Differential Human Learning Optimization Algorithm

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Human Learning Optimization (HLO) is an efficient metaheuristic algorithm in which three learning operators, i.e., the random learning operator, the individual learning operator, and the social learning operator, are developed to search for optima by mimicking the learning behaviors of humans. In fact, people not only learn from global optimization but also learn from the best solution of other individuals in the real life, and the operators of Differential Evolution are updated based on the optima of other individuals. Inspired by these facts, this paper proposes two novel differential human learning optimization algorithms (DEHLOs), into which the Differential Evolution strategy is introduced to enhance the optimization ability of the algorithm. And the two optimization algorithms, based on improving the HLO from individual and population, are named DEHLO1 and DEHLO2, respectively. The multidimensional knapsack problems are adopted as benchmark problems to validate the performance of DEHLOs, and the results are compared with the standard HLO and Modified Binary Differential Evolution (MBDE) as well as other state-of-the-art metaheuristics. The experimental results demonstrate that the developed DEHLOs significantly outperform other algorithms and the DEHLO2 achieves the best overall performance on various problems.

1. Introduction

In the past decades, traditional optimization algorithms are widely used in science, engineering, economics, and industry to solve optimization problems [1]. However, the traditional optimization algorithms need to learn the mathematical characteristics of the optimal solution in advance, which can result in added complexity in the algorithm’s designation. In addition, the traditional algorithms cannot escape the local optimal of complex problems effectively. With the development of technology, engineering problems with optimization objectives are becoming more and more complicated and the conventional algorithm to solve the NP problems has become very difficult, which forces researchers to study metaheuristic algorithms [2]. Metaheuristics are general frameworks to build heuristics for combinatorial and global optimization problems [3]. The application of natural or biology-inspired metaheuristic optimizations, such as Genetic Algorithm [4], Particle Swarm Optimization [5], Harmony Search [6], Differential Evolution (DE) [7–10], Artificial Bee Colony [11], Fruit Fly Optimization [12], Distributed Grey Wolf Optimizer (DGWO) [13], Moth Search Algorithm (MSA) [14], Slime Mould Algorithm (SMA) [15], Gaining Sharing Knowledge-Based Optimization [16, 17], Cuckoo Search with Exploratory (ECS) [18], Discrete Jaya with Refraction Learning and Three Mutation (DJRL3M) [19], and Monarch Butterfly Optimization (MBO) [20], Hunger Games Search (HGS) [21], Runge Kutta Method (RUN) [22], and Harris Hawks Optimization (HHO) [23], has been very successful to solve the complex
optimization problems, such as feature selection [24–28], image segmentation [29], controller designation [30], flowshop scheduling problem [31, 32], and the node placement of wireless sensor networks [33].

Human beings are the smartest creature in the world because of their strongest learning ability; they are smarter than other living beings, such as birds, ants, and fish. To solve complex problems effectively, humans are always repetitively learning to improve their skills for adapting to the external environment better. Many human learning activities are similar to the search process of metaheuristics. For example, when a person learns something new, he or she repeatedly practices to improve new skills and evaluates his or her performance for guiding the following study. The process of human learning just like the metaheuristic algorithms iteratively generates a new solution and calculates the corresponding fitness for adjusting the following search. Therefore, it is reasonable to consider that the metaheuristic algorithm based on the human learning mechanisms may have advantages over other biological systems-based algorithms on complicated problems. Inspired by this thought, Wang et al. [34] proposed the Human Learning Optimization Algorithm (HLO) based on a simplified human learning model, in which three learning operators, i.e., the random learning operator (RLO), the individual learning operator (ILO), and the social learning operator (SLO), are developed to search out the optimal solution, which represents that a person may learn randomly due to the lack of prior knowledge or exploring new strategies, learn from his or her previous experience, and learn from his or her friends and books, respectively.

To strengthen the search efficiency of HLO, a few enhanced variants have been subsequently developed. An adaptive simplified human learning optimization algorithm (ASHLO) [35] is proposed in which the pr and pi, two control parameters determining the rates of performing RLO, ILO, and SLO, are linearly adjusted to achieve the balance between the global search and local search. Encouraged by the success of ASHLO, a sine-cosine adaptive human learning optimization algorithm (SCHLO) [36] is proposed in which the pr and pi are dynamically tuned in a reasonable range by the sine and cosine functions so that SCHLO can efficiently escape from the local optimal. Later, a new improved adaptive human learning optimization algorithm (IAHLO) [37] is presented to accurately tune the control parameter pr so that IAHLO can keep the diversity better at the early stage and perform the local search more efficiently at the later stages of iterations. Besides, inspired by the intelligence quotient (IQ) of humans, a diverse human learning optimization algorithm (DHLLO) [38] is presented in which the control parameter pi is initialized by a Gaussian distribution and dynamically adjusted according to the pi value of the best individual. To further extend HLO, a novel hybrid-coded HLO (HcHLO) [39] is proposed to tackle mix-coded problems, in which real-coded parameters are optimized by a new continuous HLO (CHLO) [39] and the binary and discrete variables are handled by the binary learning operators of HLO. Until now, HLO has been successfully applied to engineering design problems [37], knapsack problems [40], optimal power flow calculation [41], extractive text summarization [42], financial markets forecasting [43], furnace flame recognition [44], scheduling problems [45], and intelligent control [46]. In particular, HLO obtained the best-so-far results on two well-studied sets of multidimensional knapsack problems, i.e., 5.100 and 10.100 [40], as well as the set of mixed-variable optimization problems [39] which implies the promising advantages of HLO.

In HLO, social learning adopts the greedy strategy to generate a new candidate, i.e., simply yet efficient copying the bit value from the SKD, which makes the algorithm easy to fall into local optimal. So, the relearning operator is introduced into HLO [40] to help the algorithm to escape from the local optimal. However, the relearning operator may destroy the existing optimal information, which further reduces the performance of the algorithm. On the other hand, the social learning of the HLO just learns from the global solution, which is inconsistent with the actual society. In real life, people could learn from the best solution of other individuals in the population. The Modified Binary Differential Evolution (MBDE, modified binary DE which is the previous work) [47] reverses the updating strategy of the standard Differential Evolution (DE) [7] so that DE can better keep the robustness of parameter settings and the diversity of the population to search for optimal bit information effectively. Therefore, this paper proposes two novel differential human learning optimization algorithms (DEHLOs), in which the strategy of MBDE is introduced into HLO to further improve the performance of DEHLOs algorithm by using the optimal information of other individuals.

This paper is organized as follows. Section 2 gives a brief review of the HLO and MBDE, respectively. Section 3 presents the concepts, operators, and implementation of the proposed DEHLO1 and DEHLO2 in detail. Section 4 verified that the proposed DEHLOs have significant advantages over the compared algorithms on the multidimensional knapsack problems. Finally, conclusions are drawn in Section 5.

2. Related Works

2.1. Human Learning Optimization. The HLO adopts the binary-coding framework, and consequently an individual in HLO is represented by a binary string as

\[ x_i = [x_{i1} \ x_{i2} \ \ldots \ x_{ij} \ \ldots \ x_{iM}], \]

\[ x_{ij} \in \{0, 1\}, \]

\[ 1 \leq j \leq N, \]

\[ 1 \leq i \leq M, \]

where \( x_i \) denotes the \( i \)-th individual, \( N \) is the size of the population, and \( M \) is the dimension of solutions. Each bit of binary string is initialized as “0” or “1” randomly.

Random learning operator: At the beginning of the learning process, people always keep exploring new strategies to solve problems because there is no prior knowledge [48]. Besides, an individual cannot fully replicate their previous experience and social knowledge because of the disturbance of external and forgetting. To emulate these phenomena of human random learning, the HLO executes
random learning operator (RLO) with a certain probability as

\[ x_{ij} = RE(0, 1) = \begin{cases} 0, & r_1 \leq 0.5, \\ 1, & \text{else} \end{cases} \]  

(2)

where \( r_1 \) is a stochastic number between 0 and 1.

Individual learning operator: Individual learning is defined as the ability to build knowledge through individual reflection about external stimuli and sources [49], which could be regarded as individual behavior in the trial and error process of continuous improvement. To mimic human individual learning, the best individual solutions are reserved in the individual knowledge database (IKD) as

\[
\text{IKD}_i = \begin{bmatrix}
\text{ikd}_{i1} \\
\text{ikd}_{i2} \\
\vdots \\
\text{ikd}_{ip} \\
\vdots \\
\text{ikd}_{ik}
\end{bmatrix} = \begin{bmatrix}
\text{ik}_{i1,1} & \text{ik}_{i1,2} & \cdots & \text{ik}_{i1,j} & \cdots & \text{ik}_{i1,M} \\
\text{ik}_{i2,1} & \text{ik}_{i2,2} & \cdots & \text{ik}_{i2,j} & \cdots & \text{ik}_{i2,M} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{ik}_{ip,1} & \text{ik}_{ip,2} & \cdots & \text{ik}_{ip,j} & \cdots & \text{ik}_{ip,M} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{ik}_{ik,1} & \text{ik}_{ik,2} & \cdots & \text{ik}_{ik,j} & \cdots & \text{ik}_{ik,M}
\end{bmatrix},
\]

(3)

where \( \text{IKD}_i \) denotes the individual knowledge database of the person \( i \), \( K \) is the predefined number of solutions saved in the IKD, and \( \text{ikd}_{ip} \) represents the \( p \)-th best experiment of the person \( i \). When HLO conducts the individual learning operation, (4) is operated to generate a new candidate solution.

\[ x_{ij} = \text{ik}_{ip,j}. \]  

(4)

Social learning operator: During social learning, people can acquire knowledge and experience from other individuals to further develop their ability directly or indirectly [50], and the efficiency and effectiveness of learning will be improved from experience share [51]. To simulate the social learning of humans in HLO, the social knowledge database (SKD) is adopted to reserve the best knowledge of the population as

\[
\text{SKD} = \begin{bmatrix}
\text{skd}_{11} & \text{skd}_{12} & \cdots & \text{skd}_{1j} & \cdots & \text{skd}_{1M} \\
\text{skd}_{21} & \text{skd}_{22} & \cdots & \text{skd}_{2j} & \cdots & \text{skd}_{2M} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{skd}_{q1} & \text{skd}_{q2} & \cdots & \text{skd}_{qj} & \cdots & \text{skd}_{qM} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{skd}_{s1} & \text{skd}_{s2} & \cdots & \text{skd}_{sj} & \cdots & \text{skd}_{sM}
\end{bmatrix},
\]

(5)

where \( \text{SKD} \) is the social knowledge database of the person \( i \), \( q \) is the solution in the SKD, \( q \) is a stochastic number; it decides which one of the SKD will be used. HLO performs social learning operator as (6) to generate the new candidate solution during the search process.

\[ x_{ij} = \text{sk}_{qij}. \]  

(6)

In summary, the above operators can be integrated and operated as

\[ x_{ij} = \begin{cases} RE(0, 1), & 0 \leq r \leq pr \\
\text{ik}_{ip,j}, & pr < r \leq pi, \\
\text{sk}_{qij}, & \text{else} \end{cases} \]  

(7)

where \( r \) is a stochastic number between 0 and 1, and \( pr \) and \( pi \) are the control parameters to determine the rates of HLO performing the three learning operators. Specifically, \( pr \), \( pi \), and \( 1-pi \) are the probabilities of random learning, individual learning, and social learning, respectively. Algorithm 1 describes the implementation of HLO, and more details can be found in [35].

2.2. Modified Binary Differential Evolution. The MBDE [47] adopts the binary-coding scheme and reserves the updating formulas of the standard DE, including the mutation operator, the crossover operator, and the selection operator. A probability estimation operator is introduced into MBDE to integrate the mutant operator.

Probability estimation operator: The probability estimation operator is used to build the probability distribution vector \( f(p_{ij}^{G}) \) of the parent individuals. The new mutant binary individual \( u_{ij}^{G} \) is generated from parents’ sampling randomly through the probability estimation vector as equations (8) and (9),

\[ f(p_{ij}^{G}) = \frac{1}{1 + e^{-(-2b+1+b2f)(p_{ij}^{G}+Fx(p_{ij}^{G}+p_{ij}^{G}-1)-0.5)}} \]  

(8)

\[ u_{ij}^{G} = \begin{cases} 1, & \text{if } \text{rand}() \leq f(p_{ij}^{G}) \\
0, & \text{otherwise,} \end{cases} \]  

(9)

where \( F \) is the scaling factor and \( b \) denotes the bandwidth factor which is a positive real constant; \( p_{ij}^{G}, p_{ij}^{G}, p_{ij}^{G} \) are the \( j \)-th bits of three randomly chosen individuals of \( G \) generation. \( \text{rand} \) is the random number; \( u_{ij}^{G} \) is the mutation of the current target individual according to the probability estimation vector \( f(p_{ij}^{G}) \).

Crossover operator: The crossover operator is used to produce the trailing individual by mixing the target individual and its mutant individual in MBDE. The trail vector \( v_{ij}^{G+1} \) can be obtained as

\[ v_{ij}^{G+1} = \begin{cases} u_{ij}^{G}, & \text{if } \text{rand}() \leq \text{CR} \text{ or } (j = \text{rand}i) \\
p_{ij}^{G}, & \text{otherwise,} \end{cases} \]  

(10)

where \( v_{ij}^{G} \) is the element of the trailing individual \( v_{ij} \) and \( \text{CR} \) is the crossover probability ranged \((0,1)\). The \( \text{rand} \) is a stochastic number uniformly distributed within \((0,1)\); \( \text{rand}i \) is a random integer with \(1, 2, \ldots, N\) where \( N \) is the length of the individual.
Selection: The selection operator is defined as the following equation:

$$x_i^{G+1} = \begin{cases} v_i^{G+1}, & \text{if } f(v_i^{G+1}) < f(x_i^G) \\ x_i^G, & \text{otherwise.} \end{cases}$$ (11)

As shown in (11), the MBDE reserved the selection operator of the standard DE. The trail individual $v_i$ replaces the target individual $x_i$ if its fitness value is better. Otherwise, the target individual is reserved for the next generation.

### 3. Differential Human Learning Optimization Algorithm

The three operators of HLO represent human learning randomly, learning from their own experience, and collective experience. However, people could learn from other excellent individuals in actual life. The operator of Differential Evolution (DE) is updated based on the optimal information of other individuals in the population. Inspired by this thought, this paper proposes the differential human learning optimization algorithm (DEHLO), in which the learning strategy of the MBDE is introduced into the HLO to develop a novel probability estimation operator for generating the offspring individuals. And this paper modified the HLO from two levels, i.e., individual and population, and named DEHLO1 and DEHLO2, respectively.

#### 3.1. DEHLO1

During the real learning process, different teams always adopt different strategies to search for the optimal solution for the same complex problem. To emulate the phenomena of dividing into groups, the operators of HLO and MBDE are utilized to generate the new solution in DEHLO1, so that the DEHLO1 algorithm could obtain the performance of HLO and MBDE. In DEHLO1, half of the population is updated by using the operator of HLO as (7) to generate a new solution, and the rest of the population is updated by using the mutation operator of MBDE as equations (8)–(10) to acquire the new individual. The DEHLO1 algorithm could possess both the advantages and shortcomings of the HLO and MBDE, and a dynamic competition strategy is used in DEHLO1 to avoid the disadvantages of the HLO and MBDE. At the beginning of a search, the population is divided into two equal parts which adopt the strategy of HLO and MBDE, respectively. With the progress of the search, the optimal fitness of the HLO and that of MBDE are compared under the specified iterations, and the individual proportion of better fitness value corresponding algorithm will be increased while the individual proportion of the other algorithm will be decreased correspondingly. Therefore, the DEHLO1 algorithm can adaptively compete and use the optimal learning strategy to search for the optimal solution, which effectively enhances the optimization ability of the algorithm. The procedure of DEHLO1 can be illustrated in Figure 1.

#### 3.2. DEHLO2

In real society, the same problem could be solved by using different approaches. But there might be a mainstream method in a certain period, and the mainstream method might be switched to another method due to the needs of the problem. Exactly as the way of human learning: “practice, knowledge, again practice, and again knowledge” [52], this form repeats itself in endless cycles, and with each cycle, the content of practice and knowledge rises to a higher level. This learning process is a vivid metaphor for the spiral. In DEHLO2, the HLO and the MBDE on the whole population are mixed and executed alternately by mimicking these learning behaviors. Firstly, the entire population adopts the HLO algorithm to search for the optimal solution. If it cannot be updated after a specified iteration, the learning process of HLO will be considered to encounter the
bottleneck; then the strategy of MBDE will be executed, which might make the algorithm escape from the bottleneck and vice versa: if the MBDE algorithm cannot find the optimal solution after certain iterations, the HLO algorithm will be executed to update the individual of the population. The flowchart of DEHLO2 is shown in Figure 2.

The procedure of DEHLO2 can be described as follows:

Step 1: Set control parameters, including the population size (popSize), the maximum generation (Gmax), the iterations of the search strategy, and the control parameters of HLO and MBDE; Step 2: Initialize the population randomly, and initialize the IKD and SKD; Step 3: Update the individual of the population as equations (8)–(11) of the MBDE algorithm; when the global optimal of MBDE cannot update after the set iterations, use the HLO algorithm to update the individual of the population as equation (7), and so forth, to generate the new population; Step 4: Calculate the fitness of the new individual and update the IKD and SKD; Step 5: If the terminal conditions are met, terminate the iteration; otherwise go to step 3; Step 6: Output the optimal solution.

3.3. Algorithm Complexity. DEHLO1 and DEHLO2 both have two phases, i.e., the population initialization and the iterative search. The running times of generating the initial population X, individual knowledge database (IKD), and social knowledge database (SKD) are $N \times M$, $N \times M$, and $(M + \log N)$, respectively, where $M$ and $N$ represent the dimension of solutions and the size of the population, respectively. So, the overall running time of the population initialization is $(2N + 1) \times M + \log N)$. During the iterative search of DEHLOs, generating new individuals costs time $N \times M$, performing crossover operation costs time $N \times M$, and updating the IKD and SKD costs times $N \times (M + \log K)$ and $(\log N + \log S + M)$, respectively, where $K$ is the predefined number of solutions saved in the IKD and $S$ denotes the size of the SKD.
Therefore, the running time of each iterative step is 
\((3N + 1) \times M + \log(N \times S \times K^N)\). Assume that the
maximum generation of DEHLOs algorithms is \(G\), so the
iterative search phase takes time 
\(G \times ((3N + 1) \times M + \log(N \times S \times K^N))\). In general, the
maximum generation \(G\) is much greater than \(N, K, \) and \(S,\)
and therefore the time complexity of DEHLOs is
\(O((3N + 1) \times G \times M)\).

4. Experimental Results and Discussions

To verify the performance of the two algorithms, i.e.,
DEHLO1 and DEHLO2, the proposed DEHLOs as well as
other six binary-coding optimization algorithms, i.e.,
Improved Adaptive Human Learning Optimization
(IAHLO) [37], Simple Human Learning Optimization
(SHLO) [34], Modified Binary Differential Evolution
(MBDE) [47], Novel Binary Differential Evolution
(NBDE) [53], Improved Binary Particle Swarm Optimiza-
tion (IBPSO) [54], and Novel Binary Gaining Sharing
Knowledge-based optimization (NBGSK) [17], were ap-
p lied to solve multidimensional knapsack problems [55].
The parameters \(pr, pi, CR, F, \) and \(b\) adopt the default
values of HLO and MBDE, and a set of fair parameters,
\(i.e., Cn \) and \(K\) of DEHLO1 and \(NM\) and \(NH\) of DEHLO2, is
chosen for DEHLO1 and DEHLO2 by trial and error in
this paper, that is, \(Cn = 100, K = 5\%, \) \(NM = 100,\) and
\(NH = 50.\) For a fair comparison, the recommended pa-
r ameters of all compared algorithms were used to tackle
the problem, which is listed in Table 1. Since DEHLOs are
designed for solving "single-objective" problems, the sizes
of IKDs and SKD are both set to 1 [35] to enhance search
efficiency and reduce the cost of computation. Besides, the
IKD of DEHLOs was reinitialized to further enhance the
diversity if it is not updated in the successive 100 gen-
erations. The computations were carried out using a PC
with Intel Core i5-6402P @ 2.8 GHz CPU and 8 GB RAM
while running Java 1.70 on Windows 8.1, 64-bit operating
system.

4.1. A Set of Multidimensional Knapsack Problems.

Knapsack problems have been studied intensively in the last
few decades, and multidimensional knapsack problems
(MKPs) [55] are multiconstrained problems instead of only
one constraint. It can be formulated as
Table 1: The recommended parameter values of all the algorithm.

| Algorithm | Parameters settings |
|-----------|---------------------|
| DEHLO1    | $pr = 5/M, pi = 0.85 + 2/M, CR = 0.2, F = 0.8, b = 20, Cn = 100, K = 5\%$ |
| DEHLO2    | $pr = 5/M, pi = 0.85 + 2/M, CR = 0.2, F = 0.8, b = 20, NM = 100, NH = 50$ |
| IAHLO [37]| $pr_{min} = 0.02, pr_{min2} = 0.05, pr_{max} = 0.15, pi = 0.85 + 2/M, Sp = 0.2 \times G_{max}$ |
| SHLO [34] | $pr = 5/M, pi = 0.85 + 2/M, CR = 0.2, F = 0.8, b = 20, NM = 100, NH = 50$ |
| MBDE [47] | $F = 1.0, CR = 0.5, filp = 0.2, U_{min} = 0.1 \times M, U_{max} = 0.9 \times M$ |
| NBDE [53] | $c_{min} = 0.0, c_{max} = 2.0, c_1 = 1.75, c_2 = 2.00, V_{min} = -6, V_{max} = 6$ |
| IBPSO [54]| $NP_{min} = 12, NP_{max} = 200, k_0 = 1.0, k_1 = 0.9, p = 0.1, \delta = 100, \lambda = -100$ |
| NBSGK [17]| $F = 1.0, CR = 0.5, filp = 0.2, U_{min} = 0.1 \times M, U_{max} = 0.9 \times M$ |

Note. $M$ is the dimension of solutions.

\[
\text{Max } f(x_1, x_2, \ldots, x_n) = \sum_{j=1}^{n} p_j x_j, \\
\text{s.t.} \quad \sum_{j=1}^{n} w_j x_j \leq C \\
x_j \in \{0, 1\}, j \in \{1, 2, \ldots, n\},
\]

(12)

where the binary decision variables $x_j$ are used to indicate whether the item $j$ is included in the knapsack or not. Without loss of generality, knapsack problems assume that all profits and weights are positive and all the weights are smaller than the capacity $C$. Since the maximal volume of the knapsack is limited in knapsack problems and the total volume of the items packed in the knapsack may exceed the constraint, the violation is unacceptable and must be checked. Thus, the penalty function method as (13) is adopted to deal with the infeasible solutions,

\[
\text{Max } F(x) = \sum_{j=1}^{n} p_j x_j - \beta \cdot \max \left(0, \sum_{j=1}^{n} w_j x_j - C\right), \\
\text{s.t.} \quad x_j \in \{0, 1\}, j = 1, 2, \ldots, n,
\]

(13)

where the penalty coefficient $\beta$ is a big constant which can lead the algorithm to escape from the infeasible area.

For a comprehensive comparison, a total of 30 multidimensional knapsack problems (MKPs), i.e., the instances 5.250.00-29, are adopted to test the performance of DEHLOs as well as the other metaheuristics. The population size and the maximum generation of all the algorithms are set to 100 and 5000. Four indicators, i.e., the best fitness value (Best), the mean best fitness value (Mean), the worst fitness value (Worst), and the standard deviation (Std), are used to evaluate the performance of DEHLOs. Each algorithm ran 100 times on all the problems independently. The numerical results are given in Table 2.

To better compare the performance of DEHLOs with other algorithms, the results of student’s $t$-test ($t$-test) and Wilcoxon signed-rank test ($W$-test) are also listed in Table 2 where “$t$” indicates that DEHLO2 is significantly better than the compared algorithms at the 95% confidence, “$-t$” represents that DEHLO2 is significantly worse than the compared algorithms, and “$0$” denotes that the performance of DEHLO2 is equivalent to other algorithms. Note that the $t$-test, a parameter test, needs to satisfy the normality and homogeneity of variance, while the $W$-test, a nonparametric test, does not need. Therefore, the $t$-test is more reliable when the Gaussian distribution assumption is met while the $W$-test would be more powerful when this assumption is violated [35]. For convenience, the results of the $t$-test and $W$-test are summarized in Table 3.

Table 2 shows that the proposed DEHLO2 obtains the best numerical results on 26 out of 30 instances. Besides, the summary results of the $t$-test show that DEHLO2 is obviously better than DEHLO1, IAHLO, HLO, MBDE, NBDE, IBPSO, and NBSGK on 21, 30, 30, 24, 30, 30, and 30 out of 30 instances. And $W$-test results also show that DEHLO2 is significantly superior to DEHLO1, IAHLO, HLO, MBDE, NBDE, IBPSO, and NBSGK on 21, 30, 30, 24, 30, 30, and 30 out of 30 instances. Based on Tables 2 and 3, it is fair to say that DEHLO2 outperforms other algorithms on the multidimensional knapsack problems.

4.2. Another Set of Multidimensional Knapsack Problems.

To further verify the performance of the proposed algorithm, another set of multidimensional knapsack problems [53] is adopted as the test benchmark, which is listed in Table 4. The results of all algorithms on the MKPs are given in Table 5 where the best solutions have been highlighted in bold. And the summary results of the $t$-test and $W$-test are summarized in Table 6. To analyze the superiority of the proposed DEHLOs, the convergence curves of all algorithms on the MKPs are drawn in Figure 3.

It can be seen from Tables 5 and 6 and Figure 3 that DEHLO2 provides the best results and obtained the minimum error among the other algorithms. Specifically, DEHLO2 attains the best numerical results on 13 out of 14 instances and is only inferior to DEHLO1 on the instance 5.500.01. The summarized $t$-test and $W$-test results indicate that the proposed DEHLO2 significantly surpasses IAHLO, HLO, MBDE, NBDE, IBPSO, and NBSGK on all the instances while it is better than, competitive to, and worse than DEHLO1 on 10, 4, and 0 instances on the $t$-test and 11, 3, and 0 instances on the $W$-test, respectively. Furthermore, Figure 3 shows that the proposed DEHLOs algorithm has a faster convergence rate and higher solution accuracy than the compared algorithms. Therefore, with the introduction of the strategy of MBDE, the optimization performance of the DEHLOs algorithm is significantly enhanced.
Table 2: The results of all algorithms on the multidimensional knapsack problems.

| Problem | Algorithm | Best | Mean   | Worst | Std    | t-test | W-test |
|---------|-----------|------|--------|-------|--------|--------|--------|
| 5.250.0| DEHLO2    | 59208| 59071.35| 58968 | 45.81  | —      | —      |
|         | DEHLO1    | 59196| 59054.47| 58941 | 46.52  | 1      | 1      |
|         | IAHLO     | 58541| 58145.82| 57831 | 130.21 | 1      | 1      |
|         | SHLO      | 59170| 58990.19| 58845 | 65.47  | 1      | 1      |
|         | MBDE      | 58900| 58765.98| 58643 | 47.17  | 1      | 1      |
|         | NBDE      | 58745| 58269.03| 57715 | 229.58 | 1      | 1      |
|         | IBPSO     | 58935| 58521.45| 57942 | 188.27 | 1      | 1      |
|         | NBGSK     | 57486| 56579.44| 55336 | 411.20 | 1      | 1      |
|         | DEHLO2    | 61446| 61381.94| 61268 | 50.44  | —      | —      |
|         | DEHLO1    | 61377| 61308.04| 61209 | 46.25  | 1      | 1      |
|         | IAHLO     | 60550| 60171.68| 59695 | 158.28 | 1      | 1      |
|         | SHLO      | 61435| 61274.52| 61138 | 62.09  | 1      | 1      |
|         | MBDE      | 61139| 61096.41| 60969 | 40.32  | 1      | 1      |
|         | NBDE      | 61078| 60269.88| 59566 | 380.60 | 1      | 1      |
|         | IBPSO     | 61213| 60795.96| 60073 | 214.59 | 1      | 1      |
|         | NBGSK     | 59324| 58075.21| 57806 | 516.38 | 1      | 1      |
|         | DEHLO2    | 62057| 61959.72| 61876 | 45.92  | —      | —      |
|         | DEHLO1    | 62028| 61946.21| 61855 | 43.06  | 1      | 1      |
|         | IAHLO     | 61013| 60599.87| 60309 | 154.33 | 1      | 1      |
|         | SHLO      | 62008| 61865.90| 61682 | 54.89  | 1      | 1      |
|         | MBDE      | 62057| 61937.51| 61850 | 41.77  | 1      | 1      |
|         | NBDE      | 61417| 60780.85| 60265 | 225.67 | 1      | 1      |
|         | IBPSO     | 61640| 61166.56| 60485 | 240.18 | 1      | 1      |
|         | NBGSK     | 60205| 59110.06| 58296 | 395.35 | 1      | 1      |
|         | DEHLO2    | 59343| 59235.19| 59143 | 39.21  | —      | —      |
|         | DEHLO1    | 59315| 59233.84| 59123 | 41.67  | 0      | 0      |
|         | IAHLO     | 58615| 58294.18| 58042 | 117.85 | 1      | 1      |
|         | SHLO      | 59304| 59162.28| 58988 | 61.14  | 1      | 1      |
|         | MBDE      | 59334| 59238.46| 59158 | 40.94  | 0      | 0      |
|         | NBDE      | 58760| 58388.26| 57986 | 184.56 | 1      | 1      |
|         | IBPSO     | 59168| 58752.84| 58406 | 163.98 | 1      | 1      |
|         | NBGSK     | 57855| 57014.16| 56243 | 340.69 | 1      | 1      |
|         | DEHLO2    | 58913| 58799.33| 58665 | 44.29  | —      | —      |
|         | DEHLO1    | 58935| 58791.13| 58696 | 47.27  | 0      | 0      |
|         | IAHLO     | 57865| 57540.15| 57145 | 143.82 | 1      | 1      |
|         | SHLO      | 58878| 58703.24| 58564 | 60.21  | 1      | 1      |
|         | MBDE      | 58877| 58758.46| 58631 | 44.55  | 1      | 1      |
|         | NBDE      | 58176| 57666.00| 57090 | 239.22 | 1      | 1      |
|         | IBPSO     | 58608| 58171.05| 57670 | 190.88 | 1      | 1      |
|         | NBGSK     | 56972| 55896.45| 55107 | 417.30 | 1      | 1      |
|         | DEHLO2    | 60005| 59884.27| 59786 | 43.45  | —      | —      |
|         | DEHLO1    | 59980| 59865.34| 59752 | 52.38  | 1      | 1      |
|         | IAHLO     | 58760| 58457.12| 57975 | 149.44 | 1      | 1      |
|         | SHLO      | 59969| 59784.46| 59645 | 65.58  | 1      | 1      |
|         | MBDE      | 59945| 59842.43| 59696 | 47.81  | 1      | 1      |
|         | NBDE      | 59220| 58724.95| 58246 | 209.78 | 1      | 1      |
|         | IBPSO     | 59714| 59151.86| 58576 | 258.90 | 1      | 1      |
|         | NBGSK     | 58032| 56999.98| 56025 | 441.22 | —      | —      |
|         | DEHLO2    | 60363| 60300.41| 60222 | 29.38  | —      | —      |
|         | DEHLO1    | 60358| 60281.02| 60199 | 32.38  | 1      | 1      |
|         | IAHLO     | 59378| 58953.02| 58536 | 163.95 | 1      | 1      |
|         | SHLO      | 60353| 60221.83| 59664 | 58.84  | 1      | 1      |
|         | MBDE      | 60341| 60295.39| 60216 | 31.27  | 0      | 0      |
|         | NBDE      | 59968| 59306.75| 58385 | 334.58 | 1      | 1      |
|         | IBPSO     | 60128| 59697.42| 58954 | 210.21 | 1      | 1      |
|         | NBGSK     | 58256| 57192.39| 55838 | 529.42 | 1      | 1      |
Table 2: Continued.

| Problem | Algorithm | Best Mean | Worst Std | t-test | W-test |
|---------|-----------|-----------|-----------|--------|--------|
| 5.250.7 | DEHLO2    | 61443     | 61364.97  | 61258  | 38.19  | —      | —      |
|         | DEHLO1    | 61443     | 61354.31  | 61227  | 45.12  | 0      | 0      |
|         | IAHLO     | 61443     | 61276.94  | 61141  | 61.80  | 1      | 1      |
|         | SHLO      | 61443     | 61329.36  | 61185  | 45.60  | 1      | 1      |
|         | MBDE      | 61443     | 61072.33  | 59586  | 285.43 | 1      | 1      |
|         | NBDE      | 61915     | 60793.69  | 60209  | 183.45 | 1      | 1      |
|         | IBPSO     | 59397     | 58110.16  | 57055  | 496.41 | 1      | 1      |
|         | NBGSK     | 61885     | 61783.26  | 61698  | 37.56  | —      | —      |
|         | DEHLO1    | 61873     | 61776.09  | 61688  | 38.60  | 0      | 0      |
|         | IAHLO     | 61849     | 61711.02  | 61579  | 53.10  | 1      | 1      |
|         | SHLO      | 61849     | 61750.80  | 61627  | 36.37  | 1      | 1      |
|         | MBDE      | 61332     | 60640.49  | 59841  | 293.99 | 1      | 1      |
|         | NBDE      | 61626     | 61116.24  | 60530  | 208.09 | 1      | 1      |
|         | IBPSO     | 59896     | 58378.40  | 57110  | 608.34 | 1      | 1      |
|         | NBGSK     | 58906     | 58825.17  | 58768  | 26.75  | —      | —      |
|         | DEHLO1    | 58915     | 58818.13  | 58755  | 31.43  | 0      | 0      |
|         | IAHLO     | 58865     | 58759.37  | 58618  | 51.08  | 1      | 1      |
|         | SHLO      | 58918     | 58831.57  | 58695  | 43.94  | 0      | 0      |
|         | MBDE      | 58651     | 58235.22  | 57531  | 240.98 | 1      | 1      |
|         | NBDE      | 58803     | 58407.19  | 57940  | 165.90 | 1      | 1      |
|         | IBPSO     | 57454     | 56359.20  | 55279  | 444.44 | 1      | 1      |
|         | NBGSK     | 109031    | 108945.41 | 108878 | 35.61  | —      | —      |
|         | DEHLO1    | 109051    | 108935.47 | 108850 | 37.12  | 0      | 0      |
|         | IAHLO     | 109013    | 108879.42 | 108723 | 49.85  | 1      | 1      |
|         | SHLO      | 109047    | 108930.03 | 108875 | 29.74  | 1      | 1      |
|         | MBDE      | 108652    | 108235.63 | 107873 | 188.02 | 1      | 1      |
|         | NBDE      | 108820    | 108358.03 | 107786 | 183.12 | 1      | 1      |
|         | IBPSO     | 107078    | 105016.71 | 102248 | 830.71 | 1      | 1      |
|         | NBGSK     | 109788    | 109724.02 | 109671 | 30.13  | —      | —      |
|         | DEHLO1    | 109821    | 109715.09 | 109620 | 34.97  | 0      | 0      |
|         | IAHLO     | 108834    | 108389.65 | 108106 | 157.90 | 1      | 1      |
|         | SHLO      | 109778    | 109643.79 | 109526 | 55.61  | 1      | 1      |
|         | MBDE      | 109821    | 109731.71 | 109666 | 33.94  | 0      | 0      |
|         | NBDE      | 109407    | 109035.96 | 108574 | 182.36 | 1      | 1      |
|         | IBPSO     | 109498    | 109134.90 | 108575 | 203.18 | 1      | 1      |
|         | NBGSK     | 107415    | 105664.99 | 102848 | 960.86 | 1      | 1      |
|         | DEHLO2    | 108480    | 108421.36 | 108341 | 31.26  | —      | —      |
|         | DEHLO1    | 108481    | 108391.59 | 108271 | 44.11  | 1      | 1      |
|         | IAHLO     | 107602    | 107248.20 | 106838 | 147.38 | 1      | 1      |
|         | SHLO      | 108472    | 108308.74 | 108154 | 63.91  | 1      | 1      |
|         | MBDE      | 108504    | 108402.61 | 108317 | 36.50  | 1      | 1      |
|         | NBDE      | 108108    | 107752.60 | 107255 | 177.67 | 1      | 1      |
|         | IBPSO     | 108202    | 107802.48 | 107355 | 188.54 | 1      | 1      |
|         | NBGSK     | 106129    | 104260.07 | 101348 | 956.81 | 1      | 1      |
|         | DEHLO2    | 109352    | 109291.79 | 109229 | 28.48  | —      | —      |
|         | DEHLO1    | 109356    | 109279.64 | 109210 | 31.72  | 1      | 1      |
|         | IAHLO     | 108392    | 108113.52 | 107871 | 117.43 | 1      | 1      |
|         | SHLO      | 109325    | 109220.67 | 109081 | 45.88  | 1      | 1      |
|         | MBDE      | 109351    | 109276.32 | 109208 | 31.63  | 1      | 1      |
|         | NBDE      | 109124    | 108621.42 | 108222 | 192.78 | 1      | 1      |
|         | IBPSO     | 109113    | 108650.60 | 107755 | 230.00 | 1      | 1      |
|         | NBGSK     | 107356    | 105919.36 | 104001 | 825.83 | 1      | 1      |
Table 2: Continued.

| Problem | Algorithm | Best | Mean | Worst | Std | t-test | W-test |
|---------|-----------|------|------|-------|-----|--------|--------|
| 5.250.14 | DEHLO2 | 110654 | 110559.06 | 110476 | 37.70 | — | — |
|         | DEHLO1 | 110639 | 110537.86 | 110459 | 35.69 | 1 | 1 |
|         | IAHLO | 109510 | 109124.47 | 108774 | 150.24 | 1 | 1 |
|         | SHLO | 110602 | 110469.79 | 110342 | 56.66 | 1 | 1 |
|         | MBDE | 110632 | 110553.12 | 110462 | 33.98 | 0 | 0 |
|         | NBDE | 110256 | 109752.20 | 109320 | 231.02 | 1 | 1 |
|         | IBPSO | 110359 | 109948.59 | 109246 | 222.17 | 1 | 1 |
|         | NBGSK | 108155 | 106374.74 | 104159 | 818.68 | 1 | 1 |
| 5.250.15 | DEHLO2 | 110202 | 110108.40 | 110006 | 36.40 | — | — |
|         | DEHLO1 | 110191 | 110092.18 | 109992 | 42.80 | 1 | 1 |
|         | IAHLO | 109213 | 108875.59 | 108564 | 125.81 | 1 | 1 |
|         | SHLO | 110136 | 110005.03 | 109797 | 58.11 | 1 | 1 |
|         | MBDE | 110175 | 110078.90 | 110001 | 40.38 | 1 | 1 |
|         | NBDE | 109892 | 109405.00 | 108941 | 221.35 | 1 | 1 |
|         | IBPSO | 109885 | 109526.95 | 108827 | 227.84 | 1 | 1 |
|         | NBGSK | 106879 | 106311.66 | 103800 | 828.51 | 1 | 1 |
| 5.250.16 | DEHLO2 | 108990 | 108921.89 | 108852 | 29.26 | — | — |
|         | DEHLO1 | 109002 | 108905.32 | 108811 | 33.75 | 1 | 1 |
|         | IAHLO | 107916 | 107558.11 | 107196 | 146.05 | 1 | 1 |
|         | SHLO | 108987 | 108837.38 | 108712 | 52.22 | 1 | 1 |
|         | MBDE | 109002 | 108914.46 | 108837 | 25.72 | 1 | 0 |
|         | NBDE | 108638 | 108251.11 | 107792 | 185.92 | 1 | 1 |
|         | IBPSO | 108741 | 108383.70 | 107829 | 186.15 | 1 | 1 |
|         | NBGSK | 106606 | 105029.12 | 103304 | 813.45 | 1 | 1 |
| 5.250.17 | DEHLO2 | 108798 | 108880.64 | 108798 | 38.02 | — | — |
|         | DEHLO1 | 108799 | 108765.48 | 108794 | 40.73 | 0 | 0 |
|         | IAHLO | 107931 | 107553.41 | 107164 | 154.42 | 1 | 1 |
|         | SHLO | 108942 | 108807.05 | 108662 | 58.16 | 1 | 1 |
|         | MBDE | 108931 | 108861.85 | 108756 | 33.72 | 1 | 1 |
|         | NBDE | 108555 | 108011.37 | 107658 | 197.88 | 1 | 1 |
|         | IBPSO | 108695 | 108306.38 | 107821 | 190.34 | 1 | 1 |
|         | NBGSK | 106414 | 105429.29 | 102497 | 910.07 | 1 | 1 |
| 5.250.18 | DEHLO2 | 109944 | 109831.24 | 109759 | 33.43 | — | — |
|         | DEHLO1 | 109908 | 109821.03 | 109746 | 37.57 | 0 | 0 |
|         | IAHLO | 109171 | 108759.55 | 108514 | 122.98 | 1 | 1 |
|         | SHLO | 109858 | 109722.03 | 109575 | 62.95 | 1 | 1 |
|         | MBDE | 109956 | 109814.82 | 109654 | 57.86 | 1 | 1 |
|         | NBDE | 109703 | 109325.19 | 108829 | 164.61 | 1 | 1 |
|         | IBPSO | 109647 | 109241.38 | 108573 | 212.85 | 1 | 1 |
|         | NBGSK | 108304 | 106184.02 | 103343 | 1013.96 | 1 | 1 |
| 5.250.19 | DEHLO2 | 107023 | 106954.49 | 106871 | 27.69 | — | — |
|         | DEHLO1 | 106999 | 106927.56 | 106833 | 27.89 | 1 | 1 |
|         | IAHLO | 106167 | 105667.04 | 105270 | 154.47 | 1 | 1 |
|         | SHLO | 107009 | 106872.17 | 106786 | 49.62 | 1 | 1 |
|         | MBDE | 107023 | 106952.87 | 106844 | 27.00 | 0 | 0 |
|         | NBDE | 106694 | 106226.87 | 105724 | 248.58 | 1 | 1 |
|         | IBPSO | 106679 | 106364.73 | 105897 | 181.83 | 1 | 1 |
|         | NBGSK | 104423 | 102663.29 | 99947 | 962.96 | 1 | 1 |
| 5.250.20 | DEHLO2 | 149623 | 149543.31 | 149484 | 29.41 | — | — |
|         | DEHLO1 | 149634 | 149533.39 | 149468 | 34.64 | 1 | 1 |
|         | IAHLO | 148681 | 148320.02 | 147978 | 140.74 | 1 | 1 |
|         | SHLO | 149573 | 149470.07 | 149382 | 41.14 | 1 | 1 |
|         | MBDE | 149539 | 149342.64 | 149032 | 110.93 | 1 | 1 |
|         | NBDE | 148884 | 148622.34 | 148307 | 123.10 | 1 | 1 |
|         | IBPSO | 149306 | 148955.74 | 148331 | 181.61 | 1 | 1 |
|         | NBGSK | 147760 | 146521.63 | 143993 | 672.83 | 1 | 1 |
| Problem | Algorithm | Best | Mean | Worst | Std | t-test | W-test |
|---------|-----------|------|------|-------|-----|--------|--------|
| 5.250.21 | DEHLO2 | 155940 | 155897.43 | 155838 | 23.65 | — | — |
|         | DEHLO1 | 155944 | 155875.40 | 155806 | 30.46 | 1 | 1 |
|         | IAHLO | 155065 | 154738.49 | 154326 | 144.47 | 1 | 1 |
|         | SHLO | 155890 | 155820.99 | 155677 | 41.30 | 1 | 1 |
|         | MBDE | 155898 | 155721.54 | 155546 | 99.55 | 1 | 1 |
|         | NBDE | 155431 | 155258.09 | 154912 | 91.96 | 1 | 1 |
|         | IBPSO | 155691 | 155382.19 | 154855 | 175.20 | 1 | 1 |
|         | NBGSK | 154255 | 152302.20 | 150353 | 840.25 | 1 | 1 |
| 5.250.22 | DEHLO2 | 149301 | 149239.94 | 149187 | 27.44 | — | — |
|         | DEHLO1 | 149301 | 149218.06 | 149147 | 32.76 | 1 | 1 |
|         | IAHLO | 148471 | 148143.82 | 147699 | 46.26 | 1 | 1 |
|         | SHLO | 149301 | 149172.26 | 149075 | 45.63 | 1 | 1 |
|         | MBDE | 149229 | 149013.95 | 148749 | 114.15 | 1 | 1 |
|         | NBDE | 148639 | 148381.64 | 147994 | 137.00 | 1 | 1 |
|         | IBPSO | 149091 | 148772.64 | 148339 | 160.97 | 1 | 1 |
|         | NBGSK | 147441 | 146336.57 | 144699 | 605.23 | 1 | 1 |
| 5.250.23 | DEHLO2 | 152130 | 152084.27 | 152009 | 20.64 | — | — |
|         | DEHLO1 | 152124 | 152070.18 | 151999 | 24.23 | 1 | 1 |
|         | IAHLO | 151098 | 150707.83 | 150292 | 169.01 | 1 | 1 |
|         | SHLO | 152114 | 152007.41 | 151871 | 49.62 | 1 | 1 |
|         | MBDE | 152073 | 151899.50 | 151719 | 90.65 | 1 | 1 |
|         | NBDE | 151686 | 151389.37 | 150953 | 159.61 | 1 | 1 |
|         | IBPSO | 151898 | 151463.97 | 151054 | 178.66 | 1 | 1 |
|         | NBGSK | 150151 | 148785.67 | 146882 | 693.66 | 1 | 1 |
| 5.250.24 | DEHLO2 | 150353 | 150297.60 | 150229 | 20.04 | — | — |
|         | DEHLO1 | 150351 | 150277.77 | 150199 | 30.33 | 1 | 1 |
|         | IAHLO | 149405 | 148986.69 | 148598 | 153.20 | 1 | 1 |
|         | SHLO | 150310 | 150235.86 | 150136 | 40.98 | 1 | 1 |
|         | MBDE | 150353 | 150096.92 | 149785 | 137.68 | 1 | 1 |
|         | NBDE | 149678 | 149484.92 | 149221 | 103.73 | 1 | 1 |
|         | IBPSO | 150095 | 149672.29 | 148886 | 212.06 | 1 | 1 |
|         | NBGSK | 148524 | 146966.44 | 145005 | 709.20 | 1 | 1 |
| 5.250.25 | DEHLO2 | 150045 | 149978.52 | 149870 | 31.92 | — | — |
|         | DEHLO1 | 150045 | 149954.51 | 149868 | 38.76 | 1 | 1 |
|         | IAHLO | 149308 | 148912.90 | 148632 | 131.50 | 1 | 1 |
|         | SHLO | 149983 | 149871.36 | 149720 | 53.00 | 1 | 1 |
|         | MBDE | 149918 | 149742.86 | 149387 | 99.89 | 1 | 1 |
|         | NBDE | 149352 | 149183.69 | 148878 | 83.20 | 1 | 1 |
|         | IBPSO | 149895 | 149532.97 | 148973 | 165.35 | 1 | 1 |
|         | NBGSK | 148482 | 147229.26 | 144434 | 827.86 | 1 | 1 |
| 5.250.26 | DEHLO2 | 148574 | 148507.49 | 148446 | 24.57 | — | — |
|         | DEHLO1 | 148553 | 148499.85 | 148425 | 28.71 | 1 | 1 |
|         | IAHLO | 147764 | 147416.29 | 147078 | 146.96 | 1 | 1 |
|         | SHLO | 148542 | 148445.73 | 148306 | 46.31 | 1 | 1 |
|         | MBDE | 148512 | 148362.46 | 148147 | 91.14 | 1 | 1 |
|         | NBDE | 148199 | 147972.07 | 147504 | 106.02 | 1 | 1 |
|         | IBPSO | 148405 | 148015.40 | 147518 | 206.74 | 1 | 1 |
|         | NBGSK | 146709 | 145373.45 | 143358 | 782.85 | 1 | 1 |
| 5.250.27 | DEHLO2 | 149767 | 149746.97 | 149714 | 14.84 | — | — |
|         | DEHLO1 | 149782 | 149736.77 | 149684 | 20.57 | 1 | 1 |
|         | IAHLO | 148940 | 148436.47 | 147929 | 186.75 | 1 | 1 |
|         | SHLO | 149767 | 149694.35 | 149579 | 36.13 | 1 | 1 |
|         | MBDE | 149767 | 149523.50 | 149257 | 103.60 | 1 | 1 |
|         | NBDE | 148887 | 148601.80 | 148006 | 185.60 | 1 | 1 |
|         | IBPSO | 149628 | 149230.72 | 148773 | 172.73 | 1 | 1 |
|         | NBGSK | 147575 | 146086.06 | 144103 | 771.83 | 1 | 1 |
Table 2: Continued.

| Problem | Algorithm | Best | Mean       | Worst   | Std  | t-test | W-test |
|---------|-----------|------|------------|---------|------|--------|--------|
| 5.250.28 | DEHLO2    | 155075 | 155012.04  | 154961  | 25.70|        |        |
|         | DEHLO1    | 155075 | 154993.48  | 154914  | 31.91| 1      | 1      |
|         | IAHLO     | 154135 | 153707.79  | 153291  | 165.97| 1      | 1      |
|         | SHLO      | 155029 | 154927.58  | 154814  | 38.04| 1      | 1      |
|         | MBDE      | 155032 | 154900.12  | 154715  | 69.24| 1      | 1      |
|         | NBDE      | 154664 | 154414.09  | 153963  | 144.58| 1      | 1      |
|         | IBPSO     | 154806 | 155414.11  | 153986  | 160.66| 1      | 1      |
|         | NBGSK     | 153292 | 151840.26  | 149513  | 704.28| 1      | 1      |
| 5.250.29 | DEHLO2    | 154668 | 154640.60  | 154590  | 17.70|        |        |
|         | DEHLO1    | 154668 | 154623.56  | 154542  | 21.97| 1      | 1      |
|         | IAHLO     | 153751 | 153406.13  | 153011  | 140.95| 1      | 1      |
|         | SHLO      | 154668 | 154562.83  | 154434  | 52.21| 1      | 1      |
|         | MBDE      | 154653 | 154460.96  | 154239  | 76.42| 1      | 1      |
|         | NBDE      | 154298 | 154056.73  | 153720  | 108.12| 1      | 1      |
|         | IBPSO     | 154641 | 154136.17  | 153595  | 209.88| 1      | 1      |
|         | NBGSK     | 152952 | 151403.32  | 148808  | 859.73| 1      | 1      |

Table 3: The summary results of the t-test and W-test on multidimensional knapsack problems.

| Metric | DEHLO2 | DEHLO1 | IAHLO | SHLO | MBDE | NBDE | IBPSO | NBGSK |
|--------|--------|--------|-------|------|------|------|-------|-------|
| t-test | 1      | 21     | 30    | 30   | 24   | 30   | 30    | 30    |
| W-test | 0      | 9      | 0     | 0    | 6    | 0    | 0     | 0     |

Table 4: The multidimensional knapsack problem benchmarks.

| Benchmark NO. | Benchmark name | Best known | n | M |
|---------------|----------------|------------|---|---|
| 1             | mknapcb1–5.100–00 | 244381    | 100 | 5 |
| 2             | mknapcb1–5.100–01 | 24274     | 100 | 5 |
| 3             | mknapcb2–5.250–00 | 59312     | 250 | 5 |
| 4             | mknapcb2–5.250–01 | 61472     | 250 | 5 |
| 5             | mknapcb3–5.500–00 | 120130    | 500 | 5 |
| 6             | mknapcb3–5.500–01 | 117837    | 500 | 5 |
| 7             | mknapcb4–10.100–00 | 23064    | 100 | 10 |
| 8             | mknapcb4–10.100–01 | 22801    | 100 | 10 |
| 9             | mknapcb5–10.250–00 | 59187    | 250 | 10 |
| 10            | mknapcb5–10.250–01 | 58662    | 250 | 10 |
| 11            | mknapcb6–10.500–00 | 117726   | 500 | 10 |
| 12            | mknapcb6–10.500–01 | 119139   | 500 | 10 |
| 13            | mknapcb8–30.250–29 | 150038   | 250 | 30 |
| 14            | mknapcb9–30.500–29 | 301021   | 500 | 30 |

Table 5: The results of all algorithms on the multidimensional knapsack problems.

| Problem | Algorithm | Best | Mean       | Worst   | Std  | t-test | W-test |
|---------|-----------|------|------------|---------|------|--------|--------|
| NO.1    | DEHLO2    | 24381 | 24373.92   | 24337   | 8.95 |        |        |
|         | DEHLO1    | 24381 | 24364.37   | 24315   | 18.76| 1      | 1      |
|         | IAHLO     | 24381 | 24297.24   | 24187   | 41.30| 1      | 1      |
|         | SHLO      | 24357 | 24347.09   | 24292   | 14.41| 1      | 1      |
|         | MBDE      | 24332 | 24327.72   | 24288   | 6.59 | 1      | 1      |
|         | NBDE      | 24381 | 24285.06   | 24185   | 42.22| 1      | 1      |
|         | IBPSO     | 24381 | 24177.04   | 23862   | 106.18| 1      | 1      |
|         | NBGSK     | 24047 | 23721.87   | 23395   | 140.08| 1      | 1      |
| Problem | Algorithm | Best   | Mean   | Worst  | Std   | t-test | W-test |
|---------|-----------|--------|--------|--------|-------|--------|--------|
| NO.2    | DEHLO2    | 24274  | 24274.00| 24274 | 0.00  | —      | —      |
|         | DEHLO1    | 24274  | 24262.90| 24149 | 35.50 | 1      | 1      |
|         | IAHL0     | 24274  | 24136.40| 23911 | 89.93 | 1      | 1      |
|         | SHLO      | 24250  | 24243.75| 24125 | 27.38 | 1      | 1      |
|         | MBDE      | 24225  | 24222.67| 24101 | 16.43 | 1      | 1      |
|         | NBDE      | 24274  | 24194.46| 23878 | 95.50 | 1      | 1      |
|         | IBPSO     | 24274  | 23964.76| 23575 | 143.60| 1      | 1      |
|         | NBGSK     | 23893  | 23388.82| 22930 | 174.22| 1      | 1      |
| NO.3    | DEHLO2    | 59208  | 59071.35| 58968 | 45.81 | —      | —      |
|         | DEHLO1    | 59196  | 59054.47| 58941 | 46.52 | 1      | 1      |
|         | IAHL0     | 58541  | 58145.82| 57831 | 130.21| 1      | 1      |
|         | SHLO      | 59170  | 58990.19| 58845 | 65.47 | 1      | 1      |
|         | MBDE      | 58900  | 58765.98| 58643 | 47.17 | 1      | 1      |
|         | NBDE      | 58745  | 58269.03| 57715 | 229.58| 1      | 1      |
|         | IBPSO     | 58935  | 58521.45| 57942 | 188.27| 1      | 1      |
|         | NBGSK     | 57486  | 56579.44| 55336 | 411.20| 1      | 1      |
| NO.4    | DEHLO2    | 61466  | 61381.94| 61268 | 50.44 | —      | —      |
|         | DEHLO1    | 61377  | 61308.04| 61209 | 46.25 | 1      | 1      |
|         | IAHL0     | 60550  | 60117.68| 59695 | 158.28| 1      | 1      |
|         | SHLO      | 61435  | 61274.52| 61138 | 62.09 | 1      | 1      |
|         | MBDE      | 61139  | 61096.41| 60969 | 40.32 | 1      | 1      |
|         | NBDE      | 61078  | 60269.88| 59566 | 380.60| 1      | 1      |
|         | IBPSO     | 61213  | 60795.96| 60073 | 214.59| 1      | 1      |
|         | NBGSK     | 59324  | 58075.21| 56888 | 516.38| 1      | 1      |
| NO.5    | DEHLO2    | 119661 | 119457.17| 119243| 75.81 | —      | —      |
|         | DEHLO1    | 119588 | 119409.80| 119223| 80.53 | 0      | 0      |
|         | IAHL0     | 116330 | 115483.56| 114961| 249.75| 1      | 1      |
|         | SHLO      | 119582 | 119303.70| 119008| 110.02| 1      | 1      |
|         | MBDE      | 119372 | 119153.95| 118985| 93.96 | 1      | 1      |
|         | NBDE      | 116080 | 115220.19| 114501| 406.61| 1      | 1      |
|         | IBPSO     | 118959 | 118292.17| 117429| 361.22| 1      | 1      |
|         | NBGSK     | 115208 | 112449.12| 111021| 919.05| 1      | 1      |
| NO.6    | DEHLO2    | 117579 | 117494.62| 117356| 44.63 | —      | —      |
|         | DEHLO1    | 117662 | 117498.59| 117359| 54.85 | 1      | 1      |
|         | IAHL0     | 114647 | 113959.66| 113396| 248.20| 1      | 1      |
|         | SHLO      | 117543 | 117345.74| 117099| 89.98 | 1      | 1      |
|         | MBDE      | 117501 | 117326.38| 117141| 80.53 | 1      | 1      |
|         | NBDE      | 115477 | 113941.85| 112855| 586.89| 1      | 1      |
|         | IBPSO     | 116956 | 116314.68| 115314| 330.61| 1      | 1      |
|         | NBGSK     | 113416 | 111349.51| 109234| 887.34| 1      | 1      |
| NO.7    | DEHLO2    | 23064  | 23054.91| 23026 | 3.19  | —      | —      |
|         | DEHLO1    | 23057  | 23052.57| 22959 | 11.49 | 0      | 1      |
|         | IAHL0     | 23055  | 23040.13| 22901 | 36.68 | 1      | 1      |
|         | SHLO      | 23041  | 23032.01| 23027 | 1.17  | 1      | 1      |
|         | MBDE      | 23018  | 23009.34| 23009 | 1.36  | 1      | 1      |
|         | NBDE      | 23064  | 23029.70| 22845 | 51.32 | 1      | 1      |
|         | IBPSO     | 23055  | 22663.90| 22574 | 117.69| 1      | 1      |
|         | NBGSK     | 22876  | 22593.57| 22282 | 113.85| 1      | 1      |
| NO.8    | DEHLO2    | 22801  | 22714.70| 22541 | 60.08 | —      | —      |
|         | DEHLO1    | 22801  | 22713.56| 22547 | 60.03 | 0      | 0      |
|         | IAHL0     | 22739  | 22517.76| 22344 | 78.27 | 1      | 1      |
|         | SHLO      | 22801  | 22690.79| 22502 | 79.50 | 1      | 1      |
|         | MBDE      | 22755  | 22666.18| 22539 | 53.80 | 1      | 1      |
|         | NBDE      | 22801  | 22478.81| 22323 | 77.18 | 1      | 1      |
|         | IBPSO     | 22725  | 22386.50| 21994 | 127.65| 1      | 1      |
|         | NBGSK     | 22422  | 22067.62| 21844 | 113.60| 1      | 1      |
Table 5: Continued.

| Problem | Algorithm  | Best     | Mean       | Worst      | Std      | t-test | W-test |
|---------|------------|----------|------------|------------|----------|--------|--------|
| NO.9    | DEHLO2     | 59071    | 58853.87   | 58679      | 73.36    | —      | —      |
|         | DEHLO1     | 59012    | 58796.65   | 58614      | 72.72    | 1      | 1      |
|         | IAHLO      | 58309    | 58031.44   | 57679      | 128.93   | 1      | 1      |
|         | SHLO       | 59071    | 58768.92   | 58551      | 95.55    | 1      | 1      |
|         | MBDE       | 58438    | 58254.09   | 58112      | 54.10    | 1      | 1      |
|         | NBDE       | 58410    | 57849.68   | 57416      | 212.98   | 1      | 1      |
|         | IBPSO      | 58756    | 58337.24   | 57861      | 182.21   | 1      | 1      |
|         | NBGSK      | 57378    | 56515.92   | 55741      | 420.44   | 1      | 1      |
| NO.10   | DEHLO2     | 58637    | 58519.04   | 58359      | 62.07    | —      | —      |
|         | DEHLO1     | 58567    | 58449.57   | 58324      | 53.74    | 1      | 1      |
|         | IAHLO      | 57946    | 57355.51   | 57014      | 155.67   | 1      | 1      |
|         | SHLO       | 58599    | 58447.36   | 58292      | 70.06    | 1      | 1      |
|         | MBDE       | 58596    | 58457.51   | 58348      | 54.78    | 1      | 1      |
|         | NBDE       | 57715    | 57135.82   | 56790      | 177.76   | 1      | 1      |
|         | IBPSO      | 58277    | 57812.49   | 57285      | 209.48   | 1      | 1      |
|         | NBGSK      | 56931    | 55925.43   | 55228      | 289.04   | 1      | 1      |
| NO.11   | DEHLO2     | 117149   | 116895.63  | 116606     | 103.48   | —      | —      |
|         | DEHLO1     | 117001   | 116672.01  | 116433     | 112.36   | 1      | 1      |
|         | IAHLO      | 114617   | 114048.13  | 113553     | 230.22   | 1      | 1      |
|         | SHLO       | 117194   | 116847.53  | 116390     | 130.52   | 1      | 1      |
|         | MBDE       | 116734   | 116456.38  | 116209     | 118.63   | 1      | 1      |
|         | NBDE       | 114440   | 113394.71  | 112891     | 300.95   | 1      | 1      |
|         | IBPSO      | 116597   | 115690.33  | 114316     | 391.02   | 1      | 1      |
|         | NBGSK      | 112953   | 111386.10  | 110305     | 639.62   | 1      | 1      |
| NO.12   | DEHLO2     | 118732   | 118554.12  | 118281     | 98.71    | —      | —      |
|         | DEHLO1     | 118663   | 118426.25  | 118216     | 95.64    | 1      | 1      |
|         | IAHLO      | 116171   | 115720.44  | 115233     | 236.82   | 1      | 1      |
|         | SHLO       | 118768   | 118446.03  | 118100     | 122.62   | 1      | 1      |
|         | MBDE       | 118501   | 118219.57  | 118029     | 103.17   | 1      | 1      |
|         | NBDE       | 115669   | 114706.44  | 114207     | 314.98   | 1      | 1      |
|         | IBPSO      | 118270   | 117310.97  | 116181     | 383.94   | 1      | 1      |
|         | NBGSK      | 115125   | 112837.49  | 110855     | 878.62   | 1      | 1      |
| NO.13   | DEHLO2     | 149595   | 149437.59  | 149346     | 42.40    | —      | —      |
|         | DEHLO1     | 149593   | 149432.14  | 149291     | 49.73    | 0      | 0      |
|         | IAHLO      | 148784   | 148447.93  | 148047     | 151.62   | 1      | 1      |
|         | SHLO       | 149496   | 149374.31  | 149222     | 63.78    | 1      | 1      |
|         | MBDE       | 149510   | 149352.93  | 149270     | 60.66    | 1      | 1      |
|         | NBDE       | 149204   | 148977.35  | 148506     | 128.08   | 1      | 1      |
|         | IBPSO      | 149249   | 148737.54  | 147408     | 321.85   | 1      | 1      |
|         | NBGSK      | 148428   | 146898.01  | 144999     | 821.84   | 1      | 1      |
| NO.14   | DEHLO2     | 300152   | 299931.22  | 299756     | 68.23    | —      | —      |
|         | DEHLO1     | 300933   | 299889.33  | 299704     | 87.69    | 1      | 1      |
|         | IAHLO      | 295779   | 295030.14  | 294131     | 367.14   | 1      | 1      |
|         | SHLO       | 300070   | 299778.88  | 299484     | 117.69   | 1      | 1      |
|         | MBDE       | 300107   | 299854.78  | 299698     | 71.82    | 1      | 1      |
|         | NBDE       | 298960   | 298199.49  | 295981     | 600.02   | 1      | 1      |
|         | IBPSO      | 299290   | 298355.63  | 296002     | 736.99   | 1      | 1      |
|         | NBGSK      | 296573   | 293231.65  | 287069     | 2210.58  | 1      | 1      

Table 6: The summary results of the t-test and W-test on multidimensional knapsack problems.

| Metric | DEHLO2 | DEHLO1 | IAHLO | SHLO | MBDE | NBDE | IBPSO | NBGSK |
|--------|--------|--------|-------|------|------|------|-------|-------|
| t-test | 1      | 1      | 1     | 1    | 1    | 1    | 1     | 1     |
|        | 1      | 1      | 1     | 1    | 1    | 1    | 1     | 1     |
| W-test | 1      | 1      | 1     | 1    | 1    | 1    | 1     | 1     |
|        | 1      | 1      | 1     | 1    | 1    | 1    | 1     | 1     |

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Convergence curves of the MKP Convergence curves of the MKP

![Graphs showing convergence curves of the MKP](image)

Figure 3: Continued.
Convergence curves of the MKP

**Figure 3:** Continued.
5. Conclusions and Future Work

Human learning optimization is a simplified model of human learning: it develops three learning operators, i.e. the random learning operator, the individual learning operator, and the social learning operator, to search for the optimal solution. However, the standard HLO just learns from the global optimal solution; this is inconsistent with reality. In real life, people can learn from the optimal solution of other individuals. And the operators of Differential Evolution (DE) are updated based on the optimal solution of other individuals. Inspired by this fact, this paper introduces the optimization strategy of MBDE into HLO and presents two novel differential human learning optimization algorithms based on individual and population. Inspired by this fact, this paper introduces the optimization strategy of MBDE into HLO and presents two novel differential human learning optimization algorithms based on individual and population. To comprehensively and fairly evaluate the performance of proposed algorithms, the multidimensional knapsack problems were adopted as the benchmark problems to test DEHLOs, as well as the standard HLO, MBDE, and other metaheuristics. The experimental results demonstrate that the proposed DEHLOs can utilize the learning ability of the two algorithms to search for the optimal solution more efficiently and have a robust search ability for different problems.

It is well known that humans can adaptively choose and adjust these approaches to solve problems efficiently and effectively. However, the impact of adaptive learning strategy on algorithm parameters is not considered in this paper. Therefore, one of our future works is to develop adaptive switching learning strategies to better release the power of different learning strategies for different problems, which will be very challenging for future work.

Data Availability

As the data also form part of an ongoing study, the raw/processed data required to reproduce these findings cannot be shared at this time.

Conflicts of Interest

The authors declare that they have no conflicts of interest.
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