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Stores Location Model For Distribution Network Design: An Effective Variable neighborhood Search Approach for a Two Level Capacitated Location Allocation Problem

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Abstract

Whatever the field of activity, the design of the distribution network is a strategic decision that affects both the commercial performance as the tactical and operational management of the supply chain. In this article, we address a problem of distribution network extension. The decision to open a new store and the choice of its location in an existing distribution network takes into account the customer demand and service objectives of the relevant geographic area. It also takes into account other logistics and techniques parameters. In this article we suggest a model of the distribution network, identical to a TLCLAP model (Two Level Capacitated Location Allocation Problem), with a list of parameters and logistical constraints related to business and a resolution approach based on an effective Variable Neighborhood Search VNS method.

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INTRODUCTION

Large-scale distribution has experienced a noticeable growth in recent years despite the slow improvements of the economies, market saturation, continuous increasing fees, splitting markets and an increased competitive environment. It has also faced less predictable requirements and demands. The discussion over retail policy and urban economics, mixed land use policy and retail returns has amplified attention on relationships between locations design, availability and prices (Jang and Kang, 2015). Customers have become more and more demanding and getting better informed and constantly looking for the best price/quality ratio in their favor, while demanding more services which are incorporated in the acquired product (Bowersox *et al.*, 2000). Previous research has often stressed on distribution and retailing as being one of the biggest challenges of doing business in emerging markets (Reinartz *et al.*, 2011).

Within this context, the supply chain has market power and practices markup pricing (Ahmadi-Javid and Hoseinpour, 2015). So, the decision to open a store is of strategic nature which has a direct impact on short-term profitability and long-term success (Turhan *et al.*, 2013). Although, the estimates of market needs and trade policy are essential in attracting a large number of customers and increase market shares (Cheng *et al.*, 2007), customer requirements and constant search for best quality, price and service to the customer are also important factors (Bowersox *et al.*, 2000). This has pushed companies to review their competitive strategies to innovate constantly in order to differentiate themselves from competitors (Van Riel, 2012). Several studies emphasize the critical importance of logistics as a competitive advantage that has its direct impact on the service provided to customers (performance level rays, service boxes, product availability,). Performance on these aspects improves satisfaction and perception of the image of the store (Bouzaabia and Boumaiza, 2013).

Similarly, adopting a multichannel distribution strategy in emerging markets seems a crucial point in the overall firm's business strategy (Kumar *et al.*, 2015). Also, customer proximity, interactions with the large-scale distribution which is particularly related to the localization strategy and response to demand fluctuations play a strategic role for the company (Gonzalez-Benito *et al.*, 2005).

Research on the problem of locating warehouses began in the 30s with Weber (1929), the model he proposed was to minimize the distance between the warehouse and the different sites. The international warehouse location problem is very complex due to the increase of environmental variability and increasing the number of variables involved in an international market (Bhutta, 2004).

An important model of problem of location of an unlimited store capacity in the network design using linear programming integer variables was formulated by Daskin and Jones (1993). Thus, they have shown the impact of the design of the transportation network in the optimum location of warehouses. The problem was finding the network design and the list of locations of warehouses that minimize the total cost system: the cost of building a warehouse, transportation costs, etc.

An approximate model using a linear programming model in a deterministic environment (all prices are deterministic) was the subject of research carried out by Canel and Khumawala (2001). These researchers have listed many factors to consider in locating warehouses and the objective of their model is profit maximization. In addition, the formulation of their problem includes the fact that clients are in different countries and the possibility of holding stocks in warehouses. The authors did not include the investment decisions and the cost of transportation. This problem can determine the countries in which it is best to locate these warehouses, the quantities to be produced for these warehouses and quantities to be shipped from these warehouses to customers.

In this context, a model for warehouse distribution and production was suggested by Dhaenens-Flipo (2000), The authors shows that the extension of the problem of backhaul can be used as an analogy. It suggests a model for the international warehouse location problem. Although this problem refers to geographically dispersed customers, it does not include international problems. Another model of production-distribution for the multinationals which minimize the total cost using a linear mixed-integer variables program was developed by Mohamed (1999).

In general, the location decisions of a point in a network are made for the long term. Depots, distribution centers, transshipment points are used for a period of time. In addition, the factors that influence this decision may vary with time. Particularly, the demand and cost structures can vary, but the relocation and/or resizing of a warehouse may change with a significant cost. Also, to deal with such a problem, were the dynamic location and allocation models developed? Dynamic location models have been suggested by Schilling (1980), Erlenkotter (1981) and Van Roy and Erlenkotter (1982). In the same research field, a method of dynamic programming to determine the list of pareto optimal solutions was given by

Hale and Moberg (2003). An important study of dynamic location problems and a broad overview of their mathematical formulations and case studies was the subject of Arabani and Farahani (2012).

In practice some data entries that fall within the localization model is subject to variability. An analysis of the localization of models with a tail formation; an arrival process of customers given by distribution functions, waiting times for allocation of the request, an approximated service time was introduced by Berman *et al.* (1985). A variant of the p-median problem with the use of stochastic data has been exposed by (Daskin and Jones, 1993) demand and the weights of the arcs are assumed to be random variables. Thus, under certain assumptions, a finite number of state graphs with known probabilities can be listed. The purpose of the model is to minimize the sum of the weighted distances. Other stochastic models exist (Martinez-salazar *et al.*, 2013) a branch and cut with a stochastic algorithm application was developed. Unfortunately, the stochastic models require a large number of data to empirically determine a distribution and usually, this information is not available for strategic localization problem of equipment. Probably calculator's computational solutions, supported by the sensitivity analysis for some scenarios are useful.

Recently, a new formulation and solution for location and pricing problem was given by Luer-Villagra and Marianov (2013). The article describe a situation in which an existing transport company operates a hub and spokes network type and a new company wants to enter the same market, using an incomplete network. The incoming company maximizes its profit by choosing the best locations of the nodes which are associated with optimal pricing strategy, given that the existing company applies the factory price. Customer behavior is modeled using a discrete choice model of LOGIT type. Similarly, a model of spatial interaction which seeks to simultaneously optimize the location and the choice of a set of new facilities was developed by Aboolian *et al.* (2007) Customer demand is assumed to be flexible, which is still growing as the usefulness of the service offered at the facility level increases. Service utilities can be maximized by increasing the number of facilities by making improvements of the design, or by the installation of facilities which are nearest to the clients. This article describes the specific parameters and constraints to be taken into consideration and provided a model for optimizing the decision to open one or more stores to improve the efficiency of the distribution network. To solve the proposed model, we have used an efficient metaheuristic resolution.

MATERIALS AND METHODS

In this section, we will give a brief introduction to explain issues related to the location of stores in large retails. This is a pure strategic decision which must take into account several economic and financial parameters. For example we can shed lights on the customer demand (the concentration on demand in a given geographical area), the potential of the company are reflected in its ability to conquer a new market to gain a considerable market share and to be able to compete with other businesses. The majority of the methods which are used for the optimal location of shopping centers is based on the analysis of the distribution of potential customers in a given area (eg., City). Among the theoretical methods are gravitational models, the interactive model of competition which seeks to locate the nearest point of sales which can attract most of the customers.

The origin of the location-allocation models are found to the problem of Weber 1929: "How to locate a production facility to minimize the weighted distance between the center and the sources of raw materials?" The principle of location-allocation models is that determine all the available sites simultaneously with the assessment of the application by the sites in a given geographical area and select the site (or sites) that optimize performance of the firm which will create new stores. This study shows that the purpose of location-allocation models is to optimize the number and location of the points of sale; the allocation of consumers towards these points of sale in order to determine the supply capacity of these points of sale. In present case, it has considered that the optimized design for a global network of large-scale distribution. This article is the extension of research conducted by Hlyal *et al.* (2015) that allows the location of new warehouses on existing network.

In this study, by analyzing the location of store without competition. It is supposed that a firm operate alone on the market. The problem can be described as a Capacitated P-Median Problem (CPMP). Indeed, such problem seeks to solve the optimal location of p facilities, considering distances and capacities for the service to be given by each median (Hakimi, 1964). An extensive bibliography of related problems and also a set of test problems are given in (Osman and Christofides, 1994).

This study, we continue with the research conducted by Hlyal *et al.* (2015), which addresses the issue for the two level capacitated facility location allocation, using an efficient genetic algorithm for resolution.

Problem description: We consider a retail company that wishes to open a new store in a given region where customers

and other similar retail facilities of its competitors are present. Thus this company should take in account the customers demand represented by a demand points, with each demand point representing the customers located in a small area surrounding it. Also, The Company must consider the cost of supplying its stores. Indeed, the transportation cost between its warehouses and shops must be reduced as:

• Each facility has an attractiveness ratio that is represented by a combination of several criteria, in particular
• Quality of existing infrastructure
• Economic environment
• Ease of doing business
• Political/social environment
• Availability of finance/financial environment

In this article, we have omitted the parameter of competition. It's obviously true that this approach does not represent economic reality but it aims, precisely, to analysis of the localization problem in this case.

Proposed mathematical model: The mathematical model of store location is considered as a binary integer-programming problem. The following notations are introduced to formulate the mathematical model.

Let:
i : Index for demand point, $l \in D = \{1, 2, 3, \ldots, n\}$
j : Index for store to locate, $j \in S = \{1, 2, 3, \ldots, m\}$
k : Index warehouse, $k \in W = \{1, 2, 3, \ldots, i\}$
I_j : Facility setup cost for facility, $j \in S$
d_i : Demand at demand point, $l \in D$
D_j : The total Demand at store $j \in S$ with $D_j = \sum_i d_i X_{ij}$
C_{jk} : Transportation cost from warehouse $k \in W$ and demand point, $i \in D$
Q_{ij} : Cost of service level to satisfy demand point $l \in D$ by the facility $j \in S$
A_j : Attractiveness measure of facility $j \in S$
R_j : Capacity of the store, $j \in S$

$$X_{ij} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \text{if demand point i is assigned to store j otherwise}$$

$$Y_{jk} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \text{if store j is assigned to warehouse k otherwise}$$

$$Z_j = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} 1 \text{ if store j is opened otherwise}$$

To be faithful to the real world of retail domain, we assume that n>m>i, however, m>p.

We assume that the fixed cost to establish a new store in j depend on facility attractiveness. In fact, accordingly to this model and using the terminology defined by Drezner (1994), each facility has a known attractiveness level. It is possible to

imagine a link between attractiveness and cost facility establishment. Indeed, we can see this link across the Return On Investment (ROI) parameter. If a facility has a high attractiveness rate, the investment made for establishing this facility will have a significant ROI. Thus, we can write:

$$I_j = \frac{\delta}{A_j}, \text{where} \, \delta \in \mathbb{R} > 0$$

As proposed in this equation, when attractiveness is high, the cost of establishing a facility will be reduced. However, if a facility have a minimum attractiveness rate the ROI will be most important thus the cost will be great. The problem presented is a variant of Two Levels Capacity Location Allocation Problem (TLCLAP) presented in (Hlyal *et al.*, 2015). Since we have two levels in the distribution network and we also have the capacity constraint.

The model can be formulated as follows:

$$\min \delta \sum_{j\in S} \frac{1}{A_j} Z_j + \sum_{k\in W}\sum_{j\in D} C_{jk}.D_j.Y_{jk} + \sum_{i\in D}\sum_{j\in S} Q_{ij}X_{ij} \qquad (1)$$

Subject to:

$$\sum_{j\in S} X_{ij} = 1 \quad \forall \, j \in S \qquad (2)$$

$$\sum_{k\in W} Y_{jk} = 1 \forall \, k \in W \qquad (3)$$

$$\sum_{j\in S} Z_j = p \forall \, j \in S \qquad (4)$$

$$\sum_{i\in D} d_i X_{ij} \leq \Gamma_j \forall \, j \in S \qquad (5)$$

$$X_{ij}, Y_{jk}, Z_j \in \{0,1\} \qquad (6)$$

The objective function (1) is to minimize the total cost for a given firm, the cost for establishing a store and the cost due to a level service that should be in a given facility. Constraints (2) guarantee that each demand point is assigned to some facility. Constraints (3) ensure that any store should be served by a warehouse. Constraints (4) means that the number of opened facility is exactly equal to p. Constraints (5) ensure that the total demands assigned to a store j do not exceed its capacity. Constraints (6) provide the binary condition.

Variable neighborhood search for the TLCLAP problem: In this section, we describe the components of our proposed VNS heuristics for the TLCLAP: the solution representation, the initialization process, the local search neighborhoods the shaking step. We also discuss a modification of the heuristic that allows us to solve the TLCLAP problem.

Basic variable neighborhood search: As capacitated p-median is considered as a NP-hard problem (Hakimi, 1964; Garey and Johnson, 1979), we propose a metaheuristic to solve the proposal model. In fact, we use a Variable Neighborhood Search (VNS) that is considered as a metaheuristic for solving mathematical optimization problems. This metaheuristic was introduced by Mladenovic and Hansen (1997). The fundamental idea is a systematic change of neighborhoods in two stages:

• Local search: when a local minimum is determined
• Shaking: when escaping local minimum

Let us denote by:

N_k, $k = 1,\ldots, k_{max}$ a finite set of pre-selected neighborhood structures, $N_k(x)$ the set of solutions in the kth neighborhood of x, where x is defined as a solution in X that represent the feasible set given by the set of constraints over the solution space. the algorithm of basic VNS is given as follows:

Algorithm 1: Basic VNS
Initialization:
• Select the set of neighborhood structures N_k, $k = 1,\ldots, k_{max}$
• Find an initial solution x
Choose a stopping condition Stopcondit;
While (Stopcondit =false)
    k = 1
Begin
Repeat
Shaking:
-Generate a point x' at random from the k *th* neighborhood of x,x' ∈ $N_k(x)$
Local search:
-Apply some local search method with x' as initial solution;
denote with x" the so obtained local optimum;
Move or not:
-If the local optimum x" is better than the incumbent x then
• move there(x" = x),
• continue the search with N_1 (k = 1)
Else
k = k+1
Until (k = k_{max})
End

The stopping condition can be, for example, a maximum execution time or a maximum number of iterations or maximum number of iterations since the best improvement.

As we have two levels in our problem, the VNS algorithm can be applied in two parallel phases. First, to the location of stores and allocating demand points to its stores, then for the allocation of stores to their corresponding warehouses.

Resolution approach: Let us denote by:

Ω : The Solution space;
$\ell : \Omega \to \mathbb{R}$, the objective function;
$\Psi \subset \Omega$: A feasible solution set given by problem constraints

The problem of mathematical optimization is defined as follow:

$$\min \{l(x), x \in \Psi\}$$

For resolution, we choose the same encoding used in the article (Hlyal *et al.*, 2015). Indeed, this encoding allows not only to observe some problem constraints, but also to have a unique form including all decision variables. Figure 1 shows the solution encoding, we suppose that we have n = 5, m = 4, l = 2, p = 3.

To optimize the execution time, we will achieve an algorithm that will create the solution space that will contain all feasible solutions. Indeed, encoding solution allows to quickly having a solution space. The chosen approach is built around a method that creates a sub-cluster which represents the first level in the distribution network between warehouses and stores.

The choice of the initial solution is important for every local search heuristic method. That's why we propose an efficient method for generating initial solutions.

Initial solution procedure: We can define the steps of generating the solution space as follows:

• Choose randomly from S stores given in the model, p stores that will be retained in the problem
• To perform the sub-cluster, we affect the store to its corresponding warehouse, so that the cost of transport between these two facility is minimum
• Assign each sub-cluster at a particular demand point to build the solution according to store capacity and attractiveness parameter

At step 1, we can define a fitness function, as an analogy with Genetic Algorithms method. This function will serve for the choice of the store.
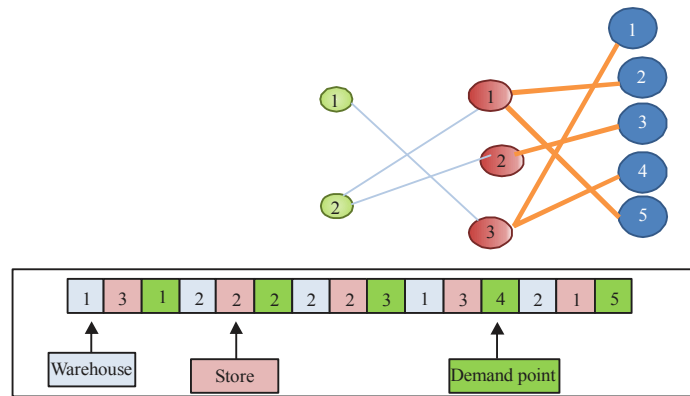
Fig. 1: Solution representation

So, let us define, $f_j = \dfrac{1}{A_j} + \dfrac{1}{\Gamma_j}$ as a fitness function. With this definition, we can retain the stores with high attractiveness and those having the capability to support flow of a large number of demand points. We can use the roulette wheel selection as an operator for having the store. The selection of a store j will be with the probability:

$$p_j = \frac{f_j}{\displaystyle\sum_{j=1}^{m} f_j}$$

Local searchers: The local search is an important step for the success of any VNS algorithm. It proceeds from an initial solution and using a sequence of local changes, improves the value of the objective function until a local optimum is reached. The VNS systematically uses the idea of change of neighborhood during the search in a dynamic way.

For similar problems to TLCLAP, some local research approaches are adopted. We can report in this context, the approach used by Ilic *et al.* (2010), based on three types of local search: Allocate, Locate and Alternate. Based on this approach, we can use only the allocate an locate procedure since the representation allows to easily have a local search by changing cluster position or changing the p store elected in the solution representation. However, the allocate and locate procedures are so particular.

Allocate: The demand point in the solution presentation can change the position to another cluster, where the store capacity allows that. According to the example in Fig. 1, we will observe the store 1 and 2:

$\Gamma_1 = d_5 + q_1$ with q_1 is the remaining capacity at the store 1.
$\Gamma_2 = d_2 + d_3 + q_2$, with q_2 is the remaining capacity at the store

2. If $q_2 \geq d_5$ then we can affect the demand point 5 to store 2, indeed we will replace the store 1 in the last cluster by 2.

In addition to this new solution we can also having:
where, $q_1 \geq d_2 + d_3$, we can affect the demand point 2 and 3 to store 1, indeed we will replace the store 2 in the second and third cluster by 1.

We can observe that the choice of store 1 and 2 is due to the fact that the two are attached to the warehouse 2. In this way we will not have to make warehouse assignments in the first network level.

In the case that the allocation procedure does not allow to have feasible solutions, especially for the first network level, procedure termination requires making reallocations of warehouse, so we will be based on the transport costs between store and warehouse only for modified clusters.

Locate: Since the selection of stores is performed using the function fitness, we can, once again, generate other stores using the best fitness value for stores that are not open. So, suppose that $f_{j'}$ is maximum where j' is a store initially not selected and $f_{j'}$ is minimum where j denotes the store in the initial solution x with the lowest fitness value. We substitute the store j' by j in in all clusters. Finally, we conclude with the allocation of warehouses in the first level. In this way, the probability of having infeasible solutions is reduced.

By this way of building local search, it will bring up two versions of VNS. Indeed, for the first version, called VNS1, we will consider the approach "Locate". Moreover, for the second version, called VNS2 the "Allocate" approach is applied.

Shaking procedure: To implement a VNS algorithm we should define a neighborhood structures. Thereby, based on research works conducted by Fleszar and Hindi (2008), neighborhood structures can be conceived as below: The kth neighborhood of solution x, denoted by $N_k(x)$, is defined as a set of solutions

Table 1: Set of problem instances

Sets	Problem parameters			
	n	m	l	p
A	30	10	2	6
B	70	20	6	8
C	120	40	6	12
D	300	20	10	20

Table 2: Results for set A of problem instances

Instance	VNS1			VNS2		
	Optimal cost	Gap (%)	CPU time (Sec)	Optimal cost	Gap (%)	CPU time (Sec)
1	2036.00	1.69	0.14	2014.00	0.61	0.12
2	2012.00	0.11	0.32	2039.00	0.12	0.20
3	2040.00	1.89	0.30	2014.00	0.48	0.48
4	2018.00	5.64	0.52	2000.00	1.11	0.64
5	2019.00	3.40	0.50	2009.00	0.65	0.55
6	2016.00	3.00	0.96	2002.00	0.58	0.96
7	2005.00	3.36	0.98	2039.00	0.39	1.12
8	2036.00	0.13	1.20	2038.00	0.06	0.96
9	2010.00	1.16	0.90	2030.00	0.16	1.26
10	2027.00	2.40	1.30	2040.00	0.60	1.50
Best	2005.00	0.11	0.14	2000.00	0.06	0.12
Avg	2021.90	2.28	0.712	2022.50	0.48	0.779

in which k elements in $\aleph(x)$ are replaced by k elements from $S \setminus \aleph(x)$, where $\aleph(x)$ is a set of all selected store in the network $card(\aleph(x)) = p$. For the example given in Fig. 1, $\aleph(x) = \{1, 2, 3\}$.

In the Shaking step, we generate a random assignment from the kth neighborhood of the current solution. As we try to test the response time, the stopping condition is a maximum number of iterations since the best improvement.

Algorithm 2 gives the approach for application the VNS for the problem TLCLAP.

Algorithm 2: Basic VNS for TLCLAP
- Generate an initial solution x
- best improvement = false;
While (best improvement = false)
l = ∞
Begin
Repeat
-Generate x', x, x' ∈ N_k (x)
-Apply some local search method with x' as initial solution;
-set x" as local optimum for x';
-If (x")>l(x) then
    - x" = x
    - continue the search with N_1 (k = 1)
Else
k = k+1
Until (k = k_{max})
l = l (x")
End
if (l in min) then best improvement = true

RESULTS AND DISCUSSION

The proposed heuristic was tested on four sets of problem instances A, B, C and D. Each set have 10 instances established according to input data. Table 1 shows the detail of all sets. Computational experiments were carried out on a Intel i5 2.53 GHz. The software was coded in C#. In order to analyze the performance of the proposed simulation embedded VNS, the said separate sets of experiments have been performed. First, to evaluate the performance of the proposed VNS under two versions VNS1 and VNS2, its performance was compared with exact results obtained using CPLEX implemented with the same computer performances.

For tests, we generate random data that contains store capacity, transportation cost the results are provided for two VNS versions VNS1 and VNS2 compared to results obtained by CPLEX, thus, we can calculate the Generalized Assignment Problem Gap value in each instance. Table 2-5 shows the counts and computation times for the various components of the VNS versions over all the instances of each set.

In Table 2, we can see that the CPU time given, respectively by VNS1 and VNS2 are close (0.712 for VNS1 and 0.779 for VNS2), but the Gap value for VNS2 is reduced compared to Gap value for VNS1. Also, average best objective function value remain approximately the same.

In Table 2, we can see that the CPU time given, respectively by VNS1 and VNS2 are close (2.2 for VNS1 and 1.988 for VNS2). However, compared to Table 2, the response time is to important. With respect to Gap value, we can see that it grows quickly for VNS1 (5.64 vs 2.28).

The results given in Table 4, allow saying that the gap value becomes, again, great for VNS1 compared to the

Table 3: Results for set B of problem instances

Instance	VNS1			VNS2		
	Optimal cost	Gap (%)	CPU time (Sec)	Optimal cost	Gap (%)	CPU time (Sec)
11	2007.00	3.41	1.76	2008.00	1.00	1.21
12	2027.00	3.75	1.8	2014.00	1.20	2.04
13	2028.00	10.44	2.08	2037.00	2.79	1.69
14	2013.00	7.42	1.82	2029.00	1.80	1.68
15	2033.00	7.08	2.25	2022.00	1.92	1.95
16	2008.00	1.29	1.76	2035.00	0.04	2.40
17	2039.00	5.78	2.72	2024.00	1.52	1.70
18	2002.00	8.73	2.34	2028.00	1.70	2.16
19	2010.00	7.81	2.47	2031.00	1.47	2.85
20	2002.00	0.70	3.0	2006.00	0.10	2.20
Best	2002.00	0.70	1.76	2006.00	0.04	1.21
Avg	2016.90	5.64	2.2	2023.40	1.35	1.988

Table 4: Results for set C of problem instances

Instance	VNS1			VNS2		
	Optimal cost	Gap (%)	CPU time (Sec)	Optimal cost	Gap (%)	CPU time (Sec)
21	2000.00	18.89	2.31	2021.00	3.46	2.52
22	2018.00	11.61	2.86	2007.00	2.85	2.42
23	2034.00	16.82	3.91	2008.00	4.10	2.30
24	2023.00	16.63	3.60	2007.00	3.69	2.64
25	2022.00	1.87	3.75	2033.00	0.22	3.5
26	2019.00	21.50	3.12	2028.00	3.80	2.6
27	2021.00	25.54	4.32	2005.00	4.60	4.05
28	2004.00	17.83	4.48	2004.00	2.83	3.08
29	2002.00	4.00	3.19	2010.00	0.47	3.77
30	2005.00	35.30	5.10	2037.00	4.29	4.50
Best	2000.00	1.87	2.31	2004.00	0.22	2.30
Avg	2014.80	17.00	3.664	2016.00	3.03	3.138

Table 5: Results for set D of problem instances

Instance	VNS1			VNS2		
	Optimal cost	Gap (%)	CPU time (Sec)	Optimal cost	Gap (%)	CPU time (Sec)
31	2026.00	40.89	3.41	2027.00	4.79	4.65
32	2006.00	7.25	4.16	2024.00	2.44	4.80
33	2036.00	2.00	5.28	2000.00	1.20	4.29
34	2001.00	4.54	4.08	2013.00	1.40	5.10
35	2026.00	5.96	6.30	2001.00	2.36	5.25
36	2034.00	1.25	5.04	2018.00	0.19	5.76
37	2014.00	15.43	6.66	2032.00	4.60	4.07
38	2014.00	0.05	5.32	2017.00	0.03	4.56
39	2024.00	16.29	6.63	2009.00	4.87	4.68
40	2022.00	0.85	6.40	2004.00	0.48	5.20
Best	2001.00	0.05	3.41	2000.00	0.03	4.07
Avg	2020.30	9.45	5.328	2014.50	2.23	4.836

previous results. The average CPU time in VNS2 is reduced compared to that of VNS1. The results of set D confirm the increase of the Gap value for the VNS1, when the Gap value for VNS2 remains substantially invariable.

The present study was concerned, in most general terms, with how location allocation in a TLCLAP is carried out, in particular with the using an adapted metaheuristic to give resolution. Indeed, a new VNS algorithm is used as a new kind of approximate algorithm which basically tries to combine basic VNS methods to a special mechanism inspired by Genetic Algorithm. The aim is efficiently and effectively exploring a search space.

The result obtained by the proposed VNS approach seems to be efficient to resolve the TLCLAP. It allows having a good solution in a short time, regarding to similar NP-Hard problem. Also, for the small instant we can use either VNS1 or VNS2. However, the VNS2 remain the efficient algorithm for the important instances.

Furthermore, the comparison of this result with that of the genetic algorithm by Hlyal *et al.* (2015), appears quite significant in terms of computing time. The power of the proposed VNS is due to several factors. First, the solution representation that allows to keep feasible solutions and to build a good space solution, based on fitness function inspired by the genetic algorithm. Secondly, the approach set out for having initials solutions is very effective. Finally, the generation of neighborhoods and local search approach are used to run the VNS in a reasonable time. These results, then, constitute support for the view that adaptive metaheuristic gives a best result regarding to the problem (Ochi *et al.*, 2001). However, a comparison at the generation of the initial solution space highlighted the effectiveness of the approach taken in this document. The new population-based hybrid meta-heuristic for the periodic vehicle routing problem with time windows proposed by Nguyen *et al.* (2011) seems be similar, in terms of performance of creating an initial solution space. This result comes from the fact that it is a kind of hybridization that explores the infeasible part of the search space to repair infeasible solutions.

Regarding the analysis of GAP values, the results obtained confirm those made by Almada-Lobo snd James (2010). The CPLEX outperforms the VNS in terms of deviation for the smaller sized problems. In fact, for most of the instances (sets A and B). The CPLEX found the optimal solution. However, the heuristics outperformed CPLEX for the larger problem instances (Sets C and D). The reason for this observation in performance can perhaps be explained by considering the shaking method used for the two search techniques.

CONCLUSION

The design and management of a distribution system is one of the most critical problems in logistics and in facility management. This paper deals with the so called facility location allocation problem, i.e., with the simultaneous decisions regarding the design and management of a distribution network. However, the said network refers to a two level capacitated location allocation problem. Because through three components (Warehouses, Stores and demand point), we can say that we have two levels in the network, furthermore we consider at the same time the store capacity for facilities. The problem is an NP-hard, combinatorial optimization problem suitable for solving by a metaheuristic. Here we develop an effective VNS heuristic for solving the TLCLAP. The proposed VNS is an effective response to the need of location stores and their allocation to several demand

point. The optimization process is based on the determination of the solution encoding that allows having an admissible solution to the problem. In this context, a suitable method is used to generate an initial solution, based on fitness value of facility.

In addition, a shaking approach is proposed to fulfill the proposed VNS. Besides, local's searches given in this paper results in two versions of VNS algorithm. An application of the introduced model and resolution is presented with a discussion of the obtained results. They demonstrate the efficacy of the VNS2 based on allocation criterion. Further research can be achieved on the application of this model taking in account the probabilistic demand.

REFERENCES

Aboolian, R., O. Berman and D. Krass, 2007. Competitive facility location and design problem. Eur. J. Operat. Res., 182: 40-62.

Ahmadi-Javid, A. and P. Hoseinpour, 2015. A location-inventory-pricing model in a supply chain distribution network with price-sensitive demands and inventory-capacity constraints. Transport. Res. Part E: Logist. Transport. Rev., 82: 238-255.

Almada-Lobo, B. and R.J.W. James, 2010. Neighbourhood search meta-heuristics for capacitated lot-sizing with sequence-dependent setups. Int. J. Prod. Res., 48: 861-878.

Arabani, A.B. and R.Z. Farahani, 2012. Facility location dynamics: An overview of classifications and applications. Comput. Ind. Eng., 62: 408-420.

Berman, O., R.C. Larson and S.S. Chiu, 1985. Optimal server location on a network operating as an *M/G*/1 queue. Operat. Res., 33: 746-771.

Bhutta, K.S., 2004. International facility location decisions: A review of the modelling literature. Int. J. Integrat. Supply Manage., Vol. 1. 10.1504/IJISM.2004.004596

Bouzaabia, O. and S. Boumaiza, 2013. Le role de la performance logistique dans la satisfaction des consommateurs: Investigation dans la grande distribution. La Revue Gestion Organisation, 5: 121-129.

Bowersox, D., D. Closs and T.P. Stank, 2000. Ten mega-trends that will revolutionize supply chain logistics. J. Bus. Logist., 21: 1-16.

Canel, C. and B.M. Khumawala, 2001. International facilities location: A heuristic procedure for the dynamic uncapacitated problem. Int. J. Prod. Res., 39: 3975-4000.

Cheng, E.W.L., H. Li and L. Yu, 2007. A GIS approach to shopping mall location selection. Build. Environ., 42: 884-892.

Daskin, M.S. and P.C. Jones, 1993. A new approach to solving applied location/allocation problems. Computer-Aided Civil Infrastr. Eng., 8: 409-421.

Dhaenens-Flipo, C., 2000. Spatial decomposition for a multi-facility production and distribution problem. Int. J. Prod. Econ., 64: 177-186.

Drezner, T., 1994. Optimal continuous location of a retail facility, facility attractiveness and market share: An interactive model. J. Retail., 70: 49-64.

Erlenkotter, D., 1981. A comparative study of approaches to dynamic location problems. Eur. J. Operat. Res., 6: 133-143.

Fleszar, K. and K.S. Hindi, 2008. An effective VNS for the capacitated *p*-median problem. Eur. J. Operat. Res., 191: 612-622.

Garey, M.R. and D.S. Johnson, 1979. Computers and Intractability: A Guide to the Theory of NP-Completeness. W.H. Freeman and Company, San Francisco.

Gonzalez-Benito, O., P.A. Munoz-Gallego and P.K. Kopalle, 2005. Asymmetric competition in retail store formats: Evaluating inter- and intra-format spatial effects. J. Retail., 81: 59-73.

Hakimi, S.L., 1964. Optimum locations of switching centers and the absolute centers and medians of a graph. Operat. Res., 12: 450-459.

Hale, T.S. and C.R. Moberg, 2003. Location science research: A review. Ann. Operat. Res., 123: 21-35.

Hlyal, M., A.A. Bassou, A. Soulhi, J. El Alami and N. El Alami, 2015. Designing a distribution network using a two level capacity location allocation problem: Formulation and efficient genetic algorithm resolution with an application to a moroccan retail company. J. Theoret. Applied Inform. Technol., 72: 294-306.

Ilic, A., D. Urosevic, J. Brimberg and N. Mladenovic, 2010. A general variable neighborhood search for solving the uncapacitated single allocation p-hub median problem. Eur. J. Operat. Res., 206: 289-300.

Jang, M. and C.D. Kang, 2015. Retail accessibility and proximity effects on housing prices in Seoul, Korea: A retail type and housing submarket approach. Habitat Int., 49: 516-528.

Kumar, V., S. Sunder and A. Sharma, 2015. Leveraging distribution to maximize firm performance in emerging markets. J. Retail., 91: 627-643.

Luer-Villagra, A. and V. Marianov, 2013. A competitive hub location and pricing problem. Eur. J. Operat. Res., 231: 734-744.

Martinez-Salazar, I.A., J. Molina, F. Angel-Bello, T. Gomez and R. Caballero, 2013. Solving a bi-objective transportation location routing problem by metaheuristic algorithms. Eur. J. Operat. Res., 234: 25-36.

Mladenovic, N. and P. Hansen, 1997. Variable neighborhood search. Comput. Operat. Res., 24: 1097-1100.

Mohamed, Z.M., 1999. An integrated production-distribution model for a multi-national company operating under varying exchange rates. Int. J. Prod. Econ., 58: 81-92.

Nguyen, P.K., T.G. Crainic and M. Toulouse, 2011. A hybrid genetic algorithm for the periodic vehicle routing problem with time windows. Technical Report CIRRELT-2011-25, April 2011, CIRRELT, Montreal, Canada.

Ochi, L.S., M.B. Silva and L. Drummond, 2001. Metaheuristics based on GRASP and VNS for solving the traveling purchaser problem. Proceedings of the 4th Metaheuristics International Conference, July 16-20, 2001, Porto.

Osman, I.H. and N. Christofides, 1994. Capacitated clustering problems by hybrid simulated annealing and tabu search. Int. Trans. Operat. Res., 1: 317-336.

Reinartz, W., B. Dellaert, M. Krafft, V. Kumar and R. Varadarajan, 2011. Retailing innovations in a globalizing retail market environment. J. Retail., 87: S53-S66.

Schilling, D.A., 1980. Dynamic location modeling for public-sector facilities: A multicriteria approach. Decis. Sci., 11: 714-724.

Turhan, G., M. Akalın and C. Zehir, 2013. Literature review on selection criteria of store location based on performance measures. Procedia-Social Behav. Sci., 99: 391-402.

Van Riel, A.C.R., 2012. Strategic Service Innovation Management in Retailing. In: Service Management: The New Paradigm in Retailing, Kandampully, J. (Ed.). Springer, New York, USA., pp: 83-95.

Van Roy, T.J. and D. Erlenkotter, 1982. A dual-based procedure for dynamic facility location. Manage. Sci., 28: 1091-1105.

Weber, A., 1929. Theory of the Location of Industries. University of Chicago Press, Chicago.