Ant Colony Optimisation on the Bin Packing Problem

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Abstract

This paper briefly reviews nature-inspired approaches to the bin packing problem (BPP), with a focus on the ant colony optimization (ACO) algorithm. The experiment tests the effectiveness of ACO for minimizing fitness and how fine tuning parameters can affect performance. The results point to the parameters providing a slight optimisation with smaller problem sizes, and little to no effect with larger ones. This study looks into how to optimise ACO for BPP effectively and in a controlled way.

1 Introduction

In this paper, I will cover approaches to the bin packing problem (BPP), which is a NP hard combinatorial optimisation problem in which there are k items with distinct weight distributed across b bins. The primary goal of BPP is traditionally to distribute items effectively, in that the capacity C of each bin is not exceeded (Alvim et al., 2004). In this implementation, the goal is to minimise the difference between the heaviest and the lightest bins (fitness), as an indicator of closeness to an even item weight distribution among b bins without any limit on bin weight. Finding an optimal approach to best solve BPP is complex and is tested with many algorithms and heuristics.

2 Nature Inspired Approaches to BPP

This section will briefly cover other works, their findings, and their approaches to the bin packing problem using nature inspired algorithms, including ant colony optimisation for further insight prior to covering experimental results.

2.1 Ant Colony Optimisation

Ant Colony Optimisation (ACO) is an iterative nature-inspired algorithm. It functions by simulating ants which navigate paths and find the shortest routes for food. Ants release pheromones when traversing their paths, influencing the decisions of the remaining colony in the following iterations. As an increased number of ants tend to travel shorter paths, the more attractive the pheromone trail is to other ants, leading to further improvement on optimisation. There is a communication between the ants through the pheromone trail that allows for a convergence to an effective solution to an optimisation problem. (Dorigo et al., 2006)

Ducatelle et al. (2002), displayed that ACO was able to minimise fitness for BPP, effectively saving space across multiple bins. ACO when tested with varying problem sizes, was consistently strong proving its scalability. Through the use of the first fit decreasing heuristic, the algorithm was able to improve its effectiveness for BPP. (Ducatelle and Levine, 2001)

Compared to other methods, such as the Reduction Algorithm and Falkenauer's Hybrid Genetic Algorithm, ACO outperformed, displaying its effectiveness as an optimisation technique for BPP. In their experiments, they found that using an equal number of ants to items led to the strongest results. This research proves ACO's potency when used in optimisation tasks, providing reason for further exploration in nature inspired algorithms for both BPP and potentially other optimisation problems. While this study provides great information regarding comparing various algorithms for BPP, it utilises a setup incorporating heuristic information of remaining bin capacity proportional to the item in addition to the pheromone influence. This is different from the way the experiments are conducted for this paper, using a solely pheromonal influence implementation of ACO. This is particularly relevant due to the observation that the ants were more receptive to the heuristics rather than the pheromone trails, meaning more insight into results from just pheromones is necessary to assess ACO as an optimisation algorithm.

2.2 Genetic Algorithm

The genetic algorithm is an evolutionary optimisation algorithm, based off natural selection, to solve grouping problems. It is a meta-heuristic approach that utilises iteration to create a random initial population, calculate the fitness of the population, select candidates, and then converge the candidates into the total population biased by their fitness in comparison with the population to mimic natural selection. (Forrest, 1996)

Falkenauer et al. (1992) utilised a hybrid grouping genetic algorithm (GGA) for both BPP and line balancing which expanded on the algorithm by including a reduction method. He found that by utilising this hybrid GGA the performance improved drastically. The findings of this study are important as it provided an algorithmic foundation from which other studies could build upon for both BPP approaches and other hybrid algorithm applications in optimisation problems. Furthermore, it provides a perspective on instituting a combination approach for BPP in the context of nature inspired algorithms, paving a way for further nature focused research for optimisation. (Falkenauer et al., 1992)

The issue with this study in the context of the experiments, lies in how their experiments were conducted. They utilised a random item weight in addition to unspecified item quantities to be distributed among the bins denoting the uncontrolled nature of the experiments, harming the reliability of the results. Furthermore, similar to the ACO implementation by Ducatelle et al. (2002), there is a dependance on a first fit descending heuristic for the genetic algorithm, whereas there is no heuristic dependancy for the ACO implementation utilised in this paper. Both implementations covered in the nature inspired approaches section use first fit heuristics which prohibits the clarity of the effectiveness of the algorithm's core functionalities. Despite this discrepancy, the study as a whole is a valuable resource for a hybrid nature inspired algorithmic approach to BPP, and even utilises the genetic algorithm against other optimisation problems revealing its practicality and general application.

3 Description of Results

3.1 Experiment Setup and Design

Using an Ant Colony Optimisation algorithm without the use of any additional heuristics, with a goal of minimising the fitness for a one dimensional bin packing problem.

3.2 Problems Addressed

The main problems being focused on in the experiment is split into two categories: BPP1 and BPP2. BPP1 and BPP2 both use 500 items. The difference between the two is the number of b bins, and the item weights. BPP1 has 10 bins, and uses an item weight equal to the item index i being $Weight = i$. BPP2 has 50 bins, and uses $Weight = i^2/2$.

3.3 Experiment Procedure

Create a matrix containing random quantities of pheromone between 0 and 1. Generate a set of ant paths for each ant p. Compute the fitness of each ant's path and add the update to existing pheromone values on the graph where the ant's path was. After all p ants have deposited pheromone, evaporate any paths by multiplying with the evaporation rate e. Repeat until all fitness evaluations are reached.

3.4 Implementation and Parameters

The experiment itself is divided into 8 separate runs of the ACO algorithm. 4 of which being for BPP1, and 4 for BPP2. For each run, there will be 5 trials comprised of 10,000 fitness evaluations, totalling 50,000 evaluations. Each trial is randomly seeded.

The parameters are p (number of ants), e (evaporation rate), k (number of items), and b (number of bins). k and b are already designated for BPP1 and BPP2, including their respective item weights. The runs are comprised of p = 100 and e = 0.90, p = 100 and e = 0.60, p = 10 and e = 0.90, and p = 10 and e = 0.60. By setting established parameters it allows for simple comparisons and a controlled experiment.

3.5 Results

Figure 1 (below) shows that for BPP1, the bin weights are relatively even, with the greatest fitness of 920. Using ACO with 100 ants and 0.6 evaporation rate has proven capable of balancing linear increases in weight without the need for any

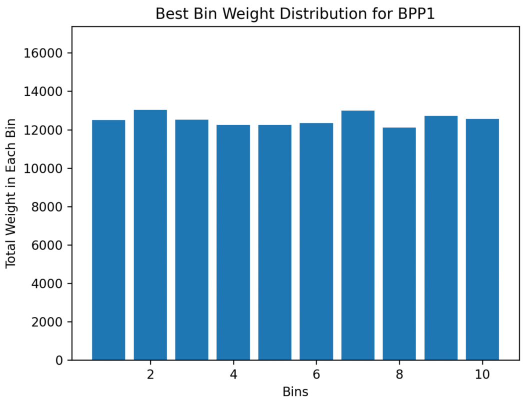

Figure 1: Best bin weight distribution for BPP1 after 5 trials (100 ants, 0.6 evaporation rate)

additional heuristic. The ants appear able to explore multiple paths rather than staying on select few paths, which avoids local optima, expanding the search space of the algorithm.

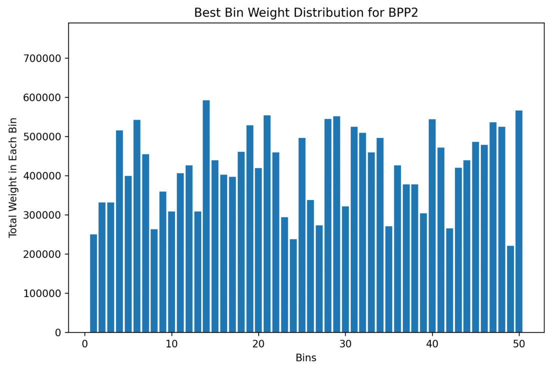

Figure 2: Best bin weight distribution for BPP2 after 5 trials (100 ants, 0.6 evaporation rate)

Comparatively from BPP1, the BPP2 trials have a significantly worse performance, even with the most optimised parameters. The distribution is uneven with large peaks and valleys, reaching over 600,000, and as low as 230,000. Due to the problem size, ACO is unable to properly equalise the bin weights, pointing to a need for additional heuristics. Giving the ants information on retaining a specific bin capacity similar to the traditional bin packing problem would allow for a more even distribution of weight. Due to the quadratic increase in item weight, toward the end of the trials, the bin weights increase drastically even with a single item creating large differences in bin weights.

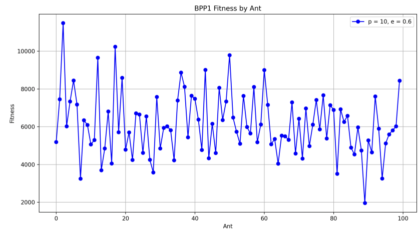

Figure 3: 10 ants, 0.6 evaporation rate fitness across 100 fitness evaluations

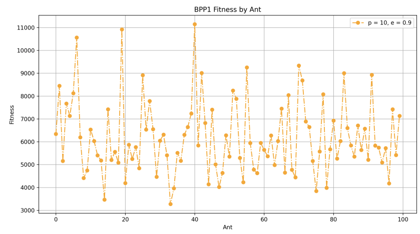

Figure 4: 10 ants, 0.9 evaporation rate fitness across 100 fitness evaluations

Figure 3 shows that a 0.6 evaporation rate has consistent peaks and valleys in fitness across 10 iterations, meaning less pheromone is on the paths allowing for a level amount of exploration over iterations. 0.9 evaporation rate has an initial jump in peaks and valleys in fitness at the beginning of 10 iterations, and then levels out to be more exploitative of select paths toward the end. More pheromone remains compared to the smaller evaporation rate of 0.6, leading to less exploration, affecting the depth of the fitness evaluations, whereas 0.6 continues to experience large explorative bursts even at the end.

	BPP1			
Number of Items	500	500	500	500
Number of Bins	10	10	10	10
Number of Ants	10	10	100	100
Evaporation Rate	0.6	0.9	0.6	0.9
Average Fitness	6.270K	6.274K	6.100K	6.197K
Best Fitness	1.165K	1.287K	0.920K	1.263K

Table 1: BPP1 Fitness Results for 5 Trials

4 Discussion and Further Work

4.1 Which combination of parameters produces the best results?

Table 1 and 2 show that for BPP1 and BPP2, better results occur when using more ants (100 instead of 10) and a lower evaporation rate (0.6 in-

	BPP2			
Number of Items	500	500	500	500
Number of Bins	10	10	10	10
Number of Ants	10	10	100	100
Evaporation Rate	0.6	0.9	0.6	0.9
Average Fitness	784.5K	785.1K	784.7K	785.2K
Best Fitness	414.0K	422.2K	371.3K	406.9K

Table 2: BPP2 Fitness Results for 5 Trials

stead of 0.9). For BPP1 the difference in performance is more noticeable, lowering the average fitness difference between the best and worst performing bins to 3%, whereas for BPP2 the difference is minimal maintaining under 0.1% difference between all averages. When looking at the best fitness for BPP2, it is substantially lower than the others, however, the average fitness remains nearly identical across all parameters, meaning that a fitness of 371.3K can be considered an outlier. The differences between the bins are greater than BPP1, however, the problem size due to the item weights make the discrepancies smaller in context with total bin weight.

4.2 What do you think is the reason for your findings in 5.1?

More ants perform better by exploring more paths prior to the next iteration. The pheromone trail is not yet updated for the next set of ants, allowing for a larger set of p ants to explore the search space prior to each pheromone influence update. This leads to a more diverse set of paths, and thus increased probability of a stronger optimised path

A lower evaporation rate improves the the performance as more of the pheromone trail is evaporating after each iteration. A higher evaporation rate would leave more pheromone along each path. Less pheromone heavy paths means that ants are more likely to follow other pathways, whereas more dense pheromone trails may cause the ants to converge on a solution too early on.

Both more ants and a lower evaporation rate as combined parameters lead to more exploration along pathways that may have not been travelled due to an early build-up of pheromone on a few pathways.

4.3 How do each of the parameter settings influence the performance of the algorithm?

More p ants will slow the algorithm, but allow for further exploration of paths and more diverse solutions. The evaporation rate parameter e affects when the algorithm will converge on a solution, with lower evaporation rate decreasing pheromone paths faster, increasing exploration. One part of the problems that affects the algorithm significantly, is the item weight. BPP1 has a linear increase in item weight, which prevents large discrepancies in bin weight at the end, whereas BPP2 has a quadratic growth in item weight, which makes it more difficult for the ants to settle on an optimal solution.

4.4 Do you think that one of the algorithms in your literature review might have provided better results? Explain your answer.

I think that the hybrid ant colony optimisation algorithm by (Ducatelle and Levine, 2001) would provide better and more effective results. This is because there are additional heuristics such as bin capacity in relation to item weight that would provide each ant with additional information to make stronger decisions. Rather than solely relying on pheromone trails the ants could decipher the after effects of placing an item into a bin in the context of its total weight after. This may slow the algorithm, however, as there are additional computations to be made before each ant can traverse, particularly when the problem size is scaled larger.

4.5 Further Work

Further exploration into the bin packing problem may reveal better alternatives than ACO, potentially in other nature inspired approaches. By instituting a hybrid approach and combining with additional heuristics to give ants more information, it may provide better results, which is especially necessary with larger problem sizes. An implementation that can manage to combine both the efficiency of the pheromone trail with the optimisation effectiveness of a greedy search or first fit decreasing heuristic, in addition to a fine tuning of parameters would be the optimal route. The ants are unable to discover a perfect solution with just the pheromone alone, particularly not for a problem size as large as BPP2. Additionally, creating an ACO implementation for other optimisation problems such as the travelling salesman or cutting stock problems could pave the way for further refinements for the bin packing variation.

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