วารสารวิศวกรรมศาสตร์และนวัตกรรม
Journal of Engineering and Innovation

บทความวิจัย

Multi-commodity supply chain network design problem considering production cost and inventory holding cost

Sreyneath Chhun[1] Saowanit Lekhavat[2]*

[1] Faculty of Logistics, Burapha University Chon Buri 20131

[2] Faculty of Logistics, Burapha University Chon Buri 20131

* Corresponding author.

E-mail: saowanit.le@go.buu.ac.th; Telephone: 0 6482 10190

Received 21 October 2020; Revised #1 7 January 2021; Revised #2 17 March 2021; Accepted 20 April 2021

Abstract

This study works on an extension of mathematical optimization model by adding more cost components which are production cost at plant and holding cost at supplier and distribution center for the purpose of evaluating the final result and the impact of said costs. To achieve this, one potential existing model of cost minimization is chosen alongside metaheuristics algorithm named Particle Swarm Optimization with multiple social learning terms (GLNPSO) which are then applied to solve the problem. The experiments are conducted based on the data set and test problems from the benchmarks. Then the comparison of optimization models, before and after inclusion of two cost elements, is determined. This comparison stage attempts to illustrate the increasing amount of total cost/solution quality before and after cost inclusion, additionally to observe the coefficient of variation (CV) and average computational time from five replications of each test case problem. Following the benchmarks, the second comparison stage is essentially implemented by re-comparing the two variants of allocation scheme sharing the same proposed Multi-Commodity Supply Chain Network Design (MCSCND) mathematical model. The re-comparison would show whether decision making result remains the same or different from benchmark. Finally, the impact of two cost components is identified and significant to include in mathematical formulation model of location-allocation problem of MCSCND.

Keywords

location-allocation problem; multicommodity network design problem; particle swarm optimization (PSO); metaheuristics algorithm.

1. Introduction

In supply chain network design problem, there is still no standardized solution for similar problem even though many works in literature have studied various intricacies of the issue [1]. Some works expanded upon the network map and they considered optimization objective, for example, based on predetermined model and purpose of the research [2]. Furthermore, most papers have obsessively attempted to make the issue broad and complex by overlooking minor essential elements like cost which might have a huge impact on strategic decision making and management. Panfilova, Dzenzeliuk [1] explains logistic cost management from the perspective of accounting perspective that all costs are listed precisely in accounting system in purpose of evaluating financial performance.

Meanwhile, logistic and supply chain optimization selected a few cost components for measuring and representing the whole costs, and kept other costs behind [3]. Consequently, partial cost consideration for network optimization is unworthy when those costs do not reflect all supply chain costs and real-world practice, resulting in inefficient decision making and an incomplete reliable result.

This paper attempts to verify the overlooked cost components especially in the field of network design problem. This paper arrives at a proposition as following: What if we include these costs in existing model, would both essential costs affect the result that has already been done before? To seek for answer, a benchmark [4] is adapted to add additional costs into the model because of the availability of source. Benchmarking an optimized total supply chain costs which are based only on costs of establishing facilities and transporting raw materials and commodities. This study adds more variable cost components such as production and holding costs into the benchmark model. By conducting experiments and comparison between proposed model and benchmark, we will be able to observe whether the decision result is changed or not.

The second section presents relevant works of MCSCND in literature. After that, section 3 introduces the problem statement carried out in this work. Next, section 4 presents the extended model. Section 5 describes about solution method. Section 6 shows the result of conducting experiments and result comparison. Finally, the conclusion and future research suggestions are presented in section 7.

2. Literature Review

Cost plays an important role as a source of information to measure between planning, and practical and hidden costs. Optimization leads to more balanced net income/profit [5, 6]. There are various means to categorize costs; yet the most vital information is that those categorized costs are precisely intertwined with costs in accounting system— resulting in a supply chain that is both reliable and accountable in terms of both planning and actual costs [7]. Concurrently, Pettersson and Segerstedt [7] suggested to categorize supply chain costs, and the reason of cost classification is to easily identify the origins of the costs that are occurred in order to obtain the adequate information that leads to the right decisions.

Likewise, network design problem is one of the critical decisions since the inception of supply chain management. Cost is the undeniable element that must be initially considered in terms of an economically-viable and sustainable supply chain network design, even if the objective function of the problem would be focused on, for example, maximizing profit, net income or net present value (NVP) [8, 9]. Moreover, costs of establishing facilities, and transporting product are taken into account whenever we configure facility location and allocate products. As seen in Table 1, most of works involve both two costs in their model and any other cost are considered according to predefined scenario of the problem. Otherwise, works that take only two mentioned costs are not enough for representing all total relevant costs, for example, work of [10, 4, 11]. Therefore, total relevant costs in this work are classified into four main activities-based costs that generally occurs at most supply chain networks. Cost components are divided into: establishment cost corresponding to initial opening costs related to physical infrastructure, transportation cost corresponding to cost of distributing materials or commodities in network. Finally, production cost sums up all costs relating to manufacturing those commodities, while holding cost represents commodity storing expenses. As a consequence, very few researches in literature have studied and observed the impact of costs on strategic decision making. On the other hand, many problems and experiments are utilized using commercial optimizers, CPLEX, LINGO, and GAMS, to conducting experiments. Those solvers are not capable to solve hard NP problem [4, 12-14]. The hard NP problem can be solved by implementing evolutionary algorithm and metaheuristic approach like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Cutting Plane algorithm.

Therefore, this work attempts to propose a mathematical optimization model by adding further costs in Lekhavat [4]'s model, then conducting experiments to compare the optimal solution of both models, and observing cost impact on solution and decision making in multi-commodity distribution network problem. To seek the optimal solution, one of evolutionary metaheuristic algorithm is implemented to handle the problem.

3. Problem Description

This study focuses on designing supply chain network problem. The network acquires a set of suppliers, plants, and DC that can satisfy demands of customers. Commodities are classified into groups of product types at DCs and manufactured at plants. Raw materials called bill of materials (BoM) are calculated according to the list of material consumption rate and are supplied from supply facility.

In this context, the facilities are multi-capacity levels for accepting products or materials from each other. In the process of designing network as can be seen the network structure in Figure 1, sets of facility candidates are potentially selected for facility configuration process under a condition of limited established number.

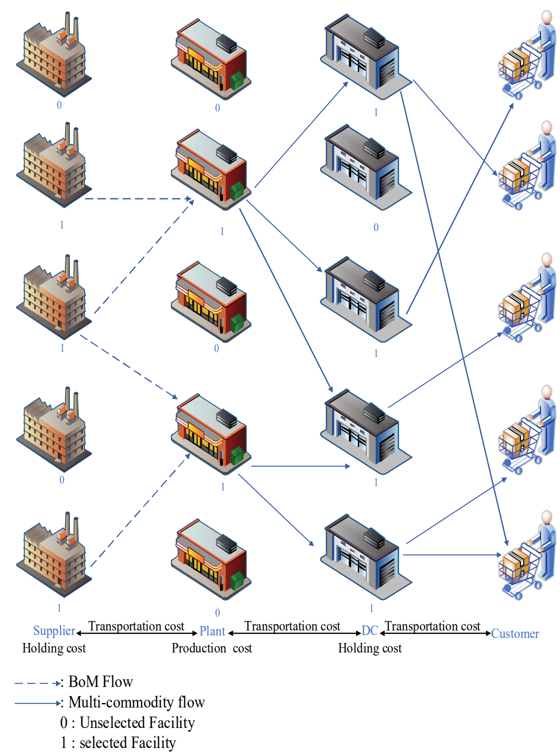

Figure 1 Multi- commodity supply chain network structure

On the other hand, allocation process between those facility types is considered to be multi-sourcing which means more than one facility is able to send products/materials to one another. For instance, two different DCs can supply commodities to customers; however, those facility would not be allowed to transfer commodities to the same facility types as supplier to supplier for example. The strategic plan horizon is considered as a single period of time.

Table 1 Comparison of current study with the literatures

N°	Author	Problem	Model	Solution Method	Objective Function	Cost Consideration
1	[15]	Location and allocation	MIP Model	CPLEX solver	Max. profit	Production, transportation, inventory, capacity reconfiguration and shortage costs
2	[10]	Location	MIP Model	LINGO solver	Min. cost and Max. service	Establishment and transportation costs
3	[16]	Allocation	MIP Model	Hierarchical approach; CPLEX solver	Min. cost	Fixed and overhead costs (vehicle)
4	[4]	Location and allocation	MIP Model	Allocation schemes; GLNPSO	Min. cost	Facility opening and transportation costs
5	[17]	Location and allocation	MIP Model	Lagrangian heuristic; LINGO solver	Min. cost	Transportation, lead-time, holding, facility opening and operating costs
6	[18]	Allocation	MIP Model	GAMS solver	Max. profit	Purchasing, disassembly, recycling, disposing, and manufacturer costs
7	[19]	Facility, capacity, and allocation	MIP	CPLEX solver	Min. cost	Investment, operation costs
8	[20]	Location inventory	Non-Linear MIP	Cutting Plane algorithm; CPLEX solver	Min. cost	Location, transportation, and inventory costs
9	[12]	Location and allocation	MIP	GA algorithm	Min. cost	Warehouse location cost, inventory, safety stock, order cost, and transportation costs
10	[21]	Location, Capacity, and allocation	MIP	Gurobi solver	Min. cost	Opening, and closing, equipment and labor, processing and storing, procurement, transportation, and disposal costs
11	[22]	Capacity, budget, and resources	MCMP	AMPL; CPLEX solver	Min. unsatisfied Demand and cost, and Max. fairness	Cost of restoring nodes, restoring arcs, and transportation
12	[23]	Location and allocation	MIP	OPL; CPLEX solver	Min. cost	Annual cost, processing cost, production, and transportation cost

Table 1 (Continued)

N°	Author	Problem	Model	Solution Method	Objective Function	Cost Consideration
13	[24]	Transportation mode selection	MIP	CPLEX solver	Min. cost, and CO_2	Costs of ordering, set up, production, transportation, and storage
14	[25]	Package best selection, storage and allocation	MIP	AMPL; Gurobi solver	Min. cost, and env. Impact	DC and pooler opening, shipping, purchasing, storage, recycling and reusable packaging costs
15	[11]	Location and allocation	MIP	CPLEX solver	Min. cost and GHG	Establishment and transportation costs
16	[13]	Inventory and location	Non-LP MIP	GA algorithm; Matlab	Min. cost	Opening, inventory and transportation costs
17	[26]	Multi-modal transportation	Non-LP; pricewise LP	SEPROG (CPLEX solver; C++)	Max. transportation flow	x
18	[14]	Multipath routing	LP	MOGA	Max. flow proportion with min. delay, and Min. flow-split number	x
19	[27]	Manufacturing scheduling	MIP	AHP and Non-preemptive approach; AMPL; CPLEX solver	Min. cost, lateness; number of commodities, and Max. minimum of the load balance	Transportation, and production, holding, and raw material and product costs
20	[28]	Facility location	MIP	AMPL with Baron solver	Min. total cost	Transportation cost, costs of operation and incinerators, and the penalty cost
This study		**Location and allocation**	**MIP**	**Allocation methods and GLNPSO**	**Min. cost**	**Facility establishment, transportation, holding and production costs**

MCMP: Multiple Criteria Programming Models; MIP: Mixed Integer Programming; SEPROG: Separable Programming; MOGA: Multi-Objective Genetic Algorithm; LP: Linear Programming; AMPL: A Mathematical Programming Language; GLNPSO: Particle Swarm Optimization with multiple social learning term; AHP: Analytic Hierarchy Process

4. Methodology

4.1 Mathematical model Notation

h = Candidate supplier; $h=1,2,3,\ldots,H$

i = Candidate plant; $i=1,2,3,\ldots,I$

j = Candidate DC; $j=1,2,3,\ldots,J$

k = Customer; $k=1,2,3,\ldots,K$

l = Product type; $l=1,2,3,\ldots,L$

m = Material; $m=1,2,3,\ldots,M$

λ = Cap. level of supplier ; $\lambda=1,2,3,\ldots,D$

δ = Cap. level of plan; $\delta=1,2,3,\ldots,E$

ϕ = Cap. level of DC; $\phi=1,2,3,\ldots,F$

g = Product's group; $g=1,2,3,\ldots,G$

Parameters

σ_{hm}^{λ}= Cap. of supplier h with cap. level λ for material m (unit of each material)

η_{il}^{δ}= Cap. of plant i with cap. level δ for product l (unit of each product)

ρ_{jg}^{ϕ}= Cap. of DC j with cap level ϕ for product's group g (unit volume)

v_m= Unit volume of material m

μ_{ml}= Consumption rate of material m per unit of product l

v_l= Unit volume of product l

u_{gl}= Indicator of group and product l

q_{kl}= Demand of customer k for product l (unit of each product)

φ_{h}^{λ}= Cost of establishing supplier h with cap. level λ

ψ_{i}^{δ}= Cost of establishing plant i with cap. level ϕ

ω_{j}^{ϕ}= Cost of establishing DC j with cap. level ϕ

c_m= Transportation cost of material m/ unit volume of material/distance

c_l= Transportation cost of product l /unit volume of product/distance

τ_{h}^{m}= Holding cost of material m / unit volume of material m at supplier h

Δ_{i}^{l}= Production cost of product l /unit volume of product l at plant i

τ_{j}^{l}= Holding cost of product l / unit volume of product l at DC j

n_{hi}= Distance from supplier h to plant i

o_{ij}= Distance from plant i to DC j

p_{jk}= Distance from DC j to customer k

α= Limited established suppliers

β= Limited established plants

γ= Limited established DCs

ξ= Distance limitation from DC to customer

Decision Variables

W_{il}= Quantity of product l made at plant i

X_{him}= Quantity of material m transported from supplier h to plant i

Y_{ijl}= Quantity of product l delivered from plant i to DC j

Z_{jkl}= Quantity of product l sent from DC j to customer k

$$S_h^{\lambda}=\begin{cases}1, \text{ Supplier } h \text{ with Cap. } \lambda \text{ is operated}\\ 0, \text{ Otherwise}\end{cases}$$

$$R_i^{\delta}=\begin{cases}1, \text{ Plant } i \text{ with Cap. } \delta \text{ is operated}\\ 0, \text{ Otherwise}\end{cases}$$

$$T_j^{\phi}=\begin{cases}1, \text{ DC j with Cap. } \phi \text{ is operated}\\ 0, \text{ Otherwise}\end{cases}$$

Economic objective function

Minimize Total Costs:

$$\begin{aligned}&= \sum_h\sum_\lambda \varphi_h^\lambda S_h^\lambda + \sum_i\sum_\delta \psi_i^\delta R_i^\delta + \sum_j\sum_\phi \omega_j^\phi T_j^\phi \\ &+ \sum_m\sum_i\sum_h c_m v_m n_{hi} X_{him} \\ &+ \sum_i\sum_j\sum_l c_l v_l o_{ij} Y_{ijl} \\ &+ \sum_j\sum_k\sum_l c_l v_l p_{jk} Z_{jkl} \\ &+ \sum_i\sum_l \Delta_i^l v_l Z_{jkl} + \sum_h\sum_m \tau_h^m v_m X_{him} \\ &+ \sum_j\sum_l \tau_j^l v_l Y_{ijl}\end{aligned} \tag{1}$$

Subject to:

$$\sum_j Z_{jkl} \geq q_{kl} \qquad \forall k, l \tag{2}$$

$$\sum_k\sum_l v_l u_{gl} Z_{jkl} \leq \sum_j \rho_{jg}^\phi T_j^\phi \qquad \forall j, g \tag{3}$$

$$\sum_\phi T_j^\phi \leq 1 \qquad \forall j \tag{4}$$

$$\sum_j\sum_\phi T_j^\phi \leq \gamma \tag{5}$$

$$p_{jk} T_J^\phi \leq \varepsilon \qquad \forall j,k,\phi \tag{6}$$

$$\sum_j Y_{ijl} \leq \sum_\delta \eta_{il}^\delta R_i^\delta \qquad \forall i, l \tag{7}$$

$$\sum_i Y_{ijl} \geq \sum_k Z_{jkl} \qquad \forall j, l \tag{8}$$

$$\sum_\delta R_i^\delta \leq 1 \qquad \forall i \tag{9}$$

$$\sum_{i}\sum_{\delta} R_i^{\delta} \le \beta \qquad (10)$$

$$\sum_{i} X_{him} \le \sum_{\lambda} \sigma_{hm}^{\lambda} S_h^{\lambda} \qquad \forall h,m \qquad (11)$$

$$\sum_{l} \mu_{ml} W_{il} \le \sum_{h} X_{him} \qquad \forall i,m \qquad (15)$$

$$\sum_{h} X_{him} \ge \sum_{j} Y_{ijl} \qquad \forall j,m,l \qquad (13)$$

$$\sum_{\lambda} S_h^{\lambda} \le 1 \qquad \forall h \qquad (14)$$

$$\sum_{h}\sum_{\lambda} S_h^{\lambda} \le \alpha \qquad (15)$$

$$X_{him},, Y_{ijl}, Z_{jkl} \ge 0 \qquad \forall h,i,j,k,l,m \qquad (16)$$

$$S_h^{\lambda}\ R_i^{\delta}\ T_j^{\phi} = Binary \qquad \forall h,i,j,\lambda,\delta,\phi \qquad (17)$$

The economic objective function (1) minimizes the sum of the facility establishment costs (suppliers, plants and DCs), the costs of transporting BoM from the suppliers to the plants and the costs of transporting commodities from the plants to the DCs and from the DCs to the customers, the inventory holding costs at the supplier and DC facilities, and the costs of plant production. Constraint (2) indicates the quantity of products distributed from DCs to customers meets demands. Constraint (3) ensures that total amount of products sent from DCs to customer are equal or less than capacity level of established DCs. Constraint (4) allows established DCs can be selected one capacity level from different sizes of capacity level. constraint (5) ensures that number of established DCs is not exceed the limited DCs that are allowed to establish. Constraint (6) makes sure that distance or time of distributing products from DCs to customers is accepted by customers. Constraint (7) represents that established plants with a capacity level that must produce enough quantity of products for sending to DCs. Constraint (8) balances amount of product that got sent from plants to DCs and total product distributed from DCs to customers. Constraints (9) allows established plants that can be selected one level from different sizes of capacity level. Constraint (10) ensures that number of established plants is not exceed the limited plants that are allowed to establish. Constraint (11) indicates that established suppliers have enough capacity to transport raw materials to plants. Constraint (12) defines that quantity of raw materials has are enough to support production capacity of established plants. Constraint (13) balances amounts of raw materials transported from suppliers to plants whether it is equal or greater than number of products distributed from plants to DCs. Constraint (14) allows established suppliers to select one capacity level from different sizes of capacity level. Constraint (15) ensures that number of established suppliers is not exceed the limited suppliers that are allowed. Constraints (16) define the quantity of products distributed from suppliers, plants, DCs are non-negativity. Constraints (17) indicate that suppliers, plants, and DCs are binary decision variables.

4.2 GLPSO algorithm

GLPSO algorithm is one of extended variants of Particle Swarm Optimization (PSO). As known, PSO is a search approach that emulates the movement behavior of bird swarm that attempts to seek for food [29]. All particles as birds in the swarm are moved based on its own learning (cognitive term or personal best particle) and global experience (social term, referred to global best particle in the swarm) during the movement. GLNPSO is introduced by [30] with intention of opening multi-reference search space for particle swarm by expanding social learning structures, which are local best and near-neighbor best as additional social learning terms. Therefore, particles in the swarm of GLNPSO algorithm use its own current velocity with personal experience (pbest), and its global best (gbest), local best (lbest) and near-neighbor best particle (nbest) to move and update its velocity and position for the next iteration.

The algorithm is correspondingly modified to complement the present location- allocation strategic approaches of MCSCND problem. Getting started with initialization phase, all relevant and required model inputs, objective function, constraints and algorithmic control parameters are input to the algorithm. Every iteration, particles make out the several potential solutions and are evaluated. Then, particles move to the new positions by updating its velocity and position. The algorithm will be terminated when it meets the stopping criterion. The implementation of GLNPSO algorithm is shown in Figure 2.

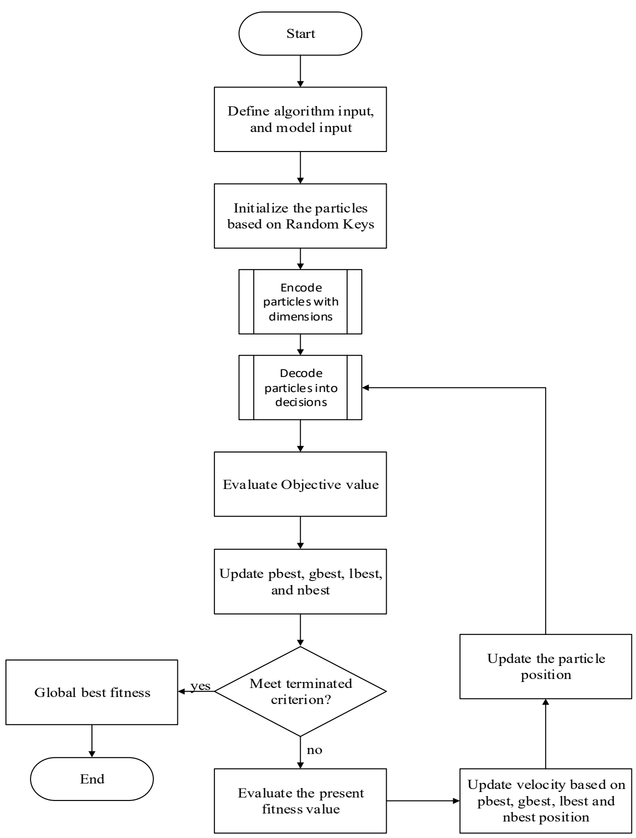

Figure 2 Flowchart of GLPSO algorithm

4.3 Location and allocation approach

The strategic approach is implemented in this study and readers are also suggested to refer work of Lekhavat [4] for exhaustive information of the approaches.

Location configuration

First of all, priority of customer sequence is arranged based on total amount of individual customer demand. Then, the choice for facilities is proceeded by random selection with the respect to limitation number.

Allocation approach

1) Highest-total-demand customer with nearest DC

Allocating commodity is proceeded by selected nearest DC to response customers' demands. Then, the plant or supplier is selected based on a list to allocate commodities/raw materials without considering distance/time of transporting.

2) Nearest all types of facilities

Allocation process works by evaluating distance/time of transporting either commodities or raw materials from one facility type to another. Then, nearest facilities such as nearest DC, plant, and supplier are prioritized to establish and receive allocated demands.

4.4 Explicit enumeration

The study conducts the experiments on test problems as can be seen in Table 2. GLNPSO algorithm as solution method is implemented for providing optimal solution and GLNPSO parameters consists of inertia weight, acceleration constant, number of particles, number of iterations. The GLNPSO parameters and the two allocation methods are utilized by adapting from [4]. All test problems are conducted experiments on MCSCND problem where each case runs five replications in order to obtain a better estimation of experimental error. The one that provides lowest total cost is the best solution quality. Those seven test problems are conducted for these experiments using two different allocation methods. The experiments were tested on a PC running Intel® core™ i5-5300U 2.30GHz, 12 GB RAM, and Microsoft Windows 10 Pro.

Table 2 Test problems from [4]

Test problem		# Cust	# DC	# Plant	# Sup.	Lim DC	Lim Plant	Lim Sup.	RM	Pro.	# Group	Dist. Limit	Cap Lev
Small Cases	Bgsr0	25	10	5	4	5	3	2	3	3	2	1	1
	Dgsr0	50	20	5	4	10	3	2	3	3	2	1	1
Medium Cases	Ggsr0	100	30	10	5	15	5	3	5	5	2	1	5
	Igsr0	100	50	10	5	25	5	3	10	10	2	1	5
Large Cases	Kgsr0	200	50	20	10	25	10	5	15	15	3	1	5
	Ogsr0	400	100	30	15	50	15	8	15	15	3	1	5
	Qgsr0	500	100	30	15	50	15	8	20	20	3	1	5

"#" referred to "number"; Lim.: Limited number; RM: Raw Materials; Dist. Limit: Distance limitation; Cap Lev: Capacity level

5. Result and comparison

5.1 Experimental result

As shown in Table 3, coefficient of variation result of MCSCND model shows the extent of variability of solution qualities is in smaller percentage. This is a proof that the MCDND model is more reliable and accountable than benchmark. Meanwhile, there is no significant difference in computational time between both models.

5.2 Comparison of optimal solution of MCSCND and Benchmark

The MCSCND and benchmark models are applied to two different allocation approaches. The comparison of both approaches is made by evaluating the decision making of which approach is better than another in term of amount of total cost where values highlighted in bold font are the favorable choices as seen in Table 4 and 5.

Table 3 Results of MCSCND and benchmark

Case	"Highest-total-demand customer to nearest DC" allocation method				"Nearest all types of facilities" allocation method			
	Benchmark		MCSCND		Benchmark		MCSCND	
	%CV	Average Time (seconds)	%CV	Average Time (seconds)	%CV	Average Time (seconds)	%CV	Average Time (seconds)
Bgsr0	3.86	7.77	0.04	11.95	2.38	7.26	0.93	9.35
Dgsr0	1.46	12.81	0.34	19.88	9.82	13.62	1.52	16.44
Ggsr0	3.78	794.77	0.09	982.90	3.89	1,148.89	2.59	886.81
Igsr0	1.93	2,188.84	0.2	2,656.98	15.63	3,081.77	1.51	2,605.93
Kgsr0	1.45	6,907.78	0.16	5,448.33	17.61	4,695.80	11.69	6,901.56
Ogsr0	14.22	55,860.10	2.65	62,752.69	6.05	64,570.63	2.82	53,569.79
Qgsr0	30.6	63,272.23	0.5	83,264.81	12.32	71,531.51	2.13	70,914.55

%CV: percentage of coefficient of variation

Table 4 Benchmarking solution result of all cases (Cost x10^2)

Benchmark								
Cases	Highest-total-demand customer to nearest DC				Nearest all types of facilities			
	Total Cost	Esta. Cost	Tran. Cost	opened Facilities	Total cost	Esta. Cost	Tran. Cost	opened Facilities
Bgsr0	101.11	47.16	53.94	1s 1p 5DC	101.11	47.16	53.94	1s 1p 5DC
Dgsr0	499.91	87.02	412.89	1s 2p 10DC	404.40	90.86	313.54	2s 2p 10DC
Ggsr0	1,233.94	108.69	1,125.25	1s 2p 15DC	1,357.20	103.51	1,253.69	1s 2p 15DC
Igsr0	1,507.82	184.22	1,323.60	1s 1p 27DC	2,601.02	220.92	2,380.10	3s 4p 27DC
Kgsr0	2,102.87	157.09	1,945.78	1s 1p 25DC	3,814.39	223.99	3,590.40	4s 8p 25DC
Ogsr0	11,901.22	359.34	11,541.88	1s 7p 50DC	4,404.48	435.60	3,968.88	8s 13p 50DC
Qgsr0	10,533.36	366.23	10,167.13	1s 3p 51DC	7,130.93	435.94	6,694.99	6s 10p 50DC

Esta. cost: Establishment cost; Tran. cost: Transportation cost; Pro. cost: Production cost; Hol. cost: Holding cost

Table 5 MCSCND's solution result of all cases (Cost x10^2)

Proposed MCSCND model						
Highest-total-demand customer with nearest DCs						
Cases	Total Cost	Esta. Cost	Tran. Cost	Pro. Cost	Hol. Cost	opened Facilities
Bgsr0	297.06	46.77	60.97	2.69	186.63	1s 1p 5DC
Dgsr0	2,343.84	85.36	420.51	8.71	1,829.26	1s 2p 10DC
Ggsr0	6,666.18	107.34	1,141.45	16.82	5,400.57	1s 2p 15DC
Igsr0	20,730.04	184.53	1,330.23	32.60	19,182.67	1s 1p 27DC
Kgsr0	55,453.38	155.77	1,973.45	70.80	53,253.36	1s 1p 25DC
Ogsr0	93,405.90	368.08	12,414.27	242.95	80,380.59	1s 7p 50DC
Qgsr0	241,351.90	356.15	14,677.73	285.74	226,032.28	1s 3p 50DC
Nearest all types of facilities						
Cases	Total Cost	Esta. Cost	Tran. Cost	Pro. Cost	Hol. Cost	opened Facilities
Bgsr0	297.06	46.77	60.97	2.69	186.63	1s 1p 5DC
Dgsr0	2,146.90	91.33	250.95	8.71	1,795.92	2s 2p 10DC
Ggsr0	6,896.30	103.59	2,149.33	16.82	4,626.56	1s 2p 15DC
Igsr0	21,875.41	203.99	4,170.10	32.60	17,468.73	2s 2p 27DC
Kgsr0	51,353.96	208.27	6,891.33	70.80	44,183.55	4s 6p 25DC
Ogsr0	93,341.82	419.90	7,799.36	242.95	84,879.62	8s 12p 50DC
Qgsr0	253,410.18	470.37	18,555.74	285.74	234,098.33	5s 11p 50DC

Esta. cost: Establishment cost; Tran. cost: Transportation cost; Pro. cost: Production cost; Hol. cost: Holding cost

In small cases, there is no significant changes in decision-making choices. Meanwhile, one of three medium cases, Kgsr0, provides different outcome. The benchmarking solution, total cost, of "Highest-total-demand customer to nearest DC" approach is lower than the other because there are fewer numbers of facilities are established. Therefore, this approach is the better one. Meanwhile, MCSCND's optimal solution that applies to "Nearest all types of facilities" method establishes many facilities, yet provided solution, total cost, is lower than the other. This proves that lowering holding cost does significantly lower the total costs as well. In large cases, both optimal solutions of Ogsr0 case from benchmark and MCSCND models remain the same, suggesting that "Nearest all types of facilities" is the better choice. The comparison of Qgsr0 case shows that total cost of benchmark with "Nearest all types of facilities" approach is lower. The Impact of transportation cost is huge enough that could descend quantity of total cost better than another. In contrast, total cost of MCSCND model is minimized better by using "Highest-total-demand customer with nearest DC" approach because smaller numbers of facilities are selected and all cost elements are minimized leading to lower total cost. Therefore, both decisions, from benchmark and MCSCND implementation in Qgsr0 case, give different choices.

According to result of both size cases, medium and large, the consideration of more additional costs, inventory holding cost and production cost in benchmark optimization model could possibly change the decision making of selecting an appropriate and effective approach based on costs for the problem.

5.3 Example of Practical Implication of MCSCND

The applications of both mathematical models are presented and implemented to solve the sample practical case here. In order to apply the models, a given case is introduced where the network is kind of multi-sourcing and it comprises of 2 customers with demands of 3 commodities. The network has 3 DCs, 3 plants, and 3 suppliers as choices to establish with some limitations that only 2 of each facility types allowed to open and distance between facilities cannot be exceeded 1 kilometer. At individual DC, commodities are categorized into the defined two groups where first two families of products are stored together and another is in second group with certain capacity level. At plant, all commodities are manufactured from BoM list which has 3 types of raw materials. The required quantities of raw materials are acknowledged by supplier facility that is responsible for sending the raw materials to plant. All essential input data are assumedly available for both modelsThe algorithm with determined location and allocation approach is implemented to initially configure the number and identity of needed facilities. Then, the quantity of allocated commodities at each selected facility types are identified. After that, amount of total cost is computed by defined model, MCSCND model. The sum of total cost based on MCSCND model are included in the costs of facility establishment, transportation costs between facilities, production and holding cost. Finally, the optimal/near optimal solution is provided by the algorithm as seen in the solution illustration presented. Location and quantities of all cost elements are shown in Table 6. Allocation result is illustrated and shown in Table 7. In column 1 and row number 3, with the value of Order set to 2, we customer id 0 allocates commodity id 2 to DC id 2, that has capacity id 0. The allocated demand is 91.2 units which required 16.42 unit volumes of DC capacity in total. As a result, the DC has enough capacity for receiving that amount, while the expense on holding cost is about 262.66. Transporting between said customer and DC within the distance 0.08km, costs 31.19. The rest of the allocation process, even from DCs to plants and from plants to suppliers have the same format as shown in Table 7.

Table 6 Practical Implication of MCSCND problem

Facility location and identity						
Facility	Supplier		Plant		DC	
(ID, Capacity)	(0,0)	(2,0)	(0,0)	(2,0)	(0,0)	(2,0)
Total amount of allocated demands						
Units of commodities	107.2, 109.5, 85.4	71.1, 25.3, 47.2	97.2, 99.5, 125.4	81.1, 35.3, 7.2	64.725, 64.9, 0	113.575, 69.9, 132.6
Total cost						
MCSCND model	**Total cost**	Esta. cost	Tran. cost	Pro. cost	Hol. cost	
	47,22.5	977.46	1,604.2	60.934	2,079.9	

Esta. cost: Establishment cost; Tran. cost: Transportation cost; Pro. cost: Production cost; Hol. cost: Holding cost

Table 7 Allocating customer demand to DCs

Allocation from Customers to DCs													
Order	Cust. ID	DC ID	Cap. Lev.	Group	Product	Allocated demand	Dist.	Tran. Cost	Hol. Cost	Demand	Enough?	Remained Demand	Used Cap.
0	0	2	0	0	0	104.3	0.08	39.63	312.9	104.3	E	0	20.86
1	0	2	0	0	1	69.9	0.08	19.92	136.31	69.9	E	0	10.49
2	0	2	0	1	2	91.2	0.08	31.19	262.66	91.2	E	0	16.42
3	1	2	0	0	0	9.28	0.06	2.74	27.83	74	Not	64.73	1.86
4	1	0	0	0	0	64.73	0.47	151.13	168.29	64.73	E	0	12.95
5	1	0	0	0	1	64.9	0.47	113.66	126.56	64.9	E	0	9.74
6	1	2	0	1	2	41.4	0.06	10.99	119.23	41.4	E	0	7.45

Cust. ID: customer ID; Cap. Lev.: Capacity Level; Dist.: Distance; Tran. cost: Transportation cost; Hol. cost: Holding cost; Used Cap.: Used Capacity; E: Enough.

6. Conclusion

MCSCND problem is to configure facility location and determine the quantity of commodities at each selected facility type and the model that enables us to cover total cost of the entire network in this study. Cost elements of MCSCND model are intentionally represented to cover all logistic and supply chain costs that occurred in current network. Facility establishment, transportation, production, and holding costs are categorized and formulated to compute total relevant cost.

The implementation of proposed model provides a more efficient and reliable result of decision making in term of lower variability of optimal solution, compared to classical model. Furthermore, the adopted allocation strategic approach confirms that the optimal solution of MCSCND model with adequate cost inclusion could lead to better outcomes. The summary of MCSCND application is essentially advantageous for analyzing the different scenarios, as well as supporting major decision makings.

For future researches, this study can help identify multi- objective functions centering around environmental impact and social sustainability. On the other hand, the relaxation of the model constrains will be another suggestion for the subsequent studies.

References

[1] Panfilova E, Dzenzeliuk N, Domnina O, Morgunova N, Zatsarinnaya E. The impact of cost allocation on key decisions of supply chain participants. *International Journal of Supply Chain Management*. 2020;9(1):552-8.

[2] Sreyneath C, Lekhavat S. Systematic literature review for location-allocation problem under economic and environmental sustainability. *Kasem Bundit Engineering Journal*. 2019;9(3):253-74.

[3] Shen ZJ. A multi-commodity supply chain design problem. *Lie Transactions*. 2005;37(8):753-62.

[4] Lekhavat S. *Allocation Methods for a Multicommodity Distribution Network Design Problem* [Doctoral dissertation]. Asian Institute of Technology; 2013.

[5] Schary PB, Skjøtt-Larsen T. *Managing the global supply chain.* Handelshøjskolens forlag; 2001.

[6] Kumar S, Chang CW. Reverse auctions: how much total supply chain cost savings are there?— A conceptual overview. *Journal of Revenue and Pricing Management*. 2007;6(2):77-85.

[7] Pettersson AI, Segerstedt A. Measuring supply chain cost. *International Journal of Production Economics*. 2013;143(2):357-63.

[8] Balaman ŞY, Matopoulos A, Wright DG, Scott J. Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy ε-constraint method. *Journal of Cleaner Production*. 2018;20(172):2594-2617.

[9] Ruiz-Femenia R, Guillén-Gosálbez G, Jiménez L, Caballero JA. Multi-objective optimization of environmentally conscious chemical supply chains under demand uncertainty. *Chemical Engineering Science*. 2013;24(95):1-1.

[10] Afshari H, Amin-Nayeri M, Jaafari AA. A multi-objective approach for multi - commodity location within distribution network design problem. *World Congress on Engineering 2012.* International Association of Engineers. July 4-6, 2012. London, UK. 2182:1526-1530.

[11] Ratnayake MN, Kachitvichyanukul V, Luong HT. A Multi-objective model for location-allocation problem with environmental considerations. In: Liu X, editor. *Environmental Sustainability in Asian Logistics and Supply Chains.* Springer. 2019. pp. 205-217.

[12] Askin RG, Baffo I, Xia M. Multi-commodity warehouse location and distribution planning with inventory consideration. *International Journal of Production Research*. 2014; 52(7):1897-1910.

[13] Orozco-Fontalvo M, Cantillo V, Miranda PA. A stochastic, multi - commodity multi-period inventory-location problem: Modeling and solving an industrial application. *Proceeding of International Conference on Computational Logistics*. Springer. Sep. 30 2019. p. 317-331.

[14] Farrugia N, Briffa JA, Buttigieg V. Solving the multi-commodity flow problem using a multi-objective genetic algorithm. *Proceeding of 2019 IEEE Congress on Evolutionary Computation (CEC).* 2019 Jun 10. p. 2816-2823.

[15] Behmardi B, Lee S. Dynamic multi-commodity capacitated facility location problem in supply chain. *Proceedings of the 2008 Industrial Engineering Research Conference.* Institute of

Industrial and Systems Engineers (IISE). p. 1914-1919.

[16] Koca E, Yıldırım EA. A hierarchical solution approach for a multicommodity distribution problem under a special cost structure. *Computers & Operations Research*. 2012;39(11):2612-24.

[17] Sadjady H, Davoudpour H. Two-echelon, multi-commodity supply chain network design with mode selection, lead-times and inventory costs. *Computers & Operations Research*. 2012;39(7):1345-54.

[18] Amin SH, Zhang G. A proposed mathematical model for closed-loop network configuration based on product life cycle. *The International Journal of Advanced Manufacturing Technology*. 2012;58(5-8):791-801.

[19] De Rosa V, Gebhard M, Hartmann E, Wollenweber J. Robust sustainable bi-directional logistics network design under uncertainty. *International Journal of Production Economics*. 2013;145(1):184-98.

[20] Wu T, Zhang K. A computational study for common network design in multi-commodity supply chains. *Computers & Operations Research*. 2014;44:206-13.

[21] Steinke L, Fischer K. Extension of multi - commodity closed-loop supply chain network design by aggregate production planning. *Logistics Research*. 2016;9(1):1-23.

[22] Ransikarbum K, Mason SJ. Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations. *International Journal of Production Research*. 2016;54(1):49-68.

[23] Farias ED, Borenstein D. Modeling the logistics design of a multi-commodity industry. *Gestão e produção*. São Carlos. 2017; 24, n. 1. p. 148-160.

[24] Gong DC, Chen PS, Lu TY. Multi-objective optimization of green supply chain network designs for transportation mode selection. *Scientia Iranica*. 2017;24(6):3355-70.

[25] Bortolini M, Galizia FG, Mora C, Botti L, Rosano M. Bi-objective design of fresh food supply chain networks with reusable and disposable packaging containers. *Journal of Cleaner Production*. 2018;184:375-88.

[26] Bevrani B, Burdett RL, Bhaskar A, Yarlagadda PK. A multi commodity flow model incorporating flow reduction functions. *Flexible Services and Manufacturing Journal*. 2019;8:1-31.

[27] Ransikarbum K, Pitakaso R, Kim N. A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi - objective optimization. *Applied Sciences*. 2020;10(15):5159.

[28] Suksee S, Sindhuchao S. Selection of locations and incinerators for infectious waste of hospitals in Northeastern Thailand. *UBU Engineering Journal*. 2021;14(1):48-57.

[29] Kennedy J, Eberhart R. Particle swarm optimization. *Proceedings of ICNN'95 - international conference on neural networks.* IEEE. Nov 27. 1995. 4: p.1942-1948.

[30] Pongchairerks P, Kachitvichyanukul V. Particle swarm optimization algorithm with multiple social learning structures. *International Journal of Operational Research*. 2009;6(2):176-94.