Dynamic location of distribution centres, a real case study

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Abstract

A review of literature indicates that a problem related with Distribution Networks Design (DND) involves several decisions to be optimized, such as location, allocation, inventory, and routing. In this paper, we focus only on the location decision, proposing and exemplifying the following hypothesis: the location of Distribution Centres (DCs) changes whether the product demand at each demand node has extremely high and unexpected variability through time and investment costs for the location of DCs are low (mobile infrastructure). The aim is to exemplify with a real case that location is not always a strategic decision.

Keywords: Distribution Networks Design; location decisions; $p$-median problem; demand variability

Nomenclature

<table>
<thead>
<tr>
<th>DC</th>
<th>Distribution Centre</th>
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<tr>
<td>V</td>
<td>set of demand nodes</td>
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<tr>
<td>p</td>
<td>number of DCs to be located</td>
</tr>
<tr>
<td>h</td>
<td>demand</td>
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1. Introduction

The problem of distribution network design (DND) involves a set of decisions to be optimized, some of which are location, allocation, inventory management and routing (Ambrosino et al., 2009). In this paper, we study the location decision to propose and exemplify the following hypothesis: the location of Distribution Centres (DCs) changes whether the product demand at each demand node has extremely high and unexpected variability through time and investment costs for the location of DCs are low (mobile infrastructure). This is a real problem; hence, companies in a similar situation must be flexible to change the location of their DCs in the short time (less than one year) to minimize costs.

Three levels of planning can be distinguished depending on the time horizon, namely strategic (decisions with horizon of more than a year to reach), operational (decisions with horizon of days, hours, or even minutes), and tactical (decisions with horizons between strategic and operational) (Miranda and Garrido, 2004). Vidal and Goetschalckx (1997) mention some examples of strategic decisions: transport mode choice, number of warehouses and DCs, location of warehouses and DCs, and capacity of warehouses and DCs. Current et al. (1997) explain that when the location of DCs involves a high capital investment, this location is a long-term decision or strategic decision. Owen and Daskin (1998) appoint that high costs associated with property acquisition and facility construction make facility location or relocation projects long-term investments, hence facilities are expected to remain operable for an extended time period. Drezner (1995) presents a case study to locate DCs when the demand of the product is variable and location costs are paid by customers. In this study, once a demand node is located as DC, it will remain as DC in the long term, and then the location of DCs is a strategic decision. In our study case, we show that the decision of location DCs can be also tactical for products with unexpected extremely high demand and with low investment costs for the location of DCs (mobile infrastructure), contrary to what is mentioned by Vidal and Goetschalckx (1997), Ratick and Revelle (1997) and Owen and Daskin (1998).

This paper presents a real case study to exemplify the hypothesis. The case study is the problem of a hazardous material company. The company wants to optimize its current distribution network. The problem is identified as a problem of Distribution Network Design (DND), which involves location of DCs, allocation of demand nodes to DCs, inventory and routing decisions. This problem of DND is solved by Carmona Benítez et al., (2013), for just a time period. For this reason, this paper is focused on the location of DCs, showing that the best location changes depending on the variability of the demand through time. Some real cases present unexpected high changes in the demand, which are difficult to forecast. These changes could be influenced by social or cultural factors, natural disasters, epidemics, and any other unexpected phenomenon.

In this case study, the company is vertically integrated but the product transportation is outsourced. The product demand is high and extremely variable, and investment costs are low because storage infrastructure is mobile. Annually, the company issues a tender to determine which transportation company will distribute the material. This decision is taken by the manager of the company, trying to minimize total cost. According to Vidal and Goetschalckx (1997) and Ratick and Revelle (1997), transportation is a strategic decision that companies must take every year. However, whether our hypothesis is true, the tender shall be made in a period of less than one year, what is a tactic decision rather than a strategic decision.
In Section 2, the role of the location decision in the Problem of DND is clarified. In Section 3, the application of the myopic algorithm to the $p$-median problem, for solving the location of DCs, is described. In Section 4, the experimental data used to exemplify the hypothesis are presented. In Section 5, results and a sensitivity analysis for the case study are shown. Finally, conclusion and references are included.

2. Location decision in the Problem of DND

The problem of distribution network design (DND) is to establish the best way to distribute products or goods from DCs to demand nodes by selecting the structure of the network, satisfying customers’ demand, and minimizing total cost. The objective function is generally expressed in terms of transportation, assembly, inventory, and opportunity costs (Ambrosino et al., 2009). The problem of DND involves a number of decisions to be taken; some of them are location, allocation, fleet assignment, inventory management, and routing. These decisions are related with the location-routing problem (LRP) and the inventory routing problem (IRP). The LRP addresses facility location and vehicle routing decisions. The IRP addresses inventory and routing decisions.

The location-routing problem (LRP) combines location of DCs and customer allocation decisions (Wesolowsky and Trustcott, 1975) (Halper, 2011) (Köksalan and Sural, 1999). The LRP solves vehicle routing and facility location decisions simultaneously (Min et al., 1998). These problems can take into account constraints on vehicle capacity, DCs storage capacity, and customer demands. The aim is to minimize transportation and location costs. Mathematical models and exact solution techniques to solve the LRP are studied by Min et al., (1998) and Nagy and Salhi (2007). Examples of LRP models applied to real situations are reported by Bruns and Klose (1995) and Lin and Kwok (2006). Min et al., (1998) explain the origin and evolution of LRP problems. Their formulations and classifications consider variations on: demand, vehicle capacities, facilities’ storage capacities, number of DC, and fleet size. Nagy and Salhi (2007) explain the classification of LRPs and heuristics and exact methodologies to solve them.

This paper only studies the location problem solving the location of DCs for a real case study in the Mexican road network. Operational costs are given for each pair of demand nodes, and investment costs for the location of DCs are given for each demand node. DCs are storage movable tankers. According to Higgins et al., (2012) the tankers are classified like warehouses and can approach the functional scale of DCs. warehouses are typically places for inventory and storage, and they perform the basic function of acting as a buffer between suppliers, manufacturers, and customer to smooth time and demand constraints in the supply chain. Some warehouses are more complex, performing distribution, maintenance, and value added activities, and can approach the functional scale of DCs.

The tankers are geographically distributed. So, the location of these movable tankers is a discrete problem based on $p$-median models according to Daskin (2008).

Location problems arise from the need to find the most suitable place to locate facilities such as DCs, manufacturing plants, landfills, fire and police stations, ambulance, airports, etc. In general, the problem can be stated as (Daskin, 1995): given the location of each demand node, demands, transportation costs, times, and distances, to determine the number of services, the geographic location, and the storage capacity of the DCs so that transportation costs and operating costs are optimized.

Location problems have been studied since the early 70's. The most named and basic location problems are cited in Current et al. (2002). Daskin (1995) classifies location problems as: continuous models, network models, and discrete models. In the discrete location models, there may or may not be an underlying distance metric. Distances or costs between any pair of nodes may be arbitrary, although they generally do follow some rule (e.g., Euclidean, Manhattan, network or great circle distances). Demands generally arise on the nodes and the facilities are restricted to a finite set of candidate locations. The median-based models minimize the average demand-weighted distance between demand nodes and the facilities to which they are assigned (Daskin, 2008). Such models are typically used in distribution planning contexts, where minimizing the total transportation costs is essential. In this case study, we study a $p$-median problem to minimize the average demand-weighted cost (distance) between demand nodes and DCs to which they are assigned. The $p$-median problem is solved by applying the myopic algorithm (Daskin, 1995).
3. Location of DCs applying the myopic algorithm to the $p$-median model

In Carmona Benítez et al., (2014), a methodology is developed to solve the problem of DND. The methodology consists of three phases to minimize the total costs associated with the distribution network; this cost is mainly formed of operational (which includes transportation cost), inventory, location or investment, and opportunity costs.

In Phase 1, a set of $p$ DCs are located. In Phase 2, end facilities are assigned based on the existing road network. Phase 1 and Phase 2 built one neighborhood for each DC, proposing a network. Phase 1 is solved as an uncapacitated $p$-median problem by applying a myopic algorithm (Church, 1974). Once the DCs are located, Phase 2 is solved by the neighbourhood search algorithm (Maranzana, 1964) or the exchange algorithm (Teitz and Bart, 1968) to create $p$ number of neighbourhoods. After the application of Phase 2 algorithms, Carmona Benitez et al., (2014) suggest to assign end facilities to DCs according with three assignment strategies (S1, S2 and S3) that are based on facilities demand: high, medium, and low. The facility assignment strategies are: S1 – all facilities are assigned to their nearest DC no matter their demand group; S2 – higher demand facilities are assigned to the main facility ($\theta$) and the other facilities are assigned to their nearest DC; and S3 – lower demand facilities are assigned to their nearest DC and higher and medium demand facilities are assigned to $\theta$. Also, inventory management strategies (IMS) have to be considered. IMS determines the quantity of product that has to be shipped to a facility $i$ every time $T$. The value of $T$ is constrained to the selected IMS. Carmona Benitez et al. (2014) discuss three IMS: IMS1 – the company requires shipping enough product to fill up the facilities warehouses every time $T$ without considering the product’s quality certificate ($T$); IMS2 – the company requires shipping the optimum quantity of product to fill the facilities warehouses up to an optimal reorder point by ordering a shipment every time $T$, in this strategy the company takes care of $T$, then $T \leq T$; IMS3 – the company requires shipping a maximum amount of product equal to $n$ times $\lambda$ to those facilities where $T > T$, in this strategy the company takes care of $T$, then $T \leq T$. Then, a set of scenarios are assessed, which includes changes on: number of DCs, assignment strategy, homogeneous or heterogeneous fleet and IMS. Finally, in Phase 3 the best scenario is chosen, hence the optimum number $p$ of DCs to locate is determined.

In this paper, phase 1 of the methodology is used to locate DCs and to exemplify the hypothesis through a sensitivity analysis, changing the demand of nodes over time and considering low location costs.

3.1. The $p$-median problem

The $p$-median problem is to find the location of $p$ facilities on a network so that the total cost is minimized. The $p$-median location problem is probably the most applied location model. Demand is generated at a set of points (nodes in a network environment). The demand at each demand point is given as a weight. A set of $p$ facilities must be located. Each customer is serviced by the closest facility. The objective function is to minimize the total travel time for all customers (Drezner and Drezner, 2007). Given a directed graph $G(V,A)$, $|V| = n$, the $p$-median problem $pMED(G)$, consists of determining $p$ nodes (the median nodes) minimizing the total distance to the other nodes of the graph (Avella et al., 2007). The cost of serving demand at node $i$ is given by the product of the demand at node $i$ and the costs between demand node $i$ and the nearest facility to node $i$. In our case study, we consider operational cost between node pairs instead of distance. The following references are suggested for greater detail about the $p$-median problem: Current et al., 2002; Mirchandani and Francis, 1990; Carling and Hakansson, 2013; Daskin, 2008, and Hakimi, 1965.

The $p$-median problem may be formulated using the Daskin (1995) notation, as follows:

**Inputs:**

- $h$ = demand at node $i$
- $d$ = operational cost between demand node $i$ and candidate site $j$
- $p$ = number of facilities to locate

**Decision Variables:**
The objective function (1) minimizes the total demand-weighted costs between each demand node and the nearest facility and the location cost \( f_j \). Constraint (2) requires each demand node \( i \) to be assigned to exactly one facility \( j \). Constraint (3) states that exactly \( p \) facilities are to be located. Constraints (4) link the location variables \( (X_j) \) and the allocation variables \( (Y_{ij}) \). They state that demands at node \( i \) can only be assigned to a facility at location \( j \) \((Y_{ij}=1)\) if a facility is located at node \( j \) \((X_j=1)\). Constraints (5) and (6) are the standard integrality conditions.

Hakimi (1965) showed that at least one optimal solution to the \( p \)-median problem consists of locating only a subset of the demand nodes. Kariv and Hakimi (1979) showed that the \( p \)-median problem is a NP-hard problem. A number of algorithms have been developed to solve the \( p \)-median model both heuristically and optimally. In this paper, we apply a myopic algorithm (Daskin, 1995).

3.2. The myopic algorithm

The uncapacitated \( p \)-median problem is solved by a myopic algorithm (Fig. 1), which let us answer the following question: what demand nodes must be DCs?

Myopic algorithm is used to build a first solution that can be the location of one or more DCs (whether locations are optimal or not).

Despite the obtained solution by this algorithm may be not optimal, this algorithm is appealing due to a number of reasons. First, it is very simple to understand and to implement. Second, in practice, many decisions are made in this way. Usually, we have to locate facilities which cannot be moved, then it is required the location of a few (often only one or two) new facilities. If we are only required to locate one additional facility and the existing facilities cannot be relocated, this approach will clearly be optimal (Daskin, 1995).
4. Experimental data

Data has been provided mainly by the company but they are confidential. The company provided five years historical demand data per demand node; this information is available for days, weeks, months and years. The myopic algorithm uses semiannual demand and transportation costs per route and type of vehicle. The product is transported by three different capacity vehicles. Heavy trucks are forbidden on secondary roads by a national norm NOM-012-SCT-2-2008 (SCT, 2008), so the number of feasible paths between DCs and demand nodes is low.

The demand-weighted costs are considered. Operational cost includes tolls, travel expenses, insurance, fuel and depreciation and is dependent on the type of vehicle and the road characteristics. Operational costs were previously calculated for each node pair, based on the Vehicle Operating Model (Archondo-Callao and Faiz, 1994) which was adapted to Mexican vehicles and roads by Lozano et al., (2012), also considering taxes and the trucks company’s profit.

5. Simulation results and sensitivity analysis

In this section, results are presented. Myopic algorithm is applied for two separate times, at \( t = 0 \) and after six months (\( t = 1 \)). For each time, the algorithm is applied for each type of vehicle (W1, W2, and W3), and for \( p = 1 \) to \( p = 4 \). Then, 24 scenarios are generated, 12 for \( t = 0 \) and 12 for \( t = 1 \). Results indicate that locations of DCs are independent of the type of vehicle. Results are shown in Fig. 2, for \( t = 0 \) and for \( t = 1 \), both for \( p = 2, 3 \) and 4.

The first DC is located at node SF. SF is a DC in all the scenarios because it is the main DC, i.e. all the product enter the network through SF.

If \( p=2 \) and \( t=0 \), the DCs are located at nodes SF and FE, but if \( p=2 \) and \( t=1 \), the DCs are located at nodes SF and AG. These situations exemplify the presented hypothesis. A similar situation is obtained for \( p=3 \) and \( p=4 \) (see Fig. 2).

These results suggest that the location of the DC’s changes over time due to the unexpected high variability of demand and low investment costs.
6. Conclusions

The presented hypothesis: the location of DCs changes whether the product demand at each demand node has unexpected extremely high variability through time and investment costs for the location of DC are low (mobile infrastructure) is exemplified for a real case study.

The results are different to other studies reported in literature, where demand and investment cost have another behavior.

In problems where demand has extreme changes over time, and investment costs to locate DCs are low, the DCs location is not for long term or a strategic decision. Examples of such problems are for attention to natural disasters (floods, earthquakes, etc.), epidemics, social or political events (elections, demonstrations, etc.).

A vast literature indicates that the location of DCs is a strategic or long-term decision due to the investment required for either the location or relocation. Investment cost is usually very large, and facilities are expected to remain operable for long term (Owen and Daskin, 1998). Thus, the location problem involves extended long planning horizon. Usually, decision makers must not only select robust locations which will effectively serve changing demand over time, but must also consider the timing of facility expansions and relocations in the long term.

In this case study, location of DCs is not a strategic decision but a tactical decision, hence decision makers must consider the change of location of DCs over time.
The results of the case study show how the locations of DCs changes over time because of the variability of the demand and low investment costs. However, a problem of the methodology exists because the myopic algorithm fixes the DCs after iteration, what means we cannot assure that an optimal solution is found. The aim of this paper is not about finding an optimal solution; it is about exemplifying that the location of DCs changes over time because of the variability of the demand and low investment costs. A future work is to find the optimum value of p for each time horizon.

References


SCT, 2008. NOM-012-SCT-2-2008 Norma Oficial Mexicana NOM-012-SCT-2-2008, Sobre el peso y dimensiones máximas con los que pueden circular los vehículos de autopartore que transitan en las vías generales de comunicación de jurisdicción federal.

