Designing a New Supply Chain Network Considering Transportation Delays Using Meta-heuristics

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Abstract. This work introduces a hierarchical tri-level modeling between manufacturer and distribution center, distribution center and customer region, and customer region and retrieval center. The important decision making in the model is usually done based on the Stackelberg game theory. Due to the inherent complexity in the proposed model, it is considered as NP-hard problem. To tackle such a complex model this work introduces three metaheuristic algorithms namely, multi-objective Tabu search (TS), multi-objective variable neighborhood search (MOVNS), and multi-objective particle mass optimization (MOPSO). Finally, the results are analyzed and found the performance of MOTS is better than other proposed MOVNS and MOPSO.

Keywords: Tri-level supply chain model · Supply chain management · Metaheuristics

1 Introduction

Supply Chain Management (SCM) is mentioned as one of the best tools to improve the performance of organizations and production centers. Information sharing is an essential aspect of the supply chain network. If the supply chain is adequately managed and the Original Equipment Manufacturer can focus on a competitive edge to allocate more share to the market. This will help the supply chain to sustain itself in the market [1–4].

In the past few decades, the design of location-allocation models in SCM has developed rapidly, which apply new approaches to integrate different locations in the supply chain. Integrated supply chain management is a planning and process-oriented approach that takes care of the complete process originating from source to destination and uses post-used products by recovering those products. Integration of supply chain also focuses on allocations of customers to distribution centers and allocation of retrieval centers to

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customers to guarantee the recovery of post-used products. All of these cases use distinct methods to reduce transportation costs in each section.

In the real world, the management of the mentioned sections is separated and determined at different levels. Customers choose the services of distribution centers based on their profit margin. Therefore, multi-level planning is a useful method for simulating other parts of the network simultaneously.

The presented model is novel and works so that if there is transportation delay, the supply chain cost will increase which results in the decrease of profit of the organization. This delay in transportation may even affect the final consumer of the chain. Therefore, this model is designed to minimize total costs in such a way that the cost of a transportation delays can also be considered. The tri-level model considering the transportation delay is a new concept, and this issue has not been discussed so far.

The remainder of the paper is organized as follows. The second section presents related literatures. The third section offers the problem statement. The fourth section deals with the solution approaches, and finally, the fifth section presents conclusions and future direction.

2 Literature Review

In this section, some papers examine the related to the supply chain network and meta-heuristic algorithms. Owen and Daskin [5] examined the issues related to the position allocation of the dynamic random facilities during 1964–1977. They pointed out that stochastic models are divided into two categories: probabilistic- and scenario-based. In this method, it is assumed that the input parameters are unknown. In another study, it was shown that location-allocation issues are NP-hard [6]. Hence, heuristics and meta-heuristics methods were proposed to solve such problems. Pirkul and Jayaraman [7] presented efficient production and distribution models with multiple products as parts of the forward network. They presented a complex integer planning with the heuristic's method based on the Lagrange method for solving a problem. Zhou et al. [8] proposed a genetic algorithm to solve location-allocation problem through multiple distribution centers. Sharma et al. [9] Proposed a multi-criteria hierarchical process to design an optimal distribution network. Lee and Quan [10] developed a combined planning algorithm according to Tabu search for optimization of distribution center problems.

3 Problem Model

This paper designs a three-echelon allocation location problem that simultaneously provides forward and reverse networks is shown in Fig. 1. Distribution centers, as high-level leaders, decide to receive the products from manufacturers and provide the appropriate needs among the potential facilities. This level focuses mainly on forward networks. Based on the decisions made by the distribution centers, the customer regions, as the middle-level follower, decide to select the distribution centers to diminish the allocation and transportation costs. Finally, the low-level follower considers the reverse network with retrieval (or recovery) centers to supply the flow of the used products.

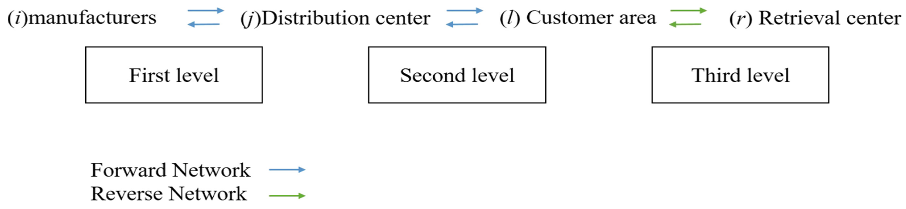


Fig. 1. Forward and reverse tri-level supply chain model.

A mathematical model is formed based on the problem statement. Model indices, parameters and variables of the proposed model are illustrated in Tables 1–3. The formulation of the three-level planning model is shown in Table 4.

Table 1. Model indices

Indices	
i	Number of manufacturers $i \in \{1, 2, \ldots, I\}$
j	Number of potential distribution centers $j \in \{1, 2, \ldots, J\}$
l	Number of costumers centre $l \in \{1, 2, \ldots, L\}$
r	Number of potential retrieval center $r \in \{1, 2, \ldots, R\}$

Table 2. Model variables

Variables	
X_{ij}	Number of products carried from manufacturer i^{th} to distribution center j^{th}
Z_{jl}	Number of products carried from distribution center j^{th} to customer region l^{th}
Z_{lr}	Number of products carried from customer region l^{th} retrieval center r^{th}
Y_{fe}	If facilitation is established 1, otherwise $fe \in \{r, j\}$
U_{fe}	If there is a delay in transportation 1, otherwise $fe \in \{r, j, l\}$

Table 3. Model parameters

Parameters	
Td_{fe}	Delay fixed cost in transportation $fe \in \{r, j, l\}$
fc_{fe}	Fixed cost of facility repayment

(*continued*)

Table 3. (*continued*)

Parameters	
$tc_{fe_{f_e^{\cdot}}}$	The cost of transportation from facility fe to facility $f_e^{\cdot}$ $fe \in \{i, r, j, l\}$
ac_{jl}	The cost for allocating customer region i^{th} to distribution center j^{th}
ac_{lr}	The unit cost for allocating retrieval center r^{th} to customer region j^{th}
P_{fe}	Facility capacity $fe \in \{r, j, l\}$
$\max_e$	Maximum number of sites created (retrieval center and customer region)
d_l	Customer demand of region l^{th}
α_l	Fraction of products used Reference from customer region l^{th}

Table 4. Formulation of the three-level planning model

$DC : Min\left(\sum_j fc_j Y_j + \sum_i \sum_j tc_{ij} X_{ij} + \sum_j U_j Td_j\right)$	(1)	$\sum_j Z_{jl} \geq d_l \forall l \in L$	(11)
$CZ : Min\left(\sum_j \sum_l \left(tc_{jl} + ac_{jl}\right) Z_{jl} + \sum_l U_l Td_l\right)$	(2)	$\sum_j Z_{jl} \leq \left(\sum_i X_{ij}\right) Y_j \forall j \in J$	(12)
$RC : Min\left(\sum_r fc_r Y_r \sum_l \sum_r (tc_{lr} ac_{lr}) Z_{lr} + \sum_r U_r Td_r\right)$	(3)	$\sum_r Z_{lr} \leq \sum_j Z_{jl} \alpha_l \forall l \in L$	(13)
$\sum_j Y_j \leq \max_j$	(4)	$U_l \in \{0, 1\}$	(14)
$\sum_j X_{ij} \leq P_i \forall i \in I$	(5)	$Z_{jl} \geq 0$	(15)
$\sum_i X_{ij} \leq P_j \times Y_j \forall j \in J$	(6)	$\sum_r Y_r \leq \max_r$	(16)
$\sum_l Z_{jl} \leq X_{ij} \forall j \in J$	(7)	$\sum_l Z_{lr} \leq P_r Y_r \forall r \in R$	(17)
$Y_j \in \{0, 1\}$	(8)	$\sum_r Z_{lr} \leq d_l \alpha_l \forall l \in L$	(18)
$U_j \in \{0, 1\}$	(9)	$Y_r \in \{0, 1\}$	(19)
$X_{ij} \geq 0$	(10)	$U_r \in \{0, 1\}$	(20)
		$Z_{lr} \geq 0$	(21)

As shown in Table 4, the objective function (1) indicates the costs minimization in distribution centers. The first, second and third term represents the fixed cost of the construction of distribution centers, the cost of the transportation between the distribution centers and manufacturers, and the cost of created delays, respectively. Constraint (4)-(10) are related to leader level. Constraint (4) indicates the maximum number of facilities that can be constructed as the distribution centers. Constraint (5) shows the number of products that must be moved between the manufacturer and the distribution center. Constraint (6) also ensures that the number of products shipped to distribution centers does not exceed to the capacity of these centers. Constraint (7) states that products carried from the manufacturers to the distribution centers meet all demand. Constraints (8) and (9) represents binary variables, and constraint (10) ensures that decision variables are positive.

The objective function (2) minimizes the costs at the customer center, which includes the shipping costs, allocation and the created delays. Constraint (11)-(15) are related to the middle-level follower. Constraint (11) ensures that each customer's demand is met through distribution centers. Constraint (12) indicates that customers can receive the services through a distribution center, if the distribution center is open. Constraint (13) shows a fraction of the returned products carried from the customer regions to retrieval centers, which is limited by a fraction of the products shipped from distribution centers to the customer regions. Constraint (14) represents binary variables, and constraint (15) ensures that decision variables are positive.

The objective function (3) shows the minimization of the costs for the retrieval centers in the reverse network. Here, the first, second and third term demonstrates the fixed cost of building the facility, the cost of transporting products from customers to the retrieval centers and the cost of the possible delays, respectively. Constraint (16)-(19) are related to the lower-level follower. Constraint (16) restricts the maximum number of facilities of recovery centers. Constraint (17) ensures that the products shipped from customer regions do not exceed the capacity of these centers. Constraint (18) ensures that the products shipped to retrieval centers by a fraction of the demand for each customer are limited. Constraints (19) and (20) represents binary variables. Constraint (21) ensures that decision variables are positive.

4 Problem Solving Approaches

This paper presents a three-tire Mixed-Integer Linear Model (MILP). The integrated network consists of the manufacturer, distribution center, customer and retrieval center. To solve a small size problem, the GAMS solver with branch and limit method has been utilized. This solver has a good performance in small size problem, but in large dimensions, this solver is computationally expensive due to the complexity of the model. Due to this, the location-allocation model in a supply chain is considered to be NP-hard [11–28]. To solve the problem instances, this work proposes three efficient multi-objective metaheuristic algorithms, namely, multi-objective Tabu search (MOTS), multi-objective variable neighbourhood search (MOVNS), and multi-objective particle mass optimization (MOPSO). Besides, set of test problems is generated and divided into small and large-sized problems shown in Table 5. The related parameters used for each algorithm is shown in Table 6.

Table 5. Examining the dimensions of the problem

Instances	Test problems	Problem dimension
Small Size	1	$2 \times 2 \times 4 \times 5$
	2	$2 \times 3 \times 2 \times 4$
	3	$3 \times 6 \times 5 \times 3$
	4	$4 \times 5 \times 4 \times 2$
	5	$6 \times 4 \times 7 \times 10$
Large Size	1	$6 \times 5 \times 7 \times 11$
	2	$7 \times 8 \times 10 \times 9$
	3	$7 \times 9 \times 13 \times 8$
	4	$9 \times 11 \times 8 \times 7$
	5	$10 \times 11 \times 9 \times 15$

Table 6. Parameters of proposed algorithms MOTS, MOVNS and MOPSO

Algorithm	Parameters	Levels			
		1	2	3	4
MOTS	A. Number of repetitions	150	250	300	350
	B. Forbidden list	40	60	90	100
MOVNS	C. Number of repetitions	150	250	300	350
	D. Number of neighbor-hood approaches	2	3	4	5
MOPSO	A. Number of repetitions	150	250	300	350
	B. Size of population	50	100	150	200
	C. Weight Inertia	0.65	0.7	0.86	0.99
	D. Acceleration coefficient ($C_{1)}$	1.3	1.6	2.5	3
	E. Acceleration coefficient (C_2)	1.4	1.7	1.9	2s

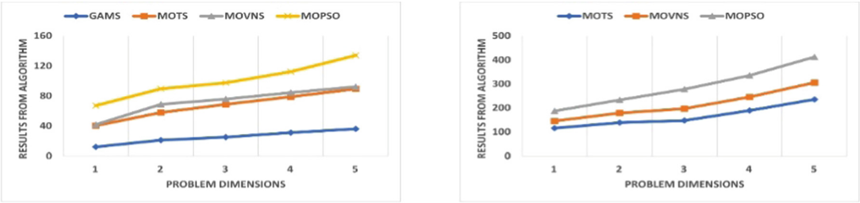
The multi-objective metaheuristic algorithms are run in MATLAB R2016 software and run on a computer with an Intel Core i5 5GHz processor. The proposed metaheuristic algorithms are run for the instance problem, and their results are reported in Table 7. It can be observed from Fig. 2 (a) that the results obtained from the GAMS solver are found better in the case of a small size problem. Figure 2 (b) reveals the performance of proposed algorithms in the large size. The multi-objective Tabu search algorithm presents a better outcome than other algorithms. Table 8 shows the computational (CPU) time of the generated test problems. In addition to this, to analyze the computational complexity, Fig. 3 (a) and (b) shows the computational time of running algorithms in the small- and large-sized problem.

Table 7. Outcomes obtained of algorithms.

Problem size	GAMS	MOTS	MOVNS	MOPSO
$2 \times 2 \times 4 \times 5$	12	40.261	41.800	67.068
$2 \times 3 \times 2 \times 4$	21	57.943	68.899	89.500
$3 \times 6 \times 5 \times 3$	25	68.766	75.809	97.566
$4 \times 5 \times 4 \times 2$	31	78.944	84.544	112.433
$6 \times 4 \times 7 \times 10$	36	89.405	92.322	134.203
$6 \times 5 \times 7 \times 11$	-	115.405	145.455	187.399
$7 \times 8 \times 10 \times 9$	-	138.899	178.677	233.390
$7 \times 9 \times 13 \times 8$	-	147.402	196.899	278.277
$9 \times 11 \times 8 \times 7$	-	189.388	245.567	335.466
$10 \times 11 \times 9 \times 15$	-	235.506	305.677	412.677

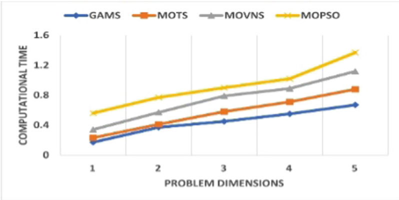
Table 8. Computational time for small and large size problems

Problem dimension	GAMS	MOTS	MOVNS	MOPSO
$2 \times 2 \times 4 \times 5$	0.17	0.23	0.34	0.56
$2 \times 3 \times 2 \times 4$	0.37	0.41	0.57	0.77
$3 \times 6 \times 5 \times 3$	0.45	0.58	0.79	0.9
$4 \times 5 \times 4 \times 2$	0.55	0.71	0.89	1.02
$6 \times 4 \times 7 \times 10$	0.67	0.88	1.12	1.37
$6 \times 5 \times 7 \times 11$	-	1.04	1.35	1.78
$7 \times 8 \times 10 \times 9$	-	1.58	1.89	2.32
$7 \times 9 \times 13 \times 8$	-	1.87	2.56	3.23
$9 \times 11 \times 8 \times 7$	-	2.02	2.91	3.56
$10 \times 11 \times 9 \times 15$	-	2.67	3.67	4.04

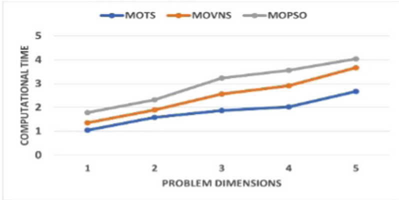


a. Small Size Problem. b. Large Size Problem.

Fig. 2. Performance of MOVNS, MOTS and MOPSO.



a. Small Size Problem.



b. Large Size Problem.

Fig. 3. Computational times of MOTS, MOVNS and MOPSO.

5 Conclusion

In this paper, a three-echelon location-allocation model in forward and reverse supply chains is introduced with the aim of minimizing whole costs at different levels of the chain. Due to the decision making of this tri-level modelling, it is capable of handling transportation delay so that supply chain members should not be affected with extra cost. The model is solved in different sizes. The results show that the problem solved in small size with GAMS using branch and limit method can have necessary responsiveness, but in large size, due to the inherent complexity of the model, it fails to achieve a result. Also, with increasing problem sizes, the problem transforms into an NP-hard problem. To achieve the solution in polynomial time, this work has utilized MOTS, MOVNS and MOPSO. This concludes that the MOTS performs wells to attain results in lesser computational time. Suggestion for future work includes the development of some hybrid algorithms to achieve more effective results, and the model can be extended for multi-objective perspective.

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