Application of Swarm Intelligence in Transportation System Optimisation

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Abstract: - Swarm intelligence is a branch of artificial and natural intelligence that studies systems with many characters that manage their activities through distributed control and self-organisation. The field focuses on the actions of social insects such as fish schools, bird flocks, ants, termites, bees, and wasp colonies. Particle swarm optimisation (PSO) and ant colony optimisation (ACO) are two of the most common systems reported by swarm intelligence. Ant Colony Optimization (ACO) is a probabilistic method used to find optimal pathways in computationally complex situations by condensing the problem. This paper analyses the use of ACO metaheuristics to find the initial basic feasible solution in an unbalanced and balanced transportation method. Then, it compares it to other traditional methods (The least cost method, Northwest Corner method, and Vogel's approximation method). The primary goal of this study is to provide a helpful framework for understanding new trends in applying swarm intelligence in system optimisation and implementing/using the ACO algorithm in a real-life situation. Examples were generated online. At the end of the paper, for the unbalanced transportation problem, the Least Cost method, Northwest Corner method, Vogel's Approximation method, and ACO method gave us (472, 547, 374, and 389) as the total cost, respectively. For the balanced transportation problem, the Least Cost, Northwest Corner, Vogel's Approximation, and ACO methods gave us (2450, 3700, 2150, and 3650) as the total cost, respectively.

Key-Words: - System, Optimization, Self-organization, Pheromone, Foraging, Scavenging.

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1 Introduction

Swarm intelligence (SI) is an artificial intelligence technique that studies essential species teaming behaviours in various distributed systems, including animal herding, ant colonies, bird flocking, and bee colonies harvesting honey. By their very nature, SI systems are composed of a population of simple agents interacting locally with one another and their surroundings. Nature, particularly biological organisms, provides stimulation, even though a simple individualistic approach is characterised primarily by autonomy, distributed function, self-organised capacities, and social communication among simple individuals, frequently leading to a universal ideal solution, [1]. This study looks into applying swarm intelligence, especially ant colony optimisation, in system optimisation. We would also look at research done by other people and some problems that can be solved by using numerous swarm intelligence models, including Self-propelled particles, Boids, Stochastic diffusion search (SDS), Particle swarm optimisation, Artificial swarm intelligence, Ant colony optimisation, are employed to address various real-world issues. This paper focuses explicitly on Ant Colony optimisation. A population-based metaheuristic for estimating solutions to complex optimisation problems is called "ant colony optimisation", [2], [3]. An established set of software agents nicknamed "artificial ants" looks for practical solutions to finding the lowest price track on a weighted graph in ant colony optimisation (ACO). As they construct solutions, the virtual ants go over the graph piece by piece. The pheromone model, a collection of inventions linked to a section of the graph (either nodes or edges), impacts the stochastic solution-building process. The ants alter the values of these inventions in real time.

Several classical combinatorial and optimisation problems with stochastic and active elements have produced valuable results using Ant Colony Optimization (ACO). Examples include the explanation of routing in communication networks, [4] and a stochastic variant of a well-known combinatorial optimisation problem, such as the probabilistic travelling salesperson problem and manufacturing scheduling, [5]. Likewise, ACO has been extended to address infinite-variable and mixed-variable optimisation issues. Because of its many practical uses, ant colony optimisation is perhaps the most well-known example of an artificial/engineering swarm intelligence system.

Ant colony optimisation (ACO) is a refinement of optimisation methods based on ant colony motions. Artificial 'ants' - model agents - find optimal solutions by traversing a constrained space containing all feasible solutions. While studying their environment, real ants set aside pheromones to guide each other to supplies. The model ants also record their locations and the characteristics of their solutions, allowing additional ants to detect better solutions in subsequent recreation cycles. One variation from this style is the bees' algorithm, which resembles honeybee scavenging habits. Ant Colony Optimization (ACO) is concerned with simulated systems that are stimulated by the scavenging activity of actual ants and are depleted to solve specific optimisation problems. The critical impression is the ants' unintentional connection via chemical pheromone trails, which qualifies them to locate short pathways between their nest and food. Different kinds of software have also been used to solve ACO modelling problems, such as lingo [6], Lindo, R, etc.

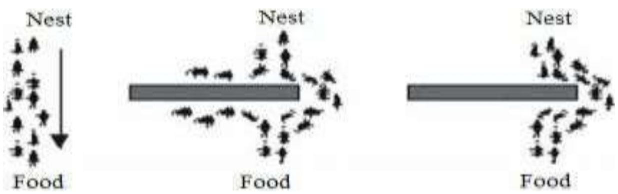

Fig. 1: Ants Finding the Shortest Path, [7]

Figure 1 shows the movement of ants from their nest to their food source and shows the shortest part of the transportation, [7]. Applications of swarm intelligence are crowd simulation, crowd control, human swarming, Swarm art, swarm robotics, swarm intelligence routing, and shortest path problem. The shortest path problem (SPP) is common in computer science society. Many people have deliberated it, but the existing standard is Dijkstra's shortest path algorithm, which exploits dynamic programming to unravel the problem, [8]. Fundamentally, what the shortest path problem deals with is if you have a graph. $G = (M, N)$,Here M is a set of points or positions, and N is a set of vertices that links points in M where N is a subset of $M \times M$. In SPP, each peak in N also has a mass related to it, and the problem that needs to be unravelled is how to get from any point in M to any other point in M with the lowest mass on the vertices used. An unsophisticated instance is to let M be all the airports examined by an airline, and N is the airline's departure. Furthermore, let the mass of N be the cost of each flight. The problem to be unravelled in this condition would be to locate the most typical way to get from any airport to any other airport.

A particular kind of Linear Programming Problem (LPP) called the "Transportation problem" entails transporting goods between several sources and destinations while accounting for supply and demand at each point to reduce the total cost of transportation, it is also known as the Hitchcock problem. The linear programming approach can tackle transportation-related challenges, starting with the most basic workable solution and working your way up to the ideal answer. The latter portion of the transportation problem solution is the main topic of this study. Transportation issues can be divided into two categories: balanced and imbalanced. When supply and demand are equal, there is a balanced transportation problem; when not, there is an imbalanced transportation problem. In this work, we investigated the ability of the Ant Colony Optimization method to locate the first fundamentally feasible solution. We compared it to Vogel's Approximation Method, the Least Cost method, and the Northwest Corner approach.

When using the ant colony optimisation (ACO) metaheuristic to solve a problem, we use the probability of an ant passing a path, which deals with the pheromone concentration, the heuristic factor of the ant. When ants deposit pheromones, evaporation occurs, leading to a second formula called the pheromone update rule. However, in this paper, we would not be looking at that. Since we are applying it to transportation, we would start allocating maximum demand and supply from the second highest probability to avoid congestion (when ants move, they tend to hit themselves, but in real life, it cannot happen with cars). There is still a chance that the allocation at the end would still fall on the highest probability. So, in this paper, we looked at both balanced and unbalanced transportation problems.

1.1 Literature Review

[9], employed the Ant Colony Optimization (ACO) algorithm to solve the transit traffic assignment problem using a line-based strategy. Additionally, numerical efficiency was demonstrated compared to the conventional multiple sequence alignment (MSA) algorithm. This was an extension of the idea put forth in an algorithm for random traffic assignment based on ant colony optimisation, which enables the simulation of mass transit systems with the same accuracy but in a shorter amount of time when compared to traditional optimisation algorithms. The ideal equivalency between mass-transit riders and artificial ants regarding hyper path-choosing behaviour was then postulated.

[10], advised that the ant colony optimisation (ACO) method should be used to find the nearest route search in the distribution of light food production because Indonesians were having trouble getting refreshments distributed around their region. The problems were resolved by placing four ants using the ant colony optimisation technique. According to the study, the ants moved from position A to position H. Four ants moved in sync, with ant 2 having the highest results and travelling the closest to point H, where the value hit 0.00015.

[11], cited three selected and comprehensively detailed examples of swarm intelligence algorithms: the Whale Optimization Algorithm (WOA), the Salp Swarm Algorithm (SSA), and the Grey Wolf Optimizer (GWO). These three were first studied in the literature, specifically about problems with antenna design optimisation. Subsequently, a comparison analysis was carried out with popular test functions. After that, they were applied to develop peak sidelobe level (pSLL) optimised linear antenna arrays. Numerical testing shows that WOA outperforms SSA, GWO, and particle swarm optimisation. Last but not least, the algorithm's ability to construct complex and compact structures for use in resolving antenna design optimisation problems was illustrated by applying WOA to the optimisation problem of an aperture-coupled E-shaped antenna.

[12], presented a novel approach for maximising the transportation problem (TP) and generating a feasible solution (BFS). In most cases, the study’s methodology produces an initial solution that is near to or ideal. Several numerical examples were presented to illustrate the new method. The suggested method is well-known for its ability to analyse transportation issues with a maximising objective function, whether the study is balanced or unbalanced. The new technique was compared with Vogel’s Approximation, Least Cost Method, South-East Corner Method, and North West Corner Method using four numerical examples from real-world applications. It was found that the new algorithm provides a more accurate response. The paper noticed that the optimum solution obtained by the novel algorithm is superior to that of existing methods based on the comparison data.

[13], used effective heuristics to tackle a cooperative transport planning challenge inspired by a situation in the food business in Germany. A set of rich vehicle routing problems (VRP) with capacity limits, maximum operating time window constraints for the vehicles, outsourcing alternatives, and order delivery deadlines were displayed following a suitable breakdown of the complete problem into smaller issues. A greedy heuristic that considers the time window constraints and the distance between the consumer locations solves each of these subproblems. The greedy heuristic is further enhanced by using an Ant Colony System (ACS). According to the results of certain early computer tests, the ACS-based heuristic performs better than the greedy heuristic.

[14], used the ant colony optimization technique to solve a problem with multiple competing objectives in the cost-entropy trade-off for projects involving reinforced concrete office buildings. The research used the average costs of fourteen components from twenty chosen projects. An ideal solution was discovered and confirmed to be consistent with the current currency equivalent within the framework of the prior development method.

[15], the modified ant colony optimisation algorithm (MACOA), a meta-heuristic approach, was used to find an initial feasible solution (IFS) for a transportation problem. The comparison analysis demonstrates that, in terms of solution quality, both the MACOA and the current Juman and Hoque's Method (JHM) are effective when compared to the methodologies under study. As a result, the MACOA is crucial for reducing transportation expenses and maximising transportation procedures, which can greatly enhance an organization's standing in the marketplace.

[16], the Modified ASM technique is intended to generate optimal solutions for transportation-related issues directly. The research process identified and created a model of transportation problems (constraint functions, objective functions,

and variable decisions), classified transportation problems as balanced or unbalanced, and found direct solutions by applying the Modified ASM method to solve transportation problems. This study demonstrates that the Modified ASM approach, which generates optimal solutions more easily than the ASM approach, effectively addresses the issue of balanced and imbalanced transportation.

[17], suggested a novel approach to the Transportation problem (TP) called the N.R. 1 method. In contrast to the three conventional approaches, the NOOR1 method provided us with an initial solution that was either ideal or very close to it. Both balanced and unbalanced TP can be easily solved using the recommended method (NOOR1), which has a minimised objective function.

The advantages of Ant Colony Optimization to a Transportation Problem are as follows:

- Complex optimisation problems like transportation problems are ideally suited for ACO, mainly when dynamic components like demand, fluctuating costs, or real-time traffic data are involved.
- ACO makes use of several agents (ants) that investigate the solution space at the same time. This makes the method naturally adapted for parallel computing, which can shorten computation times and thoroughly investigate viable options.
- Particularly for vast and complicated transportation networks, ACO provides mechanisms to escape local optima through evolving pheromone trails based on exploration and previous solutions. This increases the likelihood that it will find near-optimal or global solutions.

The limitations of Ant Colony Optimization to a Transportation Problem are as follows:

- ACO frequently takes many iterations to get an ideal or almost ideal solution, particularly when dealing with large-scale transportation issues. For conventional transportation issues with more straightforward, linear structures, this may render it less effective than alternative approaches like linear programming.
- Ant population size, the impact of pheromone vs. heuristic information, and pheromone evaporation rate are some parameter choices that significantly affect how effective ACO is. Longer computation times or less-than-ideal answers may result from improper parameter tweaking.
- ACO can be computationally demanding because it iteratively updates pheromone trails and simulates several agents. This becomes challenging when applied to extensive transportation networks with numerous nodes and pathways.

2 Problem Formulation

2.1 Mathematical Model

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{ij}^{k}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} \tag{1}$$

- Where $P_{ij}(t)$ is the probability of kth and passing a chosen path concerning time.
- $\tau_{ij}(t)$ is the concentration of pheromone associated with a path ij.
- $\eta_{ij} = \frac{1}{C_{ij}}$Is the visibility or heuristic factor favouring the path.
- C_{ij} is the path cost.
- α and β control the relative importance of the pheromone and the local heuristic factor.

Steps in applying Ant Colony Optimization (ACO) to Transportation Problems:

- Step 1: Use the formula to find the probability of each distance between the two locations. Above the probability of an ant in choosing a particular path.
- Step 2: Start allocation from the second highest probability (because we are dealing with vehicles which can cause congestion) to start allocation till all the allocations are complete.
- Step 3: Test for degeneracy. If there is degeneracy, stop at step 4.
- Step 4: Find the total cost, i.e. the initial basic feasible solution.
- Step 5: Use the MODI method to find the optimal solution.

NOTE: In this paper, let,$\tau_{ij}(t) = 0.5$ and α, β = 1.

2.2 Problem Statement

We would adopt the unbalanced transportation problem, [18], as seen in Table 1 and the balanced transportation problem [19] in Table 2.

Table 1. Example of Unbalanced Transportation Problem, [18]

	D1	D2	D3	D4	D5	Supply
O1	5	1	8	7	5	15
O2	3	9	6	7	8	25
03	4	2	7	6	5	42
03	7	11	10	4	9	35
Demand	30	20	15	10	20	

Table 2. Example of Balanced Transportation problem, [19]

	D1	D2	D3	D4	Supply
O1	3	1	7	4	250
O2	2	6	5	9	350
O3	8	3	3	2	400
Demand	200	300	350	150	

3 Problem Solution

3.1 Unbalanced

The example used for the Unbalanced transportation problem is Table 1, [18]. Below is the solution to the unbalanced transportation problem using the least cost, northwest corner, Vogel's approximation, and ant colony methods.

- LEAST-COST METHOD

Table 3 shows the solution to the unbalanced transportation problem (i.e. Table 1.) using the least cost method.

Table 3. Least Cost of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	5	1	8	7	5	0 **15**	15
O2	3 **18**	9	6	7	8	0 **7**	25
O3	4 **12**	2 **20**	7	6	5 **10**	0	42
O4	7	11	10 **15**	4 **10**	9 **10**	0	35
Demand	30	20	15	10	20	22	

Test for degeneracy=m+n-1=6+4-1=9

There is no degeneration since the number of allocations is 9.

Total Cost: (0×15) + (3×18) + (4×12) + (2×20) + (10×15) + (4×10) + (9×10) + (5×10) + (0×7) =472

- NORTHWEST CORNER METHOD

Table 4 shows the solution to the unbalanced transportation problem (i.e. Table 1.) using the Northwest corner method.

Table 4. Northwest Corner of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	5 **15**	1	8	7	5	0	15
O2	3 **15**	9 **10**	6	7	8	0	25
O3	4	2 1**0**	7 **15**	6 **10**	5 **17**	0	42
O4	7	11	10	4	9 **13**	0 **22**	35
Demand	30	20	15	10	20	22	

Test for degeneracy=m+n-1=6+4-1=9

There is no degeneration since the number of allocations is 9.

Total Cost: (5×15)+ (3×15)+ (9×10)+ (2×10)+ (7×15)+ (6×10)+ (5×7)+ (9×13)+ (0×22)=547

- VOGEL'S APPROXIMATION METHOD

Table 5 shows the solution to the unbalanced transportation problem (i.e. Table 1.) using Vogel's Approximation method.

Table 5. Vogel's Approximation of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	5	1 **15**	8	7	5	0	15
O2	3 **25**	9	6	7	8	0	25
O3	4 **5**	2 **5**	7 **12**	6	5 **20**	0	42
O4	7	11	10**3**	4 **10**	9	0 **22**	35
Demand	30	20	15	10	20	22	

Test for degeneracy=m+n-1=6+4-1=9

There is no degeneration since the number of allocations is 9.

Total Cost: (1×15)+ (3×25)+ (4×5)+ (2×5)+ (7×12)+ (10×3)+ (4×10)+ (5×20)+ (0×22)=374

- ANT COLONY OPTIMISATION METHOD

a. HEURISTIC FACTOR

$$\eta_{ij} = \frac{1}{C_{ij}}$$

Table 6. Heuristic Table of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	0.2	1.0	0.125	0.143	0.2	0	15
O2	0.333	0.111	0.167	0.143	0.125	0	25
O3	0.25	0.5	0.143	0.167	0.2	0	42
O4	0.143	0.091	0.1	0.25	0.111	0	35
Demand	30	20	15	10	20	22	

Table 6 shows the heuristic factor favouring each path in the unbalanced transportation table.

b. TAU*HEURISTICFACTOR

$$[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}$$

Table 7. Tau Heuristic Factor of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	0.1	0.5	0.063	0.072	0.1	0	15
O2	0.167	0.056	0.084	0.072	0.063	0	25
O3	0.125	0.25	0.072	0.084	0.1	0	42
O4	0.072	0.046	0.05	0.125	0.056	0	35
Demand	30	20	15	10	20	22	

Table 7 shows the tau heuristic factor of an unbalanced transportation table (i.e. tau is the concentration of pheromone level, which we assumed to be 0.5)

c. PROBABILITY TABLE

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}}{\sum_{k=1}^{m}[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}}$$

Table 8. Probability of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	0.044	0.222	0.028	0.032	0.044 **<u>15</u>**	0	15
O2	0.074 **<u>25</u>**	0.025	0.037	0.032	0.028	0	25
03	0.055 **<u>5</u>**	0.111 **<u>20</u>**	0.032 **<u>12</u>**	0.037	0.044 **<u>5</u>**	0	42
04	0.032	0.020	0.022 **<u>3</u>**	0.055 **<u>10</u>**	0.025	0 **<u>22</u>**	35
Demand	30	20	15	10	20	22	

Table 8 shows the probability of each path and the allocation of both the demand and the supply.

Table 9. ACO of Unbalanced Transportation Problem

	D1	D2	D3	D4	D5	D6	Supply
O1	5	1	8	7	5 **<u>15</u>**	0	15
O2	3 **<u>25</u>**	9	6	7	8	0	25
O3	4 **<u>5</u>**	2 **<u>20</u>**	7 **<u>12</u>**	6	5 **<u>5</u>**	0	42
O4	7	11	10**<u>3</u>**	4 **<u>10</u>**	9	0 **<u>22</u>**	35
Demand	30	20	15	10	20	22	

Table 9 shows the solution when the table is returned to its original data of the unbalanced transportation problem in Table 1 with the allocations obtained from Table 8.

Test for degeneracy=m+n-1=6+4-1=9

There is no degeneration since the number of allocations is 9.

Total Cost: (3×25)+ (4×5)+ (2×20)+ (7×12)+ (10×3)+ (4×10)+ (5×15)+ (5×5)+ (0×22)=389

3.2 Balanced

An example of Balanced Transportation is from Table 2, [19]. Below is the solution to the balanced transportation problem using the least cost, northwest corner, Vogel's approximation, and ant colony methods.

- LEAST-COST METHOD

Table 10 shows the solution to the balanced transportation problem (i.e. Table 2) using the least cost method.

Table 10. Least Cost of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	3	1 **<u>250</u>**	7	4	250
O2	2 **<u>200</u>**	6	5 **<u>150</u>**	9	350
03	8	3 **<u>50</u>**	3 **<u>200</u>**	2 **<u>150</u>**	400
Demand	200	300	350	150	

Test for degeneracy=m+n-1=4+3-1=6

There is no degeneration since the number of allocations is 6.

Total Cost: (2×200)+ (1×250)+ (3×50)+ (5×150)+ (3×200)+ (2×150)=2450

- NORTHWEST CORNER METHOD

Table 11 shows the solution to the balanced transportation problem (i.e. Table 2) using the Northwest corner method.

Table 11. Northwest Corner of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	3 **<u>200</u>**	1 **<u>50</u>**	7	4	250
O2	2	6 **<u>250</u>**	5 **<u>100</u>**	9	350
03	8	3	3 **<u>250</u>**	2 **<u>150</u>**	400
Demand	200	300	350	150	

Test for degeneracy=m+n-1=4+3-1=6

There is no degeneration since the number of allocations is 6.

Total Cost: (3×200)+ (1×50)+ (6×250)+ (5×100)+ (3×250)+ (2×150)=3700

- VOGEL'S APPROXIMATION METHOD

Table 12 shows the solution to the balanced transportation problem (i.e. Table 2) using Vogel's Approximation method.

Table 12. Vogel's Approximation of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	3	1 **250**	7	4	250
O2	2 **200**	6	5 **150**	9	350
03	8	3 **50**	3 **200**	2 **150**	400
Demand	200	300	350	10	

Test for degeneracy=m+n-1=4+3-1=6

There is no degeneration since the number of allocations is 6.

Total Cost: (2×200)+ (1×250)+ (3×50)+ (5×150)+ (3×200)+ (2×150)=2150

- ANT COLONY OPTIMISATION METHOD

c. HEURISTIC FACTOR

$$\eta_{ij} = \frac{1}{C_{ij}}$$

Table 13. Heuristic Factor of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	0.333	1.0	0.143	0.25	250
O2	0.5	0.167	0.2	0.111	350
O3	0.125	0.333	0.333	0.5	400
Demand	200	300	350	150	

Table 13 shows the heuristic factor favouring each path in the balanced transportation table.

d. TAU*HEURISTICFACTOR

$$[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}$$

Table 14. Tau Heuristic Factor of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	0.167	0.5	0.072	0.125	250
O2	0.25	0.084	0.1	0.056	350
O3	0.063	0.167	0.167	0.25	400
Demand	200	300	350	150	

Table 14 shows the tau heuristic factor of a balanced transportation table (i.e. tau is the concentration of pheromone level, which we assumed to be 0.5)

e. PROBABILITY TABLE

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}}{\sum_{k=1}^{m} \quad [\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}]^{\beta}}$$

Table 15. Probability of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	0.083	0.250 **50**	0.036 **200**	0.063	250/50/0
O2	0.125 **200**	0.042	0.050 **150**	0.028	350/150/0
03	0.031	0.083 **250**	0.083	0.125 **150**	400/250/0
Demand	200/0	300/50/0	350/200/0	150/0	

Table 15 shows the probability of each path and the allocation of both the demand and the supply.

Table 16. ACO of Balanced Transportation Problem

	D1	D2	D3	D4	Supply
O1	3	1 **50**	7 **200**	4	250
O2	2 **200**	6	5 **150**	9	350
03	8	3 **250**	3	2 **150**	400
Demand	200	300	350	150	

Table 16 shows the solution when the table is returned to its original data of the balanced transportation problem in Table 2 with the allocations obtained from Table 15.

Test for degeneracy=m+n-1=4+3-1=6

There is no degeneration since the number of allocations is 6.

Total Cost: (2×200)+ (1×50)+ (3×250)+ (7×200)+ (5×150)+ (2×150)=3650

4 Conclusion

This paper looked into swarm intelligence and used Ant Colony Optimisation (ACO) to find the initial basic feasible solution in a balanced and unbalanced transportation problem. It also compared ACO to other traditional methods (Least Cost, Northwest Corner, Vogel's Approximation method) to find the initial basic feasible solution using online generated data. This paper showed that ACO can be used to find the Initial Basic feasible solution, which was applied data and gave the total cost for unbalanced and balanced transportation problems as 389 and 3650, respectively. In contrast, the Least Cost method gave the total cost to be (472, 2450) for both unbalanced and balanced respectively; the Northwest Corner method gave the total cost to be (547, 3700) for both unbalanced and balanced respectively, Vogel's Approximation method gave the total cost to be (374, 2150) for both unbalanced and balanced respectively. With the above data, Vogel's Approximation still gave us the best result. In the transportation problem, Vogel's

Approximation Method (VAM) is well-known for identifying early feasible solutions since it frequently produces a near-ideal solution compared to other crucial techniques like the Least Cost Method or the Northwest Corner Rule. By analysing the penalty (difference) between the two lowest costs in each row and column, VAM considers the opportunity cost of not selecting the least expensive option, which is why it is still recommended. This leads to a more efficient allocation, frequently resulting in a lower total transportation cost than alternative heuristics.

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