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To Use an Ant Colony Technique to Solve a Crispy Type Bi- and Tri-Objective Transportation Problem

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Abstract: Transportation problem (TP) aims to reduce the entire transportation cost of moving resources from various supply hubs to various demand hubs. However, in real-life situations, all organizations want to achieve numerous objectives while making transportation of goods. The degree of deterioration may vary depending on the mode, route, and time of transport. In some cases, the multiobjective could be used to reduce the use of a scarce resource, such as energy. As a result, the proposed approach was discovered to be an algorithm that improves bi- and triobjective TP techniques. This is an innovative way for solving the new bi- and triobjective transportation algorithm using a modified ant colony optimization (ACO) algorithm. According to the literature, various strategies have been developed in the past to tackle the multiobjective transportation problem (MOTP). The MOTP is solved using goal programming, fuzzy programming, interactive solution algorithms, and other techniques. These strategies are occasionally good or bad in achieving better results in a reasonable amount of time. The heuristic technique used in this work is the improved ACO algorithm, which is based on the ant colony algorithm and has been found to provide solutions with a reasonable degree of satisfaction for two and three objective TPs. When the findings are compared, the solution achieved using the proposed method has delivered the best performance and provides a case study to show the new strategy.

Keywords: multi-objective, transportation problem, optimization, efficient solution, ant colony optimization algorithm

1. Introduction

Traditional transportation problem (TP) is often caused by a single purpose, which may be transportation time or cost (Hitchcock, 1941). In any case, associations are increasingly competing with one another. Therefore, while moving goods between organizations, it is not enough to accomplish just one goal at a time. An examination of different types of TPs and mathematical models has been released, better examining TP (Ekanayake et al., 2022). In light of this, multidestinations must be maintained continuously in order for businesses to maximize profit. Many analysts have developed effective ways to solve at least two locations simultaneously, such as by optimizing TPs with multiple goals. For each of the most popular solutions to linear multiobjective transportation problems (MOTPs), various methods based on linear multiobjective programming were created (Diaz, 1978, 1979; Isermann, 1979; Lee & Moore, 1973; Zeleny, 1974). Ringuest and Rinks (1987) developed two interactive methods to resolve the linear MOTP. The MOTP was approached by Kumar and Pandey (2012) and Li and Lai (2000) using the fuzzy programming technique, and they were successful in finding both reasonable compromise solutions and product-effective solutions. Gupta and Gupta (1983) created a simpler multicriteria simplex method for a linear multiple-objective transportation problem and a condensed interactive multiple-objective linear programming (Reeves & Franz, 1985), an efficient algorithm for MOTP (Kasana & Kumar, 2000), multichoice goal programming revised (Chang, 2008), a new approach to addressing the biobjective TP (Bander et al., 2015), a straightforward algorithm for a multiobjective transportation model (Bai & Yao, 2011), and more (Pandian & Anuradha, 2011), solving MOTPs (Diaz, 1979), etc. Charnes and Cooper (1977) introduced the standard version of the goal programming (GP) model in the early 1960s. Significant extensions and numerous applications have been proposed since then. An excellent literature evaluation of the GP model was published, for instance, by Tamiz et al. (1998). A target attainment approach that is computationally quicker than conventional GP methods was proposed by Hwang and Masud (2012). Fuzzy goal programming has recently been employed by Zangiabadi and Maleki (2013) to resolve MOTP using linear and nonlinear membership functions. Quddoos et al. (2013a, 2013b) used lexicographic GP to solve a biobjective TP. A multiobjective, chance-constrained, capacitated TP was solved (Gupta et al., 2013). Maity and Roy (2014) proposed updated utility functions and multichoice, multiobjective transportation issue techniques for the MOTP. Afwat et al. (2018) developed a new, effective method to resolve the MOTP in a fuzzy setting. Numerous studies have been conducted on this topic, and it is practical to take into account that different objectives in multiobjective situations have varying degrees of importance and priority. Numerous studies have been conducted on this topic, and it is practical to take into account that different objectives in multiobjective situations have varying degrees of importance and

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priority. Khan and Kabeer (2015) proposed MOTP with fuzziness and S-type membership function, and Nomani et al. (2017) developed a novel method for resolving TPs with multiple purposes that give each objective a different weight. An MOTP with a type 2 trapezoidal fuzzy number with parameter estimation and goodness of fit was published by Kamal et al. (2021). Furthermore, Osuji et al. (2014) developed a solution to a multiobjective transportation problem via a fuzzy programming algorithm.

A population-based metaheuristic called ant colony optimization (ACO) is useful for estimating solutions to challenging optimization problems. A large number of programming operators known as "artificial ants" search for good solutions to a specific optimization problem in ACO. Optimization problems are significant in the fields of both logical and mechanical optimization. Some genuine instances of these optimization problems are time table booking, nursing time conveyance planning, train planning, scope organization, mobile sales rep issues, vehicle directing issues, group-shop booking issues, portfolio advancement, and so forth. Numerous improvement calculations have been developed for this reason. ACO is one of them. D'Acierno et al. (2011), Monteiro et al. (2012), Maniezzo et al. (1996), Dorigo and Gambardella (1997), and Dorigo et al. (1999) all describe ACO as a probabilistic method for locating optimum pathways. This algorithm relies on an ant's foraging strategy to find a route between their colony and a food source.

This paper presents an overview of the concept of ant colony algorithm (ACA) and gives a survey of its applications for explaining another methodology for solving MOTPs that are exceptionally easy to apply and dependent on the solution of general TPs, so that decision makers can without much of a stretch apply it. Indeed, at each step, a new efficient solution is obtained. Artificial ants can then be seen and categorized as communicating agents that combine some qualities that are particular to them while also sharing some traits with real ants, according to Solimanpur et al. (2005). Their general traits make them capable of solving issues, if not optimally, then at least by coming up with excellent solutions. True foraging ants spend their entire lives moving from their nest to a source of food. ACO, a population-based metaheuristic, can be used to roughly resolve difficult optimization problems. The ACO metaheuristic was described as a collection of general recommendations that could be easily applied to nearly any type of combinatorial optimization problem, which increased the number of researchers and publications in the field. Since then, many problems have been solved utilizing ACO techniques, including network flow concerns (Monteiro et al., 2012), network design issues and more (Rappos & Hadjiconstantinou, 2004), assignment issues (Shyu et al., 2006), and location issues (Ekanayake et al., 2020b; Musa et al., 2010; Santos et al., 2010) that address TPs and covering problems (Chen & Ting, 2008), citing a few publications in the field of combinatorial optimization (Mehrabi et al., 2009). Surprisingly, the traveling salesman problem (TSP) still inspires researchers as shown by Tavares and Pereira (2011), who utilize the TSP to test an evolutionary method to update pheromone trails, or García-Martínez et al. (2007), who recently used ACO to solve a bicriteria TSP. This is true despite the fact that the A S and ACO metaheuristics were the first to successfully solve the TSP. In addition to other issues, Ekanayake et al. (2020a) used a modified ACA to solve the minimum spanning tree problem and the TP.

This study provides an overview of the ACA idea and surveys its applications to explain another way for resolving transportation challenges with multiple objectives, which is exceptionally simple to apply and is dependent on the resolution of general transportation issues, so that any decision can easily apply it. Indeed, at each step, a new efficient solution is obtained.

2. Definition

2.1. ACO algorithm

The colony symbolizes an independent individual behavior system with extremely basic principles. Even though each individual ant exhibits basic behavior, the colony as a whole exhibits highly clever behavior (Dorigo & Gambardella, 1997). The behavior of the colony is based on low-level interaction, which makes the entire colony an intelligent multiagent system. The ACO imitates how actual ants choose the quickest route from a food source to their colony. Pheromone trails are used by the ants (there are two kinds of ants in the colony such as artificial "ants," which find optimal solutions. Real ants lay down pheromones, guiding each other to resources) to communicate with one another and share information on the best course to take A given path (trail) gets more appealing as more ants follow it by leaving behind their own pheromones, which increases its appeal to other ants (unique chemical substance). The shortest route is determined as a result of this collective and autocatalytic behavior. With the aid of pheromone trails, ants determine the quickest route from their nest to the food source. This ant trait is used in ACO methods to solve real-world problems by utilizing both existing ant traits and brand-new ones (Shyu et al., 2006).

But because the agents first select their travel path at random, this method invariably results in a local optimal solution. Pheromone evaporation, a negative feedback mechanism, solves this issue. The density of pheromones and the amount of feedback are limited by uniform evaporation throughout the entire area. The path that took less time is consequently less likely to evaporate, and as a result, the pheromone density is higher on the ideal path (Dorigo & Gambardella, 1997; Maniezzo et al., 1996).

The algorithm's two most important steps are the creation of the visit/arrangement and the pheromone update. Before the ants may start searching for a solution, other important decisions must be made, like deciding on the solution's structure (representation) or the starting pheromone quantity to be given to each arc. Later, we will examine more closely at these queries. The ant system, the first foraging ant system, was developed using the notation in Maniezzo et al. (1996).

The ants in ACO adhere to two fundamental rules:

i. The information is provided by the algorithm and is represented as τ_{ij}, which is the pheromone strength along the route between cities i and j at time t.
ii. Depending on the problem that needs to be solved, a heuristic algorithm can determine η_{ij}, the heuristic information directing the route from city i to city j. Overall, it may be stated that,

$$\eta_{ij} = \frac{1}{d_{ij}}, \tag{1}$$

where d_{ij} is the distance between cities i and j.

The two rules are applied at time t, and the ant k at city i chooses the subsequent city j, which it has not yet visited, with the following probability:

$$p^k{}_{ij} = \begin{cases} \frac{\tau^\alpha{}_{ij}\eta_{ij}{}^\beta}{\sum_{j\in N_i{}^k} \tau^\alpha{}_{ij}\eta_{ij}{}^\beta} & if \;\; j \in N_i{}^k \\ 0 & if \;\; j \notin N_i^k \end{cases} \tag{2}$$

where $\alpha \geq 0$ and $\beta \geq 0$ are adjustable parameters describing the weights of the pheromone trail and visibility when choosing the route. When $\alpha = 0$, the nearest city is chosen, which corresponds to a greedy algorithm in the classical optimization theory. When $\beta = 0$, only the pheromone trail is taken into account, which implies that all ants select one suboptimal route. To provide good optimization dynamics, it is recommended in Maniezzo et al. (1996) to set $\beta \geq \alpha$. $N_i{}^k$ is the feasible neighborhood of ant k when it is at city i, that is, the set of cities that ant k has not visited yet. In addition, the ACO algorithm has been successfully applied to solve a wide range of combinatorial optimization problems, including the minimum spanning tree, the traveling salesman problem, transportation problems, and the quadratic assignment problem with various modifications (Baykasoglu et al., 2006; Blum, 2005; Maniezzo et al., 1996; Dorigo & Gambardella, 1997).

The ant must visit all of the cities in a single cycle before the pheromone concentration on each path may be updated. After the ant paths have been built, the pheromones for all ants are updated using the following equation:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau^k{}_{ij}, \tag{3}$$

where ρ is the residual ratio of the pheromone. However, to avoid an infinite accumulation of the pheromone, ρ must be less than 1. $\Delta\tau^k{}_{ij}$ is the increase of the trail level on edge (i, j) caused by ant k. Depending on the problem, there are three descriptions of $\Delta\tau^k{}_{ij}$, as follows:

$$\Delta\tau^k{}_{ij} = \begin{cases} \frac{Q}{T^k}; & \text{if ant } k \text{ travels on edge } (i,j) \\ 0; & \text{Otherwise} \end{cases} \tag{4}$$

$$\Delta\tau^k{}_{ij} = \begin{cases} \frac{Q}{d_{ij}}; & \text{if ant } k \text{ travels on edge } (i,j) \\ 0; & \text{Otherwise} \end{cases} \tag{5}$$

$$\Delta\tau^k{}_{ij} = \begin{cases} Q; & \text{if ant } k \text{ travels on edge } (i,j) \\ 0; & \text{Otherwise} \end{cases} \tag{6}$$

where T^k is the length of the tour that ant k has found and Q is the amount of pheromone that an ant lays each tour (where $Q > 0$ is an adjustable parameter). The first of the three descriptions above makes use of global knowledge, while the other two make use of local information. In most cases, the first description is employed.

3. Mathematical Formulation

In real-life scenarios, every coordinator typically needs to accomplish numerous goals at once while organizing the delivery of goods. As a result, analysts designed MOTP to accomplish a variety of goals. Similar to the classic TP, quantity (x_{ij}) must be carried from sources $i(i = 1, 2, \ , m)$ to destinations $j(j = 1, 2, \ , n)$ at cost $C_{ij}{}^k$, where $C_{ij}{}^k$ can be transportation cost, total delivery time, energy consumption, or limiting transportation risk, among other things.

The truth is that there are many different transportation issues. There were various objective functions that described the transportation issue. The decision-maker wants to reduce a number of p objectives at once. Quantity (x_{ij}) must be carried from sources $i(i = 1, 2, \ldots, m)$ to destinations $j(j = 1, 2 \ldots n)$ for a price $C_{ij}{}^k$, where $C_{ij}{}^k$ may refer to the cost of transportation, the cost of damage, the cost of total delivery time, the cost of energy consumption, or other factors. The reduction of the overall cost of transportation is the goal of the p objectives $f^1(x), f^2(x), \ldots, f^{p-1}(x)$ and $f^p(x)$. It is always taken for granted that the balance condition is true (i.e., the total demand is equal to the total supply). The MOTP can be written as follows under these presumptions:

$$f^1(x) = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}{}^1 x_{ij}$$

$$f^2(x) = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}{}^2 x_{ij}$$

$$\vdots$$

$$f^p(x) = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}{}^p x_{ij}$$

Subject to the constraints

$$\sum_{j=1}^{n} x_{ij} = a_i \quad i = 1, \ldots, m$$

$$\sum_{i=1}^{m} x_{ij} = b_j \quad j = 1, \ldots, n$$

$$x_{ij}0, \ i = 1, 2, \ldots., m \ \ and \ j = 1, 2, \ldots..n$$

where $C_{ij}{}^k$ coefficient of the kth objective; a_i is the supply amount of the product at source i (S_i); b_j is the demand of the product at destination j (D_j); and $a_i > 0$ for all i, $b_j > 0$ for all j and $\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j$ (balanced condition). The balanced condition is both necessary and sufficient for solving the transportation problem in both the cases single and multiple objectives.

The multiobjective transportation model's special structure can also be expressed in Table 1.

4. Algorithm for the Proposed

Finding the right answer – which should typically be either an incredibly near-optimal or an ideal solution – is crucial when trying to solve transportation challenges with many objectives. Here is a

Table 1
Transportation cost table

Destination→ source↓	D_1	D_2	...	D_n	supply(ai)
S_1	$(C_{11}{}^1, C_{11}{}^2, \ldots, C_{11}{}^p)$	$(C_{12}{}^1, C_{12}{}^2, \ldots, C_{12}{}^p)$	...	$(C_{1n}{}^1, C_{1n}{}^2, \ldots, C_{1n}{}^p)$	a_1
S_2	$(C_{21}{}^1, C_{21}{}^2, \ldots, C_{21}{}^p)$	$(C_{22}{}^1, C_{22}{}^2, \ldots, C_{22}{}^p)$	$\vdots$	$(C_{2n}{}^1, C_{2n}{}^2, \ldots, C_{2n}{}^p)$	a_2
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
S_m	$(C_{m1}{}^1, C_{m1}{}^2, \ldots, C_{m1}{}^p)$	$(C_{m2}{}^1, C_{m2}{}^2, \ldots, C_{m2}{}^p)$	...	$(C_{mn}{}^1, C_{mn}{}^2, \ldots, C_{mn}{}^p)$	a_m
Demand (bj)	b_1	b_2	...	b_n	

fundamental method for finding a compromise solution that is incredibly effective. The steps of this new algorithm are provided below to continue with the proposed new algorithm.

We are currently using the aforementioned new modified probabilistic transition rule in our multiple TP:

$$p^k{}_{ij} = \frac{1/\sum_{k=1}^{p} (c_{ij}{}^k)^2}{\sum_{i=1}^{m} \sum_{j=1}^{n} 1/\sum_{k=1}^{p} (c_{ij}{}^k)^2} \quad (7)$$

5. The MOTP Has Been Solved Using a Novel Method Called MACOA (MOTP)

Step 1: Develop a cost matrix of the given MOTP.
Step 2: The probability matrix is introduced using Equation (7).
Step 3: Assign the min (a_i, b_j) maximum probability cell to the i-j^{th} cell.
Step 4: Allocate this minimum value to the selected cell in Step 3 and delete the column or /row for which ith supply and jth demand necessities are met, then move to the next max (a_i, b_j) value.
Step 5: Continue until all supply and demand are met, at which point move on to Step 6. If not, proceed to Step 4.
Step 6: Stop and find a feasible solution using the new method.

6. The Performance of PM Is in Comparison to the Existing Methods

6.1. Results obtained from PM compared with matrix maxima

Data for the biobjective transportation problem in Table 2 have a thorough representation of the numerical data, and Table 3 represents the probability table, which was constructed using Equation (7).

Table 2
Data for biobjective transportation problem

	D_1	D_2	D_3	D_4	Supplies
S_1	[6,1]	[4,2]	[1,3]	[5,4]	14
S_2	[8,4]	[9,3]	[2,2]	[7,0]	16
S_3	[4,0]	[3,2]	[6,2]	[2,1]	5
Demands	6	10	15	4	

Table 3
Probability table using Equation (7)

	D_1	D_2	D_3	D_4	Supplies
S_1	0.036	0.068	0.136	0.033	14
S_2	0.017	0.015	0.170	0.027	16
S_3	0.085	0.104	0.034	0.272	5
Demands	6	10	15	4	

Table 4 portrays the solution of the above problem using the proposed method.

Table 4
Supply and demand allocation

	D_1	D_2	D_3	D_4	Supplies
S_1	0.036*4	0.068*10	0.136	0.033	14*4*0
S_2	0.017	0.015	0.170*15	0.027*1	$16 * 1 * 0$
S_3	0.085*2	0.104	0.034	0.272*3	$5 * 2 * 0$
Demands	6*2*0	10*0	15*0	4*3*0	

Therefore, $[f^1(x), f^2(x)] = 4[6, 1] + 10[4, 2] + 15[2, 2] + [7, 0] + 2[4, 0] + 3[2, 1] = [115, 57]$

Table 5 represents a comparative study of the proposed method over the existing method.

Table 5
A comparative study of the proposed method over the new row maxima method, product approach, and matrix maxima method

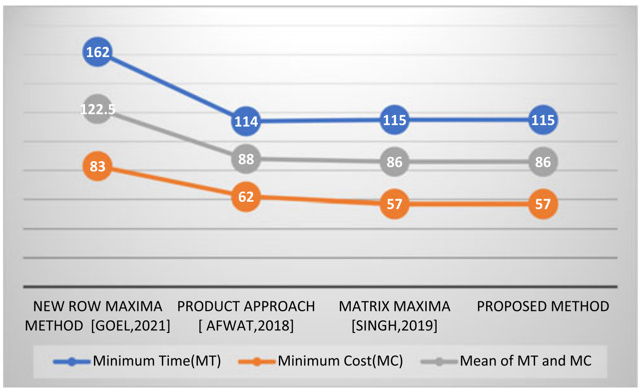
Comparison analysis	Minimum time (MT)	Minimum cost (MC)	Mean of MT and MC
New row maxima method (Goel, 2021)	162	83	122.5
Product approach (Afwat et al., 2018)	114	62	88
Matrix maxima (Singh & Rajan, 2019)	115	57	86
Proposed method	115	57	86

A comparative study of the proposed method over the new row maxima method, product approach, and matrix maxima method is illustrated in Table 5.

Figure 1 shows the significance of the proposed method.

According to Table 5 and Figure 1, the proposed method provides the best solutions obtained by other existing methods, new row maxima method, product approach, and matrix maxima method.

Figure 1
Results obtained by the proposed method over the new row maxima method, product approach, and matrix maxima method



6.2. Results obtained from the proposed method compared with the Kaur's method

Table 6 represents the data of the multiobjective transportation problem, and Table 7 portrays the allocation of the proposed method.

Table 6
Data for the multiobjective transportation problem

	D_1	D_2	D_3	Supplies
S_1	[3,5]	[4,2]	[5,1]	8
S_2	[4,3]	[5,4]	[2,3]	5
S_3	[5,2]	[1,3]	[2,1]	2
	7	4	4	

Table 7
Probability table with allocation supply and demand

Cost, time	D_1	D_2	D_3	Supplies
S_1	0.049 * 2	0.084 * 4	0.064 * 2	8
S_2	0.067 * 5	0.041	0.129	5
S_3	0.058	0.168	0.337 * 2	2
	7	4	4	

The proposed method is compared to the Kaur's method (Kaur et al., 2018) in Table 8.

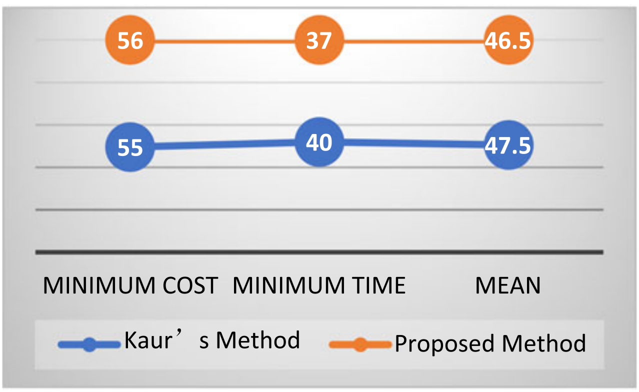
As shown in Table 8, the proposed method achieves a more promising solution than the Kaur's method (Kaur et al., 2018) considered in this study. Figure 2 provides line graphs to illustrate the comparison.

Table 8 and Figure 2 depict that the proposed method in finding a solution for the MOTP is more efficient than the formalized inspection method.

Table 8
Performance evaluation of the proposed method with the Kaur's method

Method	Minimum cost	Minimum time	Mean
Kaur's method (Kaur et al., 2018)	55	40	47.5
Proposed method	56	37	46.5

Figure 2
Results obtained by the proposed method over the Kaur's method



6.3. Results obtained from the proposed method compared with the Khan method

Table 9 is a representation of a biobjective transportation problem, while Table 10 represents the allocation of the proposed method.

Table 9
The data for the biobjective transportation problem

Cost, time	D_1	D_2	D_3	Supplies
S_1	[16,9]	[19,14]	[12,12]	14
S_2	[22,16]	[13,10]	[19,14]	16
S_3	[14,8]	[28,20]	[8,6]	12
Demand	10	15	17	

Table 10
Solution of the above problem (Table 9)

Cost, time	D_1	D_2	D_3	Supplies
S_1	0.099 * 9	0.060	0.116 * 5	14
S_2	0.045 * 1	0.125 * 15	0.060	16
S_3	0.129	0.028	0.336 * 12	12
Demand	10	15	17	

Table 11 is a representation of comparison of the proposed method with the Nomani method (Nomani et al., 2017).

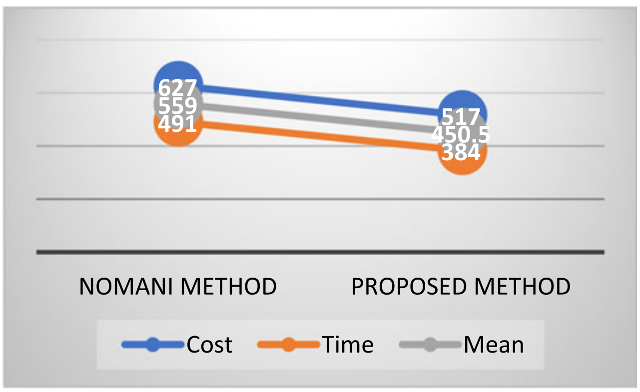
In addition, Figure 3 is a representation of the proposed method with the Nomani method (Nomani et al., 2017).

According to Table 11 and Figure 3, the proposed method is better than the solution obtained by the Nomani method (Nomani et al., 2017).

Table 11
A comparative study of the proposed method over the Nomani method

Method	Minimum cost	Minimum time	Mean
Nomani method (Nomani et al., 2017)	627	491	559
Proposed method	517	384	450.5

Figure 3
Comparative study of the result obtained by the Nomani method and the proposed method



6.4. Results obtained from the proposed method compared with the Maity George method

Table 12 shows the data for the biobjective transportation problem from the Maity George method (Maity & Roy, 2014) and shows a thorough depiction of the numerical data, and Table 13 represents the supply and demand allocation using the proposed method.

Table 12
The data for the biobjective transportation problem from Maity George method

Cost, time	D_1	D_2	D_3	D_4	Supplies
S_1	[24,14]	[29,21]	[18,18]	[23,13]	21
S_2	[33,24]	[20,13]	[29,21]	[32,23]	24
S_3	[21,12]	[42,30]	[12,9]	[20,11]	18
S_4	[25,13]	[30,22]	[19,19]	[24,14]	30
Demand	13	22	26	30	

Table 13
Probability table and solution for Table 12

Cost, Time	D_1	D_2	D_3	D_4	Dummy	Supplies
S_1	0.059*13	0.035	0.070*8	0.065	0	21
S_2	0.027	0.080*22	0.035	0.029	0*2	24
S_3	0.078	0.017	0.0202*18	0.087	0	18
S_4	0.057	0.032	0.063	0.059*30	0	30
Demand	13	22	26	30	2	

Therefore, $[f^1(x), f^2(x)] = 13[24, 14] + 8[18, 18] + 22[20, 13] + 18[12, 9] + 30[20, 14] = [1832, 1194]$

In this study, in Table 14, the researchers compare the results to determine the efficacy of the proposed method.

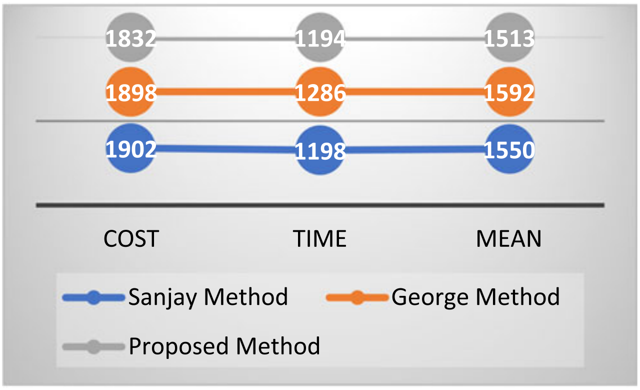
Table 14
A comparative study of the proposed method over the Sanjay method and Maity George method

Method	Minimum cost	Minimum time	Mean
Sanjay method	1902	1198	1550
George method	1898	1286	1592
Proposed method	1832	1194	1513

In addition in Figure 4, the researchers compare the results to determine the efficacy of the proposed method.

According to Table 14 and Figure 4, the proposed methods outperform the existing methods such as the Sanjay and George methods.

Figure 4
A line graph of the results obtained by the proposed method over the Sanjay method and the Maity George method



6.5. Results obtained from the proposed method compared with the Sheikhi method

Table 15 depicts the numerical data (Sheikhi, 2018) in detail, and Table 16 represents the allocation supply and demand of the proposed method.

Table 15
The data for the problem from Sheikhi

Cost, Time	D_1	D_2	D_3	D_4	Supplies
S_1	[10,15]	[14,12]	[8,16]	[12,8]	15
S_2	[8,10]	[12,6]	[14,13]	[8,12]	25
S_3	[9,13]	[6,15]	[15,12]	[9,10]	20
Demand	14	18	12	16	

Table 16
Solution from Sheikhi problem

Cost, time	D_1	D_2	D_3	D_4	Supplies
S_1	0.062	0.060*3	0.063*12	0.098	15
S_2	0.124*14	0.112*11	0.056	0.098	25
S_3	0.081	0.078*4	0.055	0.112*16	20
Demand	14	18	12	16	

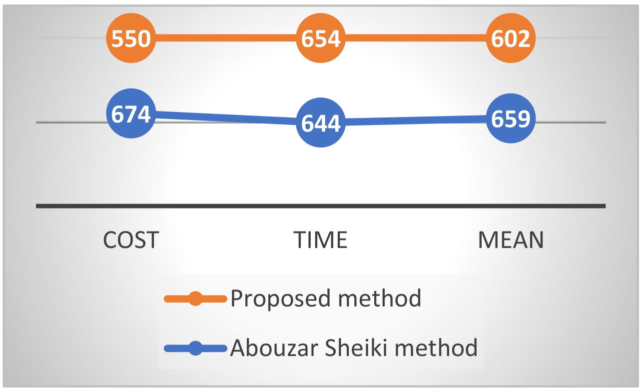
$$[f^1(x), f^2(x)] = 3[14, 12] + 12[8, 16] + 14[8, 10] + 11[12, 6] + 4[6, 15] + 16[9, 10] = [550, 654]$$

Table 17 shows that the proposed method has outperformed the existing method.

Table 17
A comparative study of the proposed method over the Sheikhi method

Method	Minimum cost	Minimum time	Mean
Sheikhi method	674	644	659
Proposed method	550	654	602

Figure 5
Comparative study of the result obtained by the Sheikhi method and the proposed method



The comparison of results presented in Table 17 is also illustrated using line graphs in Figure 5 to show the effectiveness of the proposed method.

The proposed approach is superior to the answer obtained by the Abouzar Sheikhi method (Sheikhi et al., 2018), as shown in Table 17 and Figure 5.

6.6. Results obtained from proposed method compared with the Doke method

Table 18 shows a thorough depiction of the numerical data and the comparative findings achieved by the Doke (Doke & Jadhav, 2015) and proposed method.

Solving the example using the proposed algorithm for Table 19.

Table 18
The comparative findings achieved by the Doke method and the proposed method

	D_1	D_2	D_3	D_4	Supplies
S_1	[3,2,8]	[2,5,4]	[5,7,3]	[7,9,2]	10
S_2	[4,4,5]	[3,4,3]	[3,5,4]	[5,6,2]	20
S_3	[2,3,7]	[1,2,2]	[4,6,6]	[3,8,8]	40
Demands	15	15	20	20	

Table 19
Final allocation of multiobjective TP

	D_1	D_2	D_3	D_4	Supplies
S_1	0.040	0.079	0.042*10	0.0265	10*0
S_2	0.062	0.104	0.071*10	0.054*10	20*10*0
S_3	0.057*15	0.395*15	0.040	0.025*10	40*25*10*0
Demands	15*0	15*0	20*10*0	20*10*0	

$$[f^1(x), f^2(x), f^3(x)] = 10[5,7,3] + 10[3,5,4] + 10[5,6,2] + 15[2,3,7] + 15[1,2,2] + 10[3,8,8] = [205,335,305]$$

Table 20 represents a comparative analysis of the proposed algorithm with the Doke method (Doke & Jadhav, 2015).

Table 20
Comparative assessments, for example, representation of Table 18

Method	Minimum cost	Minimum time	Minimum distance
Doke method	205	335	305
PM	205	335	305

The proposed method has a clear similarity to the Doke method (Doke & Jadhav, 2015), as shown in Table 20.

6.7. Results obtained from the proposed method compared with the Afwat method

Table 21 shows the comparative findings achieved by the existing method and the proposed method, and Table 22 represents the allocation of the proposed method.

Table 21
The data for the triobjective transportation problem from Afwat

	D_1	D_2	D_3	D_4	Supplies
S_1	[6,13,6]	[4,11,3]	[1,15,5]	[5,20,4]	14
S_2	[8,17,5]	[9,14,9]	[2,12,2]	[7,13,7]	16
S_3	[4,18,5]	[3,18,7]	[6,15,8]	[2,12,6]	5
Demands	6	10	15	4	

Table 22
Final allocation in the above problem (Table 20)

	D_1	D_2	D_3	D_4	Supplies
S_1	0.088*4	0.146*10	0.085	0.048	14
S_2	0.056*1	0.059	0.140*15	0.080	16
S_3	0.058*1	0.055	0.065	0.116*4	5
Demands	6	10	15	4	

$$[f^1(x), f^2(x), f^3(x)] = 4[6,13,6] + 10[4,11,3] + 1[8,17,5] + 15[2,12,2] + [4,18,5] + 4[2,12,6] = [114,425,118]$$

Table 23 shows the comparative findings achieved by the new row maxima method, product approach, geometric mean, Ekanayake's Method, and the proposed method.

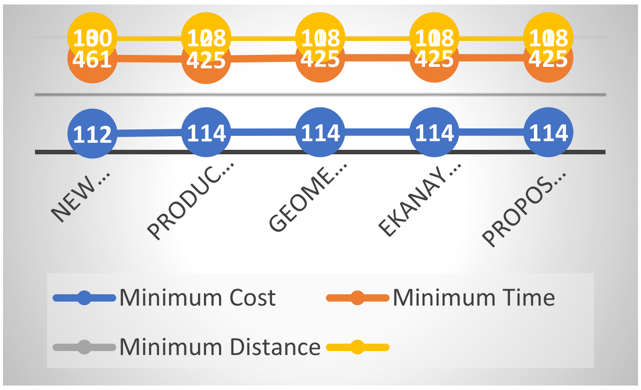
Figures 6 provides line graphs to illustrate the comparison shown in Table 23.

Based on the above results, Table 23 shows a comparison of the objectives attained using various methods, and Figure 6 shows a comparative study of the results obtained by the different existing methods and the proposed method, and it is clear that the proposed method performs similarly to the geometric mean method and Ekanayake's method.

Table 23
Comparison of the objectives attained using various methods

Methods	Minimum cost	Minimum time	Minimum distance
New Row Maxima Method	112	461	130
Product Approach	114	425	128
Geometric Mean Method	114	425	118
Ekanayake's Method	114	425	118
Proposed Method	114	425	118

Figure 6
A comparative study of the results obtained by the different existing methods and the proposed method



6.8. Performance of the proposed method compared with the fuzzy approach, interactive approach, trust region approach, parallel method, product approach

Results obtained by fuzzy approach, interactive approach, trust region approach, proposed parallel method, and product approach and proposed methods for the benchmark instance are shown in Table 24. Detailed data representations of these problems are provided in Appendix A:

Table 24
Performance measure of proposed method over MOTP approach

Method	Minimum cost	Minimum time	Minimum distance	Mean
The fuzzy approach	112	106	80	99.33
Interactive approach	127	104	76	102.33
Trust region approach	144	104	73	107
Parallel method	157	72	86	105
Product approach	157	72	86	105
Proposed method	112	81	77	90
Ideal solution	102	72	64	79.33

Figure 7
Comparative study of the result obtained by above methods

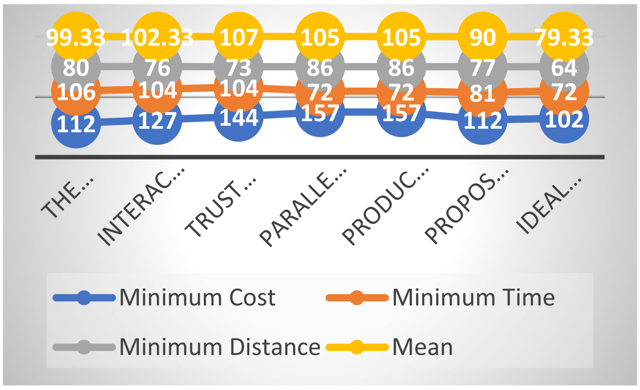


Table 24 confirms the outcome, which is depicted graphically in Figure 7 using line graph.

Based on the above results shown in Table 24 and Figure 7, it can be observed that, in case, the performance of the proposed method is marginally equivalent to the other considered approaches.

7. Conclusion

This paper investigates another alternative technique for applying MOTP (bi and triobjective), namely the modified ant colony optimization algorithm, which provides the best solution of the multiobjective transportation system as often as possible. By varying the weights, this method can generate different MOTP solution points. This investigation provides an overview of the concept of ACA as well as a review of its applications in the solution of MOTP. When compared to many existing heuristic algorithms, the proposed algorithm is heuristic in nature and less involved in its application. A few changes have been made to the ACA, as well as an update to the pheromone rate, to produce a worthy optimal solution for the MOTP. By combining the transition rule with the pheromone update rule, the ACA is changed to achieve this. The modified ant colony algorithm is a great tool for determining the MOTP solution's minimal cost. With particular parameters, it can be used to resolve any type of multiobjective optimization problem. The suggested approach might offer both compromise solutions devoid of preferences and solutions based on preferences. In general, the suggested method works better for transportation problems with several objectives. Intend to expand on this strategy in the future to account for ambiguous needs and supplies.

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Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

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Appendix A

Problem	Unit costs	Supply	Demand
(Aneja & Nair, 1979)	(9,2,2;12,9,4;9,8,6;6,1,3;9,4,6) (7,1,4;3,9,8;7,9,4;7,5,9;5,2,2) (6,8,5;5,1,3;9,8,5;11,4,3;3,5,6) (6,2,6;8,8,9;1,6,6;2,9,3;2,8,1)	(5,5,5;4,4,4;2,2,2;9,9,9)	(4,4,4;4,4,4;6,6,6;2,2,2;4,4,4)