TRANSPORT & *LOGISTICS:*
the International Journal

Article history:
Received 15 May 2018
Accepted 05 December 2018
Available online 07 December 2018

ISSN 2406-1069

Article citation info: Saif-Eddine, A., S., El-Beheiry, M., M., El-Kharbotly, A., K., Application of Vendor Managed Inventory Strategy in Inventory Location Routing Problems. Transport & Logistics: the International Journal, 2018; Volume 18, Issue 45, December 2018, ISSN 2406-1069

APPLICATION OF VENDOR MANAGED INVENTORY STRATEGY IN INVENTORY LOCATION ROUTING PROBLEMS

Ahmad Sayed Saif-Eddine [1], ***Mohammed Mostafa El-Beheiry*** [2], ***Amin Kamel El-Kharbotly*** [3]

[1] *Department of Design & Production Engineering, Faculty of Engineering, Ain Shams University, Cairo, Egypt, tel: +2 0100 948 4165, e-mail: Ahmad_saif@eng.asu.edu.eg*

[2] *Department of Design & Production Engineering, Faculty of Engineering, Ain Shams University, Cairo, Egypt, tel: +2 0122 734 0528, e-mail: Mohamed.m.mohamed@eng.asu.edu.eg*

[3] *Department of Design & Production Engineering, Faculty of Engineering, Ain Shams University, Cairo, Egypt, tel: +2 0122 748 3542, e-mail: Amin_elkharbotly@eng.asu.edu.eg*

Abstract:
Incorporating inventory, location, and routing decisions in distribution networks planning may yield considerable cost reduction. Inventory strategy also play a role in determining the cost incurred in the network. This paper compares the classical Inventory Location Routing Problem (ILRP), with the ILRP which adopts the Vendor Managed Inventory (VMI) strategy. A mathematical model is developed for the problem, with an objective that minimizes the total cost. Three instances of different sizes (10, 30, and 50 customers) are solved; to study the effect of applied inventory strategy on the total cost for different cost parameters. The parameters under consideration are: transportation cost from factory to depots, vehicle issuance cost, travel cost per unit travel distance, holding cost at the customer and at the depot, number of vehicles available at every depot, and vehicle capacity. An improved GA is used to solve the problem. The results show that, adopting the VMI strategy outperforms the classical LRP strategy at high travel cost per unit travel distance, and at low unit inventory holding cost at the customer.

Key words:
Inventory Location Routing Problem, Improved Genetic Algorithms, Vendor Managed Inventory.

INTRODUCTION

Distribution network planning is one of the complicated tasks; in order to achieve cost reduction and to maintain or improve the network responsiveness. The decisions in distribution network planning are mostly operational decisions. Among these decisions are selecting the vehicles' routes, delivery frequency to customers, … etc. Tactical decisions may be made in distribution planning, such as determining the inventory levels, delivery quantities, leasing of depots etc.

1 LITERATURE REVIEW

Different configurations and environments of the ILRP were tackled in the literature. The basic ILRP is to determine depot(s) location, vehicle routing and inventory decisions under deterministic demands. Liu & Lee [1] and Liu & Lin [2] considered the case of depot location problem and vehicle routing, while taking the inventory control decisions (order quantities and order-up-to levels) into consideration. They proposed a two-phase heuristic method to solve the problem, whose results were better than that obtained when neglecting the inventory cost and solution time as controlling decisions in both systems. On the other hand, they developed an efficient heuristic that is better than the local optima searching heuristics. Hiassat and Diabat [3] considered the problem of warehouse location, vehicle routing, and inventory of products at the customers. They aimed at determining the quantities of a perishable product to be delivered to the customers each period assuming deterministic demands over the periods. They took into account the closing inventory (at the end of each period) for the calculation of inventory holing cost. The problem was formulated as a Mixed Integer Programming problem. The results showed significant savings, compared to multi-step optimization models. Ahmadi-Javid and Seddighi [4] solved the 3-echelon location, capacity, routing, and inventory problem while considering the holding cost at the distribution center. They proposed a three-phase heuristic, incorporating Simulated Annealing and hybrid Ant Colony System, that proved its effectiveness with significant decrease in the total cost. Guerrero et al. [5] tackled a two-echelon supply chain. They dealt with the inventory costs at both the depot and the customers where products are to be consumed in following periods, to satisfy deterministic demands. The holding cost is calculated based on the amount of inventory available at the end of each period. They proposed a hybrid approach to solve the problem which proved robust performance in case of large benchmark instances for Location and Inventory Routing Problems. It also managed to optimize globally the problem, and achieved significant cost savings, when compared with the traditional approach. Zhang et al. [6] dealt with a two-echelon supply chain with deterministic period-variable demands over a finite planning horizon. They considered the holding cost at the customers, and aimed at determining the quantities to be delivered to every customer in every period, among the other decision variables they aimed to determine. To calculate the holding cost, the period's ending inventory is considered, as well as half the demand of the period. They designed a hybrid metaheuristic, that proved its efficiency and effectiveness.

One of the first relaxations made to the basic ILRP is to consider stochastic demands. Shen and Qi [7] dealt with a three-tiered supply chain with customers' stochastic demands, while fulfilling a certain service level. The aim was to determine the locations of the distribution centers, the assignment of the customers to the distribution centers, the frequency of ordering from the supplier, and the safety stock levels to maintain at the distribution centers. The problem was formulated as a Non-linear Integer Programming Problem, and solved efficiently for large-size problems. Ahmadi-Javid and Azad [8] dealt with a stochastic supply chain system, having uncertain customers' demands, following a normal distribution. They aimed at optimizing the location, allocation and capacity level of each depot, the vehicles' routing, and the order size, reorder frequency, and safety stock level for each distribution center. They presented a heuristic, and tested its effectiveness over different sizes and structures. They concluded that the number of opened distribution centers increases with increasing the weight factor of the routing cost, and decreases with increasing the weight factor of the inventory cost. On the other hand, fuzzy demands were tackled by Tavakkoli-Moghaddam and Raziei [9], where a multi-product, multi-period three-tier supply chain is considered. The fuzzy demands differ between the products, over the periods. The aim was to determine the locations of the distribution centers to open, the quantities of products to be directly shipped to the distribution centers, and the quantities to be delivered to the customers, as well as the vehicles routing to deliver to the customers. The objective was to minimize the total cost and the sum of shortages at the customers. The holding cost considered is concerned with the quantities stored from a period to another. They used CPLEX to solve the Multiple Objective probabilistic Mixed Integer Linear Programming Model formulated.

Some researchers tackled the problem in closed loop supply chain, such as: Wang et al. [10] and Jiang and Ma [11]. They considered a three-echelon supply chain for closed loop logistics system, for reusing end-of-use products, where collection and distribution demands follow a Poisson distribution. Collected products have certain probabilities of being reused in a following period. If the total usable collected products at a depot are less than the total distribution demand from that depot in the following period, new products should be ordered and delivered from the factory. They sought to determine the locations of the logistic centers, routes of the vehicles, and inventory levels at the logistic centers of reused and new products. The formers proposed a two-phase heuristic algorithm to solve the stochastic dynamic model formulated, while the they proposed a hybrid genetic algorithm. Ahmad et al. [12] dealt with the problem of Wang et al. [10], and modified it to study the selection of a customer to act as a transshipment node, to decrease the total transportation cost. They showed that considering a transshipment node can reduce the transportation cost. Shariff et al. [13] considered the same problem, but intended to select one or more customers to be the transshipment nodes, using p-center, and showed that savings can be achieved.

Recently, ILRP is solved under risk and disruptions. Seyedhosseini et al. [14], dealt with a three-level supply chain, with stochastic demands, where random disruptions may occur at the distribution centers. This can lead to lost-sales for the customers who need the product essentially, as they manage to get it from outside the supply chain, and backordering happens to the other customers. They considered the holding cost at the distribution centers of the order quantities, and the safety stocks. They implemented a metaheuristic method to solve the formulated Mixed Integer Non-Linear programming model, and conducted a sensitivity analysis on the important parameters. Also the consideration of multi-objective optimization was considered by Tavakkoli-Moghaddam et al. [15]. They tackled the problem of three-level supply chain with uncertain demand at the retailers. They aimed at determining the location and capacity of the distribution centers, allocating retailers to the distribution centers and distribution centers to the suppliers. They considered transportation decisions for all the levels, including selecting the vehicle type and the vehicle routing, and inventory control decisions, as ordering quantities of the distribution centers from the supplier, the safety stock levels at the distribution centers, and the quantities they deliver to their retailers. The objectives were to minimize the total costs and the time to transport the product along the supply chain, as a bi-objective problem. They considered the holding cost at the distribution centers, as the average of the ordered quantities from the suppliers, and the safety stock holding cost. The model was solved by using the LINGO software. Nekooghadirli et al. [16] dealt with bi-objective multi-product two-echelon ILRP, with probabilistic travelling times and stochastic demands. The objectives were to minimize the total cost and the maximum mean time for delivering to the customers. The inventory cost contained the holding cost at the distribution centers, the ordering cost, and the safety stock cost. They proposed a Multi-Objective Imperialist Competitive Algorithm, validated it, and compared its performance with three other algorithms, where it showed its superiority.

The ILRP in conjunction of electronic distribution networks is another environment, considered by Li et al. [17]. They assumed an E-supply chain with returns, where the returned merchandise has no quality defects, and can be resalable after a simple repackaging process at a merchandise center. They considered the inventory cost at the merchandise centers, of both the returned merchandise, and the newly ordered products from the supplier, in case that the returned merchandise does not cover the demand of a following period. They developed a hybrid GA-SA algorithm to solve the problem, which outperformed the GA regarding the optimal solution, computing time, and stability. Chen et al. [18] tackled the B2C E-commerce distribution system utilizing VMI strategy, with fuzzy random demands. The inventory cost considers the ordering costs, holding costs at the distribution centers, and backorder costs, where the order times and target inventory levels at the distribution centers are to be determined. They developed a two-stage hybrid heuristic, and showed the effectiveness of the model, and the reliability of the algorithm.

It is clear from the literature that most the efforts made in this subject are directed to solve the ILRP under different configurations, especially stochastic demands and closed loop supply chains. Different strategies are seldom tested such as VMI, distribution integration … etc. In this paper, VMI strategy is tested to find how it improves the efficiency of the supply chain when considering ILRP.

In Inventory Location Routing Problem (ILRP), decisions about the inventory, depot(s) location and vehicle routing are taken simultaneously. In this class of problems, researchers focused on solving the ILRP problem with different configuration. It is rare to find in the literature a strategy testing associated with the ILRP. In this paper, Vendor Managed Inventory (VMI) strategy is to be tested while taking ILRP decisions. Instead of visiting each customer every period, incurring high routing costs, customers will be visited every number of periods. This will cause elevating the inventory cost at the customers; therefore, the distributer will incur this cost totally or partially as return of keeping higher inventory levels at the customers.

A mathematical model is developed to solve the ILRP under two strategies: classical strategy, where all customers are visited every period, and VMI, where customers are visited periodically. The rest of this paper is organized as follows: in section 3, the problem definition and the developed model are illustrated, then the solution methodology is given in section 4. Section 5 includes the numerical experiments, while section 6 presents the reached results and discussion, and then, conclusions and future work are stated in section 7.

2 PROBLEM DESCRIPTION AND PROPOSED MODEL

A Third Party Logistics (3PL) provider offers the logistics activities to a plant producing a single product by transporting the goods from its factory to one or more depot(s), having inventory at the depot, if needed, then distribute these goods to customers with constant demand rates. The depots already exist, and the 3PL decides whether to use a depot in a specific period. The 3PL provider can adopt the VMI strategy by having more inventory at the customers and being charged for a part of their holding cost; to be able to have less frequent deliveries to the customers. For each planning period, the 3PL provider should decide the frequency of deliveries to customers, then subsequently, decisions about which depots to use, inventory levels at the different depots, number of vehicles dispatched, their dispatching times and routes are made. The vehicles used to transport from the factory to the depot(s) are big enough to deliver the needed quantity to each depot in one shipment. This delivery is made, such that, the goods can be delivered to the customers at the start of each period. Also, the depot's capacity is big enough to hold any quantity. The number of available vehicles at each depot is constant and limited and all vehicles have equal capacity, i.e., homogeneous fleet.

The following assumptions are taken into account on modelling the problem: no transhipment is allowed between the depots, there is no ending inventory at the depot in every period, i.e., products arrive and are distributed to customers in the same period, vehicles' routes begin and end at the same depot before the period end, known and deterministic travelling times are assumed and no waiting is permitted at the customers, the customer has an infinite storage capacity and no shortage is permitted.

The problem is formulated; aiming at minimizing the total cost, by determining the following: the delivery quantities for every customer and the periods when they should be delivered, the locations of depots to be used in every period, and the number and routes of the dispatched vehicles of every used depot, as well as the corresponding dispatching times.

2.1 Nomenclature

2.1.1 Indices and Sets:

NC - Set of customers, indexed by i, and j
ND - Set of potential depots, indexed by i, j, and o
K_o *- Set of available vehicles at depot 'o', indexed by* $k_o \in ND$
P - Total number of periods, making the repeated period, indexed by p
V_{kp} *- Set of customers served by vehicle 'k' in period 'p'*
S_{kp} *- Non-empty Subset of customers visited by vehicle 'k' in period 'p',* $S_{kp} \subseteq V_{kp}$

2.1.2 Parameters:

D_i *- Demand rate of customer 'i' per period,* $i \in NC$
C - Capacity of any vehicle in number of units,
dc_o *- Transportation cost from factory to depot 'o' per period,* $o \in ND$
fc_k *- Dispatching cost of vehicle 'k',* $k \in K_o$, $o \in ND$
tc - Transportation cost per unit distance,
hd_o *- Unit inventory holding cost at depot 'o' per period,* $o \in ND$
hc_i *- Unit inventory holding cost at customer 'i' per period,* $i \in NC$
d_{ij} *- Distance of arc (i, j),* $i, j \in NC \cup ND$, $i \neq j$
tt_{ij} *- Travelling time of arc (i, j),* $i, j \in NC \cup ND$, $i \neq j$
pt - Period time, in time units.

2.1.4 Auxiliary Variables:

st_{ijk}^p *- Start time for traversing arc (i, j) by vehicle 'k' in period 'p',* $i, j \in NC \cup ND$, $i \neq j$, $k \in K_o$, $o \in ND$, $p = 1, 2, \ldots P$

nd_i *- No. of deliveries to be made to customer 'i' within the repeated period, indexed by n,* $i \in NC$

EI_i^n *- Inventory level of product at customer 'i' just before the* 'n^{th}' *delivery,* $n = 1, 2, \ldots, nd_i$, $i \in NC$

td_i^n - *Time between delivery 'n' at customer 'i' and the following delivery 'n+1'*, $n = 1, 2, \ldots, nd_i$, $i \in NC$

2.1.3 Decision Variables:

r_i - *Period multiplier, defining the number of periods, every which, customer 'i' is visited*, $i \in NC$

q_i - *Delivery quantity for customer 'i'*, $i \in NC$

y_i^p - *A binary variable, defining whether depot 'i' is used in period 'p'*, $i \in ND$, $p = 1, 2, \ldots P$

x_{ijk}^p - *A binary variable, defining whether vehicle 'k' passes through arc (i, j) in period 'p'*, $i, j \in NC \cup ND$, $i \neq j$, $k \in K_o$, $o \in ND$, $p = 1, 2, \ldots P$

st_{ijk}^p - *Dispatching time for vehicle 'k' from depot 'i' to pass through arc (i, j) in period 'p'*, $i \in ND$, $j \in NC$, $k \in K_i$, $p = 1, 2, \ldots P$

2.2 Cost Modelling

The same model of Saif-Eddine et al. [19] is adopted here. The classical strategy is considered as a special case of their general case, where they applied the VMI strategy. The classical strategy is a special case where:

$r_i = 1\ \forall\ i \in NC$, $hc_i = 0\ \forall\ i \in NC$, $p = P = 1$, $q_i = D_i$, $J_1 = NC$.

Therefore, the total cost function becomes:

$$
\begin{aligned}
Total\ Cost = & \sum_{o \in ND} y_i \cdot dc_o^p + \sum_{o \in ND} \sum_{k \in K_o} \sum_{j \in NC} x_{ojk}^p \cdot fc_k \\
& + \sum_{o \in ND} \sum_{k \in K_o} \sum_{j \in NC \cup \{o\}} \sum_{\substack{i \in NC \cup \{o\} \\ i \neq j}} x_{ijk}^p \cdot tc \cdot d_{ij} \\
& + \sum_{o \in ND} \sum_{k \in K_o} \left(\left(\sum_{j \in NC \cup \{o\}/\{i\}} \sum_{i \in NC} x_{ijk}^p \cdot q_i \right) \right. \\
& \left. \cdot \left(\sum_{j \in NC} x_{ojk}^p \cdot st_{ojk}^p \cdot \frac{hd_o}{pt} \right) \right)
\end{aligned}
\tag{1}
$$

The constraints become:

$$\sum_{j \in NC} x_{ojk}^p \leq 1 \quad \forall\ k \in K_o, o \in ND \tag{2}$$

$$\sum_{j \in NC} x_{ojk}^p = \sum_{j \in NC} x_{jok}^p \quad \forall\ k \in K_o, o \in ND \tag{3}$$

$$\sum_{o \in ND} \sum_{k \in K_o} \sum_{i \in NC \cup \{o\}/\{j\}} x_{ijk}^p = 1 \quad \forall\ j \in NC \tag{4}$$

$$\sum_{j \in ND \cup NC/\{i\}} x_{ijk}^{p} = \sum_{j \in ND \cup NC/\{i\}} x_{jik}^{p} \quad \forall\ i \in ND \cup NC, o \in ND, k \in K_o \tag{5}$$

$$\sum_{i \in S_{kp}} \sum_{j \in S_{kp}} x_{ijk}^{p} \le |S_{kp}| - 1 \quad \forall\ S_{kp} \subseteq V_{kp}, S_{kp} \neq \emptyset, o \in ND, k \in K_o \tag{6}$$

$$\sum_{k \in K_o} \sum_{j \in NC} x_{ojk}^{p} = y_o \cdot \sum_{k \in K_o} \sum_{j \in NC} x_{ojk}^{p} \quad \forall\ o \in ND \tag{7}$$

$$y_o \le \sum_{k \in K_o} \sum_{j \in NC} x_{ojk}^{p} \quad \forall\ o \in ND \tag{8}$$

$$\sum_{j \in NC \cup \{o\}/\{i\}} \sum_{i \in NC} x_{ijk}^{p} \cdot q_i \le C \quad \forall k \in K_o, o \in ND \tag{9}$$

$$\sum_{j \in NC \cup \{o\}/\{i\}} x_{ijk}^{p} \cdot st_{ijk}^{p} = \sum_{j \in NC \cup \{o\}/\{i\}} x_{jik}^{p} \cdot \left(st_{jik}^{p} + t_{ji}\right) \quad \forall\ i \in NC, k \in K_o, o \in ND \tag{10}$$

$$\sum_{i \in NC} x_{iok}^{p} \cdot \left(st_{iok}^{p} + t_{io}\right) \le pt \quad \forall\ k \in K_o, o \in ND \tag{11}$$

$$y_o^p \in \{0, 1\} \qquad \forall\ o \in ND \tag{12}$$

$$x_{ijk}^p \in \{0, 1\} \qquad \forall\ i \in NC \cup \{o\}, j \in NC \cup \{o\}/\{i\}, k \in K_o, o \in ND \tag{13}$$

$$st_{ijk}^p \ge 0 \qquad \forall\ i \in NC \cup \{o\}, j \in NC \cup \{o\}/\{i\}, k \in K_o, o \in ND \tag{14}$$

Where:

$$V_{kp} = \left\{ i \,\middle|\, \textstyle\sum_{j \in NC} x_{ijk}^{p} = 1 \right\} \quad \forall i \in NC, o \in ND, k \in K_o \tag{15}$$

3 THE USED GENETIC ALGORITHMS

The same improved genetic algorithms of Saif-Eddine et al. [19] are used here, applying their improvement stage, but without the heuristics of: determining the period multipliers, and allocating the customers to the periods.

4 NUMERICAL EXPERIMENTS

Three problem sizes (10, 30, and 50 customers) are extracted from the p01 benchmark instance of the Multi-Depot Vehicle Routing Problem literature of the Canada Research Chair in Distribution Management web-site [20] to compare the performance of the two strategies: the ILRP under VMI strategy, and the classical ILRP (not considering the customers' holding costs). The aim is to investigate the research question: Is it beneficial to adopt the VMI strategy and pay for the holding cost at the customer for the sake of reducing the routing costs incurred every period by the classical ILRP?

To study the effect of changing the parameters values on the superiority of both strategies, some parameters have their values changed while preserving the values of the other parameters at their default values (expressed in bold in this context). The number of available vehicles at each depot has the values of 1, **2**, 3, 4, 5, 6, 7, 8 and 9 for the small problem, 1, 2, 3, 4, **5**, 6, 7, 8 and 9 for the medium problem, and 3, 4, 5, 6, 7, **8**, and 9 for the large problem. The vehicle capacity has the values of 40, 60, **80**, 120, and 200 for all the problems, with the corresponding vehicle dispatching costs of 80, 105, **120**, 150, and 200, respectively. For both problems, the transportation cost from the factory to each depot is changed between 100, 200, **400**, 700, and 1000 unit cost. The unit inventory holding cost at each depot has the values of 0.0025, 0.005, **0.01**, 0.05, and 0.1 unit cost per unit per period, while the unit inventory holding cost at each customer has the values of 0.025, 0.05, **0.1**, 0.5, and 1 unit cost per unit per period. Lastly, the travel cost per unit travel distance varies between 0.25, 0.5, **1**, 2, and 4 unit cost per unit distance.

The classical strategy has the same parameters, except that its unit inventory holding cost at the customers is zero, as well as the period multiplier for all customers is one. When adopting the VMI strategy, the unit inventory holding cost is not considered for the customers being visited every period, as no excess inventory is required to be kept in their inventories. To compare both strategies, the total cost per period is used for comparison, which is the total cost divided by the number of periods '*P*' in the repeated period.

The GA parameters used are: **population size:** 40, **number of generations before improvement:** 25, **number of repetitions:** 10, **crossover fraction:** 0.8, **number of elite chromosomes:** 1.

5 RESULTS AND DISCUSSION

According to the parameters used to study the total cost resulting from adopting VMI strategy versus the classical one, the results showed for some parameters (number of vehicles available at each depot, transportation cost from the factory to the depots, and unit inventory holding cost at the depot) that the VMI outperformed the classical strategy. On the other hand, the superiority is switched between the two strategies along the range of other parameters (travel cost per unit travel distance, the unit inventory holding cost at the customer, and the vehicle capacity).

VMI superiority in total cost can be shown in Figures 1-3. It can be concluded from Figure 1 (a) that, as the number of available vehicles at each depot increases, the total cost of both strategies decreases, with VMI having lower total cost per period for the small and medium instances. For the large instance, the VMI has a higher total cost per period because of other parameters, that can change the superiority of the classical strategy in this case. It is obvious from Figure 1 (b) that the VMI strategy outperforms the classical one in the routing cost of the resulted solution, by a saving of 14.7% on average for the small instance. For the medium instance (Figure 1 (c)), the VMI strategy outperform the classical in the routing cost, by an average saving of 27%. The corresponding saving in the total cost, caused by adopting the VMI strategy, increased from 3.2% to 5.3%, as the number of available vehicles per depot increased from 2 to 9. As the number of available vehicles increases, the number of depots used decreases, so the total transportation cost from the factory to the depots decreases. Thus, the routing cost ratio of the total cost increases, causing the saving in total cost to increase. For the small instance, since the number of vehicles per depot is low where only two depots are used, the total transportation cost from the factory to the depots is found to represent around 65% of the total cost. As the number of vehicles per depot increases, the number of used depots decreases to only one depot, which results in drastic decrease in total cost. On the other hand, for the large instance (Figure 1 (d)), the total transportation cost from the factory to the depots represents around 46% of the total cost, for low number of available vehicles per depot. Thus, when the number of depots is reduced from 4 to 2, as a result of increasing the number of vehicles per depot, less reduction takes place in the total cost. It is worth to state that, the total cost per period for both strategies in the small instance has a tiny difference. The total transportation cost from the factory to the depots coincide for both strategies.

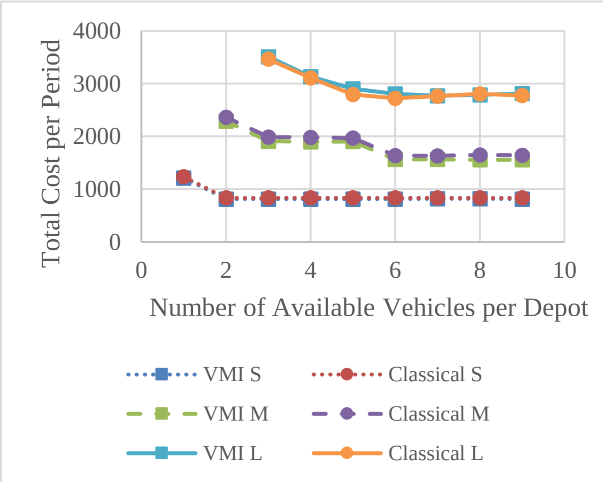

Fig. 1 (a) *Effect of number of vehicles at each depot on the total costs*

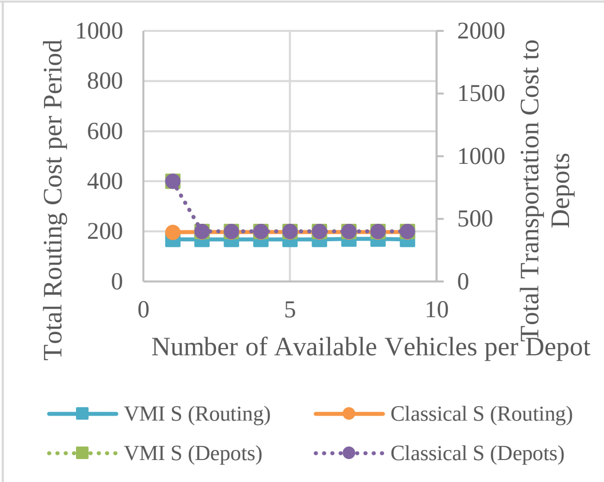

Fig. 1 (b) *Effect of number of vehicles at each depot on the routing cost and the total transportation cost from the factory to the depots for the small instance*

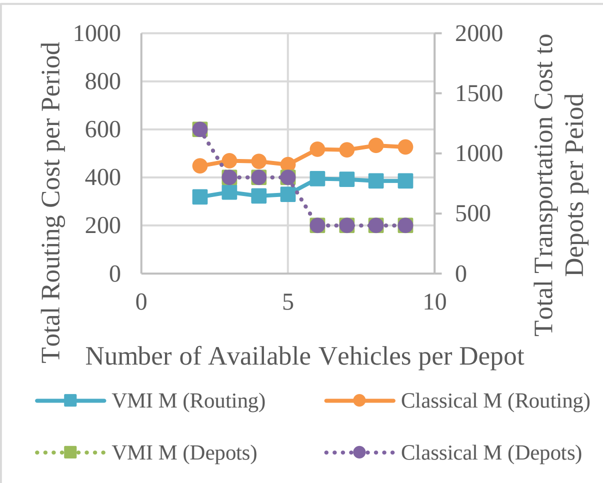

Fig. 1 (c) *Effect of number of vehicles at each depot on the routing cost and the total transportation cost from the factory to the depots for the medium instance*

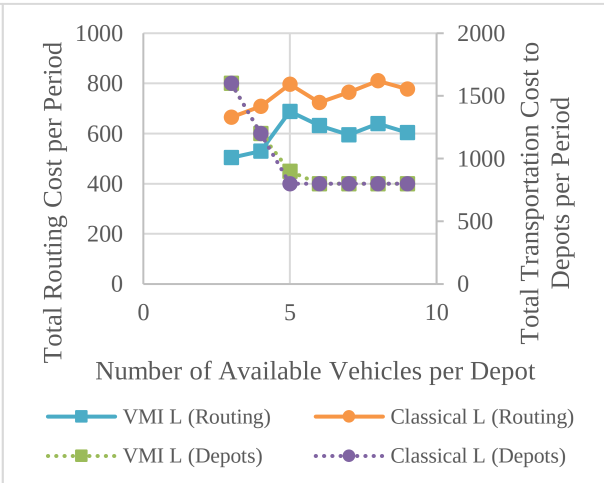

Fig. 1 (d) *Effect of number of vehicles at each depot on the routing cost and the total transportation cost from the factory to the depots for the large instance*

On increasing the transportation cost from the factory to the depot, only this transportation cost increases. This increases the total cost of both strategies, as shown in Figure 2. The VMI remains superior with constant difference in total cost value from the classical strategy in both the small and medium instances. The only difference is due to the routing cost of the VMI which is less than that of the classical strategy. As the number of depots used and dispatched vehicles remain equal and constant, therefore, both strategies are not affected by the change of the transportation cost from the factory to the depot. It is found that, the unit inventory holding cost at each depot has a negligible effect on the total cost of both strategies. This is due to the small fraction of the holding cost at the depots among the other cost elements in the total cost, as well as the tendency to dispatch the working vehicles at the early start of the period(s) in both strategies.

It can be seen from Figures 3 that the total cost of the classical strategy is not changed as no holding cost incurs at the customer. On the contrary, as the unit inventory holding cost at every customer increases, the total cost of the VMI strategy increases. This is expected, as the VMI strategy is based on storing products at the customers for future periods; to save routing costs. So, as the unit inventory holding cost for all the customers increases, the holding cost at the customers increases for the same stored quantities. This is due to the fact that, at certain value of the unit inventory holding cost at the customer, it will be more economical to adopt the classical strategy. It is worth mentioning that, as the unit inventory holding cost at the customers increases, the other cost elements are not affected. On the contrary, as the travel cost per unit travel distance increases, the VMI strategy becomes more economical, as shown in Figures 4. This is due to the fact that, the distances travelled are taken into consideration while determining the period multipliers, as the far customer is visited less often as it has a high period multiplier as implied by the period multiplier heuristic. Increasing the travel cost per unit travel distance increases the routing cost, which affects greatly the total cost of both strategies. It is observed that the increase in the routing cost of the VMI strategy has a lower rate than the increase of the classical strategy, as the VMI strategy tends to travel less distances.

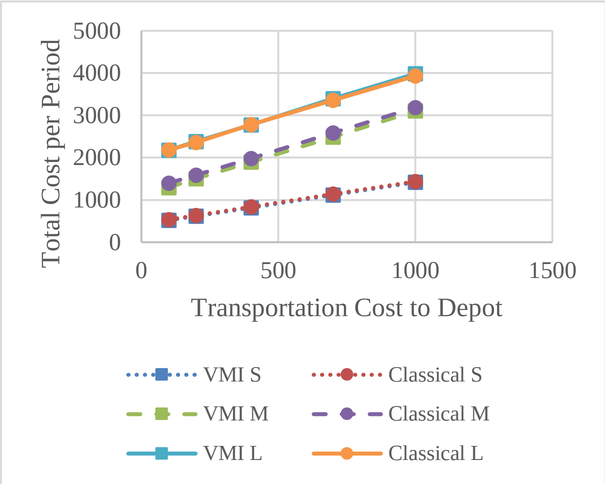

Fig. 2 *Effect of transportation cost from the factory to the depot on the total costs*

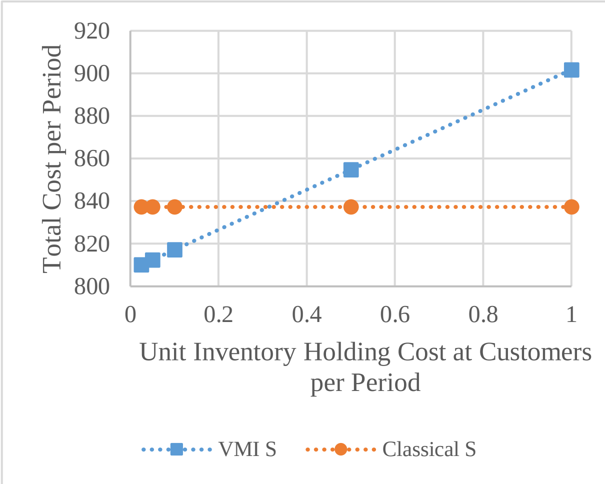

Fig. 3 (a) *Effect of unit inventory holding cost at the customers on the total costs for the small instance*

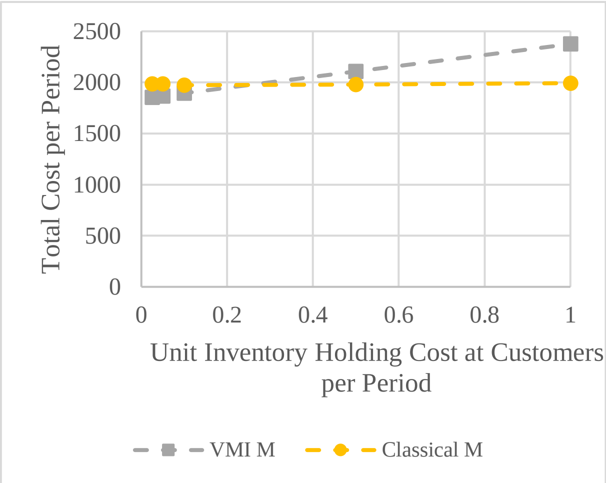

Fig. 3 (b) *Effect of unit inventory holding cost at the customers on the total costs for the medium instance*

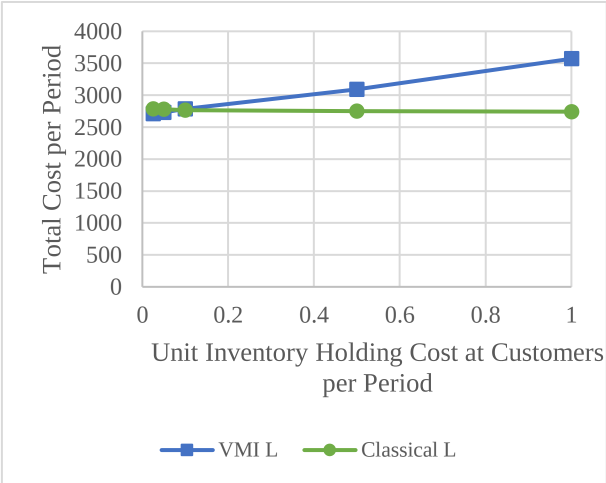

Fig. 3 (c) *Effect of unit inventory holding cost at the customers on the total costs for the large instance*

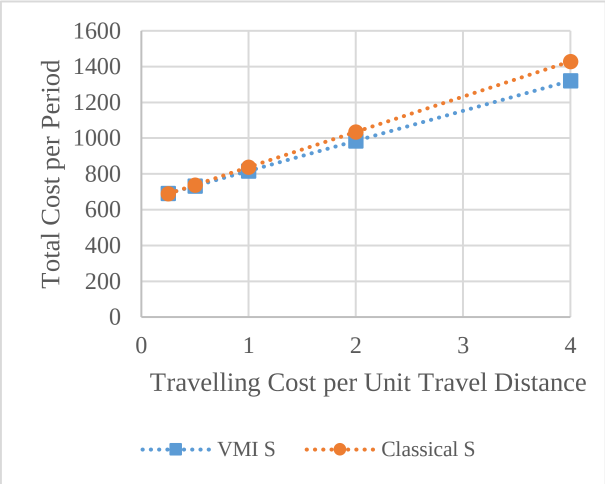

Fig. 4 (a) *Effect of travel cost per unit travel distance on the total costs for the small instance*

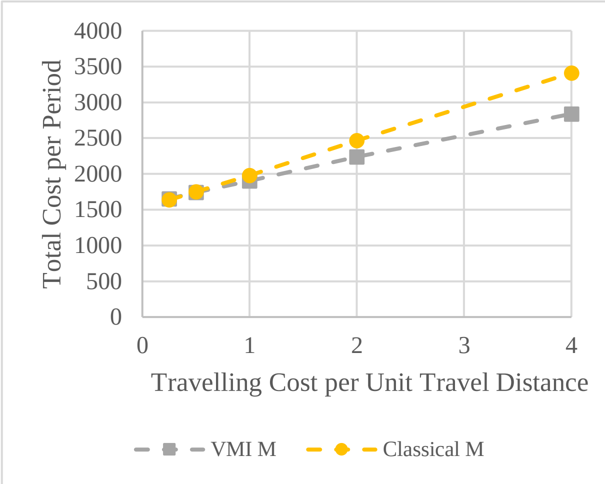

Fig. 4 (b) *Effect of travel cost per unit travel distance on the total costs for the medium instance*

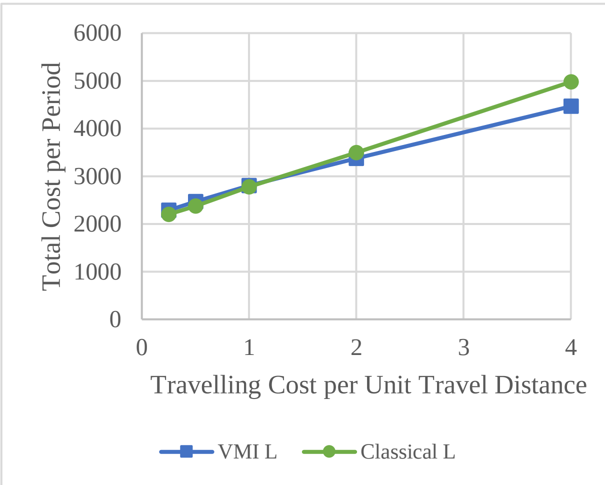

Fig. 4 (c) *Effect of travel cost per unit travel distance on the total costs for the large instance*

However, it is expected that the classical strategy outperforms the VMI strategy for higher unit inventory holding cost at the customers, and lower travel cost per unit travel distance. This is expected to be behaved regardless of the number of vehicles available at each depot, transportation cost from the factory to the depot, or the unit inventory holding cost at the depots.

The classical strategy outperforms the VMI strategy for small capacity vehicles, as shown in Figure 5 (a). At small vehicle capacity, the larger quantities which are to be delivered in the VMI strategy cannot be easily stacked in the small vehicles, hence, more vehicles are issued with worse utilization than the classical strategy (Figure 5 (b)). On increasing the vehicle capacity, both strategies use the same number of vehicles (Figure 5 (c)) and reach equal utilization, therefore, the VMI becomes more economical than the classical; as it has lower routing cost, by travelling shorter distances per period, as given in figure 5 (d).

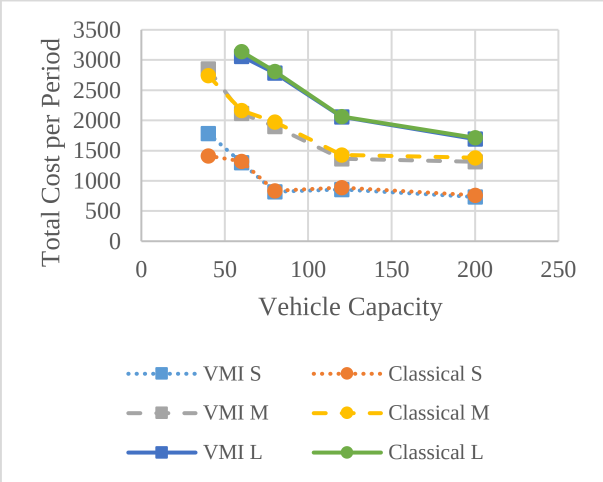

Fig. 5 (a) *Effect of vehicle capacity on the total costs*

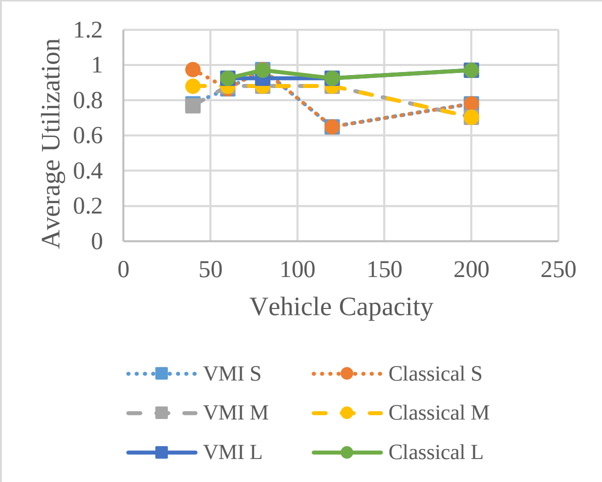

Fig. 5 (b) *Effect of vehicle capacity on the vehicles utilization*

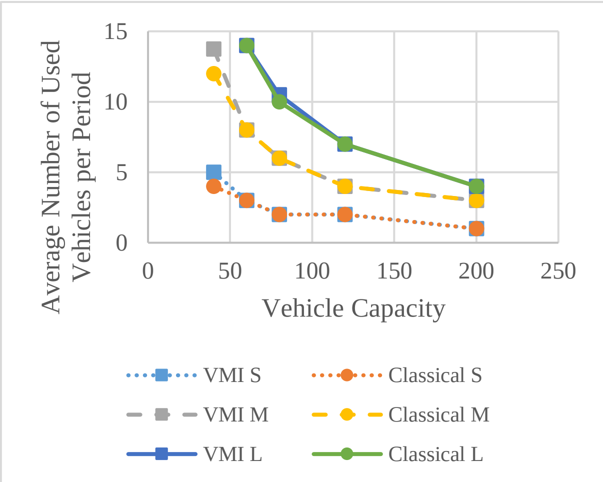

Fig. 5 (c) *Effect of vehicle capacity on the average number of vehicles used per period*

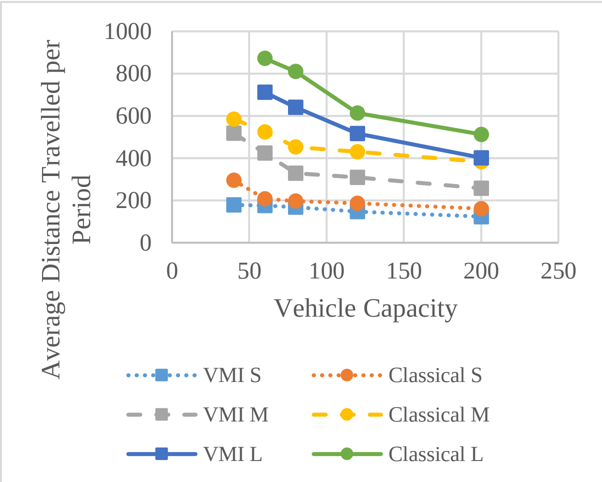

Fig. 5 (d) *Effect of vehicle capacity on the average distance travelled per period*

6 CONCLUSIONS AND FUTURE WORK

The problem tackled is considered one of the distribution management core problems, and has a great impact on the efficiency of the distribution network. Although VMI strategy is a well-known strategy in the literature, yet, local managers are reluctant to adopt it, and they prefer to offer discount in price as a return of not delivering in every period. The results showed that VMI strategy decreases the total cost at low unit inventory holding cost at the customers. The classical strategy becomes better as the unit inventory holding cost increases. Also, at low travel cost per unit travel distance, the classical strategy yields lower total cost. As the travel cost per unit travel distance increases, the superiority is switched to the VMI strategy. Increasing the transportation cost from the factory to the depot, or the unit inventory holding cost at the depot, does not change the superiority of the VMI or the classical strategy. It is concluded that, in case of high travel cost per unit travel distance and/or low unit inventory holding cost at the customers, it is better to use the VMI strategy. If the unit inventory holding cost at the customer increases, VMI can still be superior if part of the incurred holding cost is made at the customers' side.

This work can be extended by dealing with multi-echelon, considering stochastic demand, time-windowed customers, and time-dependent travel times. The cost parameters considered are mainly operational parameters, other tactical or even strategic costs could be considered in the future work.

References

[1] Liu, S. C. and Lee, S. B., 2003, "A two-phase heuristic method for the multi-depot location routing problem taking inventory control decisions into consideration," The International Journal of Advanced Manufacturing Technology, 22(11), pp. 941-950.

[2] Liu, S. C. and Lin, C. C., 2005, "A heuristic method for the combined location routing and inventory problem," The International Journal of Advanced Manufacturing Technology, 26(4), pp. 372-381.

[3] Hiassat, A. and Diabat, A, 2011, "A location-inventory-routing-problem with perishable products," In: the 41st International Conference on Computers & Industrial Engineering Los Angeles, USA: CIE, pp. 293-298.

[4] Ahmadi-Javid, A. and Seddighi, A. H., 2012, "A location-routing-inventory model for designing multisource distribution networks," Engineering Optimization, 44(6), pp. 637-656.

[5] Guerrero, W. J., Prodhon, C., Velasco, N. and Amaya, C. A., 2013, "Hybrid heuristic for the inventory location-routing problem with deterministic demand," International Journal of Production Economics, 146(1), pp. 359-370.

[6] Zhang, Y., Qi, M., Miao, L. and Liu, E., 2014, "Hybrid metaheuristic solutions to inventory location routing problem," Transportation Research Part E: Logistics and Transportation Review, 70(1), pp. 305-323.

[7] Shen, Z. J. M. and Qi, L., 2007, "Incorporating inventory and routing costs in strategic location models," European Journal of Operational Research, 179(2), pp. 372-389.

[8] Ahmadi-Javid, A. and Azad, N., 2010, "Incorporating location, routing and inventory decisions in supply chain network design," Transportation Research Part E: Logistics and Transportation Review, 46(5), pp. 582-597.

[9] Tavakkoli-Moghaddam, R. and Raziei, Z., 2016, "A new bi-objective location-routing-inventory problem with fuzzy demands," IFAC-PapersOnLine, 49(12), pp. 1116-1121.

[10] Wang, C., Ma, Z. and Li , H., 2008, "Stochastic dynamic location-routing-inventory problem in closed-loop logistics system for reusing end-of-use products," International Conference on Intelligent Computation Technology and Automation, Changsha, Hunan, China: IEEE, 2, pp. 691-695.

[11] Jiang, S. and Ma, Z., 2009, "A hybrid genetic algorithm for the stochastic dynamic location-routing-inventory problem in closed-loop logistics system for reusing end-of-use products," 2nd International Conference on Transportation Engineering, Chengdu, China: ASCE, pp. 4055-4060.

[12] Ahmad, H., Hamzah, P., Md Yasin, Z. A. M. and Shariff, S. S. R., 2014, "Location routing inventory problem with transshipment (LRIP-T)," The 2014 International Conference on Industrial Engineering and Operations Management, Bali, Indonesia: IEEE, pp. 1595-1605.

[13] Shariff, S. S. R., Omar, M. and Moin, N. H., 2016, "Location routing inventory problem with transshipment points using p-center," 2016 International Conference on Industrial Engineering, Management Science and Application (ICIMSA), Jeju Island, South Korea: IEEE, pp. 1-5.

[14] Seyedhosseini, S. M., Bozorgi-Amiri, A. and Daraei, S., 2014, "An integrated location-routing-inventory problem by considering supply disruption," iBusiness, 6(2), pp. 29-37.

[15] Tavakkoli-Moghaddam, R., Forouzanfar, F., and Ebrahimnejad, S., 2013, "Incorporating location, routing, and inventory decisions in a bi-objective supply chain design problem with risk-pooling," Journal of Industrial Engineering International, 9(1), 19.

[16] Nekooghadirli, N., Tavakkoli-Moghaddam, R., Ghezavati, V. R. and Javanmard, S., 2014, "Solving a new bi-objective location-routing-inventory problem in a distribution network by meta-heuristics," Computers & Industrial Engineering, 76, pp. 204-221.

[17] Li, Y., Guo, H., Wang, L. and Fu, J., 2013, "A hybrid genetic-simulated annealing algorithm for the location-inventory-routing problem considering returns under e-supply chain environment," The Scientific World Journal, 2013.

[18] Chen, D., Chen, D., Sun, G., and Liu, G., 2014, "Combined location routing and inventory problem of e-commerce distribution system with fuzzy random demand," International Journal of Hybrid Information Technology, 7(5), pp. 429-442.

[19] Saif-Eddine, A. S., El-Beheiry, M. M., El-Kharbotly, A. K., (In Press), "An Improved Genetic Algorithm for Optimizing Total Supply Chain Cost in Inventory Location Routing Problem", Ain Shams Engineering Journal.

[20] Canada Research Chair in Distribution Management web-site, http://neumann.hec.ca/chairedistributique/data/mdvrp/old/, last accessed: 22 July 2017.