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An Adaptive Jellyfish Search Algorithm for Packing Items with Conflict

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Abstract: The bin packing problem (BPP) is a classic combinatorial optimization problem with several variations. The BPP with conflicts (BPPCs) is not a well-investigated variation. In the BPPC, there are conditions that prevent packing some items together in the same bin. There are very limited efforts utilizing metaheuristic methods to address the BPPC. The current methods only pack the conflict items only and then start a new normal BPP for the non-conflict items; thus, there are two stages to address the BPPC. In this work, an adaption of the jellyfish metaheuristic has been proposed to solve the BPPC in one stage (i.e., packing the conflict and non-conflict items together) by defining the jellyfish operations in the context of the BPPC by proposing two solution representations. These representations frame the BPPC problem on two different levels: item-wise and bin-wise. In the item-wise solution representation, the adapted jellyfish metaheuristic updates the solutions through a set of item swaps without any preference for the bins. In the bin-wise solution representation, the metaheuristic method selects a set of bins, and then it performs the item swaps from these selected bins only. The proposed method was thoroughly benchmarked on a standard dataset and compared against the well-known PSO, Jaya, and heuristics. The obtained results revealed that the proposed methods outperformed the other comparison methods in terms of the number of bins and the average bin utilization. In addition, the proposed method achieved the lowest deviation rate from the lowest bound of the standard dataset relative to the other methods of comparison.

Keywords: metaheuristic algorithms; artificial jellyfish optimizer; bin packing problem; any-fit algorithm

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1. Introduction

The BPP is one of the main combinatorial optimization problems that has received much attention in the literature [1]. It is used in multiprocessor scheduling, phone call dispatching over transmission circuits, printed circuit board design, assembly line balance, and capacitated vehicle routing. The objective of the BPP is to pack a set of objects with particular sizes into a minimum number of fixed bins' capacities. This is done in such a way that the total items' size in a bin does not exceed the bin's capacity. Other packing procedures involve perishable items such as medicine, food, and hazardous chemicals, some of which cannot be stored together due to their biological, chemical, or physical differences [2]. The BPP has many variations such as the 2D and 3D BPP [3–5].

Along with the standard form of the BPP, various variations have been investigated in the literature, including item fragmentation and specific sets of incompatible items that cannot be put together into the same bin. Item fragmentation (i.e., breaking an item into two or more parts and putting each component into a separate container) is prohibited under the basic BPP. However, in other cases, this assumption is extremly limiting. These applications include message transmission in community television networks [6], very large-scale integrated circuit design [7], file system operation [8], vehicle routing with split delivery [9], fully optical network planning [10], and the allocation of available memory to processors in parallel processing [11]. This variation of the BPP is known as the bin packing problem with item fragmentation (BPPIF). The BPPIF is a simple problem if the fragmentation is unrestricted. Several nontrivial versions of the BPPIF have been investigated by [12], including variants with various objective functions and item fragmentation constraints.

Packing a specific set of items into the same bin is not permitted in several BPP applications. This variation of the BPP is referred to as the BPP with conflicts (BPPCs). It has many applications in scheduling evaluation [13], delivery planning for any explosive, flammable, or toxic substances that cannot be packed together in the same vehicle [14], load balancing challenges in parallel computing, process assignments to processors when some processes cannot be executed on the same processor [15], and the warehouse storage of incompatible goods (such as explosive and flammable items) [16]. When developing a viable solution, it is necessary to consider conflict elimination [17] and dense packing [18] concurrently in order to achieve global optimization.

Consequently, the authors of [15] first utilized the graph theory method to characterize the conflict connection and then developed a steady approximation algorithm by periodically finding the largest induced subgraph. In [19], the authors studied the BPPCs issue using a set cover-based approach and presented an exact branch-and-bound technique based on approximate estimates of the bottom limits. The authors of [20] defined and developed an integer programming paradigm, as well as discussed the problem's bottom limits. Elhedhli et al. [21] solved the BPPC by considering conflict constraints issues by establishing branch criteria and by applying the dynamic programming method. Khanafer [22] created a generic framework for solving the BPPCs based on the tree decomposition technique. Apart from the preceding, the BPPCs model was used to solve scheduling problems and resource assignment issues [23,24].

Standard mathematical programming or exact algorithms are severely constrained in terms of computing capability and efficiency when handling the BPPCs, which is a severely NP-hard issue from the standpoint of solving it [25]. These limited research works, which addressed the BPPCs using metaheuristic-based methods, have motivated the current work to investigate the BPPCs using the metaheuristic-based approach. The main contribution of this work is as follows:

1. To our knowledge, the BPPCs problem has not been addressed in the literature as one problem. The existing methods pack the conflict items first and then the non-conflict items as a separate problem. This investigation of packing all the conflict and non-conflict items at one stage is the first of its kind.
2. To address the BPPCs, we proposed to utilize the first adapted jellyfish algorithm. The proposed work is provided as an open source code on a GitHub repository (https:

//github.com/Ahmed-Fathalla/An-Adaptive-Jellyfish-Search-Algorithm-for-Packing-Items-with-Conflict, accessed on 1 June 2023).

3. Two solution representation methods have been provided at different levels. Subsequently, a comparison was drawn to answer the question as to whether it is better to represent the BPPCs solution at the item level or bin level.
4. The proposed methods were evaluated on a standard dataset with different levels of problem difficulties.

The structure of this paper is organized as follows. The recent related works for the BPPCs are reviewed in Section 2. Defining the BPPCs in formal terms and proposing the main objective, as well as different constraints to solve it, are discussed in Section 3. The standard jellyfish algorithm and the proposed adaptive jellyfish algorithm for solving the BPPCs are detailed in Section 4. In Section 5. The proposed method is evaluated using two popular metaheuristics, and the utilized heuristics' performance results are assessed on a real dataset. Section 6 concludes the main points in the paper.

2. Literature Review

This section summarizes the published research on the BPP and its variants that is relevant to our research. The scientific literature is replete with references to the BPP [26,27]. The BPP problem limitations can be classified into two types: (1) capacity constraint and (2) conflict constraint. Each constraint class generates an NP-hard subproblem on its own (i.e., bin packing or vertex coloring). Additionally, it is noteworthy that the majority of the research on the BPPCs has focused on approximation methods and mathematical programming approaches [28]. Mathematical programming has proven to be effective regarding the BPPCs, because decomposition techniques such as branch-and-price [16,19,21] are extremely efficient in the case of problems with few elements per bin. These studies explain the price problem using various branching rules, sub-procedures of the problem, and beginning columns. If the conflicts create an interval graph, the pricing issue may be effectively addressed using dynamic programming [16], although branch-and-bound approaches can be utilized in more general scenarios. These identical approaches can solve a large number of benchmark instances, up to 1000, in certain circumstances. Unfortunately, these exact methods are insufficient for several BPPCs applications, including those where the computing cost varies significantly between the instances and large-scale task allocation issues [24], including tens or hundreds of thousands of items. In other words, the larger the number of items and constraints of the BPP, the more the complexity there is for the problem, which also entails more required computing time.

Along with well-known performance-guaranteed approximation techniques, including First-Fit Decreasing (FFD), Worst-Fit Decreasing (WFD), and Best-Fit Decreasing (BFD) [14,29,30], many authors have proposed a basic (i.e., exact) method using different formulations to address the BPP and BPPCs problems (i.e., BPPCs are the main subject of this paper). For instance, the authors in [31] constructed a branch-and-bound algorithm based on an FFD branching approach by utilizing a polynomial formulation and reduction techniques. Similarly, Scholl et al. [32] constructed an exact method by combining multiple limits, reduction techniques, and a branch-and-bound procedure with a novel branching strategy. Delorme et al. [27] published a review of mathematical models and exact methods that have been created for the BPP. The authors in [33] extended this formulation to address a variety of cutting and packing challenges. The authors of [34] proposed and implemented a pseudopolynomial arc-flow formulation in a branch-and-price method. Moreover, researchers have focused their efforts on establishing a strict lower bound, as presented in [35].

Furthermore, several authors have implemented classical heuristic algorithms [36–38]. To this point, metaheuristics algorithms have received less attention than mathematical programming techniques for solving the BPPCs. Fernandes Muritiba et al. [19] developed an enhanced population-based metaheuristic for generating appropriate upper limits and starting columns. The approach is a sophisticated mix of a genetic algorithm utilizing the crossover operator proposed in [39] and a tabu search based on impasse class neighborhoods in [40]. Sadykov and Vanderbeck [16] presented a heuristic technique built on a supervised partial exploration of the branch-and-price search tree. It was a reasonable compromise between the exact solution and heuristics techniques. It merged the advantages of mathematical programming with a lower CPU time in the case of a few items per bin. In general, the metaheuristics for the BPPCs need more examination. Among the best-suggested metaheuristics for addressing the bin packing issue are the grouping genetic algorithms created by Falkenauer's [41], which utilize a version of the perturbation of minimum bin slack (MBS) approach by Fleszar and Charalambous's [42], as well as a grouping genetic algorithm with regulated gene transmission [43].

Although these algorithms considered different solutions for the BPP or BPPCs as an approximate method with lower bounds, none of them have addressed the problem of conflict items, along with the free items, as a whole. Table 1 lists a comparison between different conducted research works. The table shows that most of the work that utilized the metaheuristic approaches addressed different variations of the BPP, with less focus on the BPPCs. Therefore, this paper presents an adaptive optimization algorithm for achieving a solution to the BPPCs.

Table 1. A comparison of research works addressing the BPP-based problems.

Paper	BPPC Method	Methodology	Objectives and Results
[36]	Weight Annealing Methodology	Using the WA concept, develops a straightforward procedure for the one-dimensional BPP.	Covered the majority of relevant Hadoop constraints and achieved comparable performance with FIFO and Fair Schedulers.
[37]	Multi-Capacity Bin Packing Problems (MCBPP) and Machine Reassignment Problems (MRP)	Multi-Start Iterated Local Search (MS-ILS-PPs)	Maximized machine utilization and cost-efficient task reassignment, improved upper bounds and achieved near-optimal solutions.
[38]	The Island-Parallel Grouping Genetic Algorithm (IPGGA)	Creates a parallelized version of an evolutionary algorithm for the 1DBPP. Evaluates different model parameters.	Achieved optimal solutions for 23 of 28 instances of the Hard28 dataset, thus outperforming earlier models. Results showed that, for widely distributed computing, dynamic communication topologies are more suitable.
[43]	One-Dimensional Bin Packing Problem (BPP)	Grouping Genetic Algorithm with Controlled Gene Transmission (GGA-CGT)	The GGA-CGT was created to promote the transmission of the best genes of the chromosomes and to explore the search space while balancing selective pressure and population diversity to prevent premature convergence. With respect to the Hard28 set, the method outperformed state-of-the-art algorithms.

3. Problem Formulation

In this section, we identify the BPPCs as an optimization problem with a set of constraints. In addition, the problem is presented through modeling in graph theory language. To that end, after a brief introduction to the BPPCs, the mathematical model of the BPPCs problem is formulated.

3.1. Description of the Problem

In order to solve the BPPCs model, two phases should be considered: conflict exclusion and bin packing. In the conflict exclusion phase, we may utilize two graph representation approaches to express the conflict connections among the items. First, a compatible graph is designed to represent the consistent relations between the items, where the edge set describes the compatible relationships between the vertices, and the vertex set defines the item collection. Second, a conflict graph is formulated to determine the conflict connections between the items, where the edge set describes the conflict associations between the vertices, and the vertex set defines the item collection.

In the conflict graph, the BPPC items are represented by the graph's vertices, while the graph's edges represent the conflicts between them. Hence, the conflict elimination procedure may be readily translated into the grouping operations of the conflict graph's nodes. Each group can then utilize the standard bin packing techniques. The constraints with packing process capacity are the most common problems that are encountered.

3.2. Mathematical Description of BPPCs

The BPPCs conflict graph structure represents the conflict connection between the items. It can be defined as an undirected graph structure $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{1, 2, ..., n\}$ is a set of vertices and corresponds to the items, and $\mathcal{E}$ is a set of edges such that $(i, j) \in \mathcal{E}$ when i and j conflict and correspond to the conflicted relationship among the items. The following are the primary variables to consider while putting the packing process into action: Let $I = \{1, 2, ..., n\}$ identify the set of items and $B = \{1, 2, ..., m\}$ identify the set of bins. Also, let C define the maximum bin's capacity and w_i define the weight of each item i, where $i \in I$.

The challenge is packing a set of items into the fewest possible bins without violating the main constraints that the total items' weight must not exceed the bin's capacity C, and no conflict items may be packed into the same bin. Two binary variables can be used directly as follows:

$$y_b = \begin{cases} 1 & \text{If bin } b \text{ is chosen for packing; } b \in B \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$x_{ib} = \begin{cases} 1 & \text{If the item } i \text{ packed into the bin } b\text{; } i \in I \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Using the information provided, the BPPCs 0–1 integer programming paradigm can be identified as follows. First, the objective can be formulated as in Equation (3).

$$Min \sum_{b=1}^{m} y_b. \tag{3}$$

Second, different constraints have been proposed in this model to ensure that packing items into bins is feasible and applied.

$$\sum_{b=1}^{m} x_{ib} = 1; i \in I \tag{4}$$

$$\sum_{i=1}^{n} w_i \cdot x_{ib} \leq C y_b; b \in B \tag{5}$$

$$x_{ib} + x_{jb} \leq y_b; (i, j) \in \mathcal{E}, b \in B \tag{6}$$

$$y_b \in \{0, 1\}, b \in B \tag{7}$$

$$x_{ib} \in \{0, 1\}, i \in I, b \in B. \tag{8}$$

The min objective solution in Equation (3) identifies the smallest number of storage bins required to hold the items. The first constraint is represented in Equation (4); it explains that every item has a specific bin allocated to it. The second constraint, in Equation (5), states that the total weight of the packed items in each bin must not exceed the maximum capacity. The third constraint in Equation (6) explains the conflicts between the two items that make up the restrictions. The 0–1 integer variables are defined by the constraints in Equations (7) and (8). Therefore, the BPPCs is considered to be one of the NP-hard problems. An optimization algorithm is required to solve such a problem.

4. The Proposed Adaptive Jellyfish Search Algorithm

This section provides an overview of the standard jellyfish search optimizer algorithm and illustrates its main stages. Moreover, the proposed adaptive jellyfish search (AJS) algorithm for solving the BPPCs problem is described in more detail based on both of the levels of solution representation (i.e., item-wise and bin-wise).

In order to address the BPPCs using the adapted JSA, several steps need to be adopted to attain an optimal number of bins. Initially, we must initialize the jellyfish's parameters by encompassing the upper and lower limits on the number of items, the bin capacity, and the maximum number of iterations. Subsequently, the second step involves generating the initial population, which represents two solution representations: one based on individual items and the other based on individual bins. Each solution within the population consists of a collection of packed items that are organized into bins while adhering to all the imposed constraints. Next, we evaluate each jellyfish solution by applying an objective function, which specifically includes the count of bins utilized in each solution. Moving on to the jellyfish update, we employ three operators to generate a new solution by combining two existing solutions. Finally, we iterate steps 3 and 4 until the maximum number of iterations is reached, thus aiming to identify the most favorable packing solution. The proposed method's steps are depicted in Figure 1.

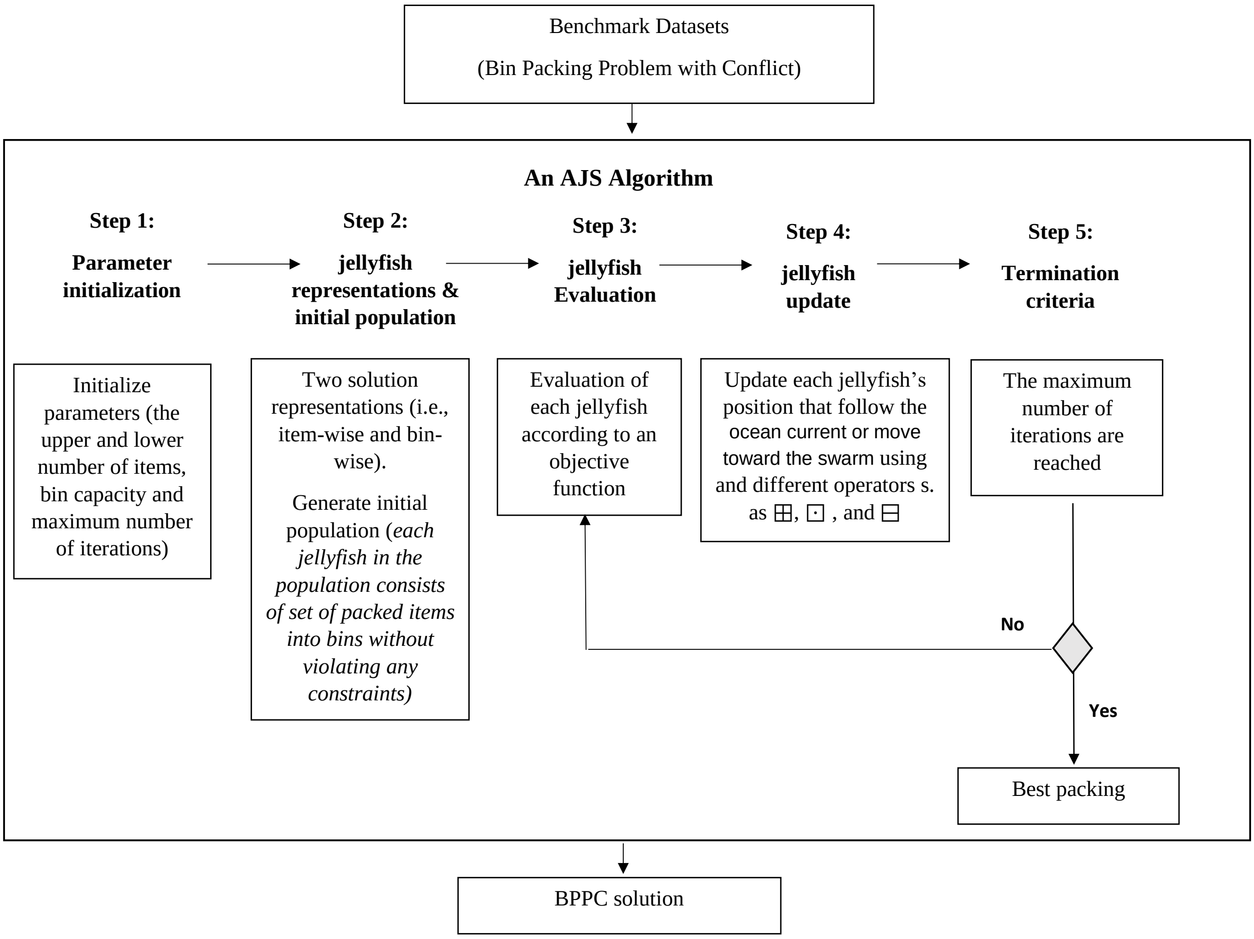

Benchmark Datasets
(Bin Packing Problem with Conflict)
An AJS Algorithm
Step 1:
Parameter initialization
Step 2:
jellyfish representations & initial population
Step 3:
jellyfish Evaluation
Step 4:
jellyfish update
Step 5:
Termination criteria
Initialize parameters (the upper and lower number of items, bin capacity and maximum number of iterations)
Two solution representations (i.e., item-wise and bin-wise).
Generate initial population (*each jellyfish in the population consists of set of packed items into bins without violating any constraints)*
Evaluation of each jellyfish according to an objective function
Update each jellyfish's position that follow the ocean current or move toward the swarm using and different operators s. as ⊞, ⊡ , and ⊟
The maximum number of iterations are reached
No
Yes
Best packing
BPPC solution

Figure 1. A flowchart of the proposed method.

4.1. The Artificial Jellyfish Search (JS) Optimizer Algorithm

Jellyfish search is one of the recently proposed metaheuristic algorithms that emulates the behavior of jellyfish in the ocean [44]. Jellyfish contain characteristics that allow them to move freely, to drive themselves ahead, and their bottoms shut like an umbrella. Despite this, they typically float in the ocean with the tides [45]. Jellyfish may swarm when conditions are good, and a large number of jellyfish is referred to as a bloom [46,47]. Jellyfish, in particular, are slow swimmers; therefore, orienting themselves toward currents is critical to keeping blooms alive and preventing stranding [46].

Ocean currents are critical because they may aggregate jellyfish into swarms [46,48,49]. This phenomenon with the individual jellyfish's motions within the swarm and their propensity to generate jellyfish blooms in response to ocean currents has enabled these species to emerge practically anywhere in the ocean. The amount of food available at jellyfish-visited locations varies; hence, the optimal spot is discovered when food proportions are examined. As a result, a novel algorithm has been devised that was motivated by jellyfish's search behavior and mobility in the water.

The proposed optimization approach is composed of three idealized principles:

1. In order to travel within the swarm, jellyfish can only travel in one of two directions: with or against the ocean current. A time control system is responsible for the switching between both modes of movement.
2. Jellyfish are continuously on the move in search of food; they are often more attracted to regions where food is readily available.
3. The objective function and location indicate the food quantities discovered.

4.1.1. Moving in the Ocean Current

Due to the high concentration of nutrients in the ocean current, jellyfish are attracted to it.

The ocean current (i.e., trend) direction is determined by taking the average of all of the position vectors from each jellyfish in the ocean to the current optimal jellyfish (i.e., the one in the most advantageous position in the water column).

Equation (9) models the flow of the ocean:

$$\overrightarrow{\text{trend}} = \frac{1}{n_{pop}} \sum \overrightarrow{\text{trend}_i} = \frac{1}{n_{pop}} \sum (X^* - e_c X_i) = X^* - e_c \frac{\sum X_i}{n_{pop}} = X^* - e_c \mu \tag{9}$$

$$\text{set } df = e_c \mu \,. \tag{10}$$

As a result, the $\overrightarrow{\text{trend}}$ is determined by the following:

$$\overrightarrow{\text{trend}} = X^* - df, \tag{11}$$

where n_{pop} is the total number of jellyfish in the swarm; X^* denotes the current jellyfish at the most-suited locations inside the swarm; e_c denotes the attraction element; and μ is the mean position of all the jellyfish. The difference between the jellyfishs' most acceptable position and the jellyfishs' mean location is df.

By assuming the normal distribution of jellyfish in all dimensions, the df can be computed as follows:

$$df = \beta \times \text{rand}(0, 1) \times \mu, \tag{12}$$

where $e_c = \beta \times \text{rand}(0, 1)$.

Then, each jellyfish's new position is specified by the following:

$$X_i(\text{t+1}) = X_i(\text{t}) + \text{rand}(0, 1) \times \overrightarrow{\text{trend}}. \tag{13}$$

Equation (13) can be expressed as follows:

$$X_i(\mathrm{t{+}1}) = X_i(\mathrm{t}) + \mathrm{rand}(0,1) \times X^* - \beta \times \mathrm{rand}(0,1) \times \mu, \tag{14}$$

where $\beta > 0$ is a distribution coefficient that is proportional to the trend's duration. Using the findings of the vulnerability analysis performed on numerical experiments of [44], we obtain $\beta = 3$.

4.1.2. Moving inside the Swarm

Jellyfish have two types of movements in a swarm: passive (type A) and active (type B) [47,50]. When the swarm first forms, the majority of jellyfish display type A motion. They gradually demonstrate more type B movements.

Type A motion refers to jellyfish moving about in their own places, and each jellyfish's updated location is provided by Equation (15).

$$X_i(\mathrm{t} + 1) = X_i(\mathrm{t}) + \gamma \times \mathrm{rand}(0,1) \times (Ub{-}Lb), \tag{15}$$

where Ub and Lb denote the upper and lower bounds of the search space, respectively. In addition, a motion coefficient with a value $\gamma > 0$ indicates how far the jellyfish move around their locations. $\gamma = 0.1$ has been acquired from the perceptiveness study results proposed in [44]. A randomly chosen jellyfish (j) imitates type B motion, and the direction of movement is defined by a vector drawn from the jellyfish of concern (i) to the randomly selected jellyfish (j). When the amount of food available to the selected jellyfish (j) exceeds the amount of food available to the jellyfish (i) of interest, the latter moves directly toward the former; when the amount of food available to the selected jellyfish (j) is less than the amount of food available to the jellyfish (i) of interest, the latter moves directly away from the former.

As a result, each jellyfish in a swarm goes in the direction that will lead to the best food. Equations (18) and (19) model the direction of travel for a jellyfish and update its position, respectively. According to some observers [51], this movement is regarded as successfully exploiting the local search space.

$$\overrightarrow{\mathrm{step}} = \mathrm{X}_i(\mathrm{t{+}1}) - \mathrm{X}_i(\mathrm{t}), \tag{16}$$

where

$$\overrightarrow{\mathrm{step}} = \mathrm{rand}(0,1) \times \overrightarrow{\mathrm{Direction}} \tag{17}$$

$$\overrightarrow{\mathrm{Direction}} = \begin{cases} \mathrm{X}_j(\mathrm{t}) - \mathrm{X}_i(\mathrm{t}) & \text{if} \quad f(X_i) \geq f(X_j) \\ \mathrm{X}_i(\mathrm{t}) - \mathrm{X}_j(\mathrm{t}) & \text{if} \quad f(X_i) < f(X_j), \end{cases} \tag{18}$$

where f denotes an objective function associated with the place X.

Hence,

$$X_i(\mathrm{t{+}1}) = X_i(\mathrm{t}) + \overrightarrow{\mathrm{step}}. \tag{19}$$

A time control mechanism, $c(t)$, is used to decide the motion that will occur throughout time. In addition to controlling the type A and B movements in a swarm, $c(t)$ is a randomly generated value that varies between 0 and 1 over time. It also regulates the movements of the jellyfish in the direction of an ocean current; it can be computed as follows:

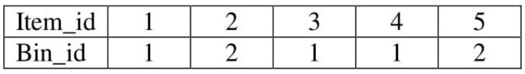
$$c(t) = |(1 - \frac{t}{Max_{iter}}) \times (2 \times (\mathrm{rand}(0,1) - 1))|, \tag{20}$$

where t is the current time, which is represented as the iteration number, and Max_{iter} is an initialized parameter specifying the maximum number of iterations.

4.2. The Proposed AJS Item-Wise Level (AJS_I)

As the standard jellyfish search optimizer algorithm is designed to solve a continuous optimization problem, it cannot be used directly to solve a discrete problem. Due to the fact that the BPPCs is a discrete optimization problem, we proposed an adaptive version of the standard JS algorithm in order to achieve a solution to the BPPCs by replacing the main operators in the standard algorithm with new operators. The overall steps of the proposed AJS are illustrated below:

1. Parameters initialization: Population size ps, the iteration counter t, the maximum number of iterations t_{max}, upper Ub and lower Lb number of items, respectively, and bin capacity C.
2. A jellyfish representation: Each individual in the population (i.e., JS) represents a solution of the BPPCs, as shown in Figure 2 as an example. This representation can be described by an n-dimensional vector of integer numbers (i.e., $Ub = n$), where the items and bins are identified using indices and values, respectively.

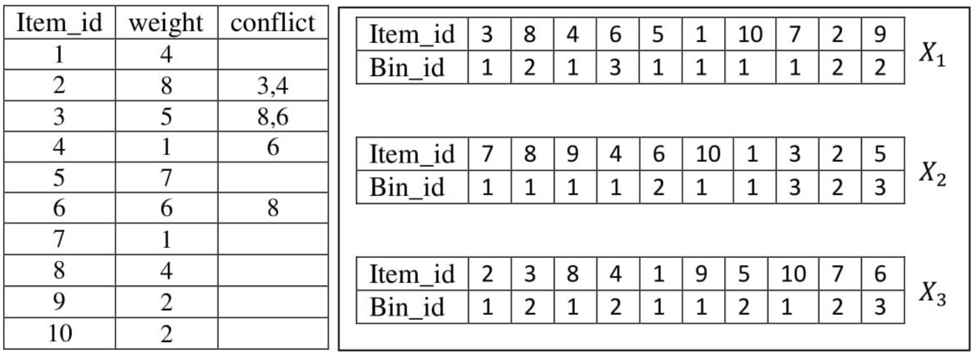


Item_id	1	2	3	4	5
Bin_id	1	2	1	1	2

Figure 2. A jellyfish representation.

Figure 2 represents the packing of five items into two bins. Item 1, 3, and 4 are packed into bin 1, while items 2 and 5 are packed into bin 2 according to the capacity constraint of the bins and the conflict constraint among items.

3. Initial population: Each individual $X_i (i = 1, \ldots, ps)$ is generated randomly based on a specific heuristic for achieving a feasible initial solution. Figure 3 illustrates an example of the initial population of three individuals. The example consists of 10 items $(Ub = 10)$, the corresponding weight of each item, the bin capacity $(C = 20)$, and a conflict set of items.



Item_id	weight	conflict
1	4	
2	8	3,4
3	5	8,6
4	1	6
5	7	
6	6	8
7	1	
8	4	
9	2	
10	2	

Item_id	3	8	4	6	5	1	10	7	2	9
Bin_id	1	2	1	3	1	1	1	1	2	2

X_1

Item_id	7	8	9	4	6	10	1	3	2	5
Bin_id	1	1	1	1	2	1	1	3	2	3

X_2

Item_id	2	3	8	4	1	9	5	10	7	6
Bin_id	1	2	1	2	1	1	2	1	2	3

X_3

Figure 3. A random initial population.

Each population solution X_i, $i = 1, ..., 3$ is generated by packing a collection of items into a collection of bins without violating any constraint. According to X_1, items 3, 4, 5, 1, 10, and 7 are packed into bin 1 with a total weight of 20 and have no conflicts. Items 8, 2, and 9 are packed into bin 2, with a total weight of 14, and item 6 is packed into bin 3, with a total of 6. The initial random-based-heuristic approach guarantees feasible initial solutions to the BPPCs.

4. Individual evaluation: Each jellyfish X_i is evaluated according to the fitness function f at each iteration t, and the one with the smallest fitness value is allocated to the best jellyfish X^* (i.e., in the case of minimization of the objective function). In contrast, the one with the maximum fitness value is assigned to X^* (i.e., in the case of the maximization of the objective function). Although minimizing the number of used bins is a primary goal of the BPP, more than one solution with different packing representations and the same total number of bins may exist. Therefore, there should

be other criteria to evaluate the solution in terms of bin utility, as in Equations (21) and (22) for minimization and maximization, respectively.

$$Minimize f(X) = 1 - (\sum_{b=1}^{B} (U_b/C)^k)/B \tag{21}$$

$$Maximize f(X) = \sum_{b=1}^{B} (U_b/C)^k/B, \tag{22}$$

where $U_b = \sum_{l=1}^{b_l} w_l$, w_l is the weight of item l, b_l is the number of items packed into bin b, k is an exponential factor that equals two, and and B is the number of used bins in the solution.

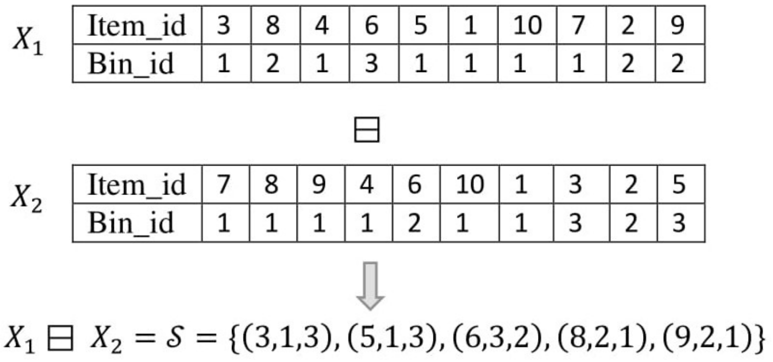
5. Individual update: The location of a JF is updated based on the time control mechanism $c(t)$ to switch the movement between the ocean current and jellyfish swarm.
   (a) In the case where a jellyfish follows the ocean current, Equations (13) and (14) can be rewritten to solve the discrete BPPCs problem as follows:

$$X_i(t+1) = X_i \boxplus rand(0,1) \boxdot trend \tag{23}$$

$$trend = X^* \boxminus X_{random}, \tag{24}$$

where $rand(0,1)$ is a randomly generated number, and X_{random} is a randomly generated jellyfish. X^* , X_i, and $X_i(t+1)$ represent the best jellyfish, the current one, and the updated location of X_i at $(t+1)$, respectively.

The new operators $\boxplus$, $\boxdot$, and $\boxminus$ can be used instead of the standard operators in the JS algorithm. The operator $\boxminus$ represents the difference between two jellyfish in the current population as a set of swaps S. Each swap s can be defined as a raw vector of three elements (p,q,r), where p represents the $item_{id}$, q represents the current assigned bin_{id}, and r represents the new assigned bin_{id}. For example, $s = (7,2,1)$ means item 7 can be packed into bin 1 instead of bin 2. Figure 4 illustrates an example as a difference between two individuals (e.g., X_1 and X_2).



X_1

Item_id	3	8	4	6	5	1	10	7	2	9
Bin_id	1	2	1	3	1	1	1	1	2	2

$\boxminus$

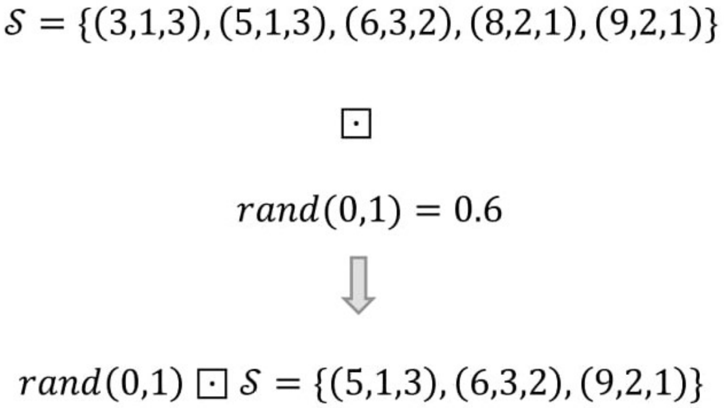
X_2

Item_id	7	8	9	4	6	10	1	3	2	5
Bin_id	1	1	1	1	2	1	1	3	2	3

$$X_1 \boxminus X_2 = S = \{(3,1,3),(5,1,3),(6,3,2),(8,2,1),(9,2,1)\}$$

Figure 4. An example of operator $\boxminus$.

The $\boxdot$ operator represents the probability of the chosen random number of swaps from the swap set S. Figure 5 illustrates an illustrative example of the results of applying the $\boxdot$ operator. According to the example, if S has five swaps, the generated random integer number is 0.6; then, the result of $\boxdot$ is a randomly selected set of three swaps from the set S.



$$\mathcal{S} = \{(3,1,3),(5,1,3),(6,3,2),(8,2,1),(9,2,1)\}$$

$$\boxdot$$

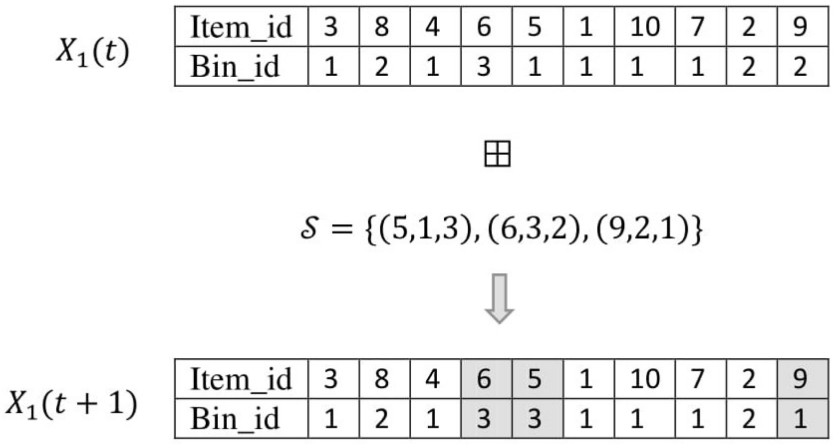
$$rand(0,1) = 0.6$$

⇩

$$rand(0,1) \boxdot \mathcal{S} = \{(5,1,3),(6,3,2),(9,2,1)\}$$

Figure 5. An example of operator $\boxdot$.

The $\boxplus$ operator takes a leading role in updating the location of a jellyfish. Therefore, it can be viewed as applying the set of swaps sequentially to the current jellyfish position in the swarm in order to obtain a new position. An illustrative example of the $\boxplus$ operator is shown in Figure 6.



$X_1(t)$

Item_id	3	8	4	6	5	1	10	7	2	9
Bin_id	1	2	1	3	1	1	1	1	2	2

$$\boxplus$$

$$\mathcal{S} = \{(5,1,3),(6,3,2),(9,2,1)\}$$

⇩

$X_1(t+1)$

Item_id	3	8	4	6	5	1	10	7	2	9
Bin_id	1	2	1	3	3	1	1	1	2	1

Figure 6. An example of operator $\boxplus$.

From the example in Figure 5, item 5 is currently packed into bin number one and can be swapped and packed into a new bin number three. This reassignment can be done with one condition, which is that the new packing does not violate both the capacity and conflict constraints. As for swap (5, 1, 3), the weight of item 5 should be less than or equal to the remaining capacity of bin 3, and item 5 must have no conflict with all the items in bin 3. For the second swap (6, 3, 2), the reassignment satisfies the capacity constraint but violates the conflict constraint, in which item 6 has a conflict with the items' list in bin two according to Figure 3. In this case, to guarantee a better exploration of a new solution, we apply an Any-Fit (AF) heuristic [26]. The main idea of an AF heuristic is that, for sequential current nonempty bins (i.e., $b_1, b_2, \ldots, b_j$), the current item will not be assigned to bin b_{j+1} unless it does not fit (i.e., it violates the capacity and conflict constraint) any of the bins in the sequence $b_1, b_2, \ldots, b_j$. Therefore, item 6 tries to be packed into bin 1 and then tries to be packed into bin 2 (i.e., both bins satisfy the capacity constraint and violate the conflict constraint); then, it remains in bin 3. Item 9 can be reassigned to bin 1 instead of 2, thus satisfying both the capacity and conflict constraint. The remaining capacity and item list for both the current and new bins is updated for any reassignment that is applied.

(b) In the case of a jellyfish moving inside a swarm, the individual can move according to type A (i.e., passive) or type B (i.e., active) movement based on a random number that is generated and compared to $c(t)$:

i. Type A update: The updating location of a jellyfish (JF) in a passive way can be achieved by rewriting Equation (15) as follows to solve the discrete problem:

$$X_i(t+1) = X_i \boxplus rand(0,1) \boxdot \gamma(Ub - Lb), \tag{25}$$

where $\gamma(Ub - Lb)$ is a randomly generated integer number between Lb and Ub in the form of swaps in a set of S. Therefore, $|S| = \gamma(Ub - Lb)$, where $|S|$ is the cardinality of a set S. For example, if the $Ub = 10$ and $Lb = 1$ (i.e., the maximum and minimum number of items) and $\gamma(Ub - Lb) = 3$, then $|S| = 3$. There are three randomly generated swaps in S. This modification in the operators guarantees multiple solutions through randomization. The $\boxdot$ and $\boxplus$ operators can be applied with the same concept as before.

ii. Type B update: This involves updating the current location of an actively based JF on a randomly selected jellyfish X_j from the current population. In order to cope with the discrete representation of the BPPCs, Equations (17)–(19) can be reformulated as follows:

$$X_i(t+1) = X_i \boxplus rand(0,1) \boxdot direction \tag{26}$$

$$direction = \begin{cases} X_j \boxminus X_i & \text{if } f(X_i) >= f(X_j) \\ X_i \boxminus X_j & \text{if } f(X_i) < f(X_j). \end{cases} \tag{27}$$

The results of operators $\boxminus$, $\boxdot$, and $\boxplus$ have been described previously according to Figure 4–6. The updating of all the jellyfish generates a new population.

6. Stopping criteria: Steps 4 and 5 are repeated for the new population and update the current best jellyfish X^* until a maximum number of iterations t_{max} is reached or an optimal assignment of items to the BPPCs has been reached.
7. Report the best jellyfish, X^*, as the best result so far.

4.3. The Proposed Bin-Wise Level (AJS_B)

The intrinsic idea of the second proposed solution representation is to update the solution based on the evaluation of the bins. Thus, each bin's utilization is computed before updating the solution, and bins satisfying certain criteria are selected as the sources of items to be swapped. Thus, the main difference between the two proposed solution representations is only the individual update step. In the following, we detail this step, while the other steps of the JS algorithm have been discussed in the previous subsection.

$$X_i(t+1) = X_i(t) \boxplus rand(0, B-1) \boxdot (\sigma(X_i(t))). \tag{28}$$

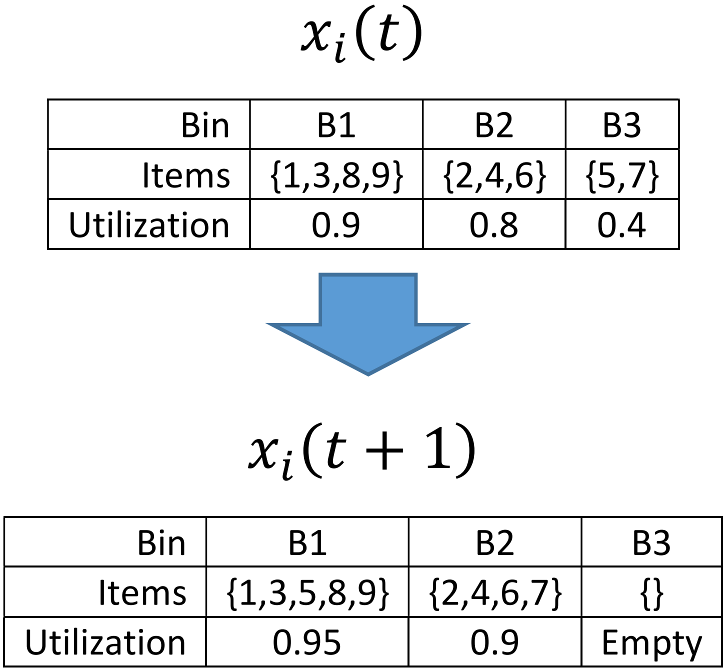
In Equation (28), the BPPCs solution, i.e., the JF, will be updated using three terms. First, $X_i(t)$ represents the current solution for the bin packing problem. Second, $rand(0, B-1)$ represents a random generator that selects one bin rather than the bin with the lowest utilization score, where B represents the number of bins in the solution. Third, the σ function selects the bin with the lowest utilization score. The $\boxdot$ operator moves the elements from the bin returned from $\sigma(X_i(t))$ to the randomly selected bin in the second term of Equation (28). Equation (28) is repeated several times until the bin returned from $\sigma(X_i(t))$ becomes empty. Thus, the BPPCs solution, i.e., the JF, is updated by removing the bin with the lowest utilization to another randomly selected bin(s).

$$X_i(t+1) = X(t)_i \boxdot direction \tag{29}$$

$$direction = \begin{cases} X_j(N \boxminus 1)X_i & \text{if } f(X_i) >= f(X_i) \\ X_i(N \boxminus 1)X_j & \text{if } f(X_i) < f(X_i). \end{cases} \tag{30}$$

In the second type of JS solution update, two JFs are used to update one of them. In the bin-wise representation, type B updating is accomplished. using Equation (30). In Equation (30), the $(N \boxminus 1)$ symbol represents the update process, where the new updated solution is produced by merging the two solutions X_i and X_j as follows. Each solution sorts its bins by the utilization of the score. The average bin utilization of each solution is computed. Then, each solution contributes to the new solution by its share, where the solution with the better utilization contributes by N bins, and the other solution contributes by one bin. When the number of bins in a solution is greater than $(N+1)$, then Equation (30) is repeated until all the problem elements are packed in the bins.

In the following motivational example, the idea of bin-wise solution representation is explained. In Figure 7, a BPPCs solution is depicted for three bins $B1$, $B2$, and $B3$, with their assigned items and the utilization score and type A solution update of a single solution. As $B3$ has the lowest utilization score, the items of $B3$ are moved to the other two bins. Thus, this operation can help in reducing the number of bins and increase the utilization of the other bins.



$x_i(t)$

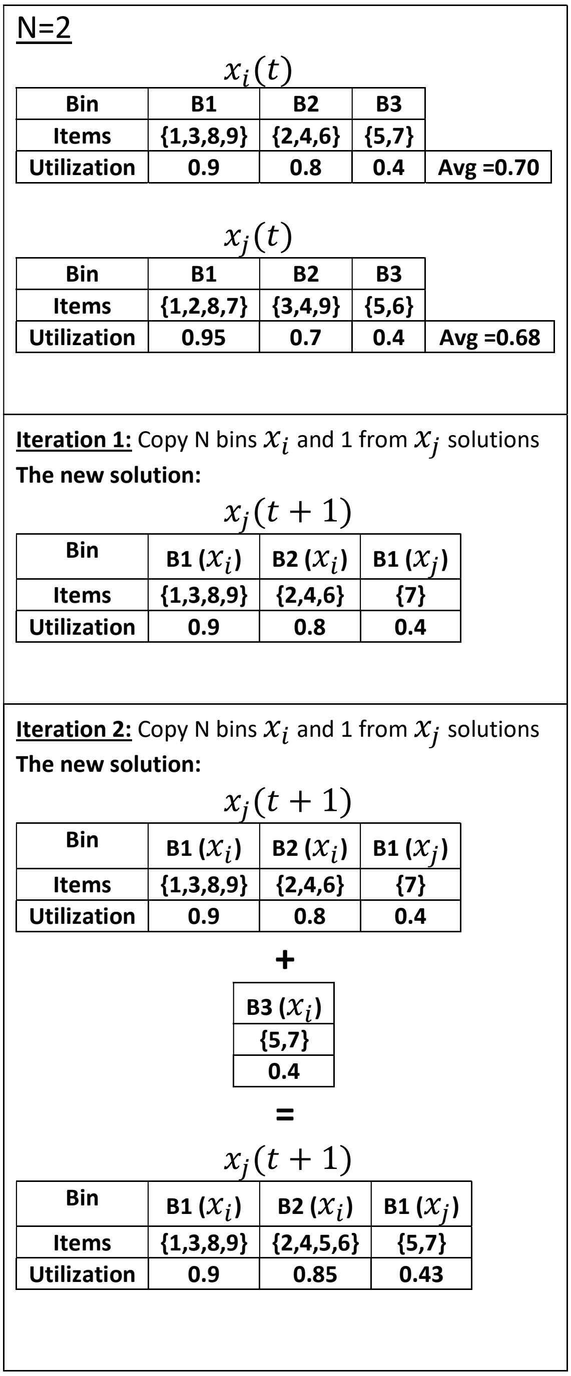
Bin	B1	B2	B3
Items	{1,3,8,9}	{2,4,6}	{5,7}
Utilization	0.9	0.8	0.4

$x_i(t+1)$

Bin	B1	B2	B3
Items	{1,3,5,8,9}	{2,4,6,7}	{}
Utilization	0.95	0.9	Empty

Figure 7. An example of type A solution update for the bin-wise representation.

In Figure 8, a JS-type B update operation for two BPPCs solutions is depicted for three bins, $B1$, $B2$, and $B3$ with their assigned items and the utilization score of the two solutions. In Figure 8, the given value is $N = 2$. The new solution is created through two iterations. In each iteration, one bin is taken from the solution with the higher average utilization and one bin is taken from the other solution, where the duplicated items are discarded. In Figure 8, the $x_i(t)$ has a higher average utilization score. In iteration 1 of Figure 8, $B1$ and $B2$ are copied from $x_i(t)$, and $B1$ is copied from $x_j(t)$, where items 1, 2, and 8 are removed, as they appear in $B1$ and $B2$ from $x_i(t)$. In the second iteration, $B3$ is copied from $x_i(t)$, and its items are assigned to the existing bins without duplication. Thus, item 5 is added to the last bin, as it is the only bin with empty space.



N=2

$x_i(t)$

Bin	B1	B2	B3	
Items	{1,3,8,9}	{2,4,6}	{5,7}	
Utilization	0.9	0.8	0.4	Avg =0.70

$x_j(t)$

Bin	B1	B2	B3	
Items	{1,2,8,7}	{3,4,9}	{5,6}	
Utilization	0.95	0.7	0.4	Avg =0.68

Iteration 1: Copy N bins x_i and 1 from x_j solutions

The new solution:

$x_j(t+1)$

Bin	B1 (x_i)	B2 (x_i)	B1 (x_j)
Items	{1,3,8,9}	{2,4,6}	{7}
Utilization	0.9	0.8	0.4

Iteration 2: Copy N bins x_i and 1 from x_j solutions

The new solution:

$x_j(t+1)$

Bin	B1 (x_i)	B2 (x_i)	B1 (x_j)
Items	{1,3,8,9}	{2,4,6}	{7}
Utilization	0.9	0.8	0.4

+

B3 (x_i)
{5,7}
0.4

=

$x_j(t+1)$

Bin	B1 (x_i)	B2 (x_i)	B1 (x_j)
Items	{1,3,8,9}	{2,4,5,6}	{5,7}
Utilization	0.9	0.85	0.43

Figure 8. An example of type *B* solution update for the bin-wise representation.

The overall steps of the proposed adaptive jellyfish search algorithm are listed in Algorithm 1 and can be summarized as follows. In lines 1 and 2, the initial parameters of the proposed algorithm are initialized, such as the number of jellyfishes in the population *ps*, the number of items to be packed into bins *Ub*, the bin capacity *C*, the optimal number of bins m^*, the number of bins in the reached solution *mbest*, the total number of iterations, and the initialization of the first iteration to 1 ($t = 1$). Line 3 generates randomly valid initial packing solutions (i.e., the population) to the BPPCs instance, which guarantees the capacity constraint and the conflict constraint. Thus, the items are placed in random bins. Each solution in the population is evaluated according to the predefined objective function and assigned the best one to the global best individual X^* according to lines 4 and 5, respectively. The motion of the jellyfish depends on the value of control parameter

$c(t)$ at each iteration, as listed in line 6. Based on that value (i.e., line 7), each jellyfish updates its position by following the ocean current at line 8 or by moving inside the swarm. Movement inside the swarm depends on a generated random value $rand(0, 1)$ compared to the $c(t)$ (line 9) to be either passive or active. In line 10, the jellyfish moves to a new position according to type A (i.e., passive) based on its representation (i.e., either item-wise or bin-wise) while moving according to type B (i.e., active) in each representation at line 11. Once all the individuals in the population are updated (i.e., the new population), the fitness value of each jellyfish in the new population can be computed and updated to the global best one as in lines 12 and 13. In line 14, if the total number of used bins has reached the optimal number of bins; then, the algorithm stops searching and reports the optimal solution. Otherwise, the iteration number is incremented, and while it does not reach the predefined maximum number of iterations t_{max}, steps 6 to 16 are repeated. In case of reaching the maximum number of iterations or the optimal number of bins, the global best solution is returned that represents the best packing of the items, as in line 17.

Algorithm 1: The proposed AJS algorithm.

```
1  Initialize the population size $ps$, total number of items $Ub$, maximum number of
     iterations $t_{max}$, bin capacity $C$. Optimal number of bins $m^*$ and number of bins in
     best solution $mbest$
2  Initialize the iteration number $t = 1$.
3  Generate the initial feasible solutions (i.e., individuals) to the BPPC problem
     $X_i = (i = 1, \ldots, ps)$ randomly.
4  Compute the fitness value of each individual $f(X_i)$ according to Equation (21) or
     Equation (22).
5  Assign the best fitness individual to $X^*$.
   do
6      Compute the value of $c(t)$ according to Equation (20)
7      if $c(t) >= 0.5$ then
8          Update the individual according to Equations (23) and (24) ;
       else
9          if $rand(0, 1) > c(t)$ then
10             Update the individual according to Equation (25) in case of item-wise
                 level and Equation (28) in case of bin-wise level;
           else
11             Update the individual according to Equations (26) and (27) in case of
                 item-wise level and Equations (29) and (30) in case of bin-wise level;
           end
       end
12     Compute the fitness value of each individual $f(X_i)$ according to Equation (21)
         or Equation (22).
13     Update the location of a jellyfish $(X_i)$ and the overall best solution $(X^*)$.
14     if $mbest == m^*$ then
15         Stop and goto step 17 ;
       else
16         $t = t + 1$
       end
   while $t <= t_{max}$;
17 return $X^*$
```

5. Results and Discussion

5.1. Dataset

To evaluate the proposed methods, the benchmark dataset proposed in [20] was utilized. It is a publicly available dataset (http://or.dei.unibo.it/library/bin-packing-problem-conflicts, accessed on 1 June 2023). The dataset consists of 10 classes; the difference between the classes is the number of items. The higher the number of the class is, the more the number of items to be packed and the harder the problem is. Within a single class, there are 100 instances with a varied number of conflict items. The level of difficulty in each class has ten levels as well. The dataset has been used to evaluate several algorithms, such as [19,33].

They do not actually group these instances by edge densities δ but based on a threshold value d. The relation between δ and d is presented in [19] and described below in Table 2.

Table 2. Relationship between δ and d.

d	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
δ	0	0.2	0.8	0.18	0.32	0.5	0.68	0.82	0.92	0.98

The values of d correspond to those derived using the formula of the edge density δ (i.e., $\delta = 2|E|/n(n-1)$) of the graph G based on d [20]. Specifically, according to the following equation, n represents the number of nodes in G.

$$\delta = f(d) = \begin{cases} \frac{2(nd)^2 - nd}{n(n-1)} & \text{for} \quad d \leq 0.5 \\ \frac{n(n-1)-2n^2(1-d)^2-n(1-d)}{n(n-1)} & \text{for} \quad d \geq 0.5. \end{cases} \tag{31}$$

Due to the computational complexity, only the first three classes of the dataset were utilized, where all ten levels of difficulty in each class were examined. In other words, the dataset in this work includes 27 different instances.

5.2. Setup

All experiments were implemented using Python 3.8. The simulation experiments were performed on a computer running a 64-bit Linux OS with two 2.3 GHz Intel 8-core processors and 250 GB RAM.

In order to validate the proposed AJS algorithm for solving the BPPCs, a set of experiments were conducted over various instances from different classes of bin packing with the conflict dataset [52]. Tables 3–5 list the characteristics of some instances for three different classes, respectively. The number of items is $N \in \{120, 250, 500\}$, the bin capacity is $C = 150$, the maximum degree for each instance is D, and the optimal number of bins is m^*. The proposed algorithm aims to minimize the number of used bins and obtain bin utilization. The results of the proposed algorithm were compared against the most popular heuristics—First-Fit (FF) and Best-Fit (BF) [53]–and metaheuristics such as Particle Swarm Optimization (PSO) [54,55] and Jaya algorithm [56]. Table 6 lists all the algorithms' setting parameters. Additionally, in order to achieve a fair comparison among the compared algorithms, all experiments were initiated with the same population size of 25 individuals (i.e., randomly packing solutions), and the maximum number of iterations ranged from 800 to 2000 iterations (i.e.,$t_{max} = 800$ for class 1, $t_{max} = 1500$ for class 2, and $t_{max} = 2000$ for class 3) as a stopping criteria, as well the optimal number of bins for each instance.

In the following subsections, the numerical results of each experiment and the performance analysis are discussed.

Table 3. Class 1 ($N = 120$ and $C = 150$).

Instance No.	Maximum Degree (D)	Optimal No. of Bins (m^*)
BPPC_1_1_1	18	48
BPPC_1_2_5	41	50
BPPC_1_3_3	73	46
BPPC_1_4_2	96	53
BPPC_1_5_5	119	57
BPPC_1_6_3	119	75
BPPC_1_7_2	119	91
BPPC_1_8_6	119	99
BPPC_1_9_4	119	110

Table 4. Class 2 ($N = 250$ and $C = 150$).

Instance No.	Maximum Degree (D)	Optimal No. of Bins (m^*)
BPPC_2_1_3	40	102
BPPC_2_2_2	99	100
BPPC_2_3_5	149	101
BPPC_2_4_6	199	109
BPPC_2_5_7	249	126
BPPC_2_6_7	249	147
BPPC_2_7_5	249	181
BPPC_2_8_5	249	205
BPPC_2_9_2	249	225

Table 5. Class 3 ($N = 500$ and $C = 150$).

Instance No.	Maximum Degree (D)	Optimal No. of Bins (m^*)
BPPC_3_1_3	105	202
BPPC_3_2_1	207	198
BPPC_3_3_9	296	196
BPPC_3_4_5	393	206
BPPC_3_5_8	499	241
BPPC_3_6_4	499	307
BPPC_3_7_5	499	343
BPPC_3_8_5	499	400
BPPC_3_9_2	499	444

Table 6. Algorithms' parameters.

Algorithm	Parameters	Definition	Value
PSO	$c1$ and $c2$	The acceleration coefficients	2
Jaya	$r1$ and $r2$	Learning parameters	$[0, 1]$
AJS	$c(t)$ γ	Switching parameter A motion coefficient	$[0, 1]$ $[Ub, Lb]$

5.3. Evaluation Metrics

Each instance of the three classes was tested and evaluated to measure the quality of the proposed solution to the BPPCs. The minimum (min.), maximum (max.), average (avg.), and standard deviation (Std.) of the fitness values were computed over five independent runs. Moreover, the efficiency of the AJS against other compared algorithms on two metrics, namely, Eff and the improvement during iterations IP, can be computed by Equations (32) and (33), respectively.

$$Eff(\%) = (f_{Algo} - f_{AJS})/f_{Algo}, \tag{32}$$

where $Algo = \{FF, BF, PSO, Jaya\}$, f_{Algo} is the bins' utilization of the compared algorithms, and f_{AJS} is the bins' utilization of the proposed adaptive jellyfish search algorithm.

$$IP = (f_i - f_j)/f_i, \tag{33}$$

where f_i and f_j are the bins' utilization of ith and jth run, respectively, and j is any consecutive run (i.e., $j > i$).

According to the number of bins, the deviation Dev from the optimal number of each instance can be computed according to Equation (34) to measure the gap between the optimal solution and the global best solution.

$$Dev(\%) = (mbest - m^*)/mbest, \tag{34}$$

where $mbest$ is the total number of used bins in the best solution, and m^* is the optimal number of bins for each instance.

5.4. Results

The proposed adaptive jellyfish search algorithm AJS (i.e., both item-wise AJS_I and bin-wise AJS_B) and the heuristics (i.e., FF and BF) results from class 1 are shown in Tables 7 and 8 in terms of the fitness values fv and number of bins, respectively.

Table 7. Class 1 fitness value (FF, BF, AJS_I and AJS_B).

Instance No.	FF	BF	AJS_I			AJS_B		
	fv	fv	**Min.**	**Max.**	**Avg. ± Std.**	**Min.**	**Max.**	**Avg. ± Std.**
BPPC_1_1_1	0.132	0.107	0.068	0.071	0.070 ± 0.001	0.033	0.033	0.033 ± 0.000
BPPC_1_2_5	0.109	0.109	0.066	0.072	0.069 ± 0.003	0.037	0.038	0.038 ± 0.000
BPPC_1_3_3	0.223	0.198	0.094	0.097	0.095 ± 0.001	0.056	0.104	0.080 ± 0.017
BPPC_1_4_2	0.266	0.267	0.191	0.207	0.197 ± 0.006	0.195	0.220	0.210 ± 0.009
BPPC_1_5_5	0.297	0.268	0.225	0.250	0.239 ± 0.011	0.229	0.250	0.236 ± 0.008
BPPC_1_6_3	0.586	0.583	0.561	0.572	0.568 ± 0.004	0.550	0.589	0.567 ± 0.015
BPPC_1_7_2	0.677	0.665	0.655	0.664	0.661 ± 0.004	0.647	0.650	0.649 ± 0.001
BPPC_1_8_6	0.734	0.730	0.714	0.718	0.716 ± 0.002	0.716	0.722	0.719 ± 0.002
BPPC_1_9_4	0.775	0.776	0.770	0.772	0.771 ± 0.001	0.766	0.770	0.769 ± 0.002
Average	0.422	0.411	0.372			**0.359**		

Table 8. Class 1 no. of bins (FF, BF, AJS_I and AJS_B).

Instance No.	Optimal	FF		BF		AJS_I		AJS_B	
	m^*	$mbest$	Dev	$mbest$	Dev	$mbest$	Dev	$mbest$	Dev
BPPC_1_1_1	**48**	51	0.059	50	0.040	49	0.020	**48**	0.000
BPPC_1_2_5	**50**	52	0.038	52	0.038	51	0.020	**50**	0.000
BPPC_1_3_3	46	53	0.132	52	0.115	48	0.042	47	0.021
BPPC_1_4_2	53	58	0.086	59	0.102	55	0.036	56	0.054
BPPC_1_5_5	57	60	0.050	60	0.050	58	0.017	59	0.034
BPPC_1_6_3	75	79	0.051	80	0.063	77	0.026	77	0.026
BPPC_1_7_2	**91**	93	0.022	93	0.022	**91**	0.000	**91**	0.000
BPPC_1_8_6	**99**	102	0.029	102	0.029	**99**	0.000	100	0.010
BPPC_1_9_4	**110**	111	0.009	111	0.009	**110**	0.000	**110**	0.000
Average			0.053		0.052		0.018		**0.016**

Based on the fitness values from Table 7, the proposed algorithm, in the case of item-wise AJS_I and bin-wise AJS_B, achieved the smallest average minimum fitness values of 0.372 and 0.359, respectively, when compared with the FF value of 0.422 and the BF value of 0.411. For instance, using BPPC_1_3_3, as an example, the AJS_B and AJS_I obtained average fitness values of 0.080 and 0.095, respectively, while the fv of the FF heuristic equaled 0.223, and the BF heuristic equaled 0.198. Additionally, the efficiency of the AJS_I improved and reached up to 58% when compared with the FF algorithm, and it reached up to 53% when compared with the BF algorithm over various instances. In the case of the AJS_B , the *eff* reached up to 75% and 72% when compared with FF and BF, respectively, over various instances.

Table 8 lists all the instances' packing solutions in terms of the number of used bins *mbest* relevant to the optimal number m^*. Although the FF and BF are standard heuristics for solving a classical BPP, they failed to reach an optimal number of bins in the BPPCs for all test instances. However, both the proposed solutions (i.e., item-wise and bin-wise) reached a lower number of bins when compared with the heuristics. In addition, they reached the optimal number of test instances for some test instances (i.e., four test instances using AJS_B and 3 test instances using AJS_I.) For example, the AJS_I for solving BPPC_1_2_5 achieved the optimal packing of items (i.e., $m^* = mbest = 50$), and both the AJS_I and AJS_B achieved the optimal packing for instance BPPC_1_9_4 (i.e., $m^* = mbest = 110$). It is well noticed from the results that the first three instances achieved the best deviations in the case of the AJS_B when compared with the AJS_I, while, for the rest of the instances, the AJS_I had the smallest deviations from the optimal solution. Generally, the AJS_I and AJS_B achieved better average deviations of 0.018% and 0.016%, respectively, compared with the FF (0.053%) and BF (0.052%).

The proposed adaptive jellyfish search algorithm, AJS, has proven its efficiency in solving the BPPCs, not only when compared with the standard heuristics, but also when compared with other popular metaheuristics such as the PSO and Jaya, as shown in Tables 9 and 10 in terms of the fitness function and the optimal number of bins, respectively.

Table 9. Class 1 fitness value (AJS, Jaya and PSO).

instance_id		AJS	Jaya	PSO
BPPC_1_1_1	Min.	**0.033**	0.062	0.432
	Max.	0.033	0.071	0.469
	Avg. ± Std.	0.033 ± 0.000	0.066 ± 0.001	0.455 ± 0.014
BPPC_1_2_5	Min.	**0.037**	0.065	0.474
	Max.	0.038	0.068	0.485
	Avg. ± Std.	0.038 ± 0.000	0.066 ± 0.017	0.480 ± 0.005
BPPC_1_3_3	Min.	**0.056**	0.098	0.522
	Max.	0.104	0.144	0.555
	Avg. ± Std.	0.080 ± 0.017	0.121 ± 0.011	0.543 ± 0.014
BPPC_1_4_2	Min.	**0.191**	0.210	0.578
	Max.	0.207	0.240	0.595
	Avg. ± Std.	0.197 ± 0.006	0.229 ± 0.014	0.589 ± 0.007
BPPC_1_5_5	Min.	**0.225**	0.247	0.583
	Max.	0.250	0.281	0.628
	Avg. ± Std.	0.239 ± 0.004	0.270 ± 0.003	0.610 ± 0.019
BPPC_1_6_3	Min.	**0.561**	0.566	0.726
	Max.	0.572	0.572	0.739
	Avg. ± Std.	0.568 ± 0.004	0.569 ± 0.000	0.734 ± 0.006
BPPC_1_7_2	Min.	**0.655**	0.661	0.749
	Max.	0.664	0.661	0.757
	Avg. ± Std.	0.661 ± 0.004	0.661 ± 0.002	0.753 ± 0.004
BPPC_1_8_6	Min.	**0.714**	0.716	0.785
	Max.	0.718	0.721	0.791
	Avg. ± Std.	0.716 ± 0.002	0.719 ± 0.001	0.787 ± 0.003
BPPC_1_9_4	Min.	0.770	0.770	0.795
	Max.	0.772	0.772	0.798
	Avg. ± Std.	0.771 ± 0.001	0.771 ± 0.004	0.797 ± 0.001
Average	Min.	**0.360**	0.377	0.627

Table 10. Class 1 no. of bins (AJS, Jaya, and PSO).

Instance No.	Optimal	AJS		Jaya		PSO	
	*m**	*mbest*	*Dev*	*mbest*	*Dev*	*mbest*	*Dev*
BPPC_1_1_1	**48**	**48**	0.000	49	0.020	65	0.262
BPPC_1_2_5	**50**	**50**	0.000	51	0.020	71	0.296
BPPC_1_3_3	46	48	0.042	48	0.042	70	0.343
BPPC_1_4_2	53	55	0.036	56	0.054	79	0.329
BPPC_1_5_5	57	58	0.017	59	0.034	82	0.305
BPPC_1_6_3	75	77	0.026	78	0.038	96	0.219
BPPC_1_7_2	**91**	**91**	0.000	**91**	0.000	104	0.125
BPPC_1_8_2	**99**	**99**	0.000	100	0.010	112	0.116
BPPC_1_9_4	**110**	**110**	0.000	**110**	0.000	115	0.043
Average			**0.013**		0.024		0.226

From the results of Table 9, the proposed algorithm achieved the lowest average fitness value for all instances when compared with the Jaya and PSO. For example, the average of the AJS was equal to 0.197, while the averages of the Jaya and PSO were 0.229 and 0.589, respectively, for instance BPPC_1_4_2. Moreover, the AJS achieved the lowest average minimum fitness value, with instances equal to 0.360. The efficiency of the proposed algorithm improved and reached up to 84% when compared with the Jaya and ranged from 3% to 92% when compared with the PSO.

Table 10 lists the *mbest* and *Dev* for the compared metaheuristics algorithms for all test instances. Although the Jaya algorithm reached the optimal number of bins in two instances (BPPC_1_7_2 and BPPC_1_9_4), the proposed AJS had a superior number of optimal bins for solving the BPPCs for five instances, with the smallest average deviation equaling 0.013% over all instances. In contrast, the PSO had the poorest results, with larger average deviations of 0.226% than the Jaya and AJS.

The main objective of the proposed work was to pack the conflict items into a minimum number of bins and achieve efficient bin utilization. For example, for solving instance BPPC_1_7_2, the AJS_I, AJS_B, and Jaya reached the optimal number of bins, but with different bins' utilization. Figures 9 and 10 show the convergence curve in terms of fitness value and the number of bins for solving that instance, respectively.

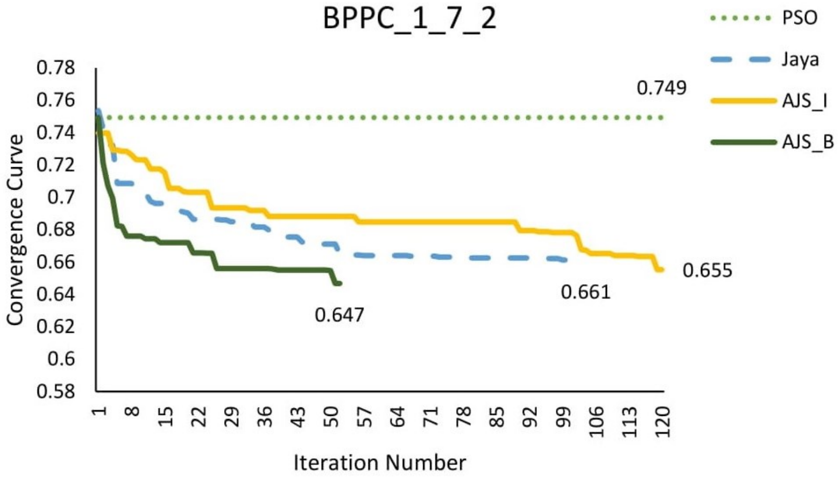


Figure 9. Convergence curve of instance BPPC_1_7_2.

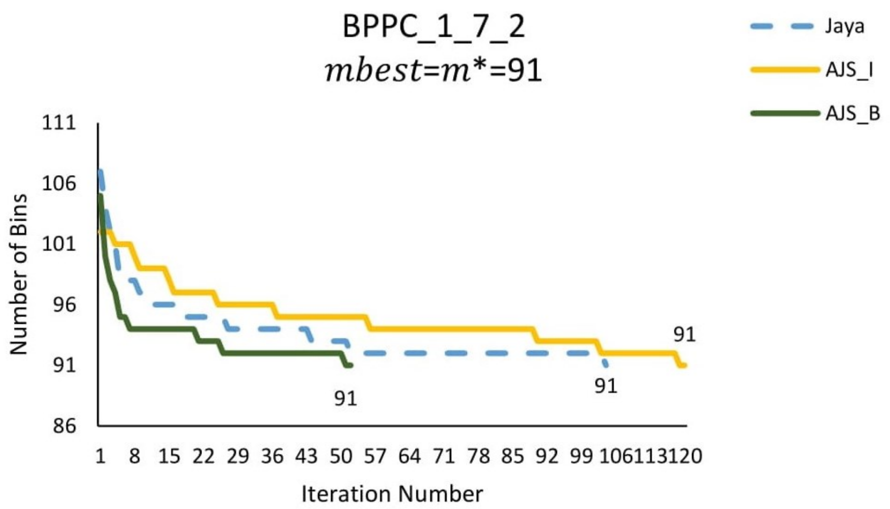


Figure 10. Number of bins of instance BPPC_1_7_2.

From Figure 9, the AJS_B achieved the smallest convergence curve during iterations, with an $fv = 0.647$, and the IP reached up to 14%. The PSO had the worst values for the iterations. Although the efficiency of the Jaya was better than the AJS_I within a range of 1% $\sim$ 3%, with more iterations, the AJS_I achieved a better efficiency with an $fv = 0.655$. In addition, the AJS_B had a superiority in reaching the optimal number of bins ($mbest = m^* = 91$) at a lower number of iterations ($t = 52$) when compared with the others, as shown in Figure 10.

For more illustration in solving the BPP_1_2_5 instance, the proposed AJS was optimal in reaching both the minimum fv, as shown in Figure 11, and the m^*, as shown in Figure 12.

At the beginning of the iterations (e.g., up to $t = 50$) at Figure 11, the proposed algorithm had a fast convergence in minimizing the fitness value when compared with the Jaya and PSO, with its $eff = 48\%$ better than the Jaya and its $eff = 79\%$ better than the PSO. With more iterations, the efficiency of AJS was up to 72% better than the Jaya and up to 92% better than the PSO. The performance of the AJS improved with increasing iterations (IP) within a range of 23$\sim$42%.

In Figure 12, both the Jaya and PSO packed the items into 71 bins, while the AJS achieved a lower packing of items equaling 70 bins. Although the Jaya improved during iterations to minimize the number of used bins, it did not reach as optimal a number of bins by the end of iterations as the PSO. However, the AJS gained the optimality in the lowest number of iterations ($mbest = m^* = 50$ at $t = 126$).

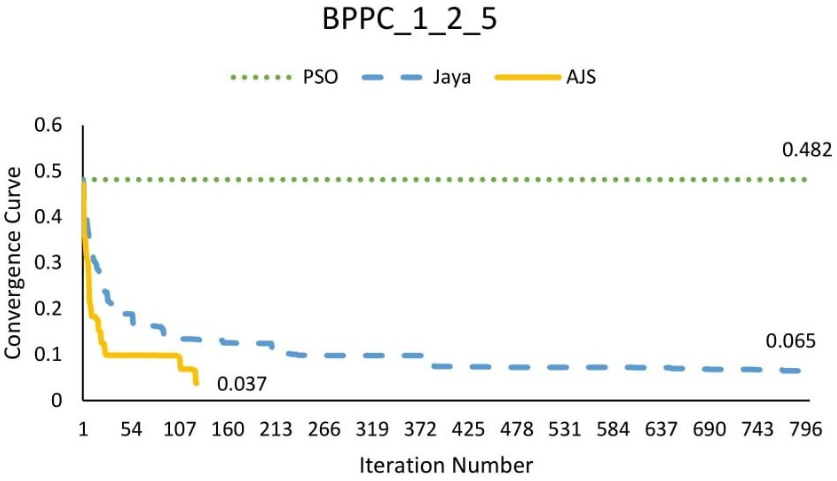
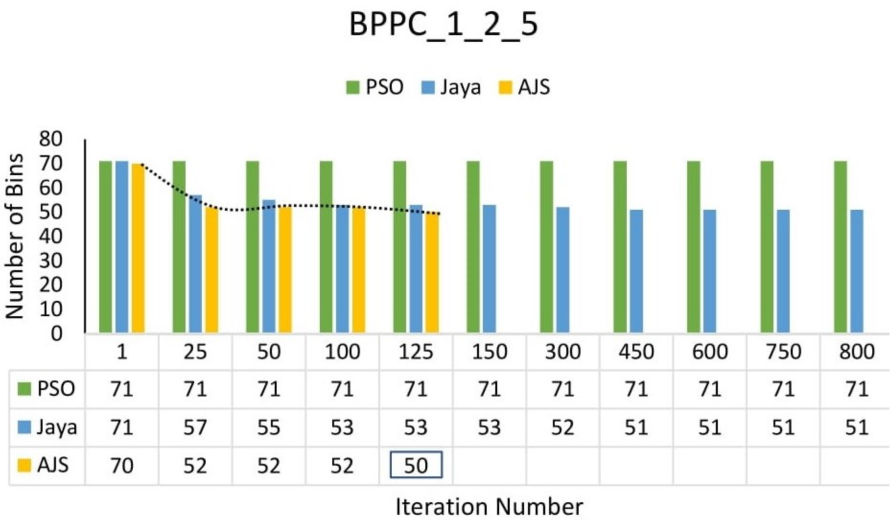


Figure 11. Convergence curve of instance BPPC_1_2_5.



	1	25	50	100	125	150	300	450	600	750	800
🟩 PSO	71	71	71	71	71	71	71	71	71	71	71
🟦 Jaya	71	57	55	53	53	53	52	51	51	51	51
🟨 AJS	70	52	52	52	$\boxed{50}$						

Figure 12. Number of bins of instance BPPC_1_2_5.

For solving a BPPCs with a large number of items ($N = 250, 500$), as in Tables 4 and 5), the proposed adaptive algorithm has proven its superiority in terms of achieving the lowest objective values compared with other heuristic and metaheuristic algorithms. Table 11 summarizes the average fitness values' results for the class 2 and 3 instances.

Table 11. Classes 2 and 3 fitness values (FF, BF, AJS, Jaya, and PSO).

Algorithm	**Average**	**Class No.**	
		Class 2	**Class 3**
FF	fv	0.402	0.371
BF	fv	0.403	0.370
	Min.	**0.343**	**0.326**
AJS	Max.	**0.350**	**0.331**
	Avg. ± Std.	**0.346** ± **0.003**	**0.329** ± **0.002**
	Min.	0.365	0.355
Jaya	Max.	0.374	0.360
	Avg. ± Std.	0.371 ± 0.003	0.358 ± 0.002
	Min.	0.636	0.641
PSO	Max.	0.651	0.653
	Avg. ± Std.	0.644 ± 0.006	0.647 ± 0.005

For class 2, the AJS algorithm attained an average minimum fv over test instances equaling 0.343, which was better than the average fv of the FF and BF by 15%. Furthermore, when compared with the Jaya, the proposed algorithm had admirable results in average min., max., and average, where it reached up to 7% and 46% when compared with the PSO, respectively. Likewise, the average fv of the AJS algorithm equaled 0.326, while the FF, BF, Jaya, and PSO equaled 0.371, 0.370, 0.355, and 0.641, respectively, over the test instances of class 3. Regarding the average results, the AJS achieved improvement in minimizing the average fitness value by 8% when compared with the Jaya and 49% when compared with the PSO.

Regarding minimizing the number of used bins to the optimal packing for solving the class 2 and 3 instances, Table 12 lists the *mbest* and *Dev* results for all the algorithms. Although the proposed solution to the bin packing problem with conflicts did not reach the optimal number of bins for all instances (i.e., except for two test instances from class 2), it packed items into the smallest number of bins *mbest* compared with the standard heuristics and metaheuristics. For example, the AJS achieved the optimal packing of items $m^* = mbest = 102$ for instance BPPC_2_2_3. However, the other compared algorithms reached a variant number of bins equal to 109, 110, 104, and 144 for the FF, BF, Jaya, and PSO, respectively.

From Table 12, the proposed adaptive jellyfish algorithm had an admirable lowest average deviation of overall test instances, which equaled 0.014. Its efficiency reached up to 70% in comparison with the FF and 75% when compared with the BF. Moreover, in comparison with the other metaheuristics, the AJS was better than the Jaya by 60% and better than the PSO by 95%.

Table 12. Classes 2 and 3 no. of bins (FF, BF, AJS, Jaya, and PSO).

Instance No.	FF		BF		AJS		Jaya		PSO	
	mbest	*Dev*	*mbest*	*Dev*	*mbest*	*Dev*	*mbest*	*Dev*	*mbest*	*Dev*
BPPC_2_1_3	109	0.064	110	0.073	**102**	0.000	104	0.019	144	0.292
BPPC_2_2_2	108	0.074	108	0.074	**100**	0.000	102	0.020	144	0.306
BPPC_2_3_5	110	0.082	109	0.073	102	0.010	105	0.038	152	0.336
BPPC_2_4_6	117	0.068	118	0.076	111	0.018	116	0.060	170	0.359
BPPC_2_5_7	132	0.045	136	0.074	129	0.023	132	0.045	181	0.304
BPPC_2_6_7	156	0.058	158	0.070	152	0.033	155	0.052	200	0.265
BPPC_2_7_5	186	0.027	188	0.037	182	0.005	185	0.022	219	0.174
BPPC_2_8_5	209	0.019	210	0.024	207	0.010	208	0.014	234	0.124
BPPC_2_9_2	228	0.013	229	0.017	226	0.004	226	0.004	242	0.070
BPPC_3_1_3	212	0.047	211	0.043	203	0.005	209	0.033	296	0.318
BPPC_3_2_1	211	0.062	210	0.057	199	0.005	205	0.034	298	0.336
BPPC_3_3_9	209	0.062	209	0.062	197	0.005	205	0.044	307	0.362
BPPC_3_4_5	226	0.088	231	0.108	216	0.046	223	0.076	336	0.387
BPPC_3_5_8	253	0.047	260	0.073	251	0.040	259	0.069	364	0.338
BPPC_3_6_4	312	0.016	318	0.035	310	0.010	316	0.028	405	0.242
BPPC_3_7_5	360	0.047	364	0.058	351	0.023	355	0.034	436	0.213
BPPC_3_8_3	410	0.024	412	0.029	405	0.012	410	0.024	468	0.145
BPPC_3_9_5	448	0.009	451	0.016	446	0.004	449	0.011	484	0.083
Average		0.047		0.055		**0.014**		0.035		0.258

For more details about the convergence curve of instance BPPC_2_2_2 as an example from class 2, Figures 13 and 14 show the efficiency of the proposed solution for packing the items in terms of the objective function and number of bins during iterations.

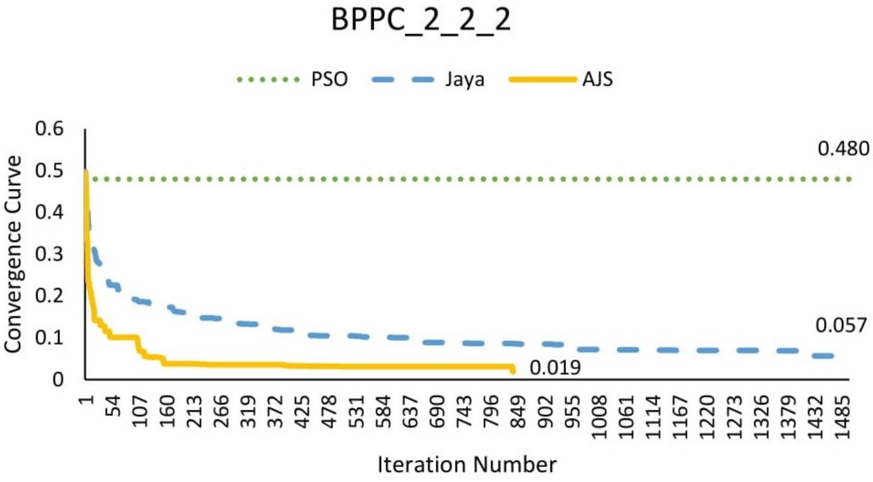


Figure 13. Convergence Curve of instance BPPC_2_2_2.

Based on the two-fold aim of packing the items into a minimum number of bins with the best bins' utilization, the AJS algorithm achieved a promising result. From Figure 13, the AJS had the smallest minimum fv of 0.019, while the PSO and Jaya had an fv equal to

0.480 and 0.057, respectively. The eff of the proposed algorithm reached up to 96% when compared with the PSO, while it improved within a range of 20% $\sim$ 78% when compared with the Jaya algorithm. During iterations, the solution was improved and reached the optimal number of bins $mbest = m^* = 100$ at $t = 841$, as shown in Figure 14. In contrast, these items were packed into 102 and 144 bins through the Jaya and PSO, respectively, at the end of the iterations.

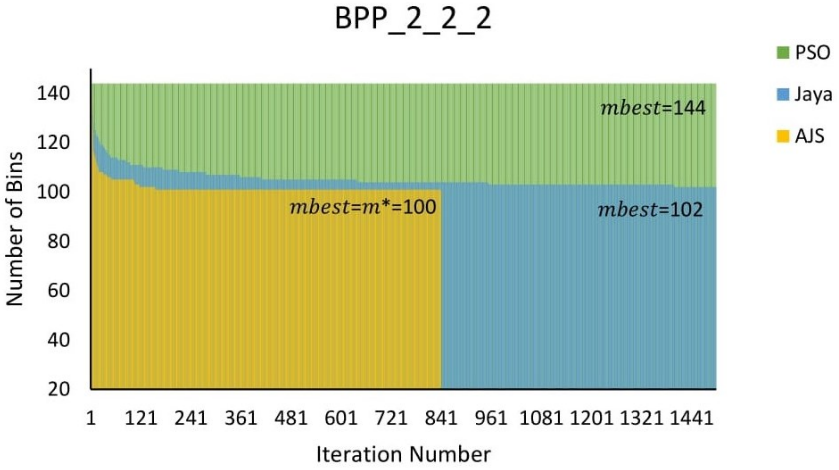


Figure 14. Number of bins of instance BPPC_2_2_2.

Figure 15 shows the convergence curve of instance BPPC_3_3_9. The fv of the proposed algorithm decreased rapidly during the first iterations, with an IP reaching up to 88%. Although the Jaya algorithm had a better minimization of the fv than the PSO until the end of the iterations, the AJS algorithm outperformed the compared algorithms with the smallest minimum of an $fv = 0.013$. The Jaya algorithm reached an $fv = 0.083$, and the PSO reached an $fv = 0.541$. The eff of the AJS ranged from 25% to 98% and from 18% to 84% in comparison with the PSO and Jaya, respectively.

Although all the compared algorithms did not reach the optimal number of bins for this instance (i.e., $m^* = 196$), the AJS packed these items into the smallest number of bins (i.e., $mbest = 197$) compared with the others, as shown in Figure 16.

The proposed adaptive jellyfish search algorithm showed the best performance compared with other representative baseline algorithms according to the above results. It achieved the lowest average fitness value and the lowest number of used bins for solving BPPCs instances. To the best of our knowledge, this work is the first one that uses the jellyfish algorithm to solve the bin packing problem, especially when dealing with conflict items from the initial solution.

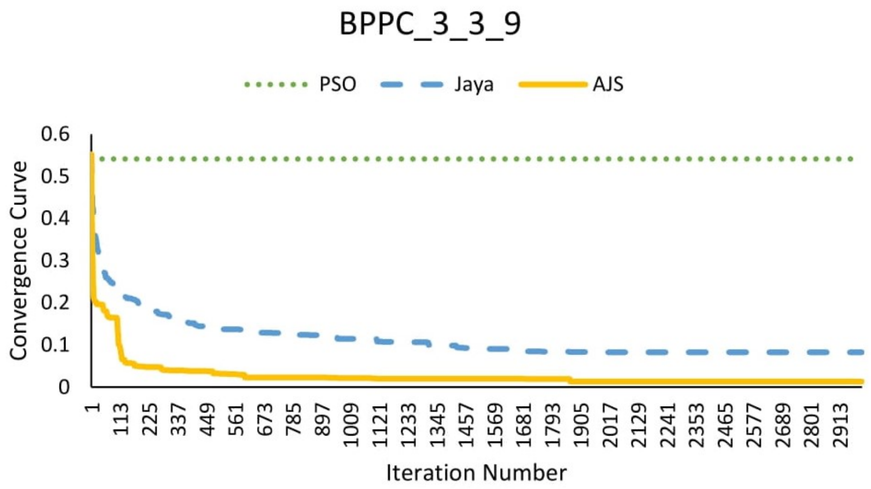
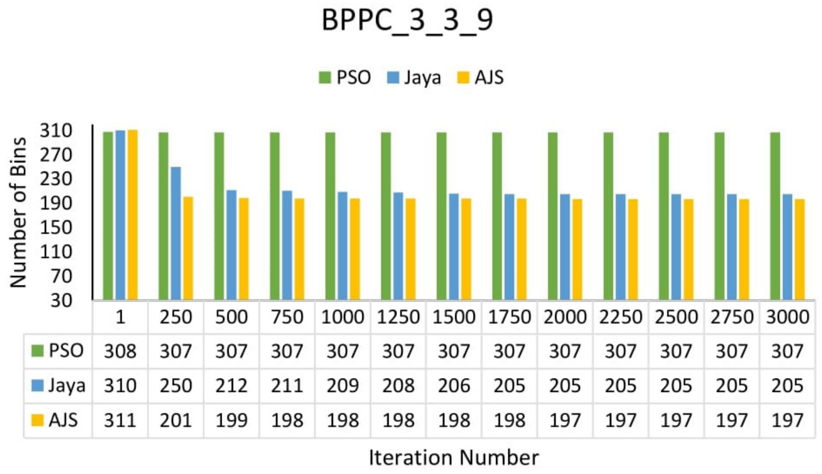


Figure 15. Convergence curve of instance BPPC_3_3_9.



	1	250	500	750	1000	1250	1500	1750	2000	2250	2500	2750	3000
🟩 PSO	308	307	307	307	307	307	307	307	307	307	307	307	307
🟦 Jaya	310	250	212	211	209	208	206	205	205	205	205	205	205
🟨 AJS	311	201	199	198	198	198	198	198	197	197	197	197	197

Figure 16. Number of bins of instance BPPC_3_3_9.

6. Conclusions

In this work, the bin packing problem with conflicts was addressed due to its impact on several applications. In addition, according to our knowledge, the literature includes very limited efforts in utilizing metaheuristic methods to address the BPPCs. In this vein, adapting the jellyfish algorithm to address the BBPCs using two solution representations was proposed. These two representations frame the BPPCs problem at two different levels: item-wise and bin-wise. The BPPCs solution representation can be framed as a sequence of item swaps, where the items to be swapped can be from any bin without any restrictions; this approach is called item-wise. On the other hand, some bins with certain conditions can be selected, and then the item swaps occur for this group of bins only; this approach is called bin-wise. Then, we proposed a set of operations that fit the BPPCs to be used as the jellyfish algorithm operations. These operations were used to update the solutions. Finally, the performance of the proposed methods was evaluated using a standard dataset with a known optimal number of bins. The evaluation included a set of methods of comparison, namely, the PSO, Jaya, and several heuristics. The comparison was performed to find solutions to two objectives: the number of bins and the average bin utilization. The obtained results showed that the proposed method's performance was better than the other methods for the two objectives, and it yielded the smallest deviation rate from the optimal number of bins. The obtained results showed an improvement on the other methods of comparison by a range of least 2 to 18 times. However, the bin packing problem remains a big challenge, especially with conflicting items. As a result, some future research directions will be considered, such as a hybrid method to acquire more benefits, a test of the AJS against real-world scenarios, and and assessment of packing items in multidimensions or other multiobjective criteria.

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Data Availability Statement: The utilized dataset of this work is publicly available: http://or.dei.unibo.it/library/bin-packing-problem-conflicts, accessed on 1 June 2023.

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