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A Novel Hybrid Cuckoo Search Algorithm with Global Harmony Search for 0-1 Knapsack Problems

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Abstract

Cuckoo search (CS) is a novel biologically inspired algorithm and has been widely applied to many fields. Although some binary-coded CS variants are developed to solve 0-1 knapsack problems, the search accuracy and the convergence speed are still needed to further improve. According to the analysis of the shortcomings of the standard CS and the advantage of the global harmony search (GHS), a novel hybrid meta-heuristic optimization approach, called cuckoo search Algorithm with global harmony search (CSGHS), is proposed in this paper to solve 0-1 knapsack problems (KP) more effectively. In CSGHS, it is the combination of the exploration of GHS and the exploitation of CS that makes the CSGHS efficient and effective. The experiments conducted demonstrate that the CSGHS generally outperformed the binary cuckoo search, the binary shuffled frog-leaping algorithm and the binary differential evolution in accordance with the search accuracy and convergence speed. Therefore, the proposed hybrid algorithm is effective to solve 0-1 knapsack problems.

Keywords: Cuckoo search, Global Harmony Search, 0-1 knapsack problems, Hybrid Encoding

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1. Introduction

Optimization problems can be found in various fields in the real world, such as engineering, manufacturing, finance, medical science, music and so on. More generally, the process of optimization is to find the best possible solution of some objective function in a given domain. Unfortunately, it is difficult for the traditional methods to cope with some high-dimensional, non-differentiable, discontinuous complicated problems. Under these circumstances, meta-heuristic techniques begin to show their powerful search ability.

Some of them include ant colony optimization (ACO)¹, bat algorithm (BA)², bacterial colony foraging (BCF)³, bird swarm algorithm (BSA)⁴, chicken swarm optimization (CSO)⁵, differential evolution (DE)⁶⁻⁷, firefly algorithm (FA)⁸⁻¹⁰, krill herd algorithm (KH)¹¹⁻¹⁸, monarch butterfly optimization (MBO)¹⁹⁻²¹, particle swarm optimization (PSO)²²⁻²³, earthworm optimization algorithm (EWA)²⁴ and elephant herding optimization (EHO)²⁵⁻²⁶. These algorithms have been used to successfully address many complicated engineering problems, such as ordinal regression²⁷, classification²⁸, data encryption²⁹, possession³⁰, scheduling³¹, test-sheet composition³², target assessment³³⁻³⁴, path planning³⁵⁻³⁷, directing orbits of chaotic systems³⁸, feature selection³⁹, and fault diagnosis⁴⁰.

Cuckoo Search (CS) is one of the latest nature-inspired meta-heuristic algorithms developed by Yang and Deb⁴¹. CS is based on the brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds. In addition, this algorithm is enhanced by Lévy flights, rather than by simple isotropic random walks⁴².

Harmony Search (HS) is a relatively novel music-inspired metaheuristic optimization algorithm developed by Geem et al.⁴³. It mimics the music improvisation process where musicians improvise their instruments' pitches striving to find pleasant harmony-it is like that the optimization method searches for the global optimal solution. Owing to its potential as an optimization technique, it has gained considerable attention and many variants are proposed to enhance the performance of HS⁴⁴⁻⁴⁶. Mahdavi et al.⁴⁷ proposed the improved version of harmony search algorithm (IHS) which dynamically updates the values

of the pitch adjustment rate (PAW) and the pitch adjustment bandwidth (BW). Due to the fact that BW in IHS is difficult to guess and problem dependent, inspired by the concept of swarm intelligence as proposed in PSO, Omran and Mahdavi⁴⁸ proposed the global harmony search (GHS) algorithm.

Owing to the significant features such as fine balance of randomization and intensification and fewer number of control parameters⁴¹, CS is becoming a new research hotspot in swarm intelligence and various variants have emerged in large numbers with an intension to further enhance the optimization ability. Walton et al.⁴⁹ developed a modified cuckoo search algorithm for solving nonlinear problems. Yang and Deb⁵⁰ extended it to multiobjective optimization problems. Yildiz⁵¹ successfully used CS to select optimal machine parameters in milling operation and proved that was more effective. Ouaraab et al.⁵² proposed a discrete cuckoo search to solve traveling salesman problem. Li et al.⁵³ introduced an adaptive parameter CS for global numerical optimization. Recently, hybridization that CS in combination with other methods has been proposed and has become ever-increasing hot topics studied by people, such as CS combined with orthogonal learning strategy⁵⁴, shuffled frog leaping algorithm (SFLA)⁵⁵, wind driven optimization (WDO)⁵⁶, artificial neural network (ANN)⁵⁷ and genetic algorithm (GA)⁵⁸. For details, see⁵⁹.

Some researchers attempt to solve knapsack problem (KP) problems by CS. In 2011, Layeb⁶⁰ proposed a hybrid optimization algorithm which combined cuckoo search and quantum-based approach to solve knapsack problems efficiently, and afterward, Gherboudj et al.⁶¹ conducted research on knapsack problems with purely binary cuckoo search. The research on knapsack problem based on CS is not enough. Additionally, although many efficient methods have emerged for the 0-1KP problems⁶²⁻⁶³, in fact, further work is needed to resolve some new and harder 0-1 knapsack problems hidden in the real world, or rather, the correlation between the weight and the profit of the items may not be more concerned. In⁶²⁻⁶³, although 10 low-dimensional and 16 randomly-generated high-dimensional 0-1KP instances are used, the latter did not consider the correlation between the profits and weights of the items. As a

result, it has a wider significance to explore some new approaches to handle the 0-1 knapsack problem.

There are some studies on hybrid harmony search and other methods, like the combination of harmony search and firefly algorithm⁶⁴, cuckoo search algorithm⁶⁵, but most of the hybridization is adopted the standard harmony search which has some shortcomings. The parameters are difficult to adjust, for example.

Based on the above analysis, we propose a novel hybrid optimization algorithm by integrating the global harmony search into the cuckoo search algorithm for solving 0-1 knapsack problems. To demonstrate the efficiency of the proposed method, a large number of experiments on 0-1 knapsack problems with six groups of instances are carried out. The experimental results show that the proposed hybrid metaheuristic method can reach the required optima more effectively than CS, SFLA, and DE, even in some cases when the problem to be solved is too complicated and complex.

The rest of paper is organized as follows. Section 2 introduces the preliminary knowledge of CS, GHS and the mathematical model of 0-1 knapsack problem (0-1KP). Then, our proposed CSGHS for 0-1 KP problems is presented in Section 3. A series of simulation experiments are conducted in Section 4. Some conclusions and comments are made for further research in Section 5.

2. Review of the Related Work

In this section, the definition and mathematical model of 0-1 knapsack problems are outlined as well as the basic CS and GHS.

2.1. 0-1 knapsack problem

0-1KP is one of the most intensively studied combinatorial optimization problem⁶⁶. The researches of 0-1 knapsack problem have very large potential application background for capital budgeting problems, resource allocation, loading problems, project selection problems and so on⁶⁷. The 0-1 knapsack problem can be generally described as follows: Given N objects, from which various possible objects will be selected to fill up a knapsack. Then, if p_j is a measure of the value given by object j , w_j its weight and c the

capacity of the knapsack. The objective is to maximize the total value of the knapsack that the knapsack capacity constraint is satisfying. Formally, the problem can be formulated as follows:

$$\begin{aligned} & \text{Maximize } f(x) = \sum_{j=1}^n p_j x_j \\ & \text{subject to } \sum_{j=1}^n w_j x_j \leq c, \\ & x_j = 0 \text{ or } 1, \quad j = 1, \dots, n, \end{aligned} \quad (1)$$

where n is the number of items. The binary decision variable x_j , with $x_j = 1$ if item j is selected, and $x_j = 0$ otherwise, is adopted.

2.2. Cuckoo search

CS⁴¹ is one of bio-inspired algorithms for imitating the brood parasitism of some cuckoo species. Because of the complexity of natural systems, they cannot be built models exactly through computer algorithm in its basic form. In order to successfully apply this as optimization method, Yang and Deb⁴¹ used the following three approximate rules:

- (1) Each cuckoo lays only one egg at a time, and dumps its egg in a randomly chosen nest;
- (2) The best nests with high-quality eggs will be carried over to the next generations;
- (3) The number of available host nests is fixed, and the egg laid by the host bird with a probability $p_a \in [0, 1]$. In this case, the host bird can either throw the egg away or simply abandon the nest and build a completely new nest.

Based on these three rules, the basic steps of the CS are shown in Algorithm 1.

2.3. The global-best harmony search

Harmony search (HS)^{43,68}, as a relatively effective optimization technique, the optimization process is generally handled by three rules: memory consideration, pitch adjustment and random selection. The three key parameters which have a far-reaching effect on the performance of the HS are harmony memory consideration rate ($HMCR$), pitch adjustment rate (PAR), and distance bandwidth (bw). Additionally, the parameters also include harmony memory size

(HMS), the number of improvisations (NI). In this paper, we employ GHS⁴⁸ as a mutation operation to ensure convergence of the CSGHS and enhance its

ability of optimization effectively. The GHS is presented in Algorithm 2.

Begin
Step 1: Initialization. Set the discovery rate (p_d); initialize the population of n host nests randomly and each egg in a nest corresponding to a potential solution to the given problem; Set stopping criterion or the generation counter ($G=1$).
Step 2: Generate new solutions X' (but keep the current best), the procedure works as follows:
 for $i=1$ to d **do**
 $x_i' = x_i + \alpha \oplus \text{Levy}(\lambda)$
 if ($\text{rand} < p_d$) **then**
 $x_i' = x_i + \text{rand} * (x_{r1} - x_{r2})$
 endif
 end for
 where x_i ($i=1, 2, \dots, d$) is the i th component of X' and $\text{rand} \sim U(0,1)$.
Step 3: Keep best solutions; Rank the solutions and find the current best ($x^{\text{best}}, f(x^{\text{best}})$)
Step 4: Check the stopping criterion. If the stopping criterion (maximum number of iterations G) is satisfied, computation is terminated. Otherwise, step 2 is repeated.
End.

Algorithm 1. The cuckoo search algorithm

3. Hybrid CS with GHS for 0-1 KPs

In this section, we will propose a hybrid metaheuristic algorithm by integrating the global-best harmony search into the cuckoo search (CSGHS) for solving 0-1 knapsack problems. First, the hybrid encoding scheme and repair operator will be introduced. And then the proposed CSGHS will be described in detail. At last, the algorithm complexity is analyzed.

3.1. Encoding scheme

It is generally known that the 0-1 knapsack problem is a special integer linear programming problem. Additionally, from formula (1), we can infer that the feasible solution of 0-1 knapsack problem is

n -dimension 0-1 vector. Hence, the individual was naturally represented by binary coding. Since the standard CS algorithm operates in continuous space, we cannot use it directly for solving optimization problems in binary space. So hybrid encoding scheme^{55, 69} was used for solving 0-1 knapsack problem with CSGHS. The formal description is as follows. Let two-tuples $\langle X_i, Y_i \rangle$ represent the i th cuckoo individual, where $X_i = (x_{i1}, x_{i2}, \dots, x_{id}) \in [-3.0, 3.0]^d$, and $Y_i = (y_{i1}, y_{i2}, \dots, y_{id}) \in \{0, 1\}^d$. Sigmoid function is used to create a mapping between X_i and Y_i . The conversion from d -dimensional real-valued vector to d -dimensional binary vector is as follows:

$$y_i = \begin{cases} 1 & \text{if } \text{sig}(x_i) \geq 0.5 \\ 0 & \text{else} \end{cases} \quad (2)$$

$\text{Sig}(x) = 1 / (1 + e^{-x})$ is Sigmoid function.

```

Begin
Step 1: Initialize the HM. Set parameters HMS, HMCR, PAR, NI.
Step 2: Improvise a new harmony: the new harmony vector  $x' = (x'_1, x'_2, \dots, x'_d)$  is generated as follows:
    for  $i = 1$  to  $d$  do
        if ( $\text{rand} \leq \text{HMCR}$ ) then //memory consideration
             $x'_i = x_i^j$ , where  $j \sim U(1, \dots, \text{HMS})$ .
        if  $\text{rand} \leq \text{PAR}$  then //pitch adjustment
             $x'_i = x_i^{\text{best}}$ , where best is the index of the best harmony
        end if
        else //random selection
             $x'_i = \text{LB}_i + r \times (\text{UB}_i - \text{LB}_i)$ , where  $r \sim U(0, 1)$ ,  $\text{rand} \sim U(0, 1)$ 
        end if
    end for
Step 3: Update harmony memory: if  $f(x') < f(x^{\text{worst}})$ ,  $x^{\text{worst}} = x'$ . (minimization objective)
    Update the best harmony vector.
Step 4: Check the stopping criterion. If the stopping criterion is satisfied, computation is terminated.
    Otherwise, step 2 is repeated.
End.

```

Algorithm 2. The global-best harmony search algorithm

3.2. Repair operator

The 0-1 knapsack problem is also a constraint optimization problem. So constraint handling technique must be employed in order to handle the infeasible solution. Nowadays the more popular constraint handling technique is penalty function method and individual optimization method. In this paper, we adopt an effective greedy transform method (GTM)⁵⁵ to modify the infeasible solution as well as optimize the feasible solution.

3.3. The proposed approach: CSGHS

In this section, we will give a reasonable explanation for how and why we combine the GHS with CS to form an effective CSGHS, which not only improves the quality of the solutions, but also increases the diversity of the population, and then the efficiency of the algorithm is improved.

Generally, the main advantages of CS algorithm are the diversity of population strategy via randomization and search strategy by Lévy flights, there are still some aspects to be improved.

For CS, the search process relies too much on random, although Lévy flights is most suitable for the randomization on the global scale⁴¹, the way of generating new solutions by random walk is less efficient than Lévy flights, so a rapid convergence rate cannot be guaranteed and at times it cannot avoid falling into local optimal. In addition, there lacks

information exchange between the individuals, moreover, new solutions are not influenced by the best individual in the swarm. To address the shortcomings of the CS and make full use of the advantages of GHS, a new hybrid algorithm, called CSGHS, is proposed in which the GHS is embedded into the CS. By intuition, this improvement makes the new approach work efficiently on both continuous and discrete problems. The distinct difference between CSGHS and CS is that GHS as the mutation operator is applied to improve the original CS generating a new solution for each nest. In this manner, this new approach can generate diverse solutions with a view to exploring the search space on the global scale by Lévy flights of the CS, and concentrate on the search in a local region where the current optimum is most likely found by the mutation of the GHS.

Several improvements of CSGHS are described as follows:

The first improvement, and most important, is that the GHS completely replaces the random walk in CS in the stage of local search. As previously is mentioned, the GHS as a mutation operator was adopted in the CSGHS, with the aim of increasing diversity of the population and accelerating the convergence speed so as to enhance the performance.

The second improvement is to add mutation operator of DE/Best/1/Bin scheme into CSGHS, as was inspired by the mutation operator in DE algorithm. Its purpose is to further strengthen the effects of global

optimal information on the new nests and the information exchange between individuals.

Based on the above analysis, concretely speaking, the evolution mechanism of the CSGHS performs in two stages. The first stage is to get a cuckoo i randomly (generate a solution) by Lévy flights and then evaluate its quality F_i . Cuckoo j is chosen randomly and then it will be replaced by cuckoo i only if F_i is superior F_j . The second stage we tune each element x_i^j ($j=1, 2, \dots, D$) of x_i ($i=1, 2, \dots, N$) using mutation operator. If $U(0, 1) \leq \text{HMCR}$, the element x_i^j

is replaced by x_k^j , where $k \sim U(1, \dots, N)$. In this case, the element x_i^j is updated by using pitch adjustment operation in GHS only if $U(0, 1) \leq \text{PAR}$, the element x_i^j is replaced by x_{best}^j ; whereas when $U(0, 1) > \text{PAR}$, we update the element x_i^j with the DE/Best/1/Bin scheme. If $U(0, 1) > \text{HMCR}$, the element x_i^j is generated randomly.

With the above special design, the mainframe of the CSGHS for 0-1 knapsack problem is shown in Algorithm 3.

Begin

Step 1: Sorting. According to value-to-weight ratio p_i / w_i ($i = 1, 2, 3, \dots, m$) in descending order, a queue $\{s_1, s_2, \dots, s_m\}$ of length m is formed.

Step2: Initialization. Set the generation counter $G=1$; set the harmony memory consideration rate HMCR , the pitch adjustment rate PAR ; Generate n cuckoo nests randomly $\{<X_1, Y_1>, <X_2, Y_2>, \dots, <X_n, Y_n>\}$. Calculate the fitness for each individual, $f(Y_i)$, $1 \leq i \leq n$, determine the global optimal individual $<X_g^{\text{best}}, Y_g^{\text{best}}>$.

Step 3: While the stopping criterion is not satisfied **do**

for $i=1$ to n

for $j=1$ to d

$x_j' = x_j + \alpha \oplus \text{Levy}(\lambda)$ // Lévy flights

if ($\text{rand} < \text{HMCR}$) **then** //memory consideration

$x_j = x_j^i$, where $i \sim U(1, n)$.

if $\text{rand} < \text{PAR}$ **then** //pitch adjustment

$x_j = x_j^{\text{best}}$

else

$x_j' = x_j^{\text{best}} + F \times (x_j^q - x_j^r)$, where $q \sim U(1, n)$, $r \sim U(1, n)$

end if

else //random selection

$x_j' = \text{LB}_j + r \times (\text{UB}_j - \text{LB}_j)$, where $r \sim U(0,1)$

end if

end for

 Perform GTM method to repair and optimize the individuals

end for

 Keep best solutions.

 Rank the solutions in descending order and find the current best $(Y^{\text{best}}, f(Y^{\text{best}}))$.

$G=G+1$

Step 4: End while

End.

Algorithm 3. The mainframe of the CSGHS algorithm for 0-1 knapsack problem

3.4. Algorithm complexity

CSGHS is composed of three stages: the sorting by value-to-weight ratio, the initialization and the iterative search. The quick sorting has time complexity $O(n \log(n))$. The generation of the initial cuckoo nests has time complexity $O(n \times d)$. The iterative search consists of four steps (comment statements in

Algorithm 3), i.e. the Lévy flights, memory consideration, pitch adjustment, and random selection which costs the same time $O(n \times d)$. Further, the major time cost of GTM is the quick sort which has calculated at the start of this section. In summary, the overall complexity of the proposed CSGHS is $O(n \log(n)) + O(n \times d) + O(n \times d) = O(n \log(n)) + O(n \times d)$. It does not change compared with the original CS algorithm.

4. Simulation Experiments

4.1. Experimental data set

Since the difficulty of knapsack problems is greatly affected by the correlation between profits and weights^{66,71}, six groups of 0-1 KP instances randomly

generated are presented in Table 1. The correlation of six types of instances is shown in Fig. 1. Here we use the function $Rand(a, b)$ to represent an integer uniformly distributed in $[a, b]$. Each group contains six 0-1 KP instances and the dimension is 300, 500, 800, 1000, 1200, and 1500. These thirty-six instances are marked as $KP_1, KP_2, \dots, KP_{36}$, respectively.

Table 1. Six groups of 0-1 KP instances

Correlation	w_i	p_i
Uncorrelated instance	$Rand(10,100)$	$Rand(10,100)$
Weakly correlated instance	$Rand(10,100)$	$Rand(w_i - 10, w_i + 10)$
Strongly correlated instance	$Rand(10,100)$	$w_i + 10$
Multiple strongly correlated instance	$Rand(10,100)$	$w_j + 30, \text{if } \text{mod}(w_j, 6) = 0$
		$w_j + 20, \text{else}$
Profit ceiling instance	$Rand(10,100)$	$3 \times \lceil w_j / 3 \rceil$
Circle instance	$Rand(10,100)$	$d \sqrt{4R^2 - (w_j - 2R)^2}$

where $d=2/3$, $R=10$. For each data set we set the value of the capacity $c = 0.75 \sum_{j=1}^n w_j$.

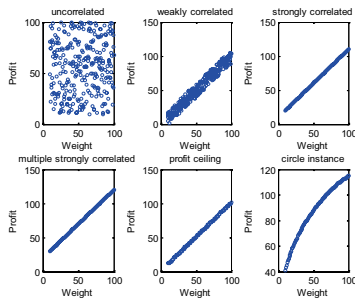


Fig.1 Six classes of instances with 300 items

4.2. Experimental setup and parameters setting

To better understand the CSGHS, we compared its performance on 36 knapsack problems (KP_1 - KP_{36}) with three other optimization approaches, which are DE, SFLA and CS. DE⁷² is a vector-based evolutionary algorithm with self-organizing tendency and does not use the information of derivatives. SFLA is a meta-heuristic optimization method that imitates the memetic evolution of a group of frogs while

casting about for the location that has the maximum amount of available food⁷³.

In our experiments, we set the parameters as follows. The proposed CSGHS includes four key parameters: the population size $P=40$, the harmony memory consideration rate $HMCR=0.9$, the pitch adjustment rate $PAR=0.3$ and amplification factor $F=0.3$. For DE, the population size $P=40$, crossover probability $Cr=0.9$, amplification factor $F=0.3$, basic DE/Rand/1/Bin scheme. For SFLA, the population size $P=40$, which is partitioned into $M=4$ memeplexes, each containing $N=10$ frogs (i.e. $P=M \times N$).

In order to make a fair comparison, all computational experiments are conducted with Visual C++ 6.0. The test environment is set up on a PC with AMD Athlon(tm) II X2 250 Processor 3.01 GHz, 1.75G RAM, running on Windows 7. The experiment on each instance was repeated 30 times independently. Further, best solution, worst solution, mean, median, standard deviation (STD) for all the solutions are given in related tables. In addition, the maximum run-time was set to 5 seconds for 300-dimensional and 500-dimensional instances, 8 seconds for 800-

dimensional, 1000-dimensional, and 1200-dimensional instances and 10 seconds for 1500-dimensional instances.

4.3. Numerical optimization

In order to make an overall investigation about the performance of CSGHS, a number of simulation and experiment research have been carried out. Six classes of 0-1 knapsack problems with large scales listed in Table 1. The number of items is set to 300, 500, 800, 1000, 1200, and 1500, respectively. The experimental results are reported in Tables 2-7. The best values are emphasized in boldface. In addition, comparisons of the best profits obtained from the CSGHS with those obtained from DE, SFLA and CS for six KP instances with 1500 items among 30 independent runs are shown in Figs 2-7, respectively. Specifically, the

convergence curves of four algorithms on 1500 items are also graphically illustrated in Figs 8-13, respectively.

From the results of Tables 2, 4-7, we can plainly perceive that CSGHS achieves decisive advantage in performance over the other three algorithms and it obtains the best results on all the instances, as can be seen from the third column to the sixth column of Tables 2, 4-7. On closer inspection, the SFLA gains the smallest STD values on more than two-thirds cases. For the other ten cases, similar numerical stabilities are observable in CS and CSGHS. With regard to DE, it may not be adept in solving 0-1 KPs as its overall performance is obviously inferior to that of the other three algorithms.

Table 2. Experimental results of four algorithms with uncorrelated KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₁	SFLA	15202	15095	15145	15141	23.45
	DE	15334	15088	15287	15301	54.45
	CS	15224	15024	15092	15081	51.37
	CSGHS	15338	15281	15304	15304	12.26
KP ₂	SFLA	26065	25915	25968	25956	32.92
	DE	26333	25751	26099	26096	135.88
	CS	26208	25786	25936	25911	103.4
	CSGHS	26387	26230	26329	26337	34.00
KP ₃	SFLA	39753	39563	39647	39642	54.87
	DE	39652	39215	39410	39399	113.28
	CS	40223	39416	39565	39514	179.98
	CSGHS	40342	40056	40182	40190	68.87
KP ₄	SFLA	49369	49185	49248	49240	46.98
	DE	49246	48835	48989	48979	101.11
	CS	49767	49024	49164	49142	143.08
	CSGHS	50027	49717	49846	49835	84.36
KP ₅	SFLA	60225	59936	60047	60049	62.89
	DE	59932	59488	59707	59727	110.39
	CS	60629	59708	59939	59884	166.43
	CSGHS	60951	60616	60788	60791	79.79
KP ₆	SFLA	74915	74662	74731	74721	74.09
	DE	74719	74189	74404	74418	126.44
	CS	75762	74461	74720	74610	336.75
	CSGHS	75889	75452	75639	75631	112.26

Table 3. Experimental results of four algorithms with weakly correlated KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₇	SFLA	13110	13089	13098	13099	6.22
	DE	13202	13158	13186	13186	9.76
	CS	13157	13069	13094	13087	21.91
	CSGHS	13178	13154	13169	13169	6.59
KP ₈	SFLA	21760	21702	21722	21717	15.82
	DE	21951	21745	21858	21859	37.61
	CS	21935	21670	21746	21722	76.53
	CSGHS	21871	21803	21832	21830	12.43
KP ₉	SFLA	34704	34651	34673	34674.5	12.55
	DE	34814	34578	34721	34718	64.50
	CS	34987	34621	34697	34654	100.38
	CSGHS	34850	34795	34824	34825	14.00
KP ₁₀	SFLA	43305	43258	43277	43276	12.63
	DE	43327	43162	43217	43211	43.64
	CS	43737	43216	43340	43264	166.53
	CSGHS	43484	43386	43440	43442	22.39
KP ₁₁	SFLA	51989	51797	51890	51875	58.65
	DE	51947	51444	51600	51569	108.83
	CS	53333	51601	51831	51788	299.35
	CSGHS	52711	52354	52556	52565	76.89
KP ₁₂	SFLA	64880	64792	64818	64812	21.31
	DE	64783	64661	64696	64697	27.06
	CS	65515	64750	65004	64860	294.16
	CSGHS	65116	64980	65045	65044	38.14

Table 3 summarizes the experimental results obtained by the four methods to the weakly-correlated instances. From Table 3 we can infer that the performance of CSGHS, CS, SFLA and DE are comparable. DE obtained the best, mean, median results for KP₇, KP₈ and CS attained the best results for the last four cases. SFLA still showed the best stability among four methods. Although the optimal solutions obtained by the CSGHS are poorer than DE or CS, the CSGHS gets the worst, mean, median results on KP₉-KP₁₂. Unfortunately, although weakly correlated knapsack problem are closer to the real world situations 66, the CSGHS does not appear overwhelming superior to the other three algorithms in solving such knapsack problems.

Figs. 2-7 show a comparison of the best profits obtained by applying the four algorithms for six classes of problems with 1500-dimensional functions in 30 runs. The search space of the 1500-dimensional functions is expanded dramatically to 2^{1500} , which is a challenge for

CSGHS, CS, SFLA and DE. Thus, DE failed to come at any global optima of all the six high-dimensional functions, while the results of SFLA fluctuated around certain value, as we had expected. Additionally, the CS can get the optimal solution occasionally, which shows it has poorer stabilization and is consistent with the STD value above. The CSGHS wins obvious advantages. As mentioned above, weakly correlated problem instances are difficult to solve in the case of CSGHS.

To investigate further the performance of the four approaches, the average convergence curves of CSGHS, CS, SFLA and DE are drawn in Figs. 8-13. The optimization of the small-size problems is simple. However, when the dimensionality is increased, the CSGHS takes the lead obviously and outperforms the other three methods. From Figs. 8-13, it is observed that CSGHS have a quick convergence speed, as is benefited from the GHS. SFLA performs the second best in hitting the optimum. DE shows premature phenomenon in the evolution and does not offer satisfactory performance.

Table 4. Experimental results of four algorithms with strongly correlated KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₁₃	SFLA	14807	14797	14799	14797	3.48
	DE	14797	14781	14789	14787	4.90
	CS	14804	14791	14797	14797	2.43
	CSGHS	14807	14797	14804	14807	4.44
KP ₁₄	SFLA	25519	25507	25514	25514	2.40
	DE	25502	25481	25492	25493	4.21
	CS	25514	25502	25506	25505	3.49
	CSGHS	25533	25515	25523	25525	4.97
KP ₁₅	SFLA	40124	40107	40113	40114	4.40
	DE	40111	40068	40089	40088	8.66
	CS	40107	40096	40103	40105	3.88
	CSGHS	40147	40126	40132	40130	5.54
KP ₁₆	SFLA	49383	49363	49374	49373	5.20
	DE	49363	49333	49346	49345	7.50
	CS	49380	49350	49364	49363	7.04
	CSGHS	49403	49383	49393	49393	6.52
KP ₁₇	SFLA	60566	60541	60551	60550	5.22
	DE	60540	60501	60519	60519	8.55
	CS	60558	60530	60542	60540	6.77
	CSGHS	60587	60567	60573	60570	5.32
KP ₁₈	SFLA	74830	74792	74801	74801	7.44
	DE	74784	74749	74764	74761	9.50
	CS	74800	74775	74787	74786	6.83
	CSGHS	74858	74817	74835	74832	9.31

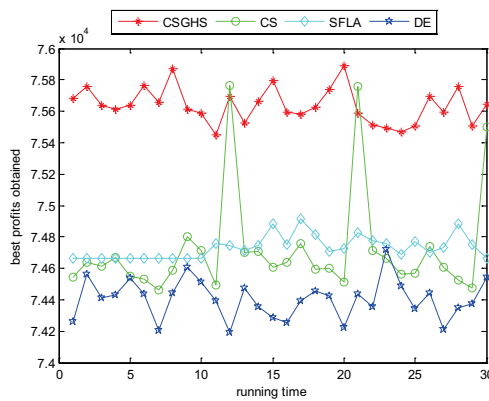
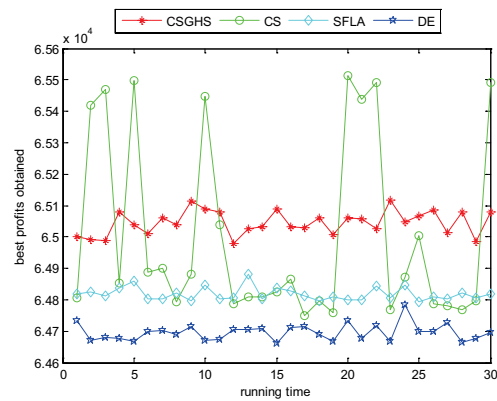
Fig. 2 The best profits obtained in 30 runs for KP₆Fig. 3 The best profits obtained in 30 runs for KP₁₂

Table 5. Experimental results of four algorithms with multiple strongly correlated KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₁₉	SFLA	18388	18368	18377	18379	7.91
	DE	18387	18335	18354	18348	15.25
	CS	18386	18355	18368	18368	4.73
	CSGHS	18388	18388	18388	18388	0.00
KP ₂₀	SFLA	29589	29560	29567	29568	5.79
	DE	29548	29488	29519	29520	14.10
	CS	29589	29527	29555	29549	13.94
	CSGHS	29627	29589	29605	29609	9.81
KP ₂₁	SFLA	47737	47695	47713	47715	10.54
	DE	47704	47620	47659	47657	20.68
	CS	47727	47673	47696	47695	15.09
	CSGHS	47797	47757	47776	47777	10.09
KP ₂₂	SFLA	60612	60575	60590	60590	8.22
	DE	60572	60508	60534	60530	13.98
	CS	60607	60540	60576	60574	16.96
	CSGHS	60672	60630	60656	60652	14.94
KP ₂₃	SFLA	72122	72072	72089	72088	11.88
	DE	72072	71973	72018	72018	19.38
	CS	72094	72031	72058	72057	15.93
	CSGHS	72212	72145	72166	72167	16.17
KP ₂₄	SFLA	88728	88660	88692	88688	17.59
	DE	88666	88562	88598	88595	25.88
	CS	88687	88626	88663	88665	14.88
	CSGHS	88828	88767	88794	88788	14.54

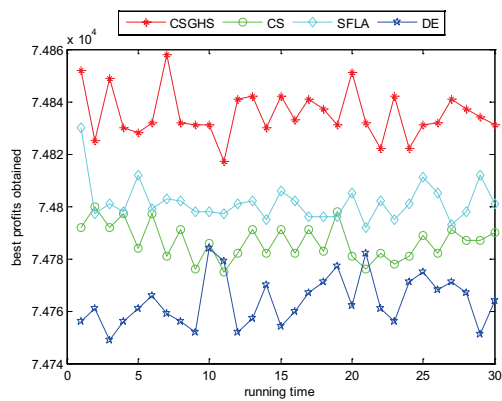
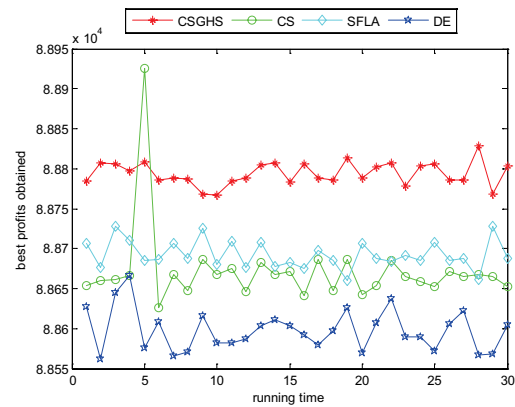
Fig. 4 The best profits obtained in 30 runs for KP₁₈Fig. 5 The best profits obtained in 30 runs for KP₂₄

Table 6. Experimental results of four algorithms with profit ceiling KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₂₅	SFLA	12957	12957	12957	12957	0.00
	DE	12957	12951	12953	12954	1.83
	CS	12957	12954	12957	12957	0.76
	CSGHS	12957	12957	12957	12957	0.00
KP ₂₆	SFLA	20307	20301	20302	20301	1.67
	DE	20301	20292	20294	20294	2.17
	CS	20304	20295	20299	20298	1.86
	CSGHS	20307	20307	20307	20307	0.00
KP ₂₇	SFLA	32814	32802	32806	32805	2.13
	DE	32802	32793	32797	32796	2.63
	CS	32811	32799	32803	32802	3.12
	CSGHS	32826	32814	32820	32820	2.65
KP ₂₈	SFLA	43263	43257	43259	43260	2.01
	DE	43257	43245	43249	43248	3.57
	CS	43269	43251	43257	43254	4.41
	CSGHS	43284	43269	43274	43275	3.12
KP ₂₉	SFLA	51396	51384	51389	51390	2.48
	DE	51384	51372	51378	51378	3.04
	CS	51399	51378	51385	51384	4.32
	CSGHS	51414	51399	51407	51405	4.29
KP ₃₀	SFLA	63960	63951	63955	63954	2.22
	DE	63951	63936	63942	63942	3.62
	CS	63975	63945	63953	63951	6.43
	CSGHS	63981	63969	63975	63975	2.41

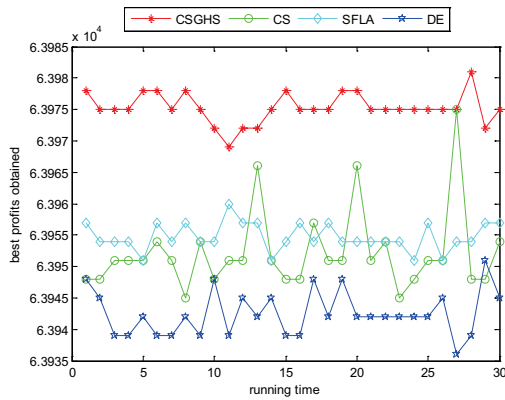
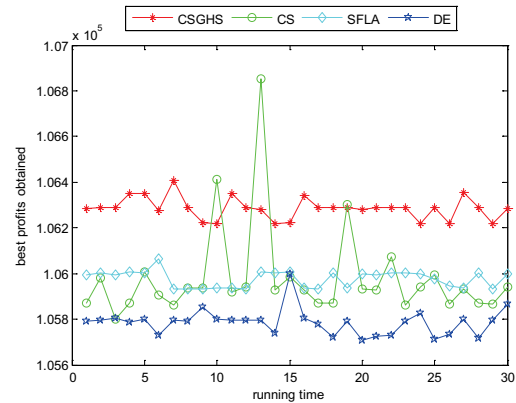
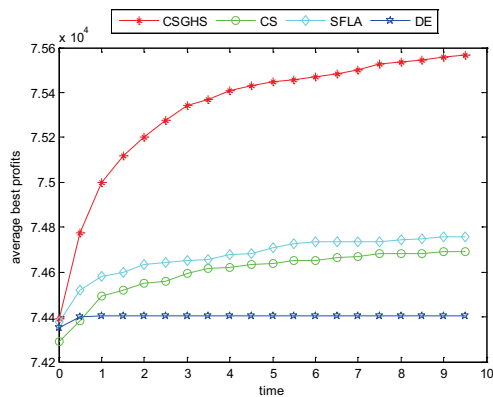
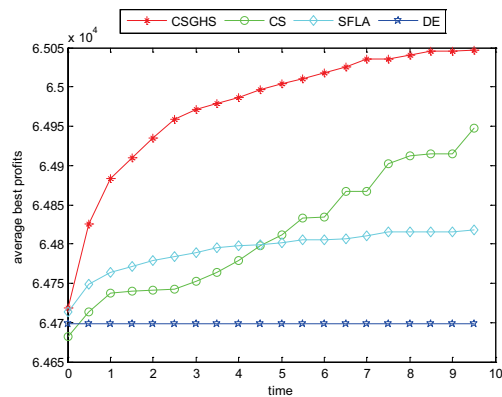
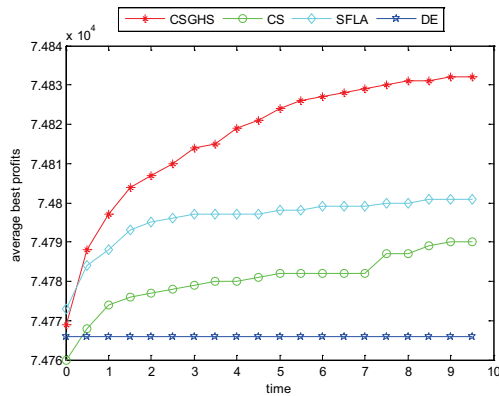
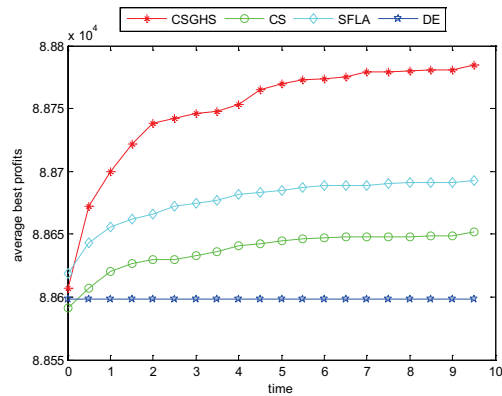
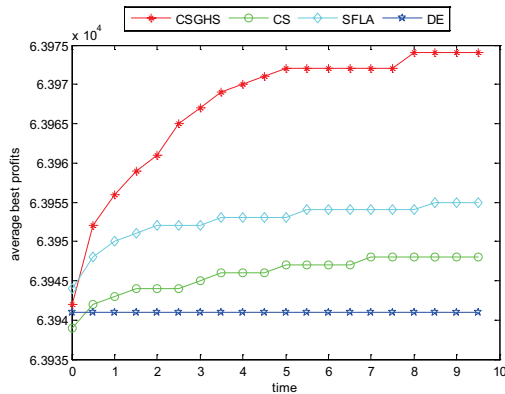
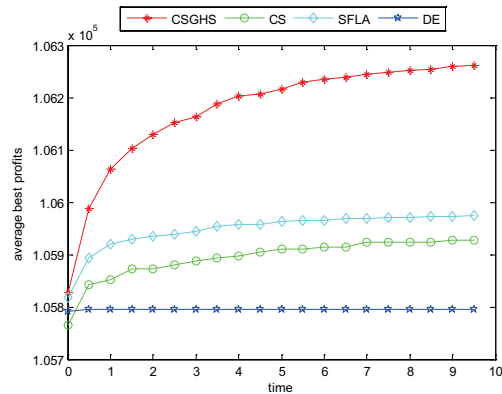
Fig. 6 The best profits obtained in 30 runs for KP₃₀Fig. 7 The best profits obtained in 30 runs for KP₃₆

Table 7. Experimental results of four algorithms with circle KP instances

Instance	Algorithm	Best	Worst	Mean	Median	STD
KP ₃₁	SFLA	21330	21262	21263	21278	25.74
	DE	21333	21192	21264	21277	32.46
	CS	21333	21194	21261	21261	18.57
	CSGHS	21335	21265	21333	21329	12.48
KP ₃₂	SFLA	35348	35341	35344	35345	1.70
	DE	35343	35184	35247	35267	38.08
	CS	35345	35271	35297	35277	31.29
	CSGHS	35419	35347	35416	35403	26.04
KP ₃₃	SFLA	56136	56063	56129	56113	29.56
	DE	56063	55914	55964	55954	44.95
	CS	56280	55988	56057	56061	55.01
	CSGHS	56346	56205	56276	56278	35.37
KP ₃₄	SFLA	70876	70798	70831	70834	33.98
	DE	70806	70641	70696	70684	38.21
	CS	70915	70729	70789	70797	42.50
	CSGHS	71085	70949	71014	71030	34.97
KP ₃₅	SFLA	84173	84038	84096	84080	39.95
	DE	84040	83820	83912	83899	56.64
	CS	84645	83954	84055	84033	121.94
	CSGHS	84396	84187	84319	84297	54.62
KP ₃₆	SFLA	106066	105931	105993	105977	36.39
	DE	106000	105706	105793	105790	57.59
	CS	106853	105799	105929	106006	206.71
	CSGHS	106407	106217	106288	106287	48.04

Fig. 8 The convergence graphs of KP₆Fig. 9 The convergence graphs of KP₁₂

Fig. 10 The convergence graphs of KP₁₈Fig. 11 The convergence graphs of KP₂₄Fig. 12 The convergence graphs of KP₃₀Fig. 13 The convergence graphs of KP₃₆

5. Conclusions

In this paper, a hybrid cuckoo search algorithm with global-best harmony search (CSGHS) was proposed to solve 0-1 KP efficiently and effectively. To address the shortcomings of the CS, the GHS as a mutation operator was adopted in the CSGHS to strengthen the search ability. Another effective mutation operator of DE/Best/1/Bin scheme in DE is embedded into CSGHS to increase the diversity of population. Finally, CSGHS was tested on different correlated knapsack problem instances with low-dimensional and high-dimensional. The experiments reveal that the proposed approach greatly outperforms CS, SFLA and DE with regard to the solution accuracy and the convergence speed, particularly on tackling the large-size intractable 0-1KPs, which shows that the proposed CSGHS is an effective optimization tool.

The future work is to consider and solve other knapsack problem, such as multi-scenario max-min knapsack problem, bi-level 0-1 knapsack problem, Multidimensional Knapsack Problem.

Secondly, in the future, more engineering optimization problems will be used to further verify our proposed method, such as flowshop scheduling problems (FSP)⁷⁴⁻⁷⁵, image processing⁷⁶⁻⁷⁷, video coding⁷⁸, and wireless sensor networks⁷⁹.

Thirdly, our proposed method will surely work well in combination with other computational intelligence algorithms, such as minimax probability machine⁷⁹, support vector classification⁸¹, fuzzy C-means⁸², and least significant bit (LSB) matching⁸³⁻⁸⁴.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this article.

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