm in [19]. In [21] a greedy-policy-based algorithm examines P4. P5 is analyzed with the information about the search space landscape to search optimum solution in [22] and [23] has solved P6 in an approach similar to the shrinking boundary method P7 and P8 are considered with a nonlinear dimensionality reduction method in [25]. P9 is used by a DNA algorithm and P10 is used in [24]. It should be noted that problems Pi where i =3, 4... 10 have reached to optimum solution in the mentioned papers. The research of [2] presents a survey of the above studies and the results.

Table 3 reports the performance evaluation of the four algorithms Binary Gravitational Search Algorithm (BGSA) [2], CDGSA [2], GA, and CA (the proposed approach) on the 10 small problems described in Table 2. The table includes optimal solution and the best, worst, average, and median solution, the standard deviation (std.dev) and average total time (Avg. time) during 20 independent runs are presented in Table 3.

It should be noted that the solution of 35 means the total value of the selected items in the knapsack is equal to the number and a best solution means the optimum selection of items where their accumulative numbers yield the total number. Moreover, the worst solution of 83 means the minimum outcome of this knapsack is 83.

Table 3 shows that our approach has the faster convergence for the large problems in comparison with BGSA and CDGSA. BGSA finds local optimum solutions for many problems (such as Pi, i =2, 5, 8, 10).

Table 2. dimension, parameters and optimum solution of ten 0-1 knapsack problems (The parameter *w* and *v* are the weight and value of items, respectively; *W* is the capacity of the knapsack)

	Dim(N)	**Parameter (w, W, v)**	**Optimum solution**

P_1	10	w=(95, 4, 60, 32, 23, 72, 80, 62, 65, 46)
		W=269
		v=(55, 10, 47, 5, 4, 50, 8, 61, 85, 87)
			295

P_2	20	w=(92, 4, 43, 83, 84, 68, 92, 82, 6, 44,32, 18, 56, 83, 25, 96, 70, 48, 14, 58)
		W=878
		v=(44, 46, 90, 72, 91, 40, 75, 35, 8, 54, 78, 40, 77, 15, 61, 17, 75, 29, 75, 63)
			1024

P_3	4	w=(6, 5, 9, 7)
		W=20
		v=(9, 11, 13, 15)
			35

P_4	4	w=(2, 4, 6, 7)
		W=11
		v=(6, 10, 12, 13)
			23

P_5	15	w=(56.358531, 80.874050, 47.987304, 89.596240, 74.660482, 85.894345, 51.353496, 1.498459, 36.445204, 16.589862, 44.569231, 0.466933, 37.788018, 57.118442, 60.716575)
		W=375
		v=(0.125126, 19.330424, 58.500931, 35.029145, 82.284005, 17.410810, 71.050142, 30.399487, 9.140294, 14.731285, 98.852504, 11.908322, 0.891140, 53.166295, 60.176397)
			481.0694

P_6	10	w=(30, 25, 20, 18, 17, 11, 5, 2, 1, 1)
		W=60
		v=(20, 18, 17, 15, 15, 10, 5, 3, 1, 1)
			52

P_7	7	w=(31, 10, 20, 19, 4, 3, 6)
		W=50
		v=(70, 20, 39, 37, 7, 5, 10)
			107

P_8	23	w=(983, 982, 981, 980, 979, 978, 488, 976, 972, 486, 486, 972, 972, 485, 485, 969, 966, 483, 964, 963, 961, 958, 959)
		W=10000
		v=(981, 980, 979, 978, 977, 976, 487, 974, 970, 485, 485, 970, 970, 484, 484, 976, 974, 482, 962, 961, 959,958, 857)
			9767

P_9	5	w=(15, 20, 17, 8, 31)
		W=80
		v=(33, 24, 36, 37, 12)
			130

P_{10}	20	w=(84, 83, 43, 4, 44, 6, 82, 92, 25, 83, 56, 18, 58, 14, 48, 70, 96, 32, 68, 92)
		W=879
		v=(91, 72, 90, 46, 55, 8, 35, 75, 61, 15, 77, 40, 63, 75, 29, 75, 17, 78, 40, 44)
			1025

In addition, we execute our approach on the other eight knapsack problems to evaluate its performance on the high dimensional problems. Weight and value of items are randomly generated in this problem and the number of items is as 100, 200, 300, 500, 800, 1000, 1200 and 1500 respectively, and the other parameter (corresponding knapsack's capacity) is 1100, 1500, 1700, 2000, 5000, 10000, 14000 and 16000 respectively. – vi (i =1,..., N)~ rand(50, 100) – wi (i =1,..., N)~ rand(5, 20)

All the reported results of this experiment have been obtained among 10 independent runs in which the best, worst, average, median solution and the standard deviation (std.dev) are presented in Table4

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Table 3. The results of the BDGSA, CDGSA, GA and CA on knapsack problems, OP means the optimum solution

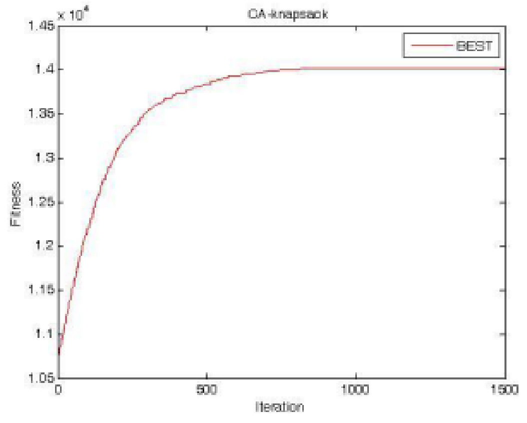
P	**OP**	**Method**	**Best**	**Worst**	**Average**	**Median**	**Avg. time (s)**
P_1	295	BGSA	295	4	269.45	204.75	0.12
		CDGSA	295	0	169.81	197.25	0.19
		GA	295	294	294.73	295	0.31
		CA	295	295	295	295	0.40
P_2	1024	BGSA	972	83	892.05	631.75	3.14
		CDGSA	1024	551	721.86	768	2.14
		GA	1024	846	1012.34	1008	0.26
		CA	1024	830	1004.63	993.52	0.35
P_3	35	BGSA	35	0	34.35	29	0.03
		CDGSA	35	0	24.52	28	0.05
		GA	35	35	35	35	0.29
		CA	35	35	35	35	0.31
P_4	23	BGSA	23	0	21.55	17.75	0.04
		CDGSA	23	0	14.96	18	0.04
		GA	23	23	23	23	0.27
		CA	23	23	23	23	0.29
P_5	481.0694	BGSA	475.4784	59.79	410.81	321.77	1.84
		CDGSA	481.0694	26.76	249.88	282.23	1.14
		GA	481.0694	398	469.78	451.50	0.25
		CA	481.0694	402.05	473.41	465.52	0.26
P_6	51	BGSA	52	1	47.06	41.5	0.21
		CDGSA	52	0	37.12	38	0.26
		GA	52	51	51.85	52	0.24
		CA	52	52	52	52	0.26
P_7	107	BGSA	107	0	94.35	74	0.03
		CDGSA	107	5	66.03	80.5	0.04
		GA	107	107	107	107	0.30
		CA	107	107	107	107	0.30
P_8	9767	BGSA	9758	2316	9740.8	8445	4.21
		CDGSA	9767	2316	8971.56	9254.1	3.26
		GA	9767	9725	9749.13	9747.6	0.32
		CA	9767	9732	9753.64	9749.2	0.36
P_9	130	BGSA	130	0	116.35	98.25	0.03
		CDGSA	130	0	94.10	106	0.04
		GA	130	130	130	130	0.25
		CA	130	130	130	130	0.26
P_{10}	1025	BGSA	953	116	875.25	633.25	3.29
		CDGSA	1025	116	749.51	832.92	3.38
		GA	1025	934	1004.97	1016	0.30
		CA	1025	1002	1015.67	1014.58	0.36

From Table 4 it is clear that the proposed method is faster to solve the high dimensional 0-1 knapsack problems in comparison to BGSA and CDGSA. Another observation that can be deduced from Table 4 is that the proposed method has gained better results in solving some of the high dimensional 0-1 knapsack problems.

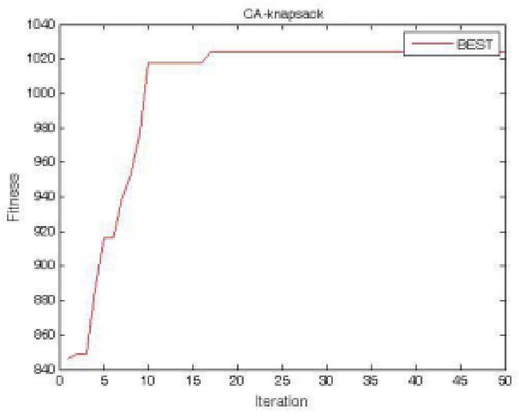
Table 4. The results of GA, CA (proposed method), DGSA and CDGSA on eight random large knapsack problems

P	Method	Best	Worst	Average	Median
P_{11}	DGSA	7029	6034	6602.01	6715
	CDGSA	7245	5172	6449.20	6581
	GA	7142	5401	6521.73	6645
	CA	7230	5358	6543.74	6613
P_{12}	DGSA	11024	9821	10429.58	10598
	CDGSA	11168	8267	11006.5	11063
	GA	11752	9498	11375.23	11401
	CA	11985	9462	11451.51	11498
P_{13}	DGSA	13892	12957	13379.2	13420
	CDGSA	14025	12730	13602.09	13732
	GA	14017	11245	13704.61	13808
	CA	14043	11176	13729.54	13784
P_{14}	DGSA	21891	20063	20957.14	21164
	CDGSA	27451	22173	25903.55	26508
	GA	27516	21542	25781.46	26461
	CA	27421	22067	25642.84	26553
P_{15}	DGSA	47213	45810	46431	46605
	CDGSA	55048	47204	52761.37	53892
	GA	54634	45006	51637.76	52953
	CA	56842	44529	52387.63	53532
P_{16}	DGSA	70825	68941	69730.12	69940
	CDGSA	73698	69752	70454.38	71653
	GA	73438	65645	69893.45	71748
	CA	72983	67632	70532.68	70985
P_{17}	DGSA	89617	86752	88013.75	88351
	CDGSA	90139	86984	89452.64	89953
	GA	91834	54738	86375.91	87840
	CA	92745	60536	87753.52	88421
P_{18}	DGSA	109541	107203	108429.8	108870
	CDGSA	111964	108927	110726.79	111248
	GA	112753	102231	109893.63	111051
	CA	115948	107255	111735.86	112372

In another experiment, we have selected four medium and large problems for evaluating the performance of our Cultural Algorithm. We have reported the convergence diagram of this experiment in Figure. 2.



(a)



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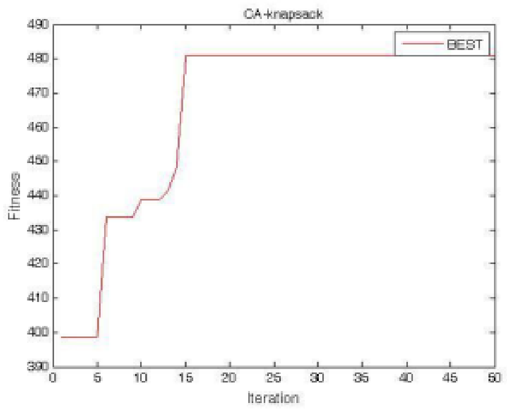

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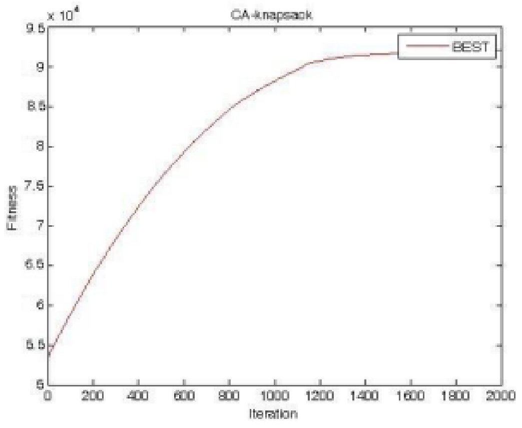

(d)

Figure. 2. Convergence diagram for different size knapsack problems(a) For large problem p13. (b) For medium problem p2 form table 3. (c) For medium problem p5 from table 3. (d) For large problem p17.

5. Conclusion

Knapsack problem is an NP-hard problem. Several algorithms have been developed to solve this problem in this paper, we improve GA by adjusting the rate of mutation and crossover in the evolution of the population. In addition, we employ the proposed cultural algorithm by constructing a belief space and considering its influence on the population. We apply both GA and CA to solve 0-1 knapsack problems. Experimental results show the superior efficiency and accuracy of the proposed method compared to the other algorithms.

While the CA method shows promise in solving the Knapsack problem, it is essential to acknowledge its limitations. One limitation is that the CA's performance may be sensitive to its parameter settings, requiring careful tuning. Additionally, the CA may struggle with high-dimensional problem spaces or problems with complex constraints. Future research should explore strategies to mitigate these limitations and improve the algorithm's robustness.

References

[1] H. Kellerer, U. Pferschy and D. Pisinger, Knapsack Problems, Springer, Berlin, 2004.

[2] S.F. Razavi and H. Sajedi, Cognitive discrete gravitational search algorithm for solving 0-1 knapsack problem, Journal of Intelligent & Fuzzy Systems 29 2015, pp. 2247–2258.

[3] E.Bas, A capital budgeting problem for preventing workplace mobbing by using analytic hierarchy process and fuzzy 0-1 bidimensional knapsack model, Expert Sys 38(10) 2011, pp. 12415–12422.
[4] O. Granmo, B. Oommen, S. Myrer and M. Olsen, Learning automata-based solutions to the nonlinear fractional knapsack problem with applications to optimal resource allocation, IEEE Trans Syst Man Cybern Part B Cybern 37(1) 2007, pp. 166–175.
[5] G. Wascher and H. Schumann, An improved typology of cutting and packing problems, Eur J Oper Res 183(3) 2007, pp. 1109–1130.
[6] G. Mavrotas, D. Diakoulaki and A.Kourentzis, Selection among ranked projects under segmentation, policy and logical constraints, Eur J Oper Res 187(1) 2008, pp. 177–192.
[7] A.Rong, J.Figueira and K.Klamroth, Dynamic programming based algorithms for the discounted {0-1} knapsack problem, Appl Math Comput 218(2) 2012, pp. 6921–6933.
[8] J.E. Gallardo, C. Cotta and A.J. Fernandez, A hybrid model of evolutionary algorithms and branch-and-bound for combinatorial optimization problems, The 2005 IEEE Congress on Evolutionary Computation 3 2005, pp. 2248–2254.
[9] H. Shi, Solution to 0-1 knapsack problem based on improved ant colony algorithm, IEEE International Conference on Information Acquisition, 2006, pp. 1062–1066.
[10] F. He, An improved particle swarm optimization for knapsack problem, International Conference on Computational Intelligence and Software Engineering, 2009.
[11] T.H. Cormen, C.E. Leiserson, R.L. Rivest and C. Steinclrs, Introduction to Algorithms, the MIT press, 2002.
[12] S. Balev, N. Yanev, A. Freville and R. Andonov, A dynamic programming-based reduction procedure for the multidimensional 0-1 knapsack problem, Eur J Oper Res 186(1) 2008, pp. 63–76.
[13] M. Liang and W. Delong, Ant Colony algorithm for knapsack problem, Computer Application 21(8) 2001, pp. 56–59.
[14] F. Hembecker, H. Lopes and W. Godoy, Particle swarm optimization for the multidimensional knapsack problem, Adapt Natur Comput Algorithms 2007, pp. 358–365.
[15] A.Liu,J. Wang, G.Han,S.Wang and J. Wen, Improved Simulated Annealing Algorithm Solving for 0-1 Knapsack Problem, Proceedings of IEEE the Sixth International Conference on Intelligent Systems Design and Applications (ISDA’06),2006.
[16] D.Zou, L.Gao, S.Li and J.Wua, Solving 0-1 Knapsack problem by a novel global harmony search algorithm, Applied Soft Computing 1- 2011, pp. 1556–1564.
[17] X. Zhang, S. Huang, Y. Hu, Y. Zhang, S. Mahadevan and Y. Deng, Solving 0-1 knapsack problems based on amoeboid organism algorithm, Applied Mathematics and Computation 219- 2013, pp. 9959–9970.
[18] N. Moosavian, Soccer league competition algorithm for solving knapsack problems, Swarm and Evolutionary Computation 20- 2015, pp. 14–22.
[19] C. An and T.J. Fu, On the sequential combination tree algorithmfor0-1knapsackproblem, Journal of Wenzhou University (Natural Science) 29- 2008, pp. 10–14.
[20] Y. Liu and C. Liu, A schema-guiding evolutionary algorithm for 0-1 knapsack problem, International Association of Computer Science and Information Technology -Spring Conference, 2009, pp. 160–164.
[21] W. You, Study of greedy-policy-based algorithm for 0/1 knapsack problem, Computer and Modernization 4- 2007, pp. 10–16.
[22] H. Yoshizawa and S. Hashimoto, Landscape analyses and global search of knapsack problems, IEEE Systems, Man and Cybernetics 3- 2000, pp. 231–2315.
[23] D.Fayard and G.Plateau, Resolution of the 0-1 knapsack problem comparisonn of methods, Mathematical Programming 8- 1975, pp. 272–307.
[24] B.D. Li, Research on the algorithm for 0/1 knapsack problem, Computer and Digital Engineering 5-2008, pp. 23–26.
[25] J.Y. Zhao, Nonlinear reductive dimension approximate algorithm for 0-1 knapsack problem, Journal of Inner Mongolia Normal University (Natural Science) 36- 2007, pp. 25–29.
[26] Lu, Bo. "Optimization of Logistics Network of Port Cluster." Cooperative Operation Optimization for Port Groups: Based on China’s Practice. Singapore: Springer Nature Singapore, 2023. 63-132.
[27] Vahdatpour, M., Sajedi, H. & Ramezani, F. Air pollution forecasting from sky images with shallow and deep classifiers. Earth Sci Inform 11, 413–422 (2018).

[28] Zhu, Wenbo. "Optimizing distributed networking with big data scheduling and cloud computing." International Conference on Cloud Computing, Internet of Things, and Computer Applications (CICA 2022). Vol. 12303. SPIE, 2022.

[29] Gu, Haotian. Mean-Field Cooperative Multi-agent Reinforcement Learning: Modelling, Theory, and Algorithms. Diss. UC Berkeley, 2023.

[30] Rostamian, Mohamad Hadi, et al. "Presenting a hybrid evolutionary algorithm for optimizing smart grids using load management in the presence of renewable energy sources and energy storage systems to the metro." Iranian Electric Industry Journal of Quality and Productivity: 0-0.

[31] Yongquan Zhou, Xin Chen, Guo Zhou, "An improved monkey algorithm for a 0-1 knapsack problem" Applied Soft Computing, Volume 38, 2016, pp 817-830.

[32] O.H. Mohammed, Yassine Amirat, M.E.H. Benbouzid, G. Feld. Optimal Design and Energy Man agement of a Hybrid Power Generation System Based on Wind/Tidal/PV Sources: Case Study for the Ouessant French Island. Smart Energy Grid Design for Island Countries, Challenges and Oppor tunities, pp.381-413, 2017, Green Energy and Technology book series (GREEN), ff10.1007/978-3-319- 50197-0_12.

[33] Fayard, D., Plateau, G. Resolution of the 0–1 knapsack problem: Comparison of methods. Mathematical Programming 8, 272–307 (1975)

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