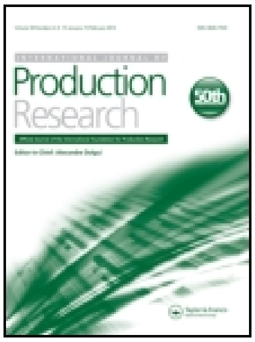

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Ant colony optimisation algorithm for distribution-allocation problem in a two-stage supply chain with a fixed transportation charge

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In a fixed charge transportation problem, each route is associated with a fixed charge (or a fixed cost) and a transportation cost per unit transported. The presence of the fixed cost makes the problem difficult to solve, thereby requiring the use of heuristic methods. In this paper, an algorithm based on ant colony optimisation is proposed to solve the distribution-allocation problem in a two-stage supply chain with a fixed transportation cost for a route. A numerical study on benchmark problem instances has been carried out. The results obtained for the proposed algorithm have been compared with that for the genetic algorithm-based heuristic currently available in the literature. It is statistically confirmed that the proposed algorithm provides significantly better solutions.

Keywords: supply chain; distribution-allocation; fixed charge transportation problem; genetic algorithm; ant colony optimisation

1. Introduction

Trends such as globalisation, diversity of products and growing customer awareness make the markets highly competitive, thereby forcing business enterprises to adopt different strategies. Supply-chain management (SCM) is considered to be the most popular and successful operations strategy for achieving a competitive edge as it creates values for companies, customers and stakeholders. According to Chang and Lee (2004), a supply chain includes all the interactions among suppliers, manufacturers, distributors, retailers and customers. SCM is a process of planning, implementing and controlling the operations of the supply chain in an efficient and responsive manner from the point of origin to the point of consumption. Abreu and Camarinha-Matos (2008) observe that collaboration among the partners in the supply chain enables the on-time delivery of orders.

Narahari and Biswas (2007) classify supply-chain decisions based on temporal and functional considerations. Dotoli *et al*. (2005), Monthatipkul and Kawtummachai (2007) and Tiwari *et al*. (2010) identify three decision levels such as strategic, tactical and operational, according to the time horizon of the decisions. As per the functional classification, there are four major decision areas namely procurement, manufacturing, distribution and logistics. The objective of each decision is to raise the supply-chain surplus. At a strategic level, decisions target on the long-term objectives of a supply chain. Strategic decisions made by companies include whether to outsource or perform a supply-chain function in-house, the location and capacities of production and warehousing facilities, the products to be manufactured or stored at various locations, the modes of transportation to be made available and the type of information system to be utilised (Ding *et al*. 2009). The decisions such as production and distribution planning, capacity planning, and inventory management that are required for the effective management of supply chains fall under tactical decisions. In this decision phase, the time frame considered is a quarter to a year. Finally, the operational decisions are taken as a part of replenishment and delivery of goods. The time horizon for this decision phase is weekly or daily.

For any supply chain, logistics or distribution plays a key role in its success. Distribution network design refers to the choices made with respect to the nature of entities included in outbound logistics and the manner in which material flow and information flow are managed across these entities (Lee *et al*. 2010). Hence, there is a need for closed-loop integration between the entities. Samaranayake and Toncich (2007) present a framework for the

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supply-chain integration using the application modules of enterprise resource planning. Wadhwa *et al.* (2008) investigate the role of flexibility in supply chains. Gunasekaran and Kobu (2007) describe the key performance measures and metrics in supply chain and logistics operations. According to Park (2005), the allocation of distributors to plants determines the supply-chain performance in a multi-plant production system. Designing and optimising the production-distribution network leads to less logistics costs and maintains a competitive position in the market.

This paper focuses on modelling the distribution-allocation problem in a two-stage supply chain with a fixed charge for a transportation route. Commonly discussed supply-chain distribution models in the literature take into account the unit transportation cost only, which is directly proportional to the shipment quantity. However, in real life situations, there is another cost associated with distribution which is known as fixed cost (or fixed charge), that is independent of the shipment quantity. When fixed cost is also taken into account, the transportation problem is known as fixed charge transportation problem (Adlakha and Kowalski 1999). Fixed charge problem is a practical problem in industries. The fixed cost transportation problem (FCTP) is an extension of the classical transportation problem (TP). Unlike TP, FCTP considers a fixed cost for a route in addition to the unit cost. Examples of these fixed costs are the toll fee paid on the highways, the reward given to the driver, landing fee at the airport, permit fee or property tax, etc. Thus, FCTP considers two types of costs in the model; *first,* a continuous cost that linearly increases with the amount transported between a source and a destination and *second,* a fixed charge which is incurred whenever a non-zero quantity is transported between a source and a destination (Jawahar and Balaji 2009). Since fixed costs cause discontinuities in the objective function, solution procedures for FCTP become more difficult and are known to be non-deterministic polynomial (NP) hard.

Last decade has witnessed a significant growth in the use of evolutionary meta-heuristics for the optimisation of computationally complex NP-hard problems of real dimensions (Aytug *et al.* 2003, Hauser and Chung 2006, Bachlaus *et al.* 2009, Pal *et al.* 2010, Tiwari *et al.* 2010). Our model in this work is aligned with the research of Jawahar and Balaji (2009) that highlighted the solution quality of genetic algorithm (GA)-based heuristic in comparison with approximation method and lower-bound solutions for a two-stage supply-chain FCTP.

Most of the works related to FCTP in the literature consider either a single-stage of a supply-chain distribution problem (i.e. between plant and distributor) or a two-stage supply-chain distribution problem. The FCTP in a single stage of a supply chain has been studied using heuristic algorithms (Adlakha *et al.* 2007, Raj and Rajendran 2009) and meta-heuristic algorithms such as genetic algorithms (Gen and Li 1999, Jo *et al.* 2007) and tabu search (Sun *et al.* 1998). To the best of our knowledge, Jawahar and Balaji (2009) have developed a two-stage distribution model with fixed cost. They have used a GA-based heuristic to solve the model. Thus, the motivation of this paper is to explore the potential of ACO-based heuristic for solving an FCTP. In the present research, we propose a novel meta-heuristic algorithm based on ant colony optimisation (ACO) for an FCTP. In essence, the objectives of this paper are as follows:

- Develop an ACO-based heuristic for solving a distribution-allocation problem for a two-stage supply chain with fixed cost.
- Compare the performance of the proposed heuristic with the GA-based heuristic currently available in the literature.

The rest of the paper is organised as follows. Section 2 reviews the literature on FCTP under three categories namely, optimisation approach, conventional heuristics and meta-heuristics. Section 3 presents the mathematical formulation. Section 4 describes the solution approach using ACO algorithm. Section 5 illustrates the solution methodology with an example of a problem. Section 6 presents the results and analyses. Section 7 provides the conclusion.

2. Literature review

A review of the literature on fixed charge transportation supply-chain models and the solution methodologies is presented in this section in three parts. In the first part, the literature on optimisation approach is reviewed. The literature on conventional heuristics is reviewed in the second part, followed by the literature on meta-heuristics. The classification of the solution methodology adopted by researchers in solving an FCTP is presented in Table 1.

Table 1. Classification of literature based on solution procedures for FCTP.

FCTP solution procedures				
		Approximation approach		
Optimisation approach		Conventional heuristics	Meta-heuristics	
Hultberg and Cardoso (1997)	Branch and bound	Adlakha and Kowalski (1999)	Gottlieb and Paulmann (1998)	GA
Xu *et al*. (2008)	Mixed integer nonlinear programming	Adlakha and Kowalski (2003)	Sun *et al*. (1998)	TS
Çakir (2009)	Benders decomposition	Adlakha *et al*. (2007)	Gen and Li (1999)	Spanning tree based-GA
		Kowalski and Lev (2008)	Jo *et al*. (2007)	Spanning tree based-GA
		Raj and Rajendran (2009)	Kannan *et al*. (2008)	Nelder-Mead
			Jawahar and Balaji (2009)	GA

2.1 *Optimisation approach*

The objective of a transportation problem model is to minimise the total cost in transporting homogeneous products from multiple sources to multiple destinations. But in real-world applications, FCTP arises more commonly than the transportation problem. This problem is often formulated and solved as an integer linear programming problem. Any general integer linear programming solution method such as the branch-and-bound method and the cutting plane method can be used to solve the FCTP. The teacher assignment problem is a special case of FCTP originated from a practical problem of assigning subjects to teachers. Hultberg and Cardoso (1997) apply branch and bound method for assigning classes to professors in such a way that the average number of distinct subjects assigned to each professor is minimised. Çakir (2009) discusses the solution of a multi-commodity, multi-mode capacitated distribution network planning problem using a primal decomposition algorithm namely, Benders decomposition. In this work, the fixed cost represents the insurance and contracting costs associated with utilising third party logistics company for handling the commodity. Xu *et al*. (2008) propose a random fuzzy multi-objective mixed-integer nonlinear programming model for the supply-chain network of a Chinese industry. This model considers a fixed cost for operating the facilities like plant or distribution centre in a supply chain.

2.2 *Approximation approach: conventional heuristics*

The optimisation methods discussed above are generally inefficient and computationally expensive since they do not take advantage of the special network structure of the FCTP. Hence, many researchers have proposed heuristic methods and meta-heuristic methods for solving FCTP. Heuristic methods are based on relatively simple common sense ideas for guiding the search for a good solution.

Adlakha and Kowalski (1999) propose a heuristic for an FCTP with the more-for-less (MFL) paradox. MFL paradox occurs when it is possible to ship more total goods for less or equal total cost while shipping the same amount or more from each origin and to each destination, keeping shipping costs non-negative. Adlakha and Kowalski (2003) develop a simple heuristic algorithm based on Hungarian and Vogel approximation methods for a single-stage FCTP. However, this simple heuristic algorithm is found to be more time-consuming than regular transportation algorithm. Adlakha *et al*. (2007) develop a simple analytical heuristic for MFL paradox in FCTP with equality constraints.

Kannan *et al*. (2008) propose a transportation model for a single-stage supply chain with fixed charge and present results using a local search heuristic, namely Nelder-Mead method. Kowalski and Lev (2008) consider the fixed cost as a step function dependent on the load in a given route. The fixed cost to open a route (i,j) is $K_{ij,1}$ if the output is less than or equal to A_{ij}. When the shipment is more than A_{ij}, an additional fixed cost of $K_{ij,2}$ units is incurred. Kowalski and Lev (2008) describe many real life situations involving a step fixed charge transportation problem formulation. Examples for step fixed charge include gradual taxes activated by a higher turnover and user fees after achieving some usage level. Raj and Rajendran (2009) present a simple heuristic algorithm for solving a single-stage FCTP and compare the performance with the existing best method by making use of bench mark problem instances. Antony and Rajendran (2009) propose fast heuristic algorithms for a single-stage FCTP.

2.3 *Approximation approach: meta-heuristics*

Modern heuristic techniques, also called meta-heuristics, are a family of procedures which involve some sort of intelligence in their search for finding the solution of a problem (Poorzahedy and Rouhani 2007, Shukla *et al*. 2009, Kumar *et al*. 2010). For a single stage FCTP, Sun *et al*. (1998) develop a heuristic based on tabu search (TS) procedure. They observe that the TS procedure provides better performance in terms of solution quality and computation time when compared with the existing conventional heuristics.

GA is found to be a very effective means to solve location-allocation problems (Gen and Cheng 1997). There are many studies in the literature applying GA for supply-chain networks. Gen *et al*. (2001) summarise the recent research on solving network design problems such as FCTPs using GA. Gottlieb and Paulmann (1998) present a GA-based permutation representation for FCTP. Gen and Li (1999) adopt an approach of spanning tree-based GA for FCTP using Prüfer number encoding. Jo *et al*. (2007) consider a nonlinear fixed charge transportation problem of a single-stage of a supply chain between a plant and a customer. The innovation of Jo *et al*. (2007) is the representation used in developing new feasibility criteria for the Prüfer number for solving nonlinear FCTP with spanning tree-based GA. Jawahar and Balaji (2009) propose a two-stage distribution-allocation model in a supply-chain with a fixed cost for a transportation route. A GA-based heuristic is proposed for solving the model. A comparison is made with two other algorithms such as lower bound value (LBV) and approximate solution (AS).

ACO is another nature-inspired meta-heuristic approach that mimics the behaviour of ant species as they move between the nest and the food source (García-Martínez *et al*. 2007). A good amount of research has been devoted to its empirical and theoretical analysis (Yang and Zhuang 2010). ACO has been and continues to be a fruitful paradigm for solving hard combinatorial optimisation problems. The ACO approach has been used for various optimisation problems such as the travelling salesman problem (Dorigo and Gambardella 1997, Middendorf *et al*. 2002), job-shop scheduling problem (Chang *et al*. 2008), quadratic assignment problem (Poura and Nosratya 2006), sequential problem (Zhu and Zhang 2011), graph-colouring problem, shortest common super sequence problem (Dorigo and Stützle 2004, Rizzoli *et al*. 2007), and distribution problem (Silva *et al*. 2009).

2.4 *Summary*

In the light of the review presented above, it is found that most of the works consider a single-stage of a supply-chain distribution model with a fixed cost between plant and distributor (or customer). There have been a few attempts to formulate and solve the FCTP in a two-stage supply chain. The present paper focuses on a two-stage supply-chain distribution-allocation problem with fixed cost. In this research, we propose a mathematical formulation for the FCTP in a two-stage supply chain. The novel approach of ACO is used to solve the problem.

3. Mathematical formulation

A deterministic two-stage, single-product, single-period supply chain with a fixed cost is considered in this research as shown in Figure 1.

The distribution-allocation problem in this supply chain is formulated as an integer programming problem as described below. The two-stage supply chain includes entities such as manufacturers (or sources/plants), distributors, and retailers (or destinations). The mathematical formulation for this two-stage supply chain with

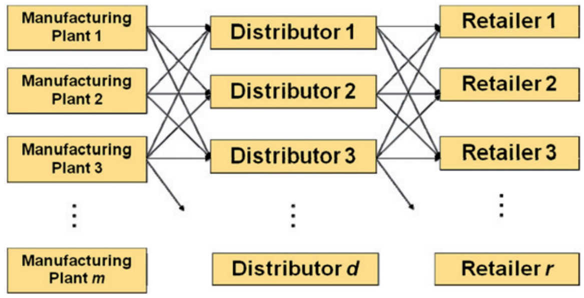

Figure 1. Two-stage supply chain for a single product and a single period.

a set of m plants ($i = 1, 2, \ldots, m$), a set of d distributors ($j = 1, 2, \ldots, d$), and a set of r retailers ($k = 1, 2, \ldots, r$) is described in this section. The suppliers in each stage incur a unit transportation cost c and a fixed cost f for a distribution route in each stage. The objective of this formulation is to minimise the cost incurred in transporting the goods from the plant to the end customer considering the possible combination of routes.

Assumptions

The following assumptions are made:

- The demand for a single-product for a single-period is considered.
- The number of plants and their capacities are known.
- The number of retailers and their demand are known.
- The number of distributors is known and each has a large capacity of M units; M takes a large number (infinite capacity).
- Retailers can be supplied with products from more than one distributor.
- Transportation damages or losses are not considered.

Indices

I Set of plants ($i = 1, 2, \ldots, m$), where m being the upper bound on the number of plants.
J Set of distributors ($j = 1, 2, \ldots, d$), where d being the upper bound on the number of distributors.
K Set of retailers ($k = 1, 2, \ldots, r$), where r being the upper bound on the number of retailers.

Decision variables

x_{ij} Number of units transported from plant i to distributor j.
x_{jk} Number of units transported from distributor j to retailer k.

Cost parameters

c_{ij} Unit cost of transportation from plant i to distributor j.
c_{jk} Unit cost of transportation from distributor j to retailer k.
f_{ij} Fixed transportation cost from plant i to distributor j.
f_{jk} Fixed transportation cost from distributor j to retailer k.

Capacity and demand parameters

S_i Capacity of plant i.
CD_k Demand of retailer k.

Objective function

The objective in the two-stage supply-chain FCTP is to minimise the total transportation cost given by Minimise:

$$Z = \sum_{i=1}^{m} \sum_{j=1}^{d} \left(f_{ij} y_{ij} + c_{ij} x_{ij}\right) + \sum_{j=1}^{d} \sum_{k=1}^{r} \left(f_{jk} y_{jk} + c_{jk} x_{jk}\right) \tag{1}$$

Subject to:

$$\sum_{j=1}^{d} x_{ij} = S_i \quad (i = 1, 2, \ldots, m) \tag{2}$$

$$\sum_{i=1}^{m} x_{ij} = \sum_{k=1}^{r} x_{jk} \quad (j = 1, 2, \ldots, d) \tag{3}$$

$$\sum_{j=1}^{d} x_{jk} = CD_k \quad (k = 1, 2, \ldots, r) \tag{4}$$

$$x_{ij}, x_{jk} \geq 0 \quad (\forall \quad i, j \text{ and } k) \tag{5}$$

$$y_{ij} = \begin{cases} 1, & \text{if } x_{ij} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$y_{jk} = \begin{cases} 1, & \text{if } x_{jk} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The objective function (1) is the sum of the transportation costs, including the unit transportation cost and the fixed cost for a route, incurred in supplying the goods from manufacturing plants to distributors and from distributors to retailers. Constraint (2) represents the supply capacity constraint. This constraint implies that the product quantity that is distributed from the manufacturing plant to the distributors cannot be more than the current capacity of the plant. Constraint (3) represents the material-balance equation. This constraint maintains that the shipment received by a distributor from plants must be equal to the quantity shipped from the distributor to the retailers. Constraint (4) provides the demand at the retailer outlet. The total quantity shipped from a distributor to a retailer must be equal to the demand of the retailer. Constraint (5) imposes the non-negativity restriction on the decision variables, x_{ij} and $x_{jk,}$ i.e. the quantity shipped from manufacturing plant to the distributor and from the distributor to the retailer must be non-negative and should be integers. Constraints (6) and (7) specify the binary variables y_{ij} and y_{jk} used in the formulation.

4. Solution approach using ACO-based heuristic

An ACO-based heuristic has been developed for solving a distribution-allocation problem for a two-stage supply chain with fixed cost. Initially, the problem is represented as a connected graph with nodes and edges as shown in Figure 2.

The nodes are the facilities to be allocated, i.e. in stage 1, the nodes are distributors and retailers, and in stage 2, they are manufacturing plants and distributors. The edges are the connection between the facilities. As shown in Figure 3, the heuristic is structured in a modular way consisting of the following modules:

- input module;
- initialisation/parameter setting module;
- probability calculation module;
- ant solution generation module;
- the best ant solution determination module;
- pheromone updating module;
- termination module;
- output module;

The salient features of these modules are described below.

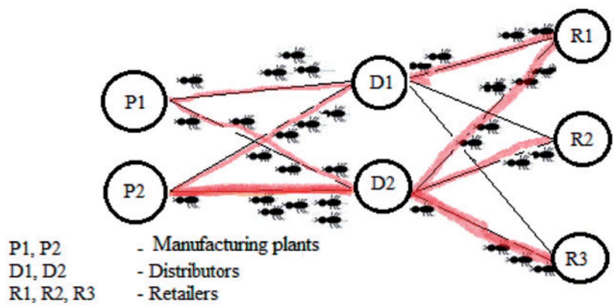

Figure 2. Diagrammatic representation of the ants in distribution allocation problem.

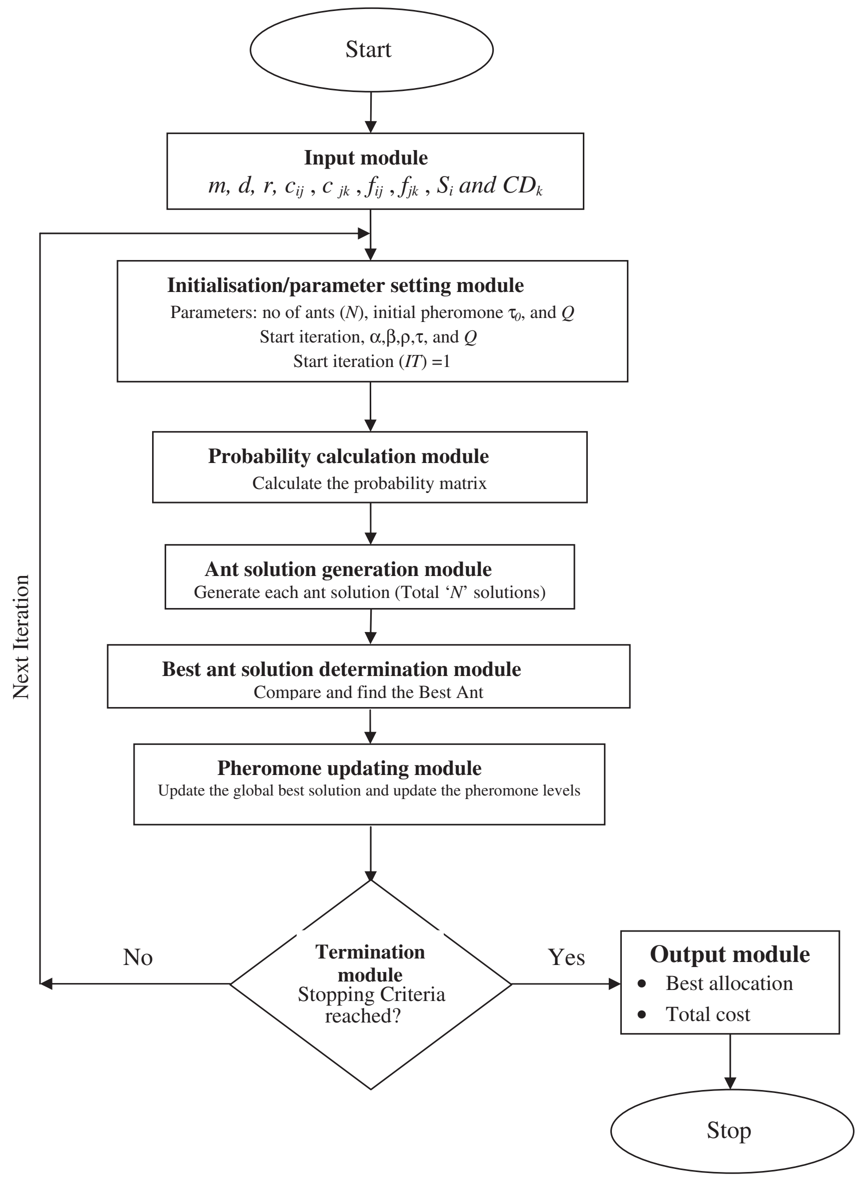

Figure 3. Structure of the proposed ACO-based heuristic.

4.1 *Input module*

The following data that govern the order quantity of customers, the capacity of all supply-chain partners and the related costs involved in the two-stage supply-chain fixed charge distribution problem are given as input in this module:

- total number of manufacturing plants m, total number of distributors d, and total number of retailers r;
- supplier capacity S_i ($\forall_i$, $i=1,2,\ldots,m$) and demand at retailer end CD_k ($\forall_k$, $k=1,2,\ldots,r$);
- the unit transportation cost matrix representing the unit cost of the product transported, c_{ij} ($\forall_i$, $i=1,2,\ldots,m$ and $\forall_j$, $j=1,2,\ldots,d$), between the plant and the distributor;
- the fixed cost matrix for each distribution route representing the fixed cost for each route, f_{ij} ($\forall_i$, $i=1,2,\ldots,m$ and $\forall_j$, $j=1,2,\ldots,d$) between the plant and the distributor;
- the unit transportation cost matrix representing the unit cost of the product transported, c_{jk} ($\forall_j$, $j=1,2,\ldots,d$ and $\forall_k$, $k=1,2,\ldots,r$), between the distributor and the retailer;
- the fixed cost matrix for each distribution route representing the fixed cost for each route f_{jk} ($\forall_j$, $j=1,2,\ldots,d$ and $\forall_k$, $k=1,2,\ldots,r$), between the distributor and the retailer.

4.2 *Initialisation/parameter setting module*

The following parameters are set up before the algorithm starts:

- N number of ants;
- IT number of iterations;
- α parameter controlling the magnitude of τ_{ij} (the parameter for an ant to represent the pheromone intensity from the ith partner to the jth partner in the next stage);
- β parameter controlling the magnitude of η_{ij} (the profitability of selecting jth partner from the next stage by the ith partner in the current stage)
- ρ evaporation rate;
- Q parameter controlling the pheromone increment amount (constant);
- τ_0 initial amount of pheromone in each edge in the graph.

These parameters are tuned parameters obtained from experimental results. Taguchi method of robust design is adopted for finding the optimum combination of parameters of the ACO-based heuristic. The ranges for the levels used in the experimentation are chosen based on the guidelines provided by Chan and Kumar (2009).

4.3 *Probability calculation module*

Probability matrix (PM) gives the probabilities of an ant's choice for the allocation in that stage. In the two-stage distribution-allocation problem with fixed transportation cost in a supply chain, allocation is to be made between retailer and distributor in stage 1, followed by distributor to plant in stage 2, minimising the total cost of transportation.

At each construction step (stage 1 and stage 2), an ant l applies a probabilistic action choice rule, called a random proportion rule, to allocate a non-assigned node at the downstream to a node at the upstream, i.e. a retailer is being allocated to a distributor in stage 1 and a distributor is being allocated to a plant in stage 2. In particular, the probability with which ant l, currently at retailer k chooses to be allocated to distributor j in stage 1 in iteration t is

$$PM^l_{kj}(t) = \begin{cases} \dfrac{[\tau_{kj}(t)]^{\alpha}\,[\eta_{kj}(t)]^{\beta}}{\sum_{j=1}^{d}[\tau_{kj}(t)]^{\alpha}\,[\eta_{kj}(t)]^{\beta}}, & \text{if } j \in N^l_k \\ 0, & \text{otherwise,} \end{cases} \tag{8a}$$

where: τ_{kj} represents the pheromone concentration in edge (k,j); N^l_k represents the feasible neighbourhood of ant l when being at retailer k, i.e. the set of distributors that ant l has not allocated yet; η_{kj} is the visibility which is usually determined by a greedy heuristic rule for conducting the search with some valuable information about the problem; α and β are the parameters to direct the search which determine the relative importance of pheromone trail and heuristic information respectively.

Similarly, the probability with which ant l, currently at distributor j chooses to be allocated to plant i in stage 2 in iteration t is

$$PM^l_{ji}(t) = \begin{cases} \frac{[\tau_{ji}(t)]^\alpha [\eta_{ji}(t)]^\beta}{\sum_{i=1}^{m} [\tau_{ji}(t)]^\alpha [\eta_{ji}(t)]^\beta}, & \text{if } i \in N^l_j \\ 0, & \text{otherwise,} \end{cases} \tag{8b}$$

where τ_{ji} represents the pheromone concentration in edge (j, i); N^l_j represents the feasible neighbourhood of ant l when being at distributor j, i.e. the set of plants that ant l has not allocated yet; η_{ji} is the visibility which is usually determined by a greedy heuristic rule for conducting the search with some valuable information about the problem.

The two-stage distribution-allocation problem with fixed transportation cost in a supply chain, as discussed earlier, involves two kinds of costs; fixed costs and unit variable costs. But for the calculation of visibility, these costs alone cannot be used, since in some cases, one of the costs may be less, but the other costs may be very high, resulting in an increased total cost. Considering these aspects, in the first iteration, the expected allocation cost matrix for stage 1 (EAC_{kj}) and stage 2 (EAC_{ji}) is calculated using Equation (9) as follows:

$$\text{Expected allocation cost (EAC)} = \text{fixed cost} + (\text{unit cost} \times \text{corresponding demand}). \tag{9}$$

Thus, the EAC represents the maximum cost for allocating a downstream entity to an upstream entity for satisfying the whole demand.

Dorigo and Gambardella (1997) suggest the use of a greedy heuristic for the computation of visibility. In the present study, the greedy heuristic involves allocation of a downstream entity to an upstream entity which results in less EAC. Accordingly, the visibility in stage 1 (η_{kj}) and stage 2 (η_{ji}) for allocation of a downstream entity to an upstream entity in a supply chain is computed. For the first iteration, visibility is computed as the reciprocal of EAC of that stage and is given by Equation (10a) and (10b) for stage 1 and stage 2 respectively.

$$\eta_{kj} = \frac{1}{\mathrm{EAC}_{kj}} \tag{10a}$$

$$\eta_{ji} = \frac{1}{\mathrm{EAC}_{ji}}. \tag{10b}$$

In further iterations, the total transportation cost incurred in the preceding iteration for both stages is used to determine the visibility.

4.4 *Ant solutions generation module*

A tour of an ant is a complete route between the nest and food source performed by one ant. In a distribution-allocation problem, it is first the allocation of the retailer to a distributor, followed by the allocation of the distributor to a plant made by an ant. Each ant provides a feasible solution (feasible distribution-allocation) in a matrix form that satisfies the requirement of a retailer from the plants through the distributors. Generally, an ant path matrix size is taken as $r \times (2m + 2)$. The matrix size depends on the number of retailers, r and the number of plants, m. A sample feasible solution represented by the ant path matrix and the decoded solution is depicted in Figure 4.

The first column of the ant path matrix represents the retailer number. The second column represents the allocated distributor number. Then, the columns 3 to $(2 + m)$ show the allocated plant numbers. The columns $(3 + m)$ to $(2m + 2)$ give the allocated quantities from the respected distributor to plant. If any element in the matrix is zero, it shows that there is no allocation.

The allocation is made in each stage following a Monte-Carlo simulation-based procedure as follows:

Step 1: In stage 1, a retailer is selected at random. If the retailer is not allocated, then proceed to step 2, else repeat step 1.

Step 2: Generate a random number between 0 and 1.

Step 3: From the probability matrix for the stage 1, obtain the cumulative probability for the selected retailer.

$$\begin{bmatrix} 1 & 1 & 2 & 0 & 150 & 0 \\ 2 & 1 & 2 & 0 & 80 & 0 \\ 3 & 2 & 1 & 0 & 100 & 0 \\ 4 & 2 & 1 & 2 & 150 & 120 \end{bmatrix}$$

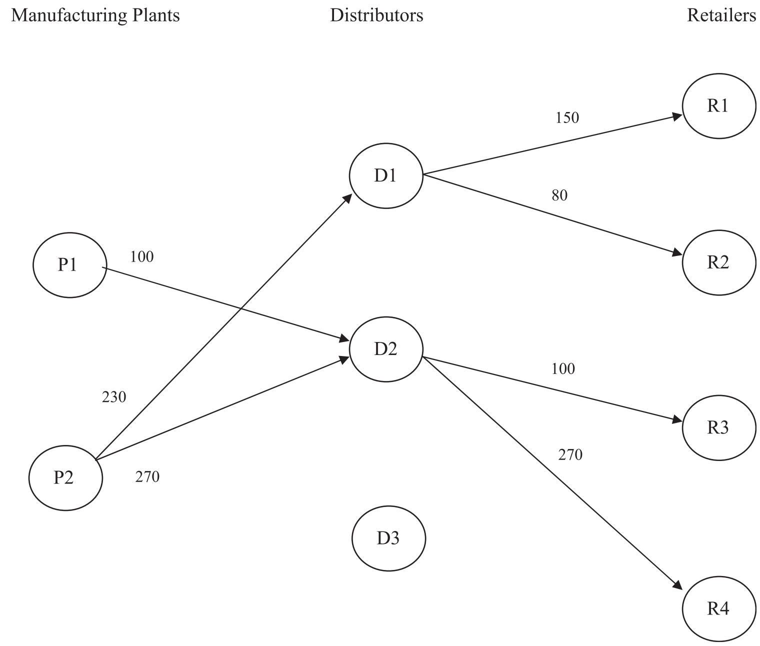

Figure 4. Sample ant path matrix and its decoded form.

Step 4: Based on the generated random number in step 2, allocate the selected retailer to that upstream entity (distributor) where the cumulative probability value first exceeds the random number.

Step 5: Generate a random number between 0 and 1.

Step 6: From the probability matrix for the stage 2, obtain the cumulative probability for the allocated distributor in step 4.

Step 7: Based on the generated random number in step 5, find that upstream entity (plant) where the cumulative probability value of distributor first exceeds the random number. If the capacity of the upstream entity is 0, go to step 5. Else allocate the distributor to that plant and proceed to step 8.

Step 8: Update the plant capacity and demand data of distributor. If the demand is met completely, one set of allocations (retailer to distributor and distributor to plant) is completed, go to step 9 for the next set of allocations. Else, go to step 5 and repeat the process.

Step 9: If the demand of all the retailers is met, terminate. Else, go to step 1 for the next set of allocations.

4.5 *Best ant solution module*

In each iteration, the number of allocations obtained is equal to the number of ants specified in the problem. From these allocations, the minimum value of total transportation cost (Z) and its allocations form the best solution in that generation. This is known as iteration-best. The iteration-best is compared with the global-best. In the initial iteration, both are same. In the other iterations, iteration-best may or may not be the same as the global-best. If the iteration-best is found to be superior (here it is minimum) to the global-best, it is retained as the global-best.

4.6 *Pheromone updating module*

After completing the current iteration t, the ants deposit pheromones on the edges corresponding to their individual allocations. The pheromone concentration is updated locally and globally according to the quality of the constructed

Table 2. Capacity of plants.

	Plant 1	Plant 2
Capacity (units)	250	350

Table 3. Retailer demand.

	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Demand (units)	150	80	100	270

tour solutions (objective function value) and the evaporation rate ρ as shown in Equations (11a) and (11b).

$$\tau_{kj}(t+1) = \rho\,\tau_{kj}(t) + \Delta\tau^l \tag{11a}$$

$$\tau_{ji}(t+1) = \rho\,\tau_{ji}(t) + \Delta\tau^l \tag{11b}$$

In Equations (11a) and (11b), the first term accounts for the pheromone reduction (local update) owing to evaporation in the iteration t, and the second term (global update) represents the additional deposit of pheromone in the iteration $t+1$ based on the total cost of the allocation done by the all ants through the tour in the iteration t. The term $\Delta\tau^l$ is the increment in the pheromone on the links where the allocation is done by ant l.

For the pheromone increment updating rule, an ant-weight strategy is used as given in Equation (12):

$$\Delta\tau^l = \begin{cases} \frac{Q}{\text{iteration}-\text{best}(t)}, & \text{if allocation is done by ant } l \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where Q is a constant, and iteration-best represents the total cost of the best allocation made by ant l in the previous iteration t. The aim of pheromone updating is to increase the pheromone values associated with better or promising solution, and decrease those that are associated with inferior solutions (Socha and Dorigo 2008).

4.7 *Termination module*

This module checks the condition for termination. Whenever the required number of iterations is reached, the algorithm is stopped. If not, the iteration number is incremented, and the whole procedure is repeated.

4.8 *Output module*

This module provides the best distribution-allocation for the fixed charge transportation problem along with the total transportation cost.

5. Illustrative example

This section describes the application of the ACO-based heuristic for a sample problem. The problem considered has 2 suppliers, 3 distributors and 4 retailers (or customers). Table 2 shows the capacity of manufacturing plants (S_i). Table 3 depicts the demand of the retailers (CD_k). Table 4 provides the fixed cost and the unit transportation cost between plants and distributors (f_{ij} and c_{ij}). Table 5 shows the fixed cost and the unit transportation cost between distributors and retailers (f_{jk} and c_{jk}).

The parameter values need to be set up before the ACO starts. There is no specific rule/framework to determine these parameters. The parameters such as α, β, ρ, Q, N and IT used in this work are tuned parameters obtained using the Taguchi method of robust design. Usually, researchers use a small number as initial pheromone. In this work, the pheromone value is taken as 0.50 initially since all the paths are accepted equally likely.

Step 1: The following data are given as input

Number of plants, $m=2$; number of distributors, $d=3$; number of retailers, $r=4$; the values of c_{ij}, c_{jk}, f_{ij}, f_{jk} S_i and CD_k ($\forall_i$, $i=1,2,\ldots,m$, $\forall_j$, $j=1,2,\ldots,d$ and $\forall_k$, $k=1,2,\ldots,r$) are given in the Tables 2–5.

Step 2: Parameter setting

Table 4. Transportation cost matrix between plants and distributors.

	Distributor 1		Distributor 2		Distributor 3	
	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)
Plant 1	1000	10	400	25	1150	30
Plant 2	900	5	200	35	1300	14

Table 5. Transportation cost matrix between distributors and retailers.

	Retailer 1		Retailer 2		Retailer 3		Retailer 4	
	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)
Distributor 1	500	43	1200	25	800	10	2000	50
Distributor 2	2250	20	1500	5	0	0	2000	30
Distributor 3	400	60	1800	32	2300	50	1000	40

Number of ants, $N = 100$; number of iterations, $IT = 10$; $\alpha = 2.00$; $\beta = 5.00$; $\rho = 0.90$; $Q = 500$.

$$\text{Initial pheromone matrix for stage I } (\tau_{kj}) = \begin{bmatrix} 0.50 & 0.50 & 0.50 \\ 0.50 & 0.50 & 0.50 \\ 0.50 & 0.50 & 0.50 \\ 0.50 & 0.50 & 0.50 \end{bmatrix}$$

$$\text{Initial pheromone matrix for stage II } (\tau_{ji}) = \begin{bmatrix} 0.50 & 0.50 \\ 0.50 & 0.50 \\ 0.50 & 0.50 \end{bmatrix}.$$

Step 3: Probability calculations

For the first iteration, the expected allocation cost calculated using Equation (9) as follows:
In stage 1, if retailer 1 is allocated to distributor 1, then the expected allocation cost is calculated as

$$\mathrm{EAC}_{11} = 500 + (43 \times 150) = 6950$$

Similarly, if retailer 2 is allocated to distributor 1, then the expected allocation cost is

$$\mathrm{EAC}_{21} = 1200 + (25 \times 80) = 3200$$

Thus, EAC_{kj} is calculated for the complete allocation and it is shown as follows:

$$\mathrm{EAC}_{kj} = \begin{bmatrix} 6950 & 5250 & 9400 \\ 3200 & 1900 & 4360 \\ 1800 & 101 & 7300 \\ 15500 & 10100 & 11800 \end{bmatrix}.$$

Table 6. Allocation procedure.

Customer	Random number	Allocated distributor	Random number	Allocated plant	Allocated quantity	Capacity sufficient	Random number	Allocated plant	Allocated quantity
1	0.0420	1	0.9885	2	150	Yes	–	–	–
2	0.0173	1	0.5535	2	80	Yes	–	–	–
3	0.5362	2	0.2801	1	100	Yes	–	–	–
4	0.6215	2	0.1906	1	150	No	0.7416	2	120

In a similar manner, the EAC_{ji} in stage 2 is calculated. The values thus obtained are as follows:

$$\mathrm{EAC}_{ji} = \begin{bmatrix} 2500 & 1650 \\ 2400 & 3000 \\ 4150 & 2700 \end{bmatrix}.$$

The probability matrix (PM) in stage 1 is calculated using Equation (8a) and the expected allocation cost for stage 1. The probability with which an ant currently at retailer 1 chooses to be allocated to distributor 1 in iteration 1 is

$$\mathrm{PM}_{11} = \frac{[0.5]^2 \times \left[\frac{1}{6950}\right]^5}{[0.5]^2 \times \left[\frac{1}{6950}\right]^5 + [0.5]^2 \times \left[\frac{1}{5250}\right]^5 + [0.5]^2 \times \left[\frac{1}{9400}\right]^5} = 0.1892.$$

In a similar manner, the PM_{ji} in stage 2 is calculated. Thus, the probability matrix for stage 1 and stage 2 are as follows:

$$\mathrm{PM}_{kj} = \begin{bmatrix} 0.1892 & 0.7690 & 0.0418 \\ 0.0677 & 0.9178 & 0.0144 \\ 0.0000 & 1.0000 & 0.0000 \\ 0.0745 & 0.6342 & 0.2913 \end{bmatrix}, \quad \mathrm{PM}_{ji} = \begin{bmatrix} 0.1113 & 0.8887 \\ 0.7532 & 0.2468 \\ 0.1044 & 0.8956 \end{bmatrix}.$$

Step 4: Ant solutions generation module

The allocation is made in each stage following a Monte-Carlo simulation-based procedure as depicted in Table 6. Each ant will generate a feasible solution at the end of its tour. One such ant solution is given below:

$$\text{First ant path } = \begin{bmatrix} 1 & 2 & 1 & 0 & 150 & 0 \\ 2 & 1 & 2 & 0 & 80 & 0 \\ 3 & 2 & 1 & 0 & 100 & 0 \\ 4 & 1 & 2 & 0 & 150 & 0 \end{bmatrix}$$

In this problem, the ant path matrix size is 4×6. The first column represents the customer number. The second column represents the allocated distributor number. Then, the columns 3 to 4 show the allocated plant numbers. The columns 5 to 6 give the allocated quantities from the respected distributor to plant. If any element in the matrix is zero, it shows that there is no allocation.

Step 5: Best ant solution module

Each ant's solution (total cost of distribution) is calculated. The best allocation among all the ant solutions (the ant with the least total cost of distribution) is found out and it is known as the iteration-best; it is compared with the global-best. If the iteration-best is less than that of the global-best, then it is assigned as the global-best.

Iteration best: 33250

$$\text{Best ant path} = \begin{bmatrix} 1 & 2 & 1 & 0 & 150 & 0 \\ 2 & 1 & 2 & 0 & 80 & 0 \\ 3 & 2 & 1 & 0 & 100 & 0 \\ 4 & 1 & 2 & 0 & 150 & 0 \end{bmatrix}.$$

Table 7. Allocation matrix between distributors and retailers.

	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Distributor 1	150	80	0	0
Distributor 2	0	0	100	150
Distributor 3	0	0	0	120

Table 8. Allocation matrix between plants and distributors.

	Distributor 1	Distributor 2	Distributor 3
Plant 1	0	250	0
Plant 2	230	0	120

Global-best: 33250

Step 6: Pheromone updating module

$$\text{Pheromone increment} = \frac{500}{\text{global} - \text{best}} = \frac{500}{33250} = 0.0150.$$

Thus, the new pheromone $= (0.5 \times 0.9) + 0.0150 = 0.4650$.
(for the routes in each stage where allocation is made).

At the edges where allocation is made, the pheromone is updated to 0.4650 and for the remaining edges, the amount is reduced to 0.4500.

$$\text{The new pheromone matrix for stage I } (\tau_{kj}) = \begin{bmatrix} 0.4500 & 0.4650 & 0.4500 \\ 0.4650 & 0.4500 & 0.4500 \\ 0.4500 & 0.4650 & 0.4500 \\ 0.4650 & 0.4500 & 0.4500 \end{bmatrix}.$$

$$\text{The new pheromone matrix for stage II } (\tau_{ji}) = \begin{bmatrix} 0.4500 & 0.4650 \\ 0.4650 & 0.4500 \\ 0.4500 & 0.4500 \end{bmatrix}.$$

Step 7: Termination module

When the number of iterations reaches 10, the algorithm is stopped. If not, iteration number is incremented and the whole procedure is repeated.

Step 8: Output module

$$\text{Global} - \text{best ant path} = \begin{bmatrix} 1 & 1 & 2 & 0 & 150 & 0 \\ 2 & 1 & 2 & 0 & 80 & 0 \\ 3 & 1 & 2 & 0 & 100 & 0 \\ 4 & 1 & 1 & 2 & 250 & 20 \end{bmatrix}.$$

The best allocation is shown in Tables 7 and 8. The associated total cost $= 32{,}150$.

For this problem, Jawahar and Balaji (2009) obtain the same allocation with the same cost of 32,150 using GA.

6. Results and analyses

The proposed ACO-based heuristic coded in MATLAB 7.8 and implemented on a 2.20 GHz Core 2 Duo processor PC with 4 GB of RAM is used to solve the model. The results thus obtained are tabulated using Microsoft Excel 2007. To demonstrate the effectiveness and efficiency of the proposed ACO-based heuristic, 20 problem instances have been chosen from Jawahar and Balaji (2009), which provide a broad coverage of situations with increasing complexity. Table 9 lists the different problem sizes considered.

Table 10 shows the results of the ACO-based heuristic. Jawahar and Balaji (2009) provide solutions for the 20 problems using GA-based heuristic, the approximate solution (AS) and the lower bound value (LBV). Further, to study the benefits obtained from the proposed ACO-based heuristic, a comparative analysis has been performed between the results of the proposed algorithm and the three other aforementioned solutions for the problem

Table 9. List of problem sizes adopted from Jawahar and Balaji (2009).

Problem instance	Number of plants	Number of distributors	Number of retailers
1	2	2	3
2	2	2	4
3	2	2	5
4	2	2	6
5	2	2	7
6	2	3	3
7	2	3	4
8	2	3	6
9	2	3	8
10	2	4	8
11	2	5	6
12	3	2	4
13	3	2	5
14	3	3	4
15	3	3	5
16	3	3	6
17	3	3	7
18	3	3	7
19	3	4	6
20	4	3	5

Table 10. Performance comparisons.

	Total cost of distribution				Percentage deviation from		
Problem instance	ACO-based heuristic solution (Z)	GA-based heuristic solution (Z')	Approximate solution (Z'')	Lower-bound value (Z''')	GA-based heuristic solution $\left(\frac{Z-Z'}{Z'}\right) \times 100$	Approximate solution $\left(\frac{Z-Z''}{Z''}\right) \times 100$	Lower-bound value $\left(\frac{Z-Z'''}{Z'''}\right) \times 100$
1	112,600	112,600	112,600	112,600	0.000	0.000	0.000
2	237,750	237,750	237,750	237,750	0.000	0.000	0.000
3	180,450	180,450	180,450	173,878	0.000	0.000	3.780
4	165,650	165,650	165,650	157,050	0.000	0.000	5.476
5	162,490	162,490	169,890	161,712	0.000	−4.356	0.481
6	59,500	59,500	59,500	56,020	0.000	0.000	6.212
7	32,150	32,150	34,130	31,522	0.000	−5.801	1.992
8	69,045	69,670	71,295	64,724	−0.897	−3.156	6.676
9	258,730	264,680	265,330	253,419	−2.248	−2.487	2.096
10	80,900	85,200	80,400	74,657	−5.047	0.622	8.362
11	80,865	94,565	95,390	73,368.5	−14.487	−15.227	10.218
12	47,140	47,140	51,620	45,470	0.000	−8.679	3.673
13	178,950	178,950	178,950	169,826	0.000	0.000	5.373
14	57,100	57,100	61,000	52,591	0.000	−6.393	8.574
15	152,800	152,800	152,800	151,394	0.000	0.000	0.929
16	132,890	132,890	132,890	132,890	0.000	0.000	0.000
17	105,715	106,615	108,435	93,111	−0.844	−2.508	13.537
18	281,730	302,350	287,360	279,514	−6.820	−1.959	0.793
19	77,250	83,500	77,250	71,463	−7.485	0.000	8.098
20	118,450	118,450	118,450	118,450	0.000	0.000	0.000

instances. The relative percentage deviation of the proposed algorithm from the three other aforementioned solutions are summarised in Table 10.

The data for the first sample problem and the distribution-allocation results are provided in Appendix 1. Owing to space limitations, the data and the distribution-allocation results for the remaining problems are not included.

Table 11. Difference in objective function.

Problem instance	Total cost of distribution: ACO-based heuristic solution (Z)	Total cost of distribution: GA-based heuristic solution (Z')	$D=Z'-Z$	Problem instance	Total cost of distribution: ACO-based heuristic solution (Z)	Total cost of distribution: GA-based heuristic solution (Z')	$D=Z'-Z$
1	112,600	112,600	0	11	80,865	94,565	13,700
2	237,750	237,750	0	12	47,140	47,140	0
3	180,450	180,450	0	13	178,950	178,950	0
4	165,650	165,650	0	14	57,100	57,100	0
5	162,490	162,490	0	15	152,800	152,800	0
6	59,500	59,500	0	16	132,890	132,890	0
7	32,150	32,150	0	17	105,715	106,615	900
8	69,045	69,670	625	18	281,730	302,350	20,620
9	258,730	264,680	5950	19	77,250	83,500	6250
10	80,900	85,200	4300	20	118,450	118,450	0

6.1 *Performance analysis of the algorithms*

The results presented in Table 10 reveal that the solution obtained from the ACO-based heuristic is either the same or better than the existing GA-based heuristic. More specifically, for seven problems, ACO-based heuristic provides better solutions than GA-based heuristic. For the other 13 problems, the ACO-based heuristic and the GA-based heuristic provide the same solution. The ACO-based heuristic provides maximum improvement of 14.487% for problem 11.

When the results of ACO-based heuristic are compared with those obtained using AS, it is found that for 10 problems, the solutions are the same. However, for the remaining 10 problems, ACO-based heuristic provides better solution than AS. As observed earlier, for problem instance 11, the ACO-based heuristic provides about 15% improvement in comparison with AS.

The comparison of results of ACO-based heuristic with LBV shows that for four problems, the solutions for ACO and LBV are the same. For the other problems, the ACO-based heuristic leads to a slight increase in the objective-function values. However, it is found that the percentage deviation of ACO-based heuristic solutions from the lower bound is less than 15%.

Summarising the above findings, it is clear that the proposed ACO-based heuristic emerges as a better heuristic for a distribution-allocation problem in a two-stage supply chain with a fixed transportation cost for a route.

For a statistical confirmation of the findings, a paired-comparison t-test has been carried out. The difference in the objective function obtained using GA and ACO is computed and is denoted as D.

$$\text{Thus, difference } D = Z' - Z, \tag{13}$$

where Z' is the solution obtained from GA-based heuristic, and Z is the solution obtained from ACO-based heuristic. The difference is tabulated in Table 11.

The purpose of the paired-comparison t-test is to determine whether there is a significant difference in the cost. The t-test is conducted at the 5% level of significance. The null and alternate hypotheses are as follows:

$$H_0\colon D \leq 0. \tag{14}$$

The null hypothesis is that the there is no deviation between the solution with GA-based heuristic and ACO-based heuristic, i.e. GA-based heuristic gives better solution than ACO-based heuristic.

$$H_1\colon D > 0. \tag{15}$$

The alternate hypothesis is that the ACO-based heuristic provides better solution than GA-based heuristic. In this paired-difference test, the average of deviations should be 0 (i.e. $\mu_D = 0$).

The test statistic (t-statistic) is calculated as follows:

$$t_{\text{statistic}} = \frac{\bar{x}_D - \mu_D}{s/\sqrt{n}} = \frac{1087.50 - 0}{2171.957/\sqrt{20}} = \frac{1087.50}{485.66} = 2.239$$

$$t_{0.025,19} = 2.093.$$

Since $t_{\text{statistic}} > t_{\text{critical,}}$ the null hypothesis is rejected. This statistically proves that ACO-based heuristic performs better than GA-based heuristic. Thus, there is a significant difference between the solution obtained using ACO-based heuristic and that of GA-based heuristic.

It can be noted that GA and ACO belong to the category of evolutionary meta-heuristic algorithms. GAs are inspired by biological systems' improved fitness through evolution. A solution to a given problem is represented in the form of a string called chromosome. At each generation, a selection operator ensures that highly fit solutions survive in the population so as to produce the next generation. Operators like crossover and mutation are applied to create new solutions based on the surviving population. A probability is applied to the crossover operation to ensure that only a part of the individuals participate in reproduction. To maintain diversity, the mutation operator goes through all the genes of the population and modifies a gene with a mutation probability. Larger population size and larger number of generations increase the likelihood of obtaining a near-optimum solution, but substantially increase processing time.

In contrast to GA, ACO algorithm evolves not in its genetics, but in its social behaviour. The ACO algorithm is inspired by the social behaviour of a colony of ants trying to reach a source of food from their nest using the shortest route. Each ant takes into consideration pheromone trails left by all other ant colony members which preceded its course. This pheromone information directs the search of the ants in the succeeding iterations. Moreover, each ant contains a memory that stores its own best solution seen so far and a global best solution obtained through communication with the neighbour ants. The parameters used in the algorithm control the magnitude of the pheromone intensity, the magnitude of visibility, the evaporation rate of pheromone, the pheromone increment amount, the number of ants and the number of iterations. Adopting the optimum combination of parameters derived from appropriate experimental designs as carried out in the present study significantly improves the performance of the ACO algorithm. Thus, the uniqueness of the ACO-based heuristic is that it is a constructive, population-based meta-heuristic that exploits an indirect form of memory of previous performance to discover the best near-optimum solution efficiently.

7. Conclusion

The fixed charge transportation problem commonly encountered in real-life situations is an NP-hard problem. This paper proposes a novel optimisation tool based on ant colony optimisation algorithm for a two-stage supply-chain distribution network with a fixed cost for a transportation route. The two-stage supply chain comprises entities such as manufacturers (or sources/plants), distributors, and retailers (or destinations). Problem instances of various sizes available in the literature are solved using the proposed ACO-based heuristic. The solutions obtained have been compared with those obtained using the GA-based heuristic, the approximate solution, and the lower bound value reported in the existing literature. It is statistically confirmed that the ACO-based heuristic provides significantly better solutions than the GA-based heuristic.

In the modern competitive business environment, the critical issue for the managers of industrial and service companies is the design and management of supply chains. For a manufacturing firm, allocation of customers to its different entities in the supply chain is an important decision that affects value addition, customer-service level, and costs. The present study highlights the importance of heuristic-based algorithms to solve an FCTP in a two-stage supply chain. As a consequence, supply-chain managers can make effective allocation decisions. The proposed ACO-based heuristic provides guidelines in this direction.

In the present work, the mathematical model developed assumes a single product environment in a single period. Further research can focus on the multi-product and multi-period situation. In this study, a deterministic environment has been assumed; it may be interesting to analyse the stochastic environment. Further, the case of finite capacity for distributors can also be analysed. The proposed model can be extended to include transportation damage cost and fixed cost for opening a facility.

ACO is increasingly getting attention from researchers to solve NP-hard problems. Apart from the allocation problem, the technique can also be used for location-routing problems, allocation-scheduling problems and other combinatorial optimisation problems in a supply chain.

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Appendix 1

Table A1. Capacity of plants.

	Plant 1	Plant 2
Capacity (units)	450	550

Table A2. Retailer demand.

	Retailer 1	Retailer 2	Retailer 3
Demand (units)	85	650	265

Table A3. Transportation cost matrix between plants and distributors.

	Distributor 1		Distributor 2	
	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)
Plant 1	1250	20	6000	55
Plant 2	8000	70	4500	85

Table A4. Transportation cost matrix between distributors and retailers.

	Retailer 1		Retailer 2		Retailer 3	
	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)	Fixed cost (units)	Unit cost (units)
Distributor 1	2500	20	6000	55	4600	20
Distributor 2	5000	40	8000	75	3400	45

Table A5. Results of allocation between distributors and retailers.

	Retailer 1	Retailer 2	Retailer 3
Distributor 1	85	650	265
Distributor 2	0	0	0

Table A6. Results of allocation between plants and distributors.

	Distributor 1	Distributor 2
Plant 1	450	0
Plant 2	550	0