ACO-Heuristic for a Multi-period Distribution-Allocation Problem in a Single-Stage Supply Chain

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Abstract— This paper considers a multi-period fixed charge distribution problem (MPDAP) associated with backorder and inventory. A time-based decision on size of the shipments from each supplier, inventory, and backorder is done with an objective to minimize the total transportation cost. A MPDAP model is difficult to solve due to the presence of fixed costs, causing nonlinearities in the objective function and are known to be Nondeterministic Polynomial-time hard. To solve the problem, an Ant Colony Optimization (ACO) based heuristic is proposed. . The solution obtained using the proposed heuristic is validated by converting the MPDAP model into a Mixed Integer Programming (MIP) model and solving the MIP using LINGO-13 solver.A problem instance from a literature is considered and is solved using the ACO-heuristic.

Keywords— multi-period fixed charge distribution problem; heuristics; ant colony optimization

I. INTRODUCTION

In business the term 'industrial logistics' refers to the overall management of the way resources are obtained, stored and moved to the locations where they are required,while in reality it is a wide-reaching concept which incorporates various forms of supporting activities. Barros et al. (2001) classify industrial logistics under three categories namely, engineering level, firm level and sector level. Industrial logistics at the sector level includes all activities which allow physical flow of raw materials, semi-finished goods and finished goods and the associated services from suppliers to industrial producers and to consumers, thus allowing the production to take placein a spatially concentrated or dispersed form. As far as production support is concerned, the finished product distribution is the best known aspect of industrial logistics which includes all services directly linked to the physicalmovement of goods from plant to customers via warehouses.

II. LITERATURE REVIEW

In the literature, given the practical and the theoretical scope of multi-period distribution problems several solution procedures have been developed based on exact algorithms and approximation algorithms. Exact algorithms have been applied for solving a fixed-charge transportation problem. Murty (1968) propose a methodology for solving a fixed charge transportation problem by concentrating the search among the adjacent extreme points of the transportation problem.Barr et al. (1981) propose a branch-and-bound procedure for solving an FCTP in a single-stage supply chain.. Adlakha and Kowalski (2003) propose a heuristic algorithm for solving small fixed charge transportation problems. However, it is stated that the proposed method is more time-consuming than the algorithms for solving a regular transportation problem. Raj and Rajendran (2009) consider a single-stage supply chain and is solved using simple heuristic algorithms and their performances are compared with the existing best method by making use of benchmark problem instances.

There are meta-heuristic based algorithms proposed for solving fixed cost transportation problem. Gottlieb &Paulmann(1998) propose a Genetic Algorithm based heuristic for solving an FCTP in a single-stage supply chain. Sunet. al(1998) propose a Tabu-search based heuristic for solving an FCTP in a single-stage supply chain. Raj and Rajendran (2012) in his paper propose genetic algorithms to solve a two-stage transportation problem with two different scenarios.). Haq et.al (1991) formulates a model for a distribution-allocation problem with backorder in fertilizer industry. Later Chandra and Fisher(1994) extended the model by considering vehicle-routing decisions.Barborsogluand Ozgur (1999) consider a just-in-time environment and solve a problem with demand pattern with no backorder using Lagrangean relaxation method. Dogan and Geotschalckx (1999) consider a deterministic demand pattern and apply a Benders decomposition method considering a case study in packaging industry. Abelmaguid and Dessouky (2006) develop a solution approach based on genetic algorithm for solving a production-distribution problem with a backorder and a penalty function. Chun and Zhang (2009) solve a production-distribution problem using a genetic algorithm.

A notable research gap in the literature is that most of the work has not included fixed charge for transportation routes, in the integration of inventory and transportation costs.

Ant Colony Optimization (ACO) is a meta-heuristic approach proposed by Colorni et al. (1991). Later the approach is improved by Dorigo et al.(1996) by developing the Ant Colony System.The earlier application of ACO is to solve the well-known NP-Hard Traveling Salesman Problem (Colorni et al. 1991, Dorigo et al., 1996, Dorigo and Gambardella 1997). Blum (2005) have provided a detailed description of the basics of the ACO algorithm, it applications, and its successful variants. Several studies have applied ACO to solve different discrete and continuous optimization problems, such as vehicle routing, quadratic assignment problems and graph coloring. Dorigo and Stutzle (2004) report more than 30 problems where ACO-based algorithms have been used successfully. Most of these problems can be represented in the form of a network or graph. With the successful implementation of the ACO approach, the significance of the approach for solving these problems has been recognized by researchers and practitioners.

I. PROBLEM ENVIORNMENT

3.1 Problem Description

Consider an MPDAP in which there are 'p' suppliers to distribute to 'r' end customers' in T planning periods. In each period P_i^t is taken as the units produced by each supplier and D_k^t as the units demanded by each customer. Each of the suppliers 'i' is free to distribute their product to any of the customer k. During these shipments, a variable cost which is directly proportional to the quantity to be shipped is included. This variable cost is called unit transportation cost denoted by C_{ik}. In addition to this cost component, a fixed cost component is also included in each shipment. It is denoted by FC_{ik}.

At any time period t, the total cumulative production of the suppliers and the total cumulative demand of the customers may or may not be equal (could be higher or lesser). The excess or shortage of production is carried over to the subsequent period t+1.The excess of production is addressed here as inventory, while the production shortage (excess demand) of the period is addressed as backorder. For the period t+1, inventory can be considered as an additional supply and the backorder as the additional demand.

At a period, when the inventory is at the supplier's side, per unit inventory holding cost is denoted as SH_i , and at the customers side it is CH_k. As the proposed model considers short planning periods (days/weeks/months), the costs associated with transportation (i.e. C_{ik} and FCij), inventory (i.e. SH_i and CH_k) and backorder (i.e. BCj) are independent of period t.The beginning period's inventory and backorder (i.e. SI_i^t, CI_k^t ,and BL_j^t) are known quantities. The objective criterion of the model is the minimization of the total costs which is the sum of the costs of transportation, the costs of holding inventory and the costs of penalty for the backorder supply.

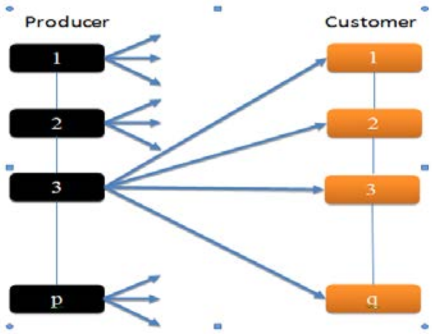


Fig.1: Operational elements of multi-period fixed charge distribution problem during the period t where 'p' suppliers can supply to any of the 'k' customers.

The assumptions used in the problem are:

(1) The number of customers (plants) and their demand (capacity) are known.

(2) The total supply of all plants may or may not be equal to the total demand of all customers

(3) The capacity of each transportation mode is not less than total demand.

(4) The entire shipment is taking place in the same transportation mode

3.2 Mathematical Model

Notation:

The indices used in the model are as follows:

i Supplier index (1, 2…p)
k Customer index (1, 2…r)
t Time index (1, 2…T)

Parameters:

C_i^p Supplier's production capacity
D_k^r Customer demand
U_{ik} Unit Transportation cost
FC_{ik} Fixed Transportation cost
CH_k Customer's inventory holding cost per unit time
SH_i Supplier's inventory holding cost per unit time
BC_j Customer backorder penalty cost per unit time

Decision Variables

$$\delta_{ik}^t \begin{cases} 1 ... when ... X_{ik}^t > 1 \\ 0 ... otherwise \end{cases}$$

X_{ik}^t Optimal size of the shipments
CI_k^t Customer's beginning inventory
SI_i^t Supplier's beginning inventory
BL_k^t Customer's beginning backorder

3.3 Objective Function

In this work, the problem environment comprises of *p* suppliers to distribute a product to *r* customers in *T* planning periods. The model integrates the production, transportation, backorder and inventory decisions in a single-stage supply

ISSN 2229-5518

chain. The mathematical model of the MPDAP considering a fixed cost for transportation route is formulated as a Pure Integer Non-Linear Programming (PINLP) problem as given below.
The objective function of the model can be stated as follows.

Minimize Z

$$Z=\sum_{t=1}^{T}\sum_{i=1}^{p}\sum_{k=1}^{r}(C_{ik}X_{ik}^{t}+FC_{ik}\delta_{ik}^{t})+\sum_{t=1}^{T-1}\sum_{i=1}^{p}(SH_i\times SI_i^t)+\sum_{t=1}^{T-1}\sum_{k=1}^{r}(CH_k\times CI_k)+\sum_{t=1}^{T-1}\sum_{k=1}^{r}(BC_k\times BL_k^t) \quad (3.1)$$

$$P_i^t+SI_i^{t-1}=\sum_{k=1}^{r}X_{ik}^t+SI_i^t \quad \forall_i \text{ and } \forall_t; \quad (1)$$

$$D_k^t+BL_k^{t-1}-CI_k^{t-1}=\sum_{i=1}^{p}X_{ik}^t+BL_k^t-CI_k^t \quad \forall_k \text{ and } \forall_t \quad (2)$$

$$X_{ik}^t\times(\delta_{ik}^t-1)=0 \quad \forall_i\, i=1,\dots p\ \forall_k \text{ and } \forall_t \quad (3)$$

$$\delta_{ik}^t-X_{ik}^t\leq 0 \quad \forall_i\ \forall_k \text{ and } \forall_t \quad (4)$$

$$\delta_{ik}^t\geq 0 \quad \forall_i\ \forall_k \text{ and } \forall_t \quad (5)$$

$$X_{ik}^t\geq 0 \quad \forall_i\ \forall_j \text{ and } \forall_t \quad (6)$$

$$SI_i^t\geq 0 \text{ and integer; } \forall_k \text{ and } \forall_t \quad (7)$$

$$CI_k^t\geq 0 \text{ and integer; } \forall_k \text{ and } \forall_t \quad (8)$$

$$BL_k^t\geq 0 \text{ and integer; } \forall_k \text{ and } \forall_t \quad (9)$$

The objective of the mathematical model is to minimize the sum of the total costs associated with production, transportation, inventory at supplier's and customer's end and backorder. The first term of the objective function provides the total cost of production for the entire period T and the second term provides the total cost of transportation for the entire period T. The third term addresses the total cost of holding inventory at supplier's locations for the entire period T. The fourth and the fifth terms indicate respectively the total cost holding inventory for the entire period T and the total cost of backorder penalty for the entire period T. The model is subjected to the following constraints:
According to constraints (1) and (2) the material should be balanced at the supplier's and customer's side respectively between any two successive time intervals. Either inventory or backorder is present in any of the side of these equations. Constraints (3), (4), (5), and (6) return a value for the binary variable when there is shipment. Constraints (7), (8), and (9) ensure that the decision variables are having integer values and are non-negative.

IV.SOLUTION METHODOLOGY

The above formulated MPDAP model is difficult to solve due to the presence of fixed costs, causing non-linearity in the objective function. In this work, the MPDAP is solved using an Ant Colony Optimization (ACO) based heuristic to obtain a near-optimal solution. The proposed heuristic comprises of the following four stages

- Initialization
- Node Transition
- Pheromone updating and
- Termination.

ACO is a meta-heuristic technique and is based on the behavior of real ants in search of food using the shortest path. ACO possesses the enhanced abilities such as memory of past actions and knowledge about the distance to other locations in the search process. The ants communicate using a chemical substance called pheromone. As an ant travels, it deposits a constant amount of pheromone that other ants can follow. Each ant moves in a somewhat random fashion, but when an ant encounters a pheromone trail, it must decide whether to follow it. If it follows the trail, the ant's own pheromone reinforces the existing trail, and the increase in pheromone increases the probability of the next ant selecting the path. Therefore, the more the ants that travel on a path, the more attractive the path becomes for subsequent ants. Hence, an ant using a short route to a food source will return to the nest sooner and therefore, mark its path twice, before other ants return. This influences the selection probability for the succeeding ant leaving the nest.

4.1 Proposed ACO-based Heuristic

The steps involved in the ACO-based heuristic are described in the following subsections.

4.1.1. Determination of various costs at different periods

The distribution-allocation at different periods involving inventory and backorder costs, variable and fixed cost is determined according to the following conditions.
Calculation of variable transportation cost:
Taking demand period as t_d and supply period as t_s,

☐ Case 1: $t_d = t_s$

When demand of a period is met in the same period itself, variable cost remains unchanged.

☐ Case 2: $t_d > t_s$

When demand of a period is met from the inventory of the previous period, existing variable cost is re-calculated by adding supplier's or customer's inventory holding cost. Minimum of this cost taken for adding to the total cost.

Variable cost = $U_{ij}+HS_i$ x $(t_d - t_s)$

Variable cost = $U_{ij}+HS_i$ x $(t_d - t_s)$

☐ Case 3: td <ts

When demand of the period td is met as backorder, from the period ts, the variable cost is recalculated by adding backorder costs also.

Variable cost = $U_{ij}+BC_j$ *(td-ts)

4.1.2. Calculation of fixed transportation cost

The calculation of fixed transportation cost depends on the period in which the shipment is done.

☐ Case 1: td = ts

Transportation is done in the same period as the demand. Thus, fixed transportation cost remains same.

- Case 2: td>ts

The demand is met from the previous period's inventory of either supplier or customer. When there is supplier's inventory, there exists no shipment and thus the quantity has to be shipped in this period and incurs a fixed cost in the transportation. Similarly, if the inventory is stored at the customer location in the previous period, no fixed cost is incurred in the period.

- Case 3: td<ts

The demand is met as backorder for the coming periods. For a period, if the shipment of backorder is taking place in the period ts, then the fixed cost of this period is zero, on the contrary; if the shipment is taking place in this period, there exists a fixed cost.

4.2 Implementation of ACO-based heuristic for MPDAP

In a single stage supply chain, using Monte-Carlo simulation procedure, a matrix is generated in which all the customers, suppliers and time-period are specified. An ant starts to move from the chosen customer. The ant selects that supplier in which the cumulative probability value is greater than the random number.

Each ant starts from the first customer and moves to the position of the supplier s, in time period t, as determined by the random number generated and transition probability. The customer demand and the supplier capacity are considered and the minimum of this is allotted as the shipment quantity. This procedure is continued till the demand of the first customer is satisfied or capacity constraint of supplier is met.

The ant selects the next customer and the same procedure is continued till an allotment pattern satisfying the demand and capacity constraints is satisfied. In the edges where an allocation is done, the ant deposits an additional pheromone as compared to other edges where there is no allocation which increases its visibility. Hence for next ant, the probability of selecting that node is more.

The total cost is computed as the objective function value for the complete allocation of the artificial ant. The ACO-based heuristic constructs the complete allocation for the first ant prior to the second ant starting its allocation. This continues until a predetermined colonies of ants m, each construct a feasible allocation.

4.3 Parameter Setting

The correct choice of parameters and operators decides the effectiveness of heuristic algorithms.Among several experimental design techniques, the Taguchi method has been successfully applied for a systematic approach for optimization (Phadke, 1989) and (Taguchi, 1986).

The Taguchi method involves reducing the variation in a process through robust design of experiments. The overall objective of the method is to produce high quality product at low cost to the manufacturer. The experimental design proposed by Taguchi involves using orthogonal arrays to organize the parameters affecting the process and the levels at which they should be varies. Instead of having to test all possible combinations like the factorial design, the Taguchi method tests pairs of combinations. The Taguchi method is best used when there are an intermediate number of variables (3 to 50), few interactions between variables, and when only a few variables contribute significantly.

4.3.1 Determining Parameter Design Orthogonal Array

Experimental design usually involves attempting to optimize process which can involve several factors.

The parameters used in ACO-based heuristic and their levels are:

α the relative importance of trail, α ≥ 0
(0.2, 0.4, 0.6, 0.9., 0.99)

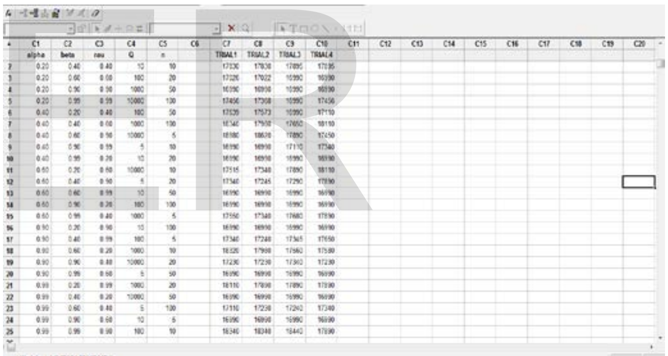
β the relative importance of visibility, β ≥ 0
(0.2, 0.4, 0.6, 0.9, 0.99)

ρ A coefficient such that (1-ρ) represents the evaporation rate ,0 ≤ ρ< 1
(0.2, 0.4, 0.6, 0.9, 0.99)

n number of ants
(5, 10, 20, 50, 100)

Q a constant related to the quantity of trail laid by ants
(5, 10, 100, 1000, 10000)

Here, in our experiment we are having 5 set of parameters with 5 levels so it's possible to take L25 array. Parameter setting using Taguchi method was done in Minitab-16 and theL25 array generated by the MINITAB is as follows:



↓	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
	alpha	beta	rau	Q	n		TRIAL1	TRIAL2	TRIAL3	TRIAL4
2	0.20	0.40	0.40	10	10		17030	17030	17095	17035
3	0.20	0.60	0.60	100	20		17026	17022	16990	16990
4	0.20	0.90	0.90	1000	50		16990	16990	16990	16990
5	0.20	0.99	0.99	10000	100		17456	17308	16990	17456
6	0.40	0.20	0.40	100	50		17536	17573	16990	17110
7	0.40	0.40	0.60	1000	100		18340	17930	17650	18110
8	0.40	0.60	0.90	10000	5		18180	18670	17890	17450
9	0.40	0.90	0.99	5	10		16990	16990	17110	17340
10	0.40	0.99	0.20	10	20		16990	16990	16990	16990
11	0.60	0.20	0.60	10000	10		17515	17348	17890	18110
12	0.60	0.40	0.90	5	20		17340	17245	17290	17890
13	0.60	0.60	0.99	10	50		16990	16990	16990	16990
14	0.60	0.90	0.20	100	100		16990	16990	16990	16990
15	0.60	0.99	0.40	1000	5		17550	17340	17680	17890
16	0.90	0.20	0.90	10	100		16990	16990	16990	16990
17	0.90	0.40	0.99	100	5		17340	17248	17565	17650
18	0.90	0.60	0.20	1000	10		18525	17990	17560	17580
19	0.90	0.90	0.40	10000	20		17230	17230	17340	17230
20	0.90	0.99	0.60	5	50		16990	16990	16990	16990
21	0.99	0.20	0.99	1000	20		18110	17890	17890	17890
22	0.99	0.40	0.20	10000	50		16990	16990	16990	16990
23	0.99	0.60	0.40	5	100		17110	17238	17240	17340
24	0.99	0.90	0.60	10	5		16990	16990	16990	16990
25	0.99	0.99	0.90	100	10		18340	18348	18440	17890

Fig 2:L25 array generated by the MINITAB

Thus the best combinations of parameter values from Taguchi method are as follows:

- α=0.90
- β=0.90
- ρ=0.99
- n=50
- Q=10

4.4 Validation of ACO-based Heuristic

According to the Jawahar et.al (2011), an optimal solution cannot be obtained using the constraints imposed in the objective function, as there exist a non-linearity function due to the presence of fixed-cost. So the linear distribution model is made by relaxing the integrality restrictions of the problem with an equivalent variable transportation cost.

The problem can now be solved in LINGO solver and an optimal cost with a distribution schedule can be determined. In order to validate the solution obtained using ACO-based heuristic, a comparison is made between the

ISSN 2229-5518

solution obtained from proposed heuristic and that of LINGO. Further a set of problem instances are randomly generated varying the number of suppliers, the number of customers and the time-periods. All these variables are varied from two to eight.

V.NUMERICAL ILLUSTRATION

The numerical illustration of the proposed heuristic for solving a MPDAP in a single-stage and two-stage supply chain with a sample problem is provided in the following subsections.

STEP 1: Input Data

Table 1: Supplier Capacity and Customer Demand

Demand (units)							
		Time period		Customer inventory	Customer holding cost	Backorder quantity	Backorder cost
		T1	T2				
Customers	C1	60	50	0	15	0	20
	C2	40	30	20	10	20	40
Capacity (units)							
		T1	T2	Supplier Inventory	Supplier holding cost		
Suppliers	S1	50	60	10	5		
	S2	40	50	0	12		

Table 2: Supplier and customer cost data

	Supplier S1		Supplier S2	
	Fixed cost	Unit cost	Fixed cost	Unit cost
Customer C1	900	20	150	40
Customer C2	90	35	1100	5

STEP 2: Applying State Transition Rule

Initially at each node a pheromone quantity of 0.5 units is assumed.
An expected allocation cost for the initial allocation is calculated assuming the total demand could be met with the capacity and then, the visibility is calculated. Probability matrices are then calculated between each supplier node and customer node.

Table 3: Transition probability matrix

	Supplier 1 (S1)	Supplier2 (S2)	Supplier1 (S1)	Supplier1 (S2)
Customer1 (C1)	0.250994	0.27495	0.213587	0.260469
Customer 2 (C2)	0.2821	0.302012	0.195892	0.219995
Customer 3 (C1)	0.263725	0.223958	0.234326	0.277991
Customer 4 (C2)	0.22768	0.246953	0.237372	0.287995

STEP 3: Ant Solution Generation

To perform the allocation, a Monte-Carlo Simulation Method is applied using the cumulative probability matrix generated from Table 3.

In the Monte-Carlo simulation process, random numbers are generated to perform the allocation of customers to the suppliers.

Table 4: Initial allocation matrix before allocation

		P1		P2		
		S1	S2	S1	S2	Demand
P1	C1					60
	C2					40
P1	C1					60
	C2					50
	Capacity	60	40	50	30	

For example; initially, customer C1 is selected by the ant and the ant starts the allocation process from this customer. A random number is generated (i.e. R1= 0.7290).The ant finds out that supplier where the cumulative probability becomes just greater than the random number R1 (i.e. cell between customer (C1) and supplier (S2)). The minimum units between the demand of customer (C1) and capacity of supplier (S2) in the corresponding selected cell is calculated (e.g.; min (40, 60) =40) and this minimum amount of units is allocated to shown in Table 4.The ant will continue the allocation with the same customer, till the complete demand of customer C1 is met, generating more random numbers.
The ant selects the next customer and the process continues. Once the process of allocation of customers to the suppliers in the same time period is completed, ant goes back to previous time-period for allocation of inventory and backorder.
The total cost is computed as the objective function value for the complete allocation of the artificial ant. The ACO-based heuristic constructs the complete allocation for the first ant prior to the second ant starting its allocation. For this example
Allocated cost of the first ant = ((20x20) +150) + ((40x40+150) + ((35x40) +90) + ((30x40) +150) + ((35x20) +90) = 1300+1750+1490+1350+790 =6680
Inventory cost = 0
Backorder cost =10x40 =400
Thus, the total Costs (in monetary units) for the allocation made by the first ant is 7080.
The same procedure will continue for all the ants and similar ant solution matrices and total allocation cost are generated.
Total costs generated by all the ants are compared and the minimum cost is considered as the best solution. The global best solution is same as the best ant solution. Using the best ant solution, the pheromone level is revised.
In the example considered; in the first iteration, the first ant solution is considered as the best ant solution.

- ☐ Total costs for First ant (in monetary units): 7080 (**Best Ant Solution)**
- ☐ Total costs for Second ant (in monetary units): 8050
- ☐ Total costs for Third ant (in monetary units): 8180

In the first iteration, the global best solution is same as the best ant solution.
Global Best solution = Best Ant Solution= 7080(in monetary units)
The pheromone value is updated using the global best solution. The pheromone value increment (global updating) is calculated an equation and it is incorporated into the edges of the best ant path. Thus a new pheromone matrix is formed.
The same procedure is applied in the successive iterations. In each iteration, based on the ant solutions, the

Best Ant Solution is updated and compared with Global Best Solution. If, the Best Ant Solution is better than the Global Best Solution, the Global Best Solution is updated. Else, the Global Best Solution is retained.

When termination condition in terms of maximum number of iterations is met, the Global Best Solution is given as the output.

Global Best solution = Best Ant Solution= 7050 (in monetary units)

Near –optimal cost =**7050**

The best cost obtained by ACO-based heuristic is Rs.7050. monetary units. For validation of the result LINGO solver is used. The best cost obtained using LINGO is Rs.6800

VI.EXPERIMENTATION

6.1 Computational Problem – Problem instance I

As problem instance I, a MPDAP in a single-stage supply chain as reported in Jawahar et.al (2011) is solved using the proposed ACO-based heuristic. This distribution problem considered consists of three periods with three suppliers and three customers. The supply capacity, demand quantity, variable and fixed costs, holding cost, inventory and backordered quantity are given in Table 5. The transportation cost data is provided in Table 6.

Table 5: Supplier's and Customer's Data

		Suppliers			Customers		
		1	2	3	1	2	3
Period	1	60	40	60	60	60	70
	2	50	30	60	60	20	30
	3	80	60	30	90	60	40
Inv. Holding cost/time		5	12	28	15	10	15
Beg. Inventory		10	0	0	0	0	30
Backorder cost/time					20	40	30
Backorder quantity					0	20	0

Table 6: Transportation Cost Data

	Customer 1		Customer 2		Customer 3	
	Fix	Var	Fix	Var	Fix	Var
S1	900	20	90	35	100	25
S2	150	40	1100	5	50	80
S3	800	30	70	70	1000	15

VII.RESULTS AND DISCUSSION

In this work, initially a problem instance from the literature (Jawahar et.al ,2011and Jawahar and Balaji ,2012) are solved by the proposed ACO-based heuristic and is validated using the LINGO software. The obtained results show the proficiency of the proposed algorithm in comparison with LINGO and the existing results in the literature.

Solution methodology adopted	Objective function value
Simulated annealing algorithm (Jawahar et.al, 2011)	17860
LINGO (Equivalent cost approach)	17347
Proposed ACO-based heuristic	17050
LINGO (Revising constraint)	16780

Using the proposed ACO-based heuristic, many problem instances are generated in which the planning horizon is varied from 2 weeks to 8 weeks. Similarly, the number of suppliers and the number of customers are varied from 2 to 8.The computational time taken by the ACO-based heuristic increases as the planning horizon increases since the decision variables and the constraints are more. The solution obtained using ACO-based heuristic is compared for its robustness, with that obtained using LINGO solver. From the comparison, it is found that, LINGO generates optimal solutions while ACO heuristic can develop only a near-optimal solution. But there exists only a very small deviation between the solutions. In terms of computational time, LINGO solver takes more time to obtain solution. This computational time further increases as the planning horizon increases. Thus, for higher size problems, the proposed ACO-based heuristic provides near-optimal solution in less time in comparison with that of LINGO. In certain problem instance, the time taken is so high that, the solver is interrupted and a non-optimal solution is found using LINGO.

VI.CONCLUSION AND FUTURE SCOPE FOR THE WORK

In this work, a mathematical model for the MPDAP associated with backorder and inventory is formulated. The transportation cost component in the MPDAP considered in this work involves variable cost and fixed cost. The objective of the model is to determine the size of the shipments, backorder and inventory at each period, so that the total cost incurred during the entire period towards transportation, backorder and inventory is minimized.

The above formulated MPDAP model is difficult to solve due to the presence of fixed costs, causing nonlinearities in the objective function and are known to be Nondeterministic Polynomial-time hard. Hence, to solve the formulated MPDAP, an ACO-based heuristic is developed to get a near-optimal solution in this work.

The solution obtained using the proposed heuristic is validated by converting the MPDAP model into a Mixed Integer Programming (MIP) model and solving the MIP using LINGO-13 solver.A set of problem instances are randomly generated varying the number of suppliers, the number of customers and the time-periods from two to eight. The percentage deviation in the objective function value (total cost) obtained using ACO-based heuristic is more, ranging from 1.25% to 3.54% with that of LINGO solver.

As a future scope, the MPDAP model formulated in this work can be extended by including more supply chain partners.

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