An Improved Monkey Algorithm for a 0-1 Knapsack Problem

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Abstract: The 0-1 knapsack problem is a classic combinatorial optimization problem. However, many exiting algorithms have low precision and easily fall into local optimal solutions to solve the 0-1 knapsack problem. In order to overcome these problems, this paper proposes a binary version of the monkey algorithm where the greedy algorithm is used to strengthen the local search ability, the somersault process is modified to avoid falling into local optimal solutions, and the cooperation process is adopted to speed up the convergence rate of the algorithm. To validate the efficiency of the proposed algorithm, experiments are carried out with various data instances of 0-1 knapsack problems and the results are compared with those of five metaheuristic algorithms.

Keywords: monkey algorithm; binary version of the monkey algorithm; knapsack problem; cooperation process; greedy strategy.

1. Introduction

Knapsack problems (KPs) were first proposed by Dantzing in the 1950s [1] and subsequently attracted many scholars. KPs appear in real-world decision-making processes in a wide variety of fields, for example, finding the least wasteful way to cut raw materials, selection of capital investments and financial portfolios, selection of assets for asset-backed securitization, resource allocation, cargo loading, etc. Thus far, people have put forward many effective algorithms based on exact algorithms and heuristic algorithms for solving knapsack problems.

Zou et al described a novel global harmony search (HS) algorithm that includes two important operations, position updating and genetic mutation, for solving 0-1 knapsack problems [2]. The experiment shows the proposed algorithm has good performance for solving large-scale knapsack problems. Xiang et al also considered a novel global-best harmony search algorithm that combines a two-phase repair operator to repair an infeasible harmony vector and to further improve a feasible solution [3]. Changdar et al considered an improved ant colony optimization (ACO) approach to solve 0-1 knapsack problems in a fuzzy environment [4]. The proposed algorithm creates n candidate groups for n objects; each ant selects a candidate value from each group. Bansal et al proposed a modified particle swarm optimization called MBPSO based on binary particle swarm optimization (BPSO) [5] for solving 0-1 knapsack problems and multidimensional knapsack problems [6]. Azad et al proposed a simplified binary version of the artificial fish swarm algorithm (AFSA) for solving 0-1 quadratic knapsack problems [7]; the random heuristic drop_item procedure is used to make the points feasible, and the heuristic add_item is also implemented to improve the quality of the solutions. Glover used an improved greedy algorithm and surrogate constraints for linear and quadratic knapsack problems [8]. Sitarz studied the relations between multiple criteria dynamic programming (MCDP) and the multiple knapsack problem[9]; the paper also showed how to use MCDP methods to solve multiple knapsack

problems. Gao et al presented a novel quantum-inspired artificial immune system called MOQAIS, which is composed of a quantum-inspired artificial immune algorithm (QAIS) and an artificial immune system (BAIS) for multiobjective knapsack problems [10]. QAIS is responsible for exploration of the search space, and BAIS is applied for exploitation of the search space. García-Martínez proposed a tabu-enhanced destruction mechanism for an iterated greedy search in studying quadratic multiple knapsack problems [11]; the method records the last removed objects and avoids removing them again in subsequent iterations. Baykasoğlu et al used a priority-based encoding technique for a firefly algorithm (FA) to construct feasible solutions and prevent infeasibility for solving dynamic multidimensional knapsack problems [12]. Hifi et al used a dichotomous search-based exact method based on decomposing the original problem into a series of knapsack problems and introduced new upper bounds and incremental valid lower bounds in the interval search [13]. Levin et al studied the stochastic behavior of the knapsack problem and defined a variant problem in which item values are deterministic and item sizes are independent random variables [14]. Zhao used a nonlinear reductive dimension approximate algorithm for the knapsack problem [15]. Liu et al removed useless solution regions before applying simulated annealing (SA) to solve a knapsack problem and extracted the most possible part of the optimal solution space from the whole optimal solution space [16]. Saraç et al used a genetic algorithm (GA) and a hybrid solution approach for solving a developed model called the generalized quadratic multiple knapsack problems (G-QMKP) [17]. The experiment shows the proposed hybrid solution approach can obtain good solutions in a reasonable time for a large-scale problem. Lin investigated using GA in solving the fuzzy knapsack problem [18]; this method simulates a fuzzy number by distributing it into partition points and uses GA to evolve the values in each partition point.

The monkey algorithm (MA) is a new type of swarm intelligence based algorithm. It was proposed by Zhao and Tang in 2008 and is derived from simulation of the mountain-climbing processes of monkeys [19]. It consists of three processes: the climb process, watch-jump process and somersault process. The climb process is designed to gradually improve the objective function value. However, MA will spend considerable computing time searching for local optimal solutions in the climb process. To reduce the computing time and speed up the convergence rate, Chen and Zhou introduced the inertial step in the climb process and combined the simple method after the somersault process [20]. The watch-jump process can speed up the convergence rate of the algorithm, the purpose of the somersault process is to make monkeys find new search domains to avoid falling into local search. The algorithm has the advantages of simple structure, strong robustness, and not easy falling into local optimal solutions. Therefore, MA has been successfully applied in solutions to various optimization problems, such as transmission network expansion planning [21], intrusion detection technology [22], optimal sensor placement in structural health monitoring [23], the optimization of gas filling station project scheduling problem [24], the clustering analysis problem [25], etc. In this paper, the 0-1 knapsack problem will be studied, and a binary version of the monkey algorithm which combines cooperation process and greedy strategy (CGMA) is proposed. The algorithm improves the calculation accuracy and increases the convergence speed of the algorithm to a certain degree. The numerical experiment results show that the proposed algorithm has good performance in solving the 0-1 knapsack problem. It can be an efficient alternative for solving the 0-1 knapsack problem.

2. The 0-1 Knapsack Problem

The 0-1 knapsack problem is a typical NP-hard problem in operations research. The problem is defined

as follows:

Given a set of items $O = \{o_1, o_2, \dots, o_n\}$, each with a weight w_i and a value p_i , determine the number of each item to include in a collection so that the total weight WX is less than or equal to a given limit and the total value PX is as large as possible. It derives its name from the problem faced by someone who is constrained by a fixed-size knapsack and must fill it with the most valuable items. Its mathematical model is as follows:

$$\begin{cases} \max imize & f(x_1, x_2, \dots, x_n) = PX = \sum_{i=1}^n p_i x_i \\ \text{subject to} & WX = \sum_{i=1}^n w_i x_i \leq V \end{cases} \quad (1)$$

and $x_j \in \{0,1\}$, $j=1,2,\dots,n$. Where $P=(p_1, p_2, \dots, p_n)$, $W=(w_1, w_2, \dots, w_n)$ represent the value vector and weight vector of all items. V is the maximum capacity of the knapsack. $x_i = 1$ indicates that item i is included in the knapsack and $x_i = 0$ that it is not.

3. Description of Modified Monkey Algorithm

The monkey algorithm was first proposed to solve numerical optimization problems as a new swarm intelligence based algorithm stemmed from the mountain-climbing behavior of monkeys [19]. Assume that there are many mountains in a given field. At the beginning, the monkeys climb up from their respective positions to find the mountaintops (this action is called climb process). When a monkey get the top of its mountain, it will find a higher mountain within the sight and jump somewhere of the mountain from the current position (this action is called watch-jump process), then repeat the climb process. After repetitions of the climb process and the watch-jump process, each monkey will somersault to a new search domain to find a much higher mountaintop (this action is called somersault process).

This paper proposed a binary version of the monkey algorithm where the greedy algorithm is used to correct the infeasible solutions and to improve the quality of the feasibility, the somersault process is modified to avoid falling into local search, the cooperation process is implemented to speed up the convergence rate, and the control parameter is used to keep the population diversity. The algorithm consists of 5 parts, the climb process, watch-jump process, greedy strategy repair process, cooperation process and somersault process.

3.1. Coding method

For the 0-1 knapsack problem, each item has two different status, namely the item has been included in the knapsack or it remains out. First, M is defined as the population size of monkeys. For monkey i , its position is denoted as a vector $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$, and this position will be employed to express a solution of the 0-1 knapsack problem, where $x_{ij} \in \{0,1\}$ and $j=1,2,\dots,n$, n is the number of the items. $x_{ij} = 1$ indicates the item j is included in the knapsack and $x_{ij} = 0$ indicates it is not.

3.2. Initial population

In CGMA, the initial population is randomly generated. The random initialization process of M monkeys and n items is as follows:

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for  $i=1$  to  $M$  do
    for  $j=1$  to  $N$  do
         $x[i][j] = rand()$ ;
        If  $x[i][j] < 0.5$ 
             $x[i][j] = 0$ ;
        else
             $x[i][j] = 1$ ;
        endif
    endfor
endfor

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where $x_{i,j}$ represents the j th component in the vector X_i .

3.3. Climb Process

According to the idea of pseudo-gradient-based simultaneous perturbation stochastic approximation (SPSA) [27], the climb process is a step-by-step procedure to improve the objective function by choosing a better one between two positions that are generated around the current position. For the monkey i , its position is $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$, $i = 1, 2, \dots, M$, respectively. $f(X_i)$ is the corresponding objective function value. The improved climb process is given as follows:

- (1) Randomly generate two vectors $\Delta x_i' = (\Delta x_{i1}', \Delta x_{i2}', \dots, \Delta x_{in}')$ and $\Delta x_i'' = (\Delta x_{i1}'', \Delta x_{i2}'', \dots, \Delta x_{in}'')$,

where

$$\Delta x_{ij}', \Delta x_{ij}'' = \begin{cases} a & \text{with probability } \frac{1}{2} \\ -a & \text{with probability } \frac{1}{2} \end{cases} \quad (2)$$

$j = 1, 2, \dots, n$, respectively. The parameter a ($a > 0$), called the step of the climb process, can be determined by specific situations. Here, set the climb step $a=1$ for the 0-1 knapsack problem.

- (2) Set $x_{ij}' = |x_{ij} - \Delta x_{ij}'|$ and $x_{ij}'' = |x_{ij} - \Delta x_{ij}''|$, $j = 1, 2, \dots, n$, respectively, where $|x|$ represents the absolute value of x . Set $X_i' = (x_{i1}', x_{i2}', \dots, x_{in}')$, $X_i'' = (x_{i1}'', x_{i2}'', \dots, x_{in}'')$.

- (3) Calculate $f(X_i')$ and $f(X_i'')$, $i = 1, 2, \dots, M$, respectively.

- (4) If $f(X_i') > f(X_i'')$ and $f(X_i') > f(X_i)$, set $X_i = X_i'$. If $f(X_i'') > f(X_i')$ and $f(X_i'') > f(X_i)$, $X_i = X_i''$.

- (5) Repeat steps (1) to (4) until the maximum allowable number of iterations (called the climb

number, denoted by Nc) has been reached.

3.4. Watch-jump Process

When the monkeys reach the top of the mountains, each monkey will take a look and determine whether there are higher points than the current one within its sight. If yes, it will jump somewhere of the mountain from the current position and then repeat the climb process. For the monkey i , its position is $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$, $i = 1, 2, \dots, M$. The improved watch-jump process is given as follows:

- (1) Randomly generate a real y_j in interval $[x_{ij} - b, x_{ij} + b]$, $j = 1, 2, \dots, n$, respectively, where b eyesight of the monkey can be determined by specific situations. Set $Y = (y_1, y_2, \dots, y_n)$.
- (2) Because of the real $y_j \in [-1, 2]$, if $y_j < 0.5$, set $y_j = 0$; otherwise, set $y_j = 1$.
- (3) Calculate $f(Y)$, $i = 1, 2, \dots, M$, respectively.
- (4) If $f(Y) > f(X_i)$, then $X_i = Y$.
- (5) Repeat the climb process steps (1) to (4) until the maximum allowable number of iterations (called the watch-jump number, denoted by Nw) has been reached.

3.5. Greedy Strategy

An abnormal encode individual (who does not meet the constraint conditions) may be obtained in solving the 0-1 knapsack problem using the metaheuristic algorithms. In [28], the local search strategy-greedy algorithm (GTA) is introduced to correct the infeasible solutions and to improve the quality of the feasibility. Assume that $P = (p_1, p_2, \dots, p_n)$ and $W = (w_1, w_2, \dots, w_n)$ represent the value vector and weight vector of all items. V is the maximum capacity of the knapsack. $X = (x_1, x_2, \dots, x_n)$ is an abnormal encode individual, and $Y = (y_1, y_2, \dots, y_n)$ is the adjusted normal solution. GTA is described as follows according to the 0-1 knapsack problem:

Let $Q(q_1, q_2, \dots, q_n)$ be a sequence that sorts by value density p_i / w_i from large to small for all items $x_i = 1$ in the vector $X = (x_1, x_2, \dots, x_n)$. $GTA(X, W, P, V)$ Algorithm [28]:

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    k = 1;
    Temp = WQ[k];
    while Temp ≤ V do
        yQ[k] = 1;
        k = k + 1;
        Temp = Temp + WQ[k];
    endwhile
    for j = k to n do
        yQ[j] = 0;
    endfor

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3.6. Cooperation Process

After the climb process and the watch-jump process, each monkey will arrive at the top mountain in its neighborhood. However, they differ among all the monkeys. The purpose of the cooperation process is to make the monkeys find a better solution by cooperating with the monkey that has the best position. The monkeys will go forward along the direction of the best monkey. This process can speed up the convergence rate. Assume that the optimal position is $X^* = (x_1^*, x_2^*, \dots, x_n^*)$. For the monkey i , its position is $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$, $i = 1, 2, \dots, M$. The cooperation process is given as follows:

- (1) Randomly generate a real number α from the interval $[0,1]$.
- (2) If $\alpha < 0.5$, then $y_j = x_j$, otherwise, $y_j = x_j^*$, $j = 1, 2, \dots, n$, respectively.
- (3) Update the monkeys' position X_i with Y .

3.7 Somersault Process

Monkeys will reach the maximal mountaintops around their initial points after repetitions of the climb process and the watch-jump process, respectively. To find a higher mountaintop, each monkey will somersault to a new search domain. The new position is not blind to choose, but limited within a certain region, which is determined by the pivot and the somersault interval. Figure 1 shows the somersault process of the original MA [8]. The points A , B , C , D represent monkeys. The point P is the center of all monkeys, the somersault interval $[c,d] = [-1, 1]$. For example, the monkey A can reach any point (such as point P , $A1$, $A2$) within the circle $r1$ with the somersault interval $[c,d] = [-1, 1]$.

Figure 1. The somersault process of the original MA.

The somersault process can effectively prevent monkeys falling into the local search. However, after many iterations, the somersault process may lose efficacy. The monkeys will fall into the local optima domain, and the population diversity will decrease. In the original MA, the monkeys will somersault along the direction pointing to the pivot, which is equal to the barycenter of all monkeys' current positions. Here, we randomly choose a monkey's position as the pivot to replace the center of all monkeys and adopt a new somersault process. For the monkey i , its position is $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$, $i = 1, 2, \dots, M$. The improved somersault process is given as follows:

- (1) Randomly generate real numbers θ from the interval $[c,d]$ (called the somersault interval,

which governs the maximum distance that monkeys can somersault).

(2) Randomly generate an integer k , $k = 1, 2, \dots, M$, respectively. Let the location of the monkey k be the somersault pivot.

(3) Calculate

$$y_j = x_{kj} + \theta(x_{kj} - x_{ij}) \quad (5)$$

(4) Set $y_j = 0$, if $y_j < 0.5$; otherwise, set $y_j = 1$. Update the monkey's position X_i with Y .

After repetitions of the somersault process, monkeys may reach the same domain to make the somersault process lose efficacy. In case of this problem, we set a parameter called “**limit**” to control monkeys running into the local optima solution. If the global optimal solution is not improved by a predetermined number of trials, the monkeys are abandoned and then reinitialized.

3.8. Termination Condition

Following the climb process, watch–jump process, greedy method optimization process, cooperation process and somersault process, all monkeys are ready for their next actions. The condition for terminating CGMA iteration could either be when the optimal solution has been found or when a relatively large number of iterations have been reached. To summarize, the whole flowchart of the CGMA to find the optimal solution of the 0-1 Knapsack problem is shown in Figure 2.

Figure 2. The flow chart of CGMA

4. Simulation Experiments

In this section, the experiments were performed using a desktop computer with a 3.01GHz AMD Athlon(tm) II X4640 processor, 3GB of RAM, running a minimal installation of Windows XP. The application software was Matlab 2012a.

4.1. Small-Scale Knapsack Problems

To evaluate the performance of CGMA, it is compared with BPSO [6], MBPSO [6], NGHS [2], DGHS [3], and S-bAFSA [7]. To make a fair comparison, we use the maximum number of function evaluations (maxFEs) as the evaluation standard. In addition, the other specific parameters of the algorithms are given as follows:

For BPSO and MBPSO, the population size is set to 5. The acceleration coefficients are $c1 = 2, c2 = 2$. The maximum velocity $V_{\max}$ is set to 2.

For NGHS, the harmony memory size HMS, namely, the population size, is set to 5; the mutation probability $p_m = 2/N$, and the penalty coefficient is set to 10^{20} , which is the same as those utilized in [13].

For DGHS, HMS=5. The maximum and minimum harmony memory consideration rate $HMCR_{\max}$, $HMCR_{\min}$ are set to 0.95 and 0.3, respectively. The pitch adjusting rate $PAR = 0.75$.

For CGMA, the population size is 10. The climb number $Nc = 2$, watch-jump number $N_w = 2$, climb step $a = 1$, eyesight $b = 1$, and somersault interval $[c, d] = [-1, 1]$.

Here, two sets of small-scale knapsack problems are selected to test the performance of CGMA. The first set that contains 10 instances is taken from [2]. The second set comes from [6] and is tested in [4] [29] also. The number of items in these instances range between 8 and 24, and the maxFEs are listed in the table 2. For every instance, each algorithm is run 50 times individually with random initial solutions.

Table 1. Results obtained by the algorithms for the first set

Problem	The optimal value	Algorithm	The optimal solution vector	Best	Worst	Mean
F1	295	CGMA	0111000111	295	295	295
F2	1024	CGMA	1111111111110101011	1024	1024	1024
F3	35	CGMA	1101	35	35	35
F4	23	CGMA	0101	23	23	23
F5	481.07	CGMA	001010110111011	481.07	481.07	481.07
F6	52	CGMA	0010111111	52	52	52
F7	107	CGMA	1001000	107	107	107
F8	9767	CGMA	11111111001000011000000	9767	9767	9767
F9	130	CGMA	11110	130	130	130
F10	1025	CGMA	1111111101111010111	1025	1025	1025

Table 1 shows the results of CGMA for the first set. Here, the control parameter is set as $limit = 10$ (10 refers to iterations, and each iteration may need multiple function evaluations), the maxFEs is set to 1000 for all algorithms. As observed from the results, for the small-scale knapsack problems, CGMA can obtain the global optimal solution in all runs. Shi [32] proposed an improved ant colony algorithm to solve the knapsack problems (test problem 1 and 2), but the optimal solutions

cannot be obtained in the paper. The optimal value of test problem 1 obtained by CGMA is 295, and the best value of test problem 2 is 1024. For the test problems F3, F4, and F5, the optimal solutions can be obtained by CGMA in all runs. For the test problem F6, Zou proposed a global harmony search algorithm to solve the problem in [2]. Unfortunately, the optimal solution of the problem cannot be found by NGHS [2]. The optimal solution for F6 obtained by CGMA is $x = (0, 0, 1, 0, 1, 1, 1, 1, 1)$, and the optimal value is 52. For the test problem F7, F8, F9, F10, the optimal solution can be found by CGMA, HS, and NGHS in all runs. The optimal values of the test problem F7, F8, F9 and F10 are 107, 9767, 130 and 1025, respectively.

Table 2. Results obtained by the algorithms for the second set

Problem	Instance		BPSO	MBPSO	NGHS	DGHS	S-bAFSA	CGMA
F11	ks_8a	Mean	3921857.19	3924400	3924400	3924400	3924400	3924400
		Best	3924400	3924400	3924400	3924400	3924400	3924400
F12	ks_8b	Mean	3807911.86	3813669	3813669	3813669	3813669	3813669
		Best	3813669	3813669	3813669	3813669	3813669	3813669
F13	ks_8c	Mean	3328608.71	3347452	3347452	3347452	3347452	3347452
		Best	3347452	3347452	3347452	3347452	3347452	3347452
F14	ks_8d	Mean	4186088.27	4187707	4187707	4187707	4187707	4187707
		Best	4187707	4187707	4187707	4187707	4187707	4187707
F15	ks_8e	Mean	4932737.28	4954571.72	4955555	4955555	4955555	4955555
		Best	4955555	4955555	4955555	4955555	4955555	4955555
F16	ks_12a	Mean	5683694.29	5688552.41	5687724.44	5687460.74	5688498.02	5688887
		Best	5688887	5688887	5688887	5688887	5688887	5688887
F17	ks_12b	Mean	6478582.96	6493130.57	6486450.92	6498597	6498597	6498597
		Best	6498597	6498597	6498597	6498597	6498597	6498597
F18	ks_12c	Mean	5166957.08	5170493.3	5165079.86	5165079.80	5170626	5170626
		Best	5170626	5170626	5170626	5170626	5170626	5170626
F19	ks_12d	Mean	6989842.73	6992144.26	6991971.10	6992404	6992404	6992404
		Best	6992404	6992404	6992404	6992404	6992404	6992404
F20	ks_12e	Mean	5316879.59	5337472	5273974.06	5335555.92	5337472	5337472
		Best	5337472	5337472	5337472	5337472	5337472	5337472
F21	ks_16a	Mean	7834900.26	7843073.29	7795177.56	7850983	7850983	7850983
		Best	7850983	7850983	7850983	7850983	7850983	7850983
F22	ks_16b	Mean	9334408.62	9350353.39	9253153.36	9352998	9352998	9352998
		Best	9352998	9352998	9352998	9352998	9352998	9352998
F23	ks_16c	Mean	9118837.47	9144118.38	9055853.46	9151147	9151147	9151147
		Best	9151147	9151147	9151147	9151147	9151147	9151147
F24	ks_16d	Mean	9321705.87	9337915.64	9310913.74	9316797.66	9321195.66	9345229.60
		Best	9348889	9348889	9348889	9348889	9348889	9348889
F25	ks_16e	Mean	7758572.21	7764131.81	7738799.78	7748285.68	77613877.20	77679297.20
		Best	7769117	7769117	7769117	7769117	7769117	7769117
F26	ks_20a	Mean	10707360.91	10720314.03	10592304.82	10727049	10727049	10727049

		Best	10727049	10727049	10727049	10727049	10727049	10727049
F27	ks_20b	Mean	9791306.65	9805480.48	9728979.66	9818261	9818261	9818261
		Best	9818261	9818261	9818261	9818261	9818261	9818261
F28	ks_20c	Mean	10703423.34	10710947.05	10585114.14	10709663.64	10710831.94	10712553.74
		Best	10714023	10714023	10714023	10714023	10714023	10714023
F29	ks_20d	Mean	8910152.57	8923712.21	8859297.78	8916496.80	8917872.80	8918423.20
		Best	8929156	8929156	8929156	8929156	8929156	8929156
F30	ks_20e	Mean	9349546.98	9355930.35	9324698.84	9357518.34	9357331.86	9357922.38
		Best	9357969	9357969	9357969	9357969	9357969	9357969
F31	ks_24a	Mean	13510432.96	13532060.07	13508995.14	13527887.56	13524874.30	13538097.18
		Best	13549094	13549094	13549094	13549094	13549094	13549094
F32	ks_24b	Mean	12205346.16	12223442.61	12160953.58	12233713	12233713	12233713
		Best	12233713	12233713	12233713	12233713	12233713	12233713
F33	ks_24c	Mean	12427880.56	12443349.03	12424467.44	12448158.86	12448550.28	12448618.30
		Best	12448780	12448780	12448780	12448780	12448780	12448780
F34	ks_24d	Mean	11792064.76	11803712.38	11736314.98	11810261.56	11810893.24	11808614.90
		Best	11815315	11815315	11815315	11815315	11815315	11815315
F35	ks_24e	Mean	13922797.55	13932526.16	13827901.40	13940099	13940099	13940099
		Best	13940099	13940099	13940099	13940099	13940099	13940099

Table 2 shows the results for all the algorithms for the second test set, which includes 25 test problems. “lim *it*” is the control parameter. It is set to 10 for the test problems 11 to 20 and 20 for the other problems. The value of maxFEs is set to 1000 for the test problems 11 to 20 and 5000 for the other problems. The results of BPSO and MBPSO are from [6]. For the test problems F11 to F23, F26, F27, F32 and F35, CGMA can obtain the global optimal values in all runs, and the success rate (SR) can reach 100%. For other test problems, the mean values of CGMA are obviously better than BPSO, MBPSO, NGHS and DGHS. BPSO cannot find the global optimal value on all problems with SR=100%. MBPSO can find the global optimal values in all runs on F11 to F14, F20. NGHS can also find the global optimal values on five test problems with SR=100%, that is, F11 to F15. However, the mean values of NGHS on all the test problems are worse than that of MBPSO except F15. In addition, the mean values of MBPSO on all the test problems are better than that of BPSO. DGHS can find the global optimal values on 14 problems with SR=100%, that is, F11 to F15, F17, F19, F21 to F23, F26, F27, F32, F35. BPSO and NGHS are inferior to MBPSO. For the test problems F11 to F15, F17 to F23, F26, F27, F32, F35, S-bAFSA can obtain the global optimal values in all runs, and the success rate (SR) can reach 100%. Only the mean value of S-bAFSA on the test problem F34 is better than that of CGMA. Its performance is obviously better than BPSO, MBPSO, NGHS and DGHS. BPSO and NGHS are inferior to MBPSO and DGHS.

In this subsection, for the small-scale knapsack problems, CGMA has a higher success rate than other algorithms on all the test problems. The proposed algorithm has better performance than BPSO, MBPSO, NGHS, DGHS and S-bAFSA.

4.2. The Large-Scale Knapsack Problems

4.2.1. Experimental results

To evaluate the performance of CGMA further, this subsection will test many large-scale problems. The details of the instances are given as follows:

The test problem F36 [30], F37 [28], F38 [28], F39 [3] include 50, 50, 80, 100 items, respectively. The corresponding maximum capacities of the knapsacks are 1000, 959, 1173, 6718, respectively.

Weakly correlated problems F40 to F44 [31]: the weights w_j are random integers uniformly distributed in $[10,100]$, and the profits p_j are random integers uniformly distributed in $[w_j - 10, w_j + 10]$.

Strongly correlated problems F45 to F49 [31]: the weights w_j are random integers uniformly distributed in $[10,100]$, and the profits p_j are set to $w_j + 10$.

Multiple strongly correlated problems F50 to F54 [31]: the weights w_j are randomly distributed in $[10,100]$. If the weight w_j is divisible by 6, we set the $p_j = w_j + 30$; otherwise, set it to $p_j = w_j + 20$.

Profit ceiling problems F55 to F59 [31]: the weights w_j are randomly distributed in $[10, 100]$, and the profits p_j are set to $p_j = 3 \lfloor w_j / 3 \rfloor$.

For the test problems F40 to F59, the maximum capacity of the knapsack is $V = 0.75 \sum_{j=1}^n w_j$.

For every test problem, each algorithm is run 50 times individually with random initial solutions. For all the test problems, the maxFEs is set to 50000.

Table 3. Results obtained by the algorithms for 50 different runs on the test problems F36 to F39

Problem	Algorithm	Best	Worst	Mean	Median	Std	SR
F36	BPSO	3071	2886	3006.08	3007.50	36.3159	0%
	MBPSO	3103	3039	3077.80	3080	15.2235	2%
	NGHS	3098	2912	3057	3066	35.1167	0
	DGHS	3103	3103	3103	3103	0	100%
	S-bAFSA	3103	3103	3103	3103	0	100%
	CGMA	3103	3103	3103	3103	0	100%
F37	BPSO	4843	4475	4681.90	4697	89.1486	0%
	MBPSO	4882	4773	4840.22	4846	28.3717	8%
	NGHS	4860	4538	4747.16	4771.50	83.4301	0
	DGHS	4882	4882	4882	4882	0	100%
	S-bAFSA	4882	4882	4882	4882	0	100%
	CGMA	4882	4882	4882	4882	0	100%
F38	BPSO	5138	4700	4937.04	4951.50	108.4808	0%
	MBPSO	5183	5052	5131.82	5137	33.7939	2%
	NGHS	5143	4849	5017.46	5020	78.0657	0%
	DGHS	5181	5178	5179.56	5181	1.5140	0%

	S-bAFSA	5178	5178	5178	5178	0	0%
	CGMA	5183	5167	5180.22	5181	2.9643	36%
F39	BPSO	26325	25010	25815.78	25820.50	280.3619	0%
	MBPSO	26547	25919	26337.88	26363	142.1435	0%
	NGHS	26507	24830	26066.14	26316	510.3133	0%
	DGHS	26559	26547	26558.28	26559	2.8788	94%
	S-bAFSA	26559	26541	26547.48	26544	7.6030	28%
	CGMA	26559	26559	26559	26559	0	100%

Four test problems are selected to test the performance of the six algorithms. The best value, the worst value, the mean value, the median value, the standard deviation and the success rates (SR) are recorded in table 3. As observed from the results, CGMA can easily find the optimal values with SR=100% in most test problems except F38. DGHS and S-bAFSA can find the optimal values in all runs for F36 and F37. However, they fail to search the global optimal solution for F38. Only CGMA and MBPSO can find the optimal value with SR=36% and SR=2%, respectively. The mean values of NGHS, MBPSO and PSO are obviously inferior to CGMA, DGHS and S-bAFSA for all test problems. The SR of BPSO, MBPSO, NGHS, DGHS and S-bAFSA are 0%, 0%, 0%, 94% and 28%, respectively. We note that CGMA has the lowest standard deviation for all test problems. The performance of S-bAFSA and DGHS is better than that of BPSO, MBPSO and NGHS.

Table 4 shows the optimal solutions for CGMA for the four test problems, where TV / TW represents the corresponding total value and weight of the optimum solution. It is clear to see the improvement in CGMA over BPSO, MBPSO, NGHS, DGHS and F-bAFSA in terms of the boxplot as shown in Figure 3 to 6. These boxplots show the difference in CGMA, F-bAFSA, DGHS, NGHS, MBPSO and BPSO regarding the results for 50 independent runs. The boxplots for CGMA have greater value and less height than those of MBPSO, BPSO and NGHS. This means that the optimal value, the worst value, the mean value and the median value of CGMA are more than those of MBPSO, BPSO and NGHS.

Table 4. The results of CGMA for four test problems

Problem	The optimal solution vector	TV / TW
F36	110101011101101101101111110100001010011000001000	3103/1000
F37	111110111100110010101100010000011100001111111111	4882/959
F38	1111111111111111111111111111011010100100 0101100010000000000010000100000000000000	5183/1170
F39	111011111 11101000101101101111111000111011000000000000001	26559/6717

Figure 3. The boxplot of F36

Figure 4. The boxplot of F37

Figure 5. The boxplot of F38

Figure 6. The boxplot of F39

Table 5. Results obtained by the algorithms for 50 different runs on weakly correlated problems

Problem	Dim	Algorithm	Best	Worst	Mean	Median	Std
F40	200	BPSO	8671	8520	8600.74	8596.50	32.5713
		MBPSO	8757	8649	8701.70	8695.50	25.8727
		NGHS	8685	8486	8586.74	8588.50	32.8023
		DGHS	8822	8821	8821.70	8822	0.4629
		S-bAFSA	8822	8822	8822	8822	0
		CGMA	8823	8821	8822.18	8822	0.5226
F41	300	BPSO	13201	13032	13126.12	13131.50	39.0429
		MBPSO	13314	13712	13246.84	13252.50	33.4520
		NGHS	13168	12963	13048.96	13055.50	39.7563
		DGHS	13489	13486	13488.34	13488	0.7722
		S-bAFSA	13489	13488	13488.98	13489	0.1414
		CGMA	13489	13489	13489	13489	0
F42	500	BPSO	20488	20263	20359.98	20357.50	51.7555
		MBPSO	20601	20374	20486.92	20487	48.8934
		NGHS	20295	20001	20147.84	20156.50	63.6266
		DGHS	20961	20955	20958.64	20959	1.6383
		S-bAFSA	20961	20959	20959.84	20960	0.4677
		CGMA	20961	20959	20959.84	20960	0.4677

		CGMA	20961	20960	20960.52	20961	0.5047
F43	800	BPSO	33561	33217	33385.60	33376	74.8997
		MBPSO	33657	33328	33495.20	33490	67.2786
		NGHS	33133	32841	32983.30	32983	71.1854
		DGHS	34471	34447	34455.64	34455	4.5164
		S-bAFSA	34472	34442	34463.50	34465	8.3696
		CGMA	34472	34452	34463.96	34463.50	5.5841
F44	1000	BPSO	40751	40445	40591.90	40583.50	77.9778
		MBPSO	40819	40527	40663.52	40667.50	80.1965
		NGHS	40214	39858	40024.58	40008	78.8388
		DGHS	41958	41916	41948.44	41948	6.7557
		S-bAFSA	41961	41944	41957.04	41961	5.2720
		CGMA	41961	41921	41950.56	41952.50	8.8275

Table 6. Results obtained by the algorithms for 50 different runs on strongly correlated problems

Problem	Dim	Algorithm	Best	Worst	Mean	Median	Std
F45	200	BPSO	10409	10319	10365.24	10367	21.7749
		MBPSO	10449	10359	10418.94	10419	19.2528
		NGHS	10429	10345	10389.94	10389	19.2613
		DGHS	10519	10519	10519	10519	0
		S-bAFSA	10519	10516	10518.74	10519	0.6328
		CGMA	10519	10519	10519	10519	0
F46	300	BPSO	14420	14280	14338.42	14340	27.9614
		MBPSO	14469	14350	14399.54	14400	26.1879
		NGHS	14409	14270	14352.52	14359.50	33.9683
		DGHS	14589	14589	14589	14589	0
		S-bAFSA	14590	14587	14589.60	14590	0.8081
		CGMA	14589	14589	14589	14589	0
F47	500	BPSO	24675	24504	24608.58	24605	41.7818
		MBPSO	24775	24625	24704.94	24705	38.96701
		NGHS	24695	24562	24631.46	24635	32.5013
		DGHS	25075	25055	25065	25065	6.3887
		S-bAFSA	25075	25070	25073.84	25074	1.2513
		CGMA	25075	25075	25075	25075	0
F48	800	BPSO	37975	37745	37879.12	37885	51.8903
		MBPSO	38073	37834	37949.88	37953.50	49.6632
		NGHS	38045	37805	37916.82	37910	55.5866
		DGHS	38705	38685	38696.80	38695	8.0026
		S-bAFSA	38705	38705	38705	38705	0
		CGMA	38705	38685	38699.80	38705	7.8870
F49	1000	BPSO	48822	48612	48712.76	48712	48.1692
		MBPSO	48872	48672	48764.12	48766.50	46.6820
		NGHS	48859	48600	48766.56	48772	59.6128

		DGHS	49722	49692	49705.80	49702	8.0534
		S-bAFSA	49731	49731	49731	49731	0
		CGMA	49731	49711	49722.68	49721	6.4884

Table 7. Results obtained by the algorithms for 50 different runs on multiple strongly correlated problems

Problem	Dim	Algorithm	Best	Worst	Mean	Median	Std
F50	300	BPSO	19166	18766	18928.48	18924.50	88.4098
		MBPSO	19236	18876	19100.28	19114.50	73.8670
		NGHS	19076	18572	18803.18	18802.50	95.2834
		DGHS	19546	19536	19536.20	19536	14.1421
		S-bAFSA	19546	19546	19546	19546	0
		CGMA	19546	19546	19546	19546	0
F51	500	BPSO	31823	31323	31633.98	31641	105.2533
		MBPSO	31973	31569	31772.14	31777.50	97.2997
		NGHS	31560	30920	31268.60	31280	141.4740
		DGHS	32713	32703	32712.80	32713	1.4142
		S-bAFSA	32723	32720	32720.78	32720	1.0554
		CGMA	32723	32723	32723	32723	0
F52	800	BPSO	49652	49080	49373.62	49355	146.6236
		MBPSO	49643	48993	49339.66	49357.50	146.3074
		NGHS	49273	48227	48704.32	48701.50	205.2844
		DGHS	51312	51273	51290.28	51293	7.7276
		S-bAFSA	51312	51276	51309.50	51310	4.8582
		CGMA	51313	51273	51302.32	51313	12.9385
F53	1000	BPSO	63341	62710	63073.92	63086	150.2352
		MBPSO	63241	62581	62964.92	62979	168.0327
		NGHS	62820	61991	62357.04	62367.50	185.9067
		DGHS	65391	65361	65376	65371	9.5298
		S-bAFSA	65391	65371	65384.22	65385.50	5.1992
		CGMA	65391	65361	65385	65391	8.8063
F54	1200	BPSO	76240	75400	75715.82	75729	170.9516
		MBPSO	75981	74810	75409.46	75440	218.0730
		NGHS	75206	74350	74788.40	74781.50	192.9648
		DGHS	78721	78681	78703.40	78701	10.7968
		S-bAFSA	78721	78672	78716.36	78721	12.0995
		CGMA	78721	78671	78710.96	78721	19.5873

Table 8. Results obtained by the algorithms for 50 different runs on profit ceiling problems

Problem	Dim	Algorithm	Best	Worst	Mean	Median	Std
F55	300	BPSO	12717	12684	12700.26	12699	6.6142
		MBPSO	12723	12693	12710.04	12711	6.3694
		NGHS	12717	12687	12700.98	12699	6.4886
		DGHS	12771	12771	12771	12771	0

		S-bAFSA	12771	12771	12771	12771	0
		CGMA	12771	12771	12771	12771	0
F56	500	BPSO	20790	20748	20767.56	20766	9.4915
		MBPSO	20796	20763	20781.42	20781	7.4972
		NGHS	20790	20745	20769.12	20770.50	10.1411
		DGHS	20880	20880	20880	20880	0
		S-bAFSA	20880	20880	20880	20880	0
		CGMA	20880	20880	20880	20880	0
F57	800	BPSO	33666	33618	33639.36	33639	9.7662
		MBPSO	33669	33621	33645.90	33645	11.3592
		NGHS	33669	33618	33643.98	33645	10.3142
		DGHS	33834	33831	33833.57	33834	1.0757
		S-bAFSA	33834	33834	33834	33834	0
		CGMA	33834	33831	33833.94	33834	0.4243
F58	1000	BPSO	42345	42300	42324.12	42324	12.7993
		MBPSO	43339	42312	42359.06	42342	141.8400
		NGHS	42345	42294	42323.58	42324	11.1430
		DGHS	42561	42561	42561	42561	0
		S-bAFSA	42561	42561	42561	42561	0
		CGMA	42561	42561	42561	42561	0
F59	1200	BPSO	49803	49743	49777.74	49777.50	14.9705
		MBPSO	49815	49761	49785.26	49785	13.5177
		NGHS	49812	49758	49790.76	49791	11.5132
		DGHS	50091	50082	50086.62	50088	2.9200
		S-bAFSA	50091	50091	50091	50091	0
		CGMA	50091	50079	50088.42	50088	2.9698

For the test problems F40 to F59, the best value, the worst value, the mean value, the median value, and the standard deviation are recorded in table 5 to 8.

For the weakly correlated problems, the mean values of CGMA are better than those of other algorithms except F44. CGMA can find the same global optimal value in 50 runs on the test problem F41. However, the standard deviation of DGHS is better than that of CGMA on the test problems F40, F43, F44. The mean values of CGMA are better than that of the other five algorithms except F44. The mean values of BPSO, MBPSO and DGHS are obviously inferior to that of CGMA, S-bAFSA and DGHS.

Table 6 records the results of the six algorithms on the strongly correlated problems. Because the profits p_j are set to w_j+10 , the profits are strongly correlated with the weights. CGMA can find the same global optimal values with Std=0 on the test problems F45, F46 and F47, and DGHS can also find the same global optimal values with Std=0 on the test problems F45 and F46. However, the mean values of S-bAFSA are better than CGMA for F48 and F49.

For the multiple strongly correlated problems, CGMA can find the same global optimal values in all runs on the test problems F50 and F51. The mean values of CGMA are smaller than those of S-bAFSA for F52 and F54.

The standard deviation of BPSO, MBPSO and NGHS are great, but CGMA, S-bAFSA and DGHS still have lower standard deviations on all the test problems.

Table 8 records the results of the five algorithms on the profit ceiling problems. The profits p_j are set to $p_j = 3 \lfloor w_j / 3 \rfloor$, that is, the profits have a strong relation with weights. CGMA and DGHS can find the same global values in all runs on the test problem F55, F56 and F58. S-bAFSA can easily find the optimal value in all test problems. All the algorithms have a small standard deviation on all the test problems. The mean value of S-bAFSA is obviously better than that of other algorithms.

CGMA has the best global exploration ability, and the mean values of CGMA are better than other algorithms on most test problems. The performance of DGHS is somewhat inferior to that of S-bAFSA. The global exploration ability of MBPSO is stronger than that of NGHS and BPSO.

4.2.2. Algorithm Evaluation

1) Algorithm comparison

For most swarm intelligence based algorithms, the maxFE impacts the precision of the solution. In this subsection, eight 0-1 knapsack problems of large size are devised to testify and compare the performance of CGMA, S-bAFSA, DGHS, NGHS, MBPSO and BPSO with different maxFEs. N is set to 100, 200, 300, 500, 800, 1000, 1200 and 1500, respectively, where N represents the size of the test problem. For each N , the values of weight and profit are generated randomly: The weight w_j ($j = 1, 2, \dots, N$) is between 5 and 20; the profit p_j ($j = 1, 2, \dots, N$) is between 50 and 100. For the eight values of N , the maximum capacity of knapsack V is accordingly set to 1100, 1500, 1700, 2000, 5000, 10000, 14000 and 16000, respectively. For each N , once the randomly generated parameters are determined, the same parameters are used to test the performance of three algorithms for 50 independent runs. The results obtained by six algorithms are presented in table 9 to 16.

Table 9. The results of the test problems F60 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	7481	7382	7452.86	7459	24.1475
	30000	7482	7322	7433.24	7448.50	42.4591
	50000	7478	7363	7439.42	7446	28.8883
MBPSO	10000	7482	7449	7474.94	7478	7.5442
	30000	7482	7430	7472.42	7476	10.9807
	50000	7482	7414	7473.50	7477.50	12.8575
NGHS	10000	7482	7480	7481.26	7481	0.4870
	30000	7482	7476	7481.16	7481	1.1669
	50000	7482	7476	7481.18	7481	1.4097
DGHS	10000	7480	7478	7478.50	7478	0.6776
	30000	7481	7476	7479.78	7480	0.6788
	50000	7481	7480	7480.84	7481	0.3703
S-bAFSA	10000	7480	7474	7475.64	7475	2.1643

	30000	7480	7274	7476.18	7475	2.2010
	50000	7480	7474	7475.36	7475	1.7930
CGMA	10000	7481	7480	7480.44	7480	0.5014
	30000	7481	7480	7480.84	7481	0.3703
	50000	7481	7481	7481	7481	0

Table 10. The results of the test problems F61 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	11057	10455	10811.96	10794.50	127.1729
	30000	11090	10434	10829.02	10820.55	129.5015
	50000	11276	10935	11121.68	11113	70.9019
MBPSO	10000	11287	10900	11106.62	11112.50	89.7804
	30000	11331	10916	11123.60	11120	92.0459
	50000	11429	11140	11307.08	11308	63.78242
NGHS	10000	10570	9472	10062.98	10066	194.2577
	30000	10535	9919	10211.36	10190.50	166.0890
	50000	10673	9756	10256.52	10283	188.2011
DGHS	10000	11537	11529	11528.38	11529	4.6418
	30000	11537	11532	11534.98	11535	1.9005
	50000	11543	11537	11540.04	11540	2.2220
S-bAFSA	10000	11539	11533	11537.92	11538	0.7239
	30000	11538	11538	11538	11538	0
	50000	11543	11538	11538.10	11538	0.7071
CGMA	10000	11543	11530	11538.36	11538	2.6936
	30000	11543	11537	11540.04	11540	2.2220
	50000	11543	11537	11541.16	11542	2.1887

Table 11. The results of the test problems F62 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	13252	12450	12863.14	12863	165.8154
	30000	13537	12465	12938.54	12931.50	194.0300
	50000	13923	13423	13701.98	13685	110.5425
MBPSO	10000	13814	12910	13448.32	13431.50	158.6587
	30000	13720	13136	13478.86	13482	120.6970
	50000	13786	13518	13498.40	13520	139.2587
NGHS	10000	11550	9407	10816.60	10893	446.7960
	30000	11920	9801	10873.92	10936	518.6333
	50000	11558	9768	10920.60	13510	507.6646
DGHS	10000	14319	14302	14312.26	14312.50	5.1142
	30000	14322	14316	14318.78	14319	1.7296
	50000	14325	14307	14320.44	14321.50	3.6821
S-bAFSA	10000	14325	14307	14320.60	14320	3.8439
	30000	14325	14311	14321.04	14321	3.2132

	50000	14325	14315	14322.02	14322	2.5911
CGMA	10000	14325	14303	14316.98	14318	5.6442
	30000	14325	14307	14320.44	14321.50	3.6821
	50000	14325	14312	14321.50	14323	3.3335

Table 12. The results of the test problems F63 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	15613	14582	15086.96	15085.50	218.9724
	30000	15770	14636	15199.24	15199	212.0181
	50000	16529	15848	15086.96	15085.50	218.9724
MBPSO	10000	16313	15643	15920.50	15897	173.8603
	30000	16569	15784	16146.80	16127	170.7027
	50000	16836	15826	16187.52	16166.50	189.3395
NGHS	10000	13999	12111	13202.14	13255	376.7673
	30000	14207	12696	133.9190	13331	382.5406
	50000	14041	12692	134.7992	13510	327.4805
DGHS	10000	17708	17650	17688.06	17690	16.3138
	30000	17712	17706	17708.38	17708	1.7944
	50000	17718	17704	17713.78	17715	3.4004
S-bAFSA	10000	17718	17686	17707.22	17706	5.5633
	30000	17718	17706	17711.04	17711	3.8859
	50000	17718	17706	17712.54	17713	3.5869
CGMA	10000	17715	17664	17698.38	17701	12.2072
	30000	17718	17704	17713.78	17715	3.4004
	50000	17718	17704	17715.28	17716	4.4109

Table 13. The results of the test problems F64 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	36768	35237	35933.88	35909.50	363.5089
	30000	37070	35732	36374.58	36317	279.3405
	50000	37854	36525	37305.26	37322.50	301.1055
MBPSO	10000	37623	36441	36978.36	36934	301.6178
	30000	38124	37131	37742.14	37769	245.5838
	50000	38261	37194	37794.84	37832.50	262.4363
NGHS	10000	31409	28445	30133.76	30187	619.9649
	30000	31276	28760	30072.04	30153.50	574.1515
	50000	31666	29140	30223.06	30197	459.6279
DGHS	10000	39994	39566	39901.06	39906	75.1245
	30000	40211	39999	40100.80	40111	63.9793
	50000	40211	39999	40122.10	40111	78.6790
S-bAFSA	10000	40215	40211	40211.82	40211	1.5345
	30000	40215	40211	40212.56	40212	1.6801
	50000	40215	40211	40213.28	40214	1.7147

CGMA	10000	40211	39999	40122.10	40111	78.6790
	30000	40211	40160	40187.08	40188	14.0231
	50000	40211	40201	40209.64	40211	3.0288

Table 14. The results of the test problems F65 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	64551	63224	63979.54	63992	280.4874
	30000	64915	63250	64118.12	64176.50	316.8198
	50000	64959	63817	64428.70	64410.50	274.0309
MBPSO	10000	65013	64293	64706.54	64723	180.4052
	30000	65963	65038	65536.22	65524	20.68221
	50000	66102	65004	65598.82	65579.50	224.0022
NGHS	10000	63391	61792	62264.76	62157	350.3046
	30000	63164	61863	62472.68	62496	317.9862
	50000	63361	61531	62528.88	62542.50	365.7676
DGHS	10000	67426	67391	67404.58	67401	10.1521
	30000	67426	67401	67416.58	67417	5.1233
	50000	67427	67401	67418.76	67419.50	5.6625
S-bAFSA	10000	67428	67405	67415..28	67416	5.6026
	30000	67426	67410	67418.96	67419	3.5746
	50000	67427	67414	67420.54	67420	3.0319
CGMA	10000	67424	67412	67417.90	67418.50	2.4265
	30000	67427	67401	67418.76	67419.50	5.6625
	50000	67428	67412	67425.10	67426	3.1960

Table 15. The results of the test problems F66 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	85371	84280	84924.70	84939	214.7547
	30000	85815	84872	85319.46	85349.50	257.0525
	50000	85080	85498	85833.02	85823	127.2609
MBPSO	10000	85528	84693	85171.40	85198.50	204.7106
	30000	86342	85505	85945.10	85943.50	175.2100
	50000	86310	85670	86029.50	86029	132.3053
NGHS	10000	85366	84384	84924.40	84938	382.8406
	30000	85541	84567	85125.42	85129	240.0429
	50000	85512	84357	85170.88	85200.50	265.7676
DGHS	10000	87164	87162	87163.82	87164	0.4375
	30000	87167	87160	87163.34	87164	1.5066
	50000	87167	87151	87165.18	87167	4.9844
S-bAFSA	10000	87166	87158	87161.16	87161	2.1887
	30000	87167	87158	87162.22	87163	2.3672
	50000	87166	87160	87163.44	87164	1.2803
CGMA	10000	87167	87149	87164.46	87167	5.6648

	30000	87167	87151	87165.18	87167	4.9844
	50000	87167	87149	87166.34	87167	3.1919

Table 16. The results of the test problems F67 with different maxFEs

Algorithm	maxFEs	Best	Worst	Mean	Median	Std
BPSO	10000	97444	96054	96704.26	96729.50	346.4074
	30000	97945	96077	97187.82	97243	391.1740
	50000	98895	97928	98463.44	98492.50	231.5866
MBPSO	10000	99337	97971	98614.96	98647.50	289.4599
	30000	100754	100081	100388.91	100366	185.7568
	50000	101142	100132	100701.62	100720.5 0	224.9488
NGHS	10000	97394	95681	96626.90	96648.50	382.8406
	30000	97664	95456	96847.78	96902.50	414.1766
	50000	98032	95860	97064.34	97011	383.1199
DGHS	10000	103146	103123	103136.92	103137.50	5.9551
	30000	103147	103140	103145.54	103146	1.8321
	50000	103152	103116	103143.58	103144	6.0836
S-bAFSA	10000	103151	103113	103137.24	103142	13.2396
	30000	103152	103119	103142.36	103147.50	10.7737
	50000	103152	103119	103144.52	103151	10.2405
CGMA	10000	103147	103134	103142.90	103144	4.0489
	30000	103152	103116	103143.61	103144	6.0836
	50000	103151	103133	103145.70	103147	5.4595

The tables 9 to 16 record the results of all the algorithms with different maxFEs for the test problems F60 to F67. The mean values of CGMA are better than that of other algorithms for most test problems with the same maxFEs; even the worst values are better than that of BPSO, MBPSO and NGHS on all the test problems except F60. For most test problems, the mean values of all the algorithms obviously present a positive relation with the increase in maxFEs. However, the mean values of NGHS may fall for some test problems, such as F60. In particular, the growth rates of mean values are great for BPSO and MBPSO.

The most significant characteristic of MA compared to other algorithms is the somersault process, which effectively avoids monkeys running into the local optimal solutions. However, the somersault process may lose efficacy, and monkeys may fall into the local optimal solutions after many iterations. To overcome this problem, this paper improves the somersault process and introduces a control parameter.

For the MBPSO algorithm, the position update equation is redesigned [6]. MBPSO provides better exploration than BPSO in solving the 0-1 knapsack problem. However, it is evident that MBPSO is highly dependent on the constant maximum velocity [6]. Sometimes, it is difficult to set a proper maximum velocity in solving different knapsack problems. For BPSO, it is easy to fall into local solutions and the stability of BPSO is poor compared with CGMA.

For the DGHS algorithm, the two-phase repair operator [3] is introduced to strengthen its local search ability. It is observed that the standard deviation of DGHS is small on all test problems; that is, it has strong stability for solving the 0-1 knapsack problem. For NGHS, the global exploration ability is obviously inferior to DGHS. It is easy to fall into the local optima.

For the S-bAFSA algorithm [7], the random heuristic drop_item procedure is used to make the points feasible, and the heuristic add_item is also implemented to improve the quality of the solutions. S-bAFSA has better performance than CGMA in solving strongly correlated problems, such as F48, F49, F52, F54, F58, F59. In addition, S-bAFSA presents strong robustness.

2) The robustness test of CGMA

As observed in table 9, CGMA can obtain the same value 7481 in all runs on the test problem F60 with maxFEs=50000. It is also worth mentioning that the standard deviation obtained by CGMA is very small on each test problem. So, CGMA has strong robustness. To test the robustness of CGMA, here, we generate 5 instances with the size $n=100, 120, 130, 140, 150$, and the maximum capacity of knapsack $V=1100, 1200, 1230, 1270, 1300$; the results of CGMA are recorded in the table 10 for 50 independent runs.

Table 17. The results of CGMA for the different sizes

Problem	Dimension	Best	Worst	Mean	Median	Std
F68	100	6654	6654	6654	6654	0
F69	120	7933	7933	7933	7933	0
F70	130	8554	8554	8554	8554	0
F71	140	8358	8355	8357.58	8358	0.9278
F72	150	8704	8702	8703.45	8704	0.8256

As observed in table 17, when the size of the problem is less than or equal to 130, CGMA can obtain the same global optimal value for 50 runs. When the size is greater than or equal to 140, the same value cannot be found for every experiment. Here, we generate 5 different instances with the same size of 130 to test; table 18 shows the results. For the five test problems, CGMA can obtain the same value except the problem F56. The results show that CGMA has strong robustness and stability for solving the 0-1 Knapsack problem.

Table 18. The results of CGMA for 5 different instances with the same size

Problem	Dimension	Best	Worst	Mean	Median	Std
F73	130	8924	8924	8924	8924	0
F74	130	8308	8308	8308	8308	0
F75	130	8551	8551	8551	8551	0
F76	130	8238	8235	8238	8237.88	0.4798
F77	130	8028	8028	8028	8028	0

3) The effect of different climb numbers on the performance of MA and CGMA

For the original MA, the experiment demonstrating the precision of the solution is determined by the climb step and the climb number for the optimization problem [8]. For the knapsack problem, the climb step is set to 1, so the precision of the solution is determined by the climb number. The larger the climb number, the better is the value. To test the impact of the climb number, the maxFE is set to 50000. The population size is set to 50. Table 19 shows the results for MA with different climb numbers N_c for the test problems F36 to F39. As observed from the results, when the climb number is 50, the mean value of MA is better, and the standard deviation is smaller. So, for MA, we can improve the quality of the solution by increasing the climb number. However, the precision of the solution is not impacted by different climb numbers due to the optimization of the greedy algorithm for CGMA.

Table 19. The effect of climb number on the performance of MA

Problem	Climb number	Best	Worst	Mean	Median	Std
F36	5	3019	2958	2979.94	2976.50	14.8945
	20	3022	2969	2998	2998.50	11.6128
	50	3103	2997	3059.71	3083	38.6101
F37	5	4691	4374	4488.61	4477.50	67.5480
	20	4712	4465	4552.31	4541	52.8072
	50	4749	4523	4603.82	4603	46.9814
F38	5	4473	4158	4278.73	4255.50	78.6377
	20	4564	4263	4386.14	4383.50	68.1235
	50	4619	4349	4442.90	4431.50	64.4660
F39	5	23714	22746	23253.31	23235.50	242.8209
	20	23930	22962	23413.42	23411	213.1916
	50	24647	23178	23662.13	23611.50	280.1857

5. Conclusions

This paper proposed a binary monkey algorithm for solving 0-1 knapsack problems. The algorithm used the greedy algorithm to correct the infeasible solutions and to improve the feasibility, introduced the cooperation process to speed up the convergence rate, modified the somersault process by randomly choosing one monkey as the pivot of another to avoid falling into the local optimal solutions, and reinitialized the population if the global optimal solution was not improved after a predetermined number of generations. The experiments show that the proposed CGMA algorithm has strong advantages in solving 0-1 knapsack problems for testing fixed and random problems and small- and large-scale problems. CGMA can be an efficient alternative for solving the 0-1 knapsack problem.

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