Rail-Road terminal locations: aggregation errors and best potential locations on large networks

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In network location problems, the number of potential locations is often too large in order to find a solution in a reasonable computing time. That is why aggregation techniques are often used to reduce the number of nodes. This reduction of the size of the location problems makes them more computationally tractable, but aggregation introduces errors into the solutions. Some of these errors will be estimated in this paper.
A method that helps to isolate the best potential locations for rail-road terminals embedded in a hub-and-spoke network will further be outlined. Hub location problems arise when it is desirable to consolidate flows at certain locations called hubs. The basic idea is to use the flows of commodities and their geographic spreading as input to determine a set of potential locations for hub terminals. The exercise will be done for the trans-European networks. These potential locations can then further be used as input by an optimal location method.

1. Introduction

There is a growing imbalance between modes of transport in the European Union. However, the increasing success of road transport increases congestion, environmental nuisances and accidents. That's why one of the objectives of the Common Transport Policy is to restore the balance between modes of transport and to develop intermodality.

Among the various types of intermodal transport, this paper deals with rail-road combined transport for which the terminals are embedded in a hub-and-spoke network. This kind of topology plans a reduction of the transportation costs, consolidating volumes at the hubs. This can classically be solved by a p-hub median problem which optimally locates a given number, p, of hubs and allocates each non-hub node to a single hub.

For real-world network location problems, the number of potential locations is too large to be solved by the p-hub median formulation. Therefore, one has to start with a subset of nodes

that can be considered as good potential locations. Unfortunately, in a majority of the relevant literature, the way these potential locations are chosen is not well documented. Often, a spatial aggregation of the demand nodes is used to reduce the size of the problems.

In some rare researches (see for instance Macharis, 2004), the potential locations are determined using "common sense" reflections and a lot of data collected on the field. If such an approach can be suitable on rather small geographical areas, it becomes much more difficult to implement for the whole European territory, for which a much more systematic approach is needed.

Some kind of systematization can be found in Arnold (2002) where three different approaches are presented: a Belgian case study for which the potential locations are just the nodes were both railroads and highways are available, an Iberian case based on a "grid" approach (the territory is divided in 200 km grids, in which the most accessible point is kept as potential location), and an European exercise for which the already existent terminals are considered as the set of potential locations.

It is also worthwhile to note that most of the known location methods are node based, in the sense that they use the locations of the demands and the supplies as main input. Doing so, they ignore the network effects that can only be captured if the flows of commodities and their geographic spreading are taken into account. This is a limitation because the main objective of a hub is to consolidate flows. Therefore, we will use the flows of commodities and their geographic spreading as input to determine a set of potential locations.

After a brief description of some classical clustering methods and of the p-hub median problem, Section 2 will cope with aggregation errors. Section 3 describes a method which helps to determine the best potential locations, using flows of goods and their geographical dispersion as input. A comparison between the results obtained by this method and by the aggregating method will be presented. Finally, some directions for future research and concluding remarks are provided in the last section.

2. Demand node aggregation for hub location problems

As the number of nodes, n, increases, the p-hub median problem becomes intractable due to the explosive growth of the number of variables and constraints. Spatial aggregation of demand nodes is therefore often used to reduce the size of the location problems, but aggregation also introduces errors in the solutions.

Different aggregation errors are discussed in Current and Schilling (1987), who also give methods to reduce them. Most of the relevant literature concerns the p-median or covering problem: Bach (1981); Casillas (1987); Current et al. (1987) and (1990); Francis et al. (1996); Goodchild (1979), Francis et al. (1999), Zhao and Batta (1999, 2000) and Plastria (2001).

The estimation of aggregation errors for the p-hub median problem is studied in this section. Node aggregation is often performed using clustering techniques. Clustering is the partitioning of a data set into subsets, or clusters, in such a way that the nodes in each subset share some common characteristics and are different from those in other cluster.

2.1 The cluster problem definition

Mulvey and Crowder (1979) and Rao (1971) formulated the clustering problem as follows:

Inputs:
n =   number of nodes

d_{ij} = measures the dissimilarity or distance between node i and node j
k = number of clusters
J = clusters set
N = nodes set

Decision variables:

x_{ij} = 1 if node i is assigned to cluster j
    0 otherwise
y_j = 1 if j is selected
    0 otherwise

Minimize:

$$Z = \sum_i \sum_j d_{ij} x_{ij} \tag{1}$$

Subject to:

$$\sum_{j \in J} x_{ij} = 1 \;\; \forall i \in N \tag{1.1}$$

$$\sum_{j \in J} y_j = k \tag{1.2}$$

$$x_{ij} \leq y_j \;\; \forall i, j \in N \tag{1.3}$$

$$x_{ij} \in \{0,1\} \;\; \forall i, j \in N \tag{1.4}$$

$$y_j \in \{0,1\} \;\; \forall j \in N \tag{1.5}$$

Constraints (1.1) ensure that every node belongs to one and only one cluster. Constraint (1.2) implies that k clusters have to be formed and constraints (1.3) that a node must be assigned to an already defined cluster. Constraints (1.4) and (1.5) insure that the location variables, y_j, and the allocation variables, x_{ij}, are binary.

Conceptually, clustering aims at computing k centroïds and assigning each node to one and only one centroïd so that the sum of the distances from each point to its cluster median centroïd is minimized. This is a combinatorial problem.

2.2 Clustering methods

There are mainly two types of clustering methods: hierarchical and non-hierarchical. Non-hierarchical methods (such as relocation methods, topographic clustering, mixture models …) use different techniques to build clusters. These methods need an a priori specification of the desired number k of clusters.

Hierarchical clustering produces a hierarchy of encased clusters C, identifying a classification at various levels of detail. It may be represented by a two dimensional diagram known as dendrogram: a binary tree data structure which illustrates the fusions made at each successive stage of the analysis, a cluster being the union of its two children. This structure allows for an intuitive interpretation of the results. Hierarchical clustering is subdivided into agglomerative methods, which proceed by series of fusions of the n objects into groups, and divisive methods, which separate n objects successively into smaller groups. Groupings or divisions produced by a hierarchical method are irrevocable; thus, defects in clusters, once introduced,

cannot be repaired. Hierarchical agglomerative methods which are more widely used than divisive methods can be outlined as:

- Step 0. Each node is considered as a cluster
- Step 1. Search a pair of "most similar" clusters
- Step 2. Merge it with its parent cluster
- Repeat 1-2 until all the nodes are merged into one single cluster

The agglomerative methods (single linkage, complete linkage, average linkage, centroid linkage, Ward's method …) differ in the way the distance (similarity) between clusters is computed.

In the "single linkage" method, the distance between two clusters is defined as the minimum distance between any pair of items (one from each cluster). This can be formulated as:

$$D(C_a, C_b) = \min\{d(x, y), x \in C_a, y \in C_b\} \tag{2}$$

In this case, a Minimum Spanning Tree is generated. This method can produce clusters of different shapes and sizes, but tends to link entities together through a series of close intermediates. This phenomenon is known as "chaining effect". Chaining often results in the creation of one large cluster that contains most of the data with the remaining clusters having only a few items; very dissimilar entities at the end-points of a chain of paired similar entities are assigned to this same large cluster. This is represented in figure 1 where clusters G_1 and G_2 are merged into cluster C because they are separated by a set of intermediate close points. This problem may cause the algorithm to fail to indentify distinct clusters when intermediates lie between them.
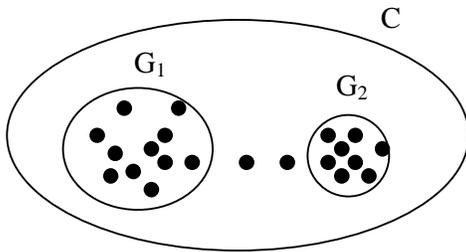

Figure 1. Chaining effect

In the complete-link clustering, the dissimilarity between two clusters is the maximum distance between any pair of items (the farthest pair of points between each cluster):

$$D(C_a, C_b) = \max\{d(x, y), x \in C_a, y \in C_b\} \tag{3}$$

Complete-link clustering may be affected by a "dissection effect": very similar entities are assigned to different clusters (Hansen and Delattre, 1978). Thus, outliers are given more weight during the cluster building process.

Between these two extreme methods' one find the average-link clustering in which the proximity between two clusters is the arithmetic average of distances between all pairs of items:

$$d(C_a, C_b) = \frac{\sum_{i=1}^{n_a} \sum_{j=1}^{n_b} d(x_i, y_j)}{n_a n_b} x_i \in C_a, y_j \in C_b \tag{4}$$

where n_a and n_b the number of nodes in respectively C_a and C_b

Another method is the centroid method, in which the distance between two clusters is defined as the distance between their centroids, $\bar{x}_i$:

$$d(C_a, C_b) = \left\| \bar{x}_a - \bar{x}_b \right\|^2 \tag{5}$$

where $\bar{x}_i = \sum_{i \in C_i} \dfrac{x_i}{n_i}$ (6)

This method tends to favour spherical shapes and the method can fail in separating clusters of different shapes, densities, or sizes.

The Ward minimum variance method has been shown to be one of the best techniques. This method uses an analysis of the variances to evaluate the distances between clusters. At each reduction, the method merges the two clusters resulting in the smallest increase in the total sum of squares of the distances of each point to its cluster centroid. Thus, the aim of the Ward procedure is to unify groups such that the variation inside these groups does not increase too drastically: the resulting groups are as homogeneous as possible. Ward's method is sensitive to outliers in the data and produces clusters with roughly the same number of nodes. Like the most agglomerative methods, it can also lead to suboptimal partitions because, once a node is merged in a cluster, it can never be taken away even if a better solution exists (no feedback loop). In Ward's minimum-variance method, the distance between two clusters is defined by:

$$d(C_a, C_b) = \frac{\left\| \bar{x}_a - \bar{x}_b \right\|^2}{\dfrac{1}{n_a} + \dfrac{1}{n_b}} \tag{7}$$

The interested reader by the fusion criteria and their influence on the obtained classifications can refer to Duda et al. (2001).

2.3 The *p*-hub median problem

This section deals with the aggregation errors due to hierarchical clustering in the *p*-hub median problem. In multiple-hub networks, three constraints are identified: it is assumed that all the hubs are connected directly to each other, that there is no direct connection between non-hub nodes and that these latest nodes are connected to a single hub. The hub-to-hub links consolidate the total flow coming from the origin hub or from any of its spoke nodes to the destination hub (or any of its spoke nodes). The location of the hubs must be chosen among the set of nodes. Economies of scale can be associated to the transportation system between the hubs. The objective is to minimise the total transportation cost.

The *p*-Hub Median Problem (*p*-HMP) was first formulated as a quadratic integer program by O'Kelly (1987). Campbell (1994) formulates this problem as a mixed integer linear programming problem. Our work is based on the Ernst et al. (1996) formulation which reduced the problem size, both in number of variables and constraints by a factor *N*. In this formulation Y^i_{km} defines the total flow of commodity *i* (i.e., traffic emanating from node i) that is routed through hubs *k* and *m*. If the total flow from the node *i* is denoted: $O_i = \sum_{j \in N} W_{ij}$ and the total flow to the node *i* is denoted $D_i = \sum_{j \in N} W_{ji}$, the formulation becomes:

Inputs:

p = number of hubs to be opened

W_{ij} = flow from origin i to destination j

C_{ij}^{km} = unit cost between origin i and destination j when going via the hubs located at nodes k and m,

       = $\chi\, C_{ik} + \alpha\, C_{km} + \delta\, C_{mj}$

where :

      χ is the relative cost of the pre-haulage ;

      α is the inter-hub discount ($0 \leq \alpha \leq 1$);

      δ is the relative cost of the post-haulage;

C_{ij} = unit travel cost on link between origin i and destination j.

Decision variables:

$X_{ij} =$ 1 if node i is connected to a hub located at node j $\forall i, j \in N$

      0 if not

$Y_{km}^{i} \geq 0$ $\forall i, k, m \in N$

Minimize:

$$\sum_{i \in N} \sum_{k \in N} C_{ik} X_{ik} (\chi\, O_i + \delta\, D_i) + \sum_{i \in N} \sum_{k \in N} \sum_{m \in N} \alpha\, C_{km} Y_{km}^{i} \tag{8}$$

Subject to:

$$\sum_{x \in N} X_{kk} = p \tag{8.1}$$

$$\sum_{k \in N} X_{ik} = 1 \qquad\qquad\qquad \forall i \in N \tag{8.2}$$

$$X_{ik} \leq X_{kk} \qquad\qquad\qquad \forall i, k \in N \tag{8.3}$$

$$\sum_{m \in N} Y_{km}^{i} - \sum_{m \in N} Y_{mk}^{i} = O_i X_{ik} - \sum_{j \in N} W_{ij} X_{jk} \qquad \forall i, k \in N \tag{8.4}$$

$$X_{ij} \in \{0,1\} \qquad\qquad\qquad \forall i, j \in N \tag{8.5}$$

$$Y_{km}^{i} \geq 0 \qquad\qquad\qquad \forall i, k, m \in N \tag{8.6}$$

The objective function (8) minimizes the total transportation cost on the system. Constraint (8.1) stipulates that exactly p hubs should be located. Equation (8.2) together with equation (8.5) ensure that each node is allocated to a single hub and that a hub node cannot be allocated. Equation (8.3) prevents allocations to non-hub nodes. Equation (8.4) is the divergence equation for commodity i at node k in a complete graph, where the demand and supply at the nodes is determined by the allocations X_{ik}. Constraints (8.5) restrict X_{ij} to be binary. This problem involves ($N^3 + N^2$) variables and requires ($1 + N + 2N^2$) linear constraints.

Each (i,j) pair in a p-HMP is analogous to a demand point in a p median problem (p-MP). In the p-MP, the demand nodes are assigned to the nearest facilities. However, in the p-HMP, it may not be optimal to assign demand nodes to the nearest hub.

2.4 Aggregation errors for the *p*-hub median problem

Let $P=\{P_1,...P_n\}$ denote the demand node set, $W=\{W_{11},\ W_{12},\ ...,W_{ij},...,W_{nn}\}$ the flow set (W_{ij} = from origin *i* to destination *j*) and let $X=\{X_1,\ ...,\ X_p\}$ the hub location set . If $f(X)$ denotes the total cost, we have:

$$f(X) = \sum_{i=1}^{n}\sum_{k=1}^{p} \chi\, C(P_i, X_k)\, W_{ik} + \sum_{k=1}^{p}\sum_{m=1}^{p} \alpha\, C(X_k, X_m)\, W_{km} + \sum_{m=1}^{p}\sum_{j=1}^{k} \delta\, C(X_m, P_j)\, W_{mj} \qquad (9)$$

where: $C(P_i,X_k)$ is the unit cost between the demand node P_i and the hub X_k

$C(X_k,X_m)$ is the unit cost between the hub X_k and the hub X_m

$C(X_m,P_j)$ is the unit cost between the hub X_m and the demand node P_j.

The *p*-hub median problem has to identify the hub location sites $X=\{X_1,\ ...,\ X_p\}$ such that $f(X)$ is minimized. Clustering divides the demand data set in *q* clusters: $C_1,\ C_2,\ ...,C_q$. The set of nodes of each cluster is represented by an aggregated node A_g, *g=1, ...,q*, representing the set of nodes the cluster agglomerates.

First, A'_g is computed for each cluster

$$A'_g = \frac{\displaystyle\sum_{i\in C_g}(\sum_{j=1}^{n}W_{ij} + \sum_{j=1}^{n}W_{ji} - W_{ii})P_i}{\displaystyle\sum_{i\in C_g}(\sum_{j=1}^{n}W_{ij} + \sum_{j=1}^{n}W_{ji} - W_{ii})} \qquad (10)$$

If such an obtained node doesn't correspond to one of the existing nodes of the cluster, the closest (lowest transportation cost) node from A'_g in the cluster is chosen as aggregated node:

$$A_g = \min C(P_i, A'_g) \qquad\qquad \forall\ P_i\in C_g \qquad (11)$$

Aggregated flows, W'_{ij}, are computed as follows:

$$W'_{C_l,C_k} = \sum_{i\in C_l}\sum_{j\in C_k}W_{ij} \qquad (12)$$

Knowing the aggregated nodes, the aggregated cost function is given by:

$$g(X) = \sum_{i=1}^{q}\sum_{k=1}^{p} \chi\, C(A_i, X_k)\, W'_{ik} + \sum_{k=1}^{p}\sum_{m=1}^{p} \alpha\, C(X_k, X_m)\, W'_{km} + \sum_{m=1}^{p}\sum_{j=1}^{q} \delta\, C(X_m, A_j)\, W'_{mj} \qquad (13)$$

If X_0 is the optimal solution to the unaggregated *p*-hub median problem and X'_0 the optimal solution to the aggregated *p*-hub problem, we can use two types of errors that have been discussed in the literature:

Cost error:

$$\frac{[f(X'_0) - g(X'_0)]}{f(X'_0)} \qquad (14)$$

Optimality error:

$$\frac{[f(X'_0) - f(X_0)]}{f(X_0)} \qquad (15)$$

The latest can only be computed if the optimal solution for the unaggregated problem has been successfully computed.

2.5 Computational experiments

Our computational experiments are based on the AP data set from the OR-Library, originally described in J.E. Beasley (1990). This data consists of 200 nodes, which represent postcode districts, along with their coordinates and flow volumes (mail). The transport unit costs are constants: $\chi = 3$, $\alpha = 0.75$ and $\delta = 2$. In order to generate a 100 nodes problem, which can be solved with CPLEX 10.0, we divided the two dimensional area into boxes and then amalgamated all the nodes in the same box into a single node. More details on this process (and the data it was applied to) can be found in Ernst et al (1996). Figure 2 gives a representation of the original 200 nodes problem and figure 3 illustrates the 100 nodes problem.
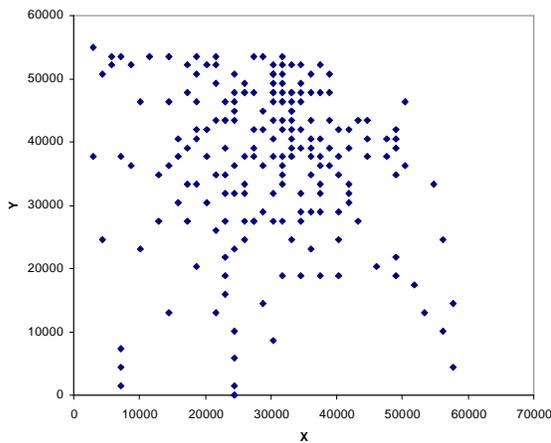
Figure 2. AP data set.   *Figure 3. AP data set reduced to 100 nodes.*
X and Y are the cities coordinates used in Ernst *et al.* (1996).

This problem is solved for *p* varying from 2 to 10, for three aggregation levels (20, 30, 40 aggregated nodes) and for three clustering methods: average linkage (*A*), centroid linkage (*C*) and Ward's minimum variance (*W*).
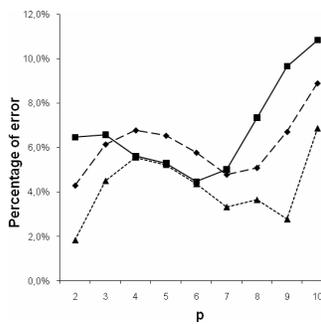

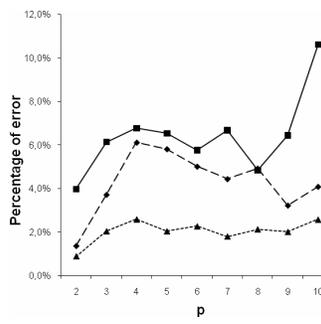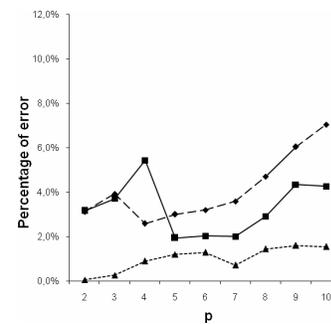*Figure 4. Optimality error for 20 aggregated nodes.*   *Figure 5. Optimality error for 30 aggregated nodes.*   *Figure 6. Optimality error for 40 aggregated nodes.*

Figures 4 to 6 show that the optimality error due to the aggregation of the data is smallest when the method of Ward is chosen. This is true for all the levels of aggregation and for all the values of *p*. Note that, although the method of Ward provides the best results, the error can reach 7% for a relatively low level of aggregation that reduces by five only the number of nodes.

Figures 7 to 9 show that, in each case, the cost error due to the aggregation of the data is smallest when the method of Ward is chosen. They also show that this error increases with the level of aggregation and the number of hubs to be located. However, although the method of Ward provides the best results, the error reached 36% when *p* = 10 for a level of relatively low aggregation that reduces by five only the number of nodes.
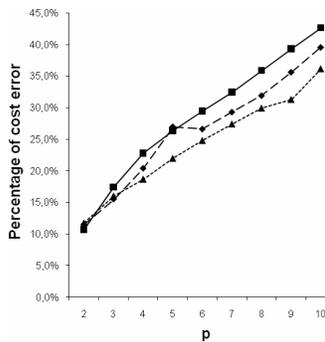

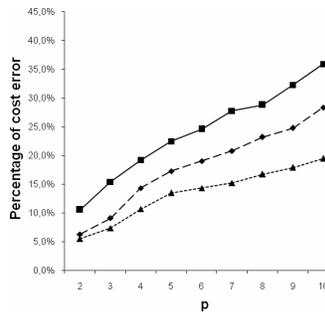*Figure 7. Cost error for 20 aggregated nodes.*
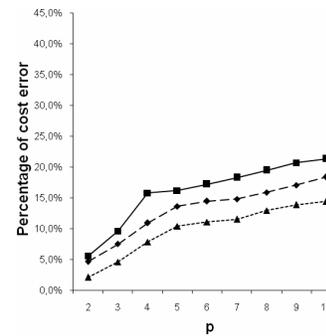
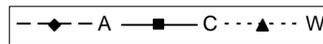*Figure 8. Cost error for 30 aggregated nodes.*

Figure 9. Cost error for 40 aggregated nodes.

2.6 Conclusion

This example clearly shows that the aggregation techniques must be employed with caution because they can generate important errors, even for low levels of aggregation.

In the next section, a methodology will be proposed to reduce the number of potential locations using selection criteria rather than aggregation.

3. Illustration of a selection based approach

The objective of this section is to describe a method which helps to determine the best potential locations, using flows of goods and their geographical dispersion as input. A comparison between the costs obtained by this flow based method and by an aggregation (Ward) method will be performed. In order to obtain the flows on the networks, the demand contained in origin-destination matrices (OD), and the supply (the networks and its associated costs) are needed.

3.1 The demand

We had the opportunity to use, in the framework of this research, the freight OD matrices for the year 2000, produced by NEA Transport Research and Training. The matrices give

information about the type of transported commodities, using the Standard Goods Classification for Transport Statistics / Revised (NST/R chapters). Only the demand for NST/R chapter 9 is taken into account in this exercise, because it contains the demand for containers, among other manufactured products. The database contains region-to-region relations at the NUTS (Nomenclature of Territorial Units for Statistics) 2 level, for the enlarged European area (EU25, Norway, and Switzerland).

Moreover, only the origin-destination pairs separated by at least 300 km are taken into account. Indeed, the intermodal rail-road transport is competitive compared to road only for long distances. The European Conference of Ministers of transport (1998) also estimates that the shortest distance over which combined transport is competitive is 300 km. Moreover, according to the UIRR (International Union of combined Road-Rail Transport companies) statistics (2000), 92% of the intermodal transport unit (ITU) are used on trips that are longer than 300 km. Therefore, the demand for shorter distances was left out of our matrices.

3.2 The network

A reasonable detailed representation of the networks for the different transportation modes (road, railroads and inland waterways) is also needed. The used railroads and roads networks were taken from the Digital Chart of the World and updated. The inland waterways network was digitized internally by the Group Transport and Mobility (GTM) team.

In addition to these main layers, the ferry lines (and the Chunnel) were also digitized. Finally, the borders of the NUTS2 regions were freely provided by "Geophysical Instrument Supply Co" (GISCO). A centroid for each region was located at the center of the most urbanized area of the zone. When a NUTS2 region includes several important residential areas of equivalent sizes, the centroid was located in the most inhabited zone. These centroids are used as origin or destination for the goods.

All these separate layers were then connected together, using "connectors" from each centroïd to each modal layer located not further than a given distance. These connectors have an average length of 4.66 km for roads, 3.23 km for railways and 32 km for waterways; with respective standard deviation of 9.95, 6.34 and 38.85. The complete set of layers can be considered as a "geographical graph", made of 110,000 edges and of 90,000 vertices.

3.3 The costs

The RECORDIT (REal COst Reduction of Door-to-door Intermodal Transport, 2002) study defined and validated a methodology for the calculation of the costs of intermodal freight transport in Europe. RECORDIT also compares costs between intermodal and all-road solutions. The methodology used for collecting data and for cost calculations is based on the description of the intermodal chain, defined as a sequence of activities classified in nine main blocks: loading a consignment, pre-haulage to a terminal (a transshipment point can be inserted in between), a first terminal handling, the main haulage (by train, truck, ship or barge), a second terminal handling, the post haulage and finally the consignee receiving the consignment. Loading units can be of different types with tree main options: containers (20-feet or 40-feet long), swap bodies (20-feet or 40-feet long) and semi-trailers. Internal costs are classified in eight main categories: depreciation costs, wage costs, consumption costs, maintenance costs, insurance costs, tolls and charges, third party services and other costs. Each cost category can further be broken down in a series of detailed cost items.

The costs used in this exercise are essentially based on RECORDIT. The PINE report (Prospective customers of Inland Navigation within the enlarged Europe report, 2004) was

also used, to refine the costs for inland waterways. For road transport, the data of the French Road National Committee (CNR) were also used. Finally, railway costs were validated on the basis of a report of the Ministry for the Mobility of the Netherlands (2005).

The distribution between containers sizes is about 60 % for 40' and 40 % for a 20' boxes. In average, the (un)loading costs are estimated to 1.297 €/t, while the costs for the different haulages are:

- pre and post haulage: 0.105 €/t
- road haulage: 0.072 €/t
- rail haulage: 0.042 €/t
- inland waterways haulage: 0.014€/t.

RECORDIT also estimates that a 20 % cost reduction assumption for rail haulage, for short or medium ranges, can be considered as likely. In a first step, this value is set to 10% in our exercise.

Further, Ballis et al. (2002) study the variation of the transshipment costs according to the number of ITU really transshipped and for different terminal configurations. This can lead to the conclusion that, for terminals that handle more than 150,000 ITU/year, a transshipment cost of 2.24 €/t can be considered.

3.4 The flows

The assignment of the OD matrices over the network gives information about the flow of commodities that comes along each node of the network. This information is useful to determine a set of potential locations because the flow gives a good idea of the attractiveness of each node. In order to consolidate the flows which can be spread over different itineraries belonging to the same corridor, an All-or-Nothing assignment, which computes the cheapest path between each origin-destination pair and assigns the whole quantity on this single route, is performed on the road network. The obtained results are represented by figure 10.

A first selection of potential locations can be performed, keeping the nodes along which the estimated flow is larger than a given threshold, that will be outlined later. The selection can be further reduced using one or more of the following criteria:

- A minimum distance to an already existing terminal;
- A minimum distance to a port;
- A maximum distance to the waterway network;
- A maximum distance to the railway network.

In the exercise presented in this paper, the maximum distance to water infrastructure and the minimum to a port or an existing terminal were ignored. The maximum allowed distance to the railway infrastructure was set to 5 km.

As stated earlier, we are trying to locate rail-road container terminals embedded in a "hub-and-spoke" network and operating at the country level in Europe. Wiegmans (2003), estimated that the annual volume for this kind of terminals must be at least 100,000 Twenty-feet Equivalent Unit (TEU). As we try to locate large terminals, we fixed this threshold to 150,000. According to the statistics of the UIRR, the average net weight of a TEU is about 15 or 16 tons. KombiConsult (2002) gives the flows handled by the main terminals for the year 2000. These flows made it possible to estimate that, on average, the ratio between the total flows observed in the neighborhood of a terminal and the amount of commodities that effectively handled by these terminals is about 17%. The minimum flow to consider on our network was thus set to 880,000 TEU.
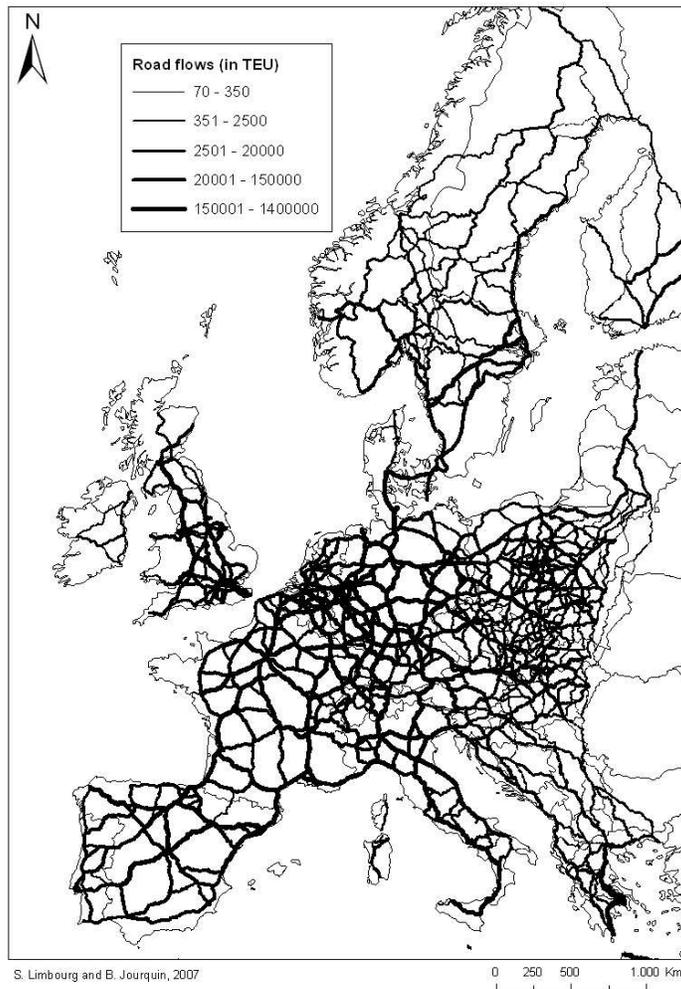
Figure 10. All or Nothing assignment for NSTR chapter 9 over more than 300 km.

The remaining set of nodes after filtering is still rather important, mainly because many of these nodes are close to each other, having about the same characteristics (chain effect). If it is true that, at the micro or regional level, these nodes can be very different (availability of enough ground surface for instance), these considerations are less important at the macro European level at which it is important to know in which region a terminal could be helpful. That's why we only considered the node that has the maximum weighted flows in each NUTS2 region. This reduction of the number of potential location, i.e. 34, (figure 11) can be handled more easily by optimal location models.

In section 2, we conclude that the best classification method tested was the Ward's minimum variance method. If this method is used with the same number of nodes than the one retained in figure 11, the pattern illustrated by figure 12 is obtained.
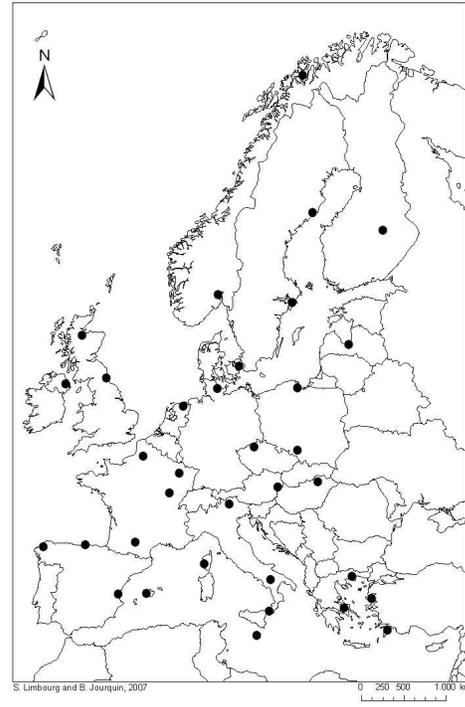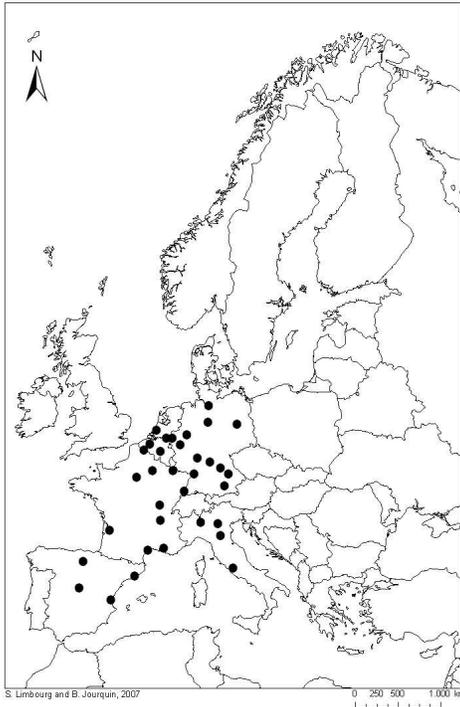
Figure 11. Set of selected potential locations   Figure 12. Ward aggregated nodes

For both cases the costs and the flow matrices were generated to solve the corresponding *p*-hub median problem. Note that, in order to take account the transshipment costs into account, the objective function (8) was replaced by

$$\sum_{i \in N} \sum_{k \in N} (C_{ik} + T) X_{ik} (\chi O_i + \delta D_i) + \sum_{i \in N} \sum_{k \in N} \sum_{m \in N} \alpha C_{km} Y_{km}^i \tag{16}$$

where *T* is the transshipment cost.

Once the optimal locations determined, they are integrated in the network and an assignment is performed, during which transshipments are now possible at the optimal located facilities. The demand can be assigned over all the transportation modes, with the possibility (and not the obligation) to use the transshipment facilities. Combined transport is thus considered as one of the possible transport solutions among others, and the three constraints of the *p*-hub

median problem (see section 2.3) are relaxed. Figure 13 shows the relative difference $\dfrac{C_W - C}{C_W}$

between the costs obtained using the set of Ward (C_W) and the costs obtained using our set of selected potential locations (*C*). Except the configuration where only two hubs are located, the relative cost difference is each time about 5% in favor of the flow based method.
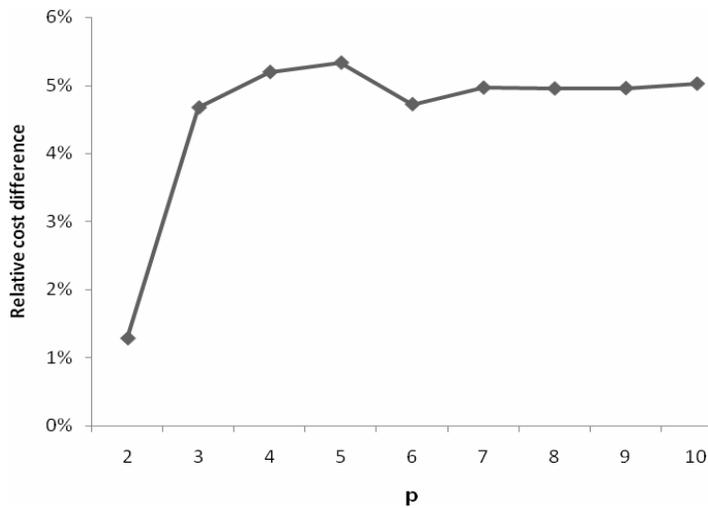
Figure 13. Relative cost difference

Hubs are for the time being located in Metz, Villeneuve St. Georges (Paris), Schaerbeek (Brussels), Koln, Hannover and Mannheim, thus in the North of Europe. Ballis (2002), also pointed out that a hub nearby Milan would be useful. In other words, Ballis concludes that a 7 hubs configuration would be an interesting one. Figures 14 and 15 represent the 7 hubs that we obtained by minimizing (16) using data corresponding to the selected potential locations and the Ward aggregated nodes respectively. The set of hubs obtained using the 34 potential locations that result from the selection approach is similar to the topology described by Ballis, which is not the case for the hub locations calculated on the basis of the 34 nodes obtained by aggregation.

Taking into account the topology of the network and other geographic considerations, our flow based approach also gives more realistic locations.

A more important remark is that the locations obtained by means of the aggregation method don't capture enough flows, which can lead to an increase of the transshipment costs and consequently, a lower market share for combined transport. This is not the case for locations obtained by our flow based selection. Indeed, the flows that can be captured by these hubs are large enough to permit a transshipment cost reduction, and thus an increase of the market share of combined rail-road transport. Taking these considerations into account, the relative gap between the two methods would be even larger than what is represented by figure 13.
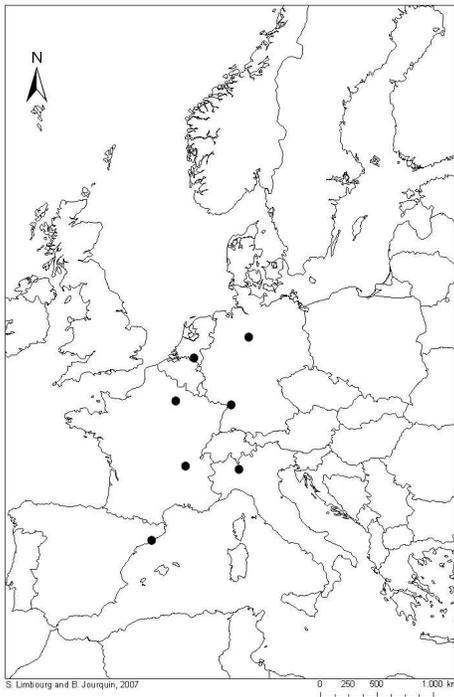
Figure 14. The 7 hubs obtained using data corresponding to the selected potential locations.
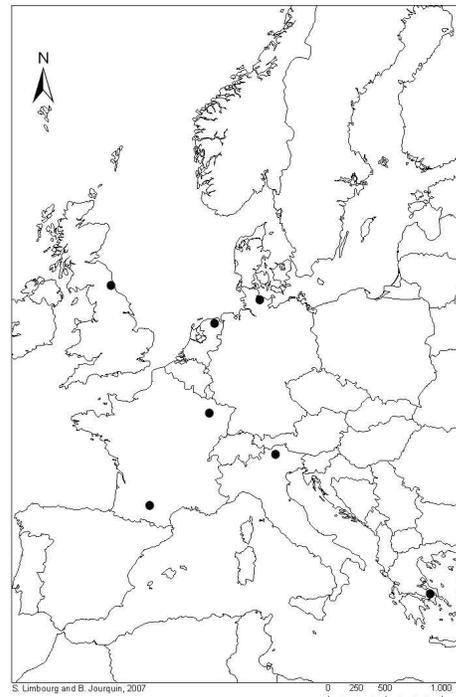

Figure 15. The 7 hubs obtained using data corresponding to the Ward aggregated nodes.

4. Conclusions

This paper shows that aggregation techniques used to solve the *p*-hub median problem must be employed with caution because they may generate important errors even for a low level of aggregation. An alternative methodology, based on flows, is proposed to reduce the set of potential locations. The *p*-hub median problem was applied to a set of potential locations obtained both by clustering and by the flow based approach. The total transportation cost on the system appeared to be systematically lower with our method and this for all the tested configurations. This is obviously an advantage as our goal is to maximise the efficiency of the transport system.

In the future, the variation of the transshipment costs according to the number of UTI really transshipped should be taken into account to refine the hypothesis that the transshipment cost is fixed at 2.24 €/t for all the terminals.

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European freight transport at the NUTS 2 level. The use of such a database has greatly contributed to the set-up of a credible case study.

References

Arnold, P. (2002). *Localisations optimales, logique multi-réseaux et terminaux de transport multimodal: formalisation et applications*. Thesis, Département de Géologie et de Géographie, Université catholique de Louvain.

Ballis, A. (2002). *Innovative Technologies for Intermodal transfer Points*. European Community project.

Ballis, A. and Golias, J. (2002). Comparative evaluation of existing and innovative rail-road freight transport terminals. *Transportation Research Part A*, vol. 36, pp. 593-611.

Beasley, J.E. (1990). OR-Library: distributing test problems by electronic mail. *Journal of the Operational Research Society*, vol. 41, no. 11, pp. 1069-1072.

Campbell, J.F. (1994). Integer Programming Formulations of Discrete Hub Location Problems. *European Journal of Operational Research*, vol. 72, no. 2, pp. 387-405.

Casillas, P.A. (1987). Data aggregation and the p-median problem in continuous space. In: Ghosh, A., Rushton, G. (eds.) *Spatial analysis and location allocation models*. Van Nostrand Reinhold Publishers, New York, pp. 327-344.

Comité National Routier (http://www.cnr.fr/).

Current, J.R. and Schilling, D.A. (1987). Elimination of source A and source B errors in p-median location problem. *Geographical Analysis*, vol. 19, no. 2, pp. 95-110.

Current, J.R. and Schilling, D.A. (1990). Analysis of errors due to demand data aggregation in the set covering and maximal covering location problems. *Geographical Analysis*, vol. 22, pp. 116-126.

Duda, R.O., Hart, P.E. and Stork, D.G. (2001). *Pattern Recognition*. John Wiley & Sons, New York.

E.C.M.T. (1998). Rapport sur la situation actuelle du transport combiné en Europe.

Ernst, A.T. and Krishnamoorthy, M. (1996). Efficient Algorithms for the Uncapacitated Single Allocation p-Hub Median Problem. *Location Science*, vol. 4, no. 3, pp. 139-154.

Francis, R.L., Lowe, T.J. and Rayco, M.B. (1996). Row-column aggregation for rectilinear distance p-median problems. *Transportation Science*, vol. 30, no. 2, pp. 160-174.

Francis, R.L., Lowe, T.J., Rushton, G. and Rayco, M.B. (1999). Aggregation methods for .multi-facility location problems: Strategies for containing error. *Geographical Analysis*, vol. 31, pp. 67–87.

Goodchild, M.F. (1979). The aggregation problem in location-allocation. *Geographical Analysis*, vol. 11, no. 3, pp. 240-55.

Hansen, P. and Delattre, M. (1978). Complete-Link Cluster Analysis by Graph Coloring. *Journal of the American Statistical Association*, vol. 73, no. 362, pp. 397-403.

KombiConsult (2002). *Study on infrastructure capacity reserves for combined transport by 2015*. Prepared for international union of railways combined transport group, Freiburg/Frankfurt am Main/Paris, May 2004.

Macharis, C. (2004). A Methodology to Evaluate Potential Location for Intermodal Barge Terminals: A Policy Decision Support Tool. In: Beuthe, M., Himanen, V. and Reggiani, A. (eds.) *European Strategies in the Globalising Markets*.

Mulvey, J.M. and Crowder, H.P. (1979). Cluster analysis: an application of Lagrangian relaxation. *Management Science*, vol. 25, no. 4, pp. 329-340.

O'Kelly, M. (1987). A quadratic integer program for the location of interacting hub facilities. *European Journal of Operational Research*, vol. 32, pp. 393–404.

PINE, (2004). *Prospects of Inland Navigation in an Enlarged Europe*. Available at: http://europa.eu.int/comm/transport/iw/prospect/index_fr.htm (assessed December 2007).

Plastria, F. (2001). On the choice of aggregation points for continuous p-median problems: A case for the gravity center. *TOP*, vol. 9, pp. 217–242.

Rao, M.R. (1971). Cluster analysis and mathematical programming. *Journal of the American Statistical Association*, vol. 66, pp. 622-626.

RECORDIT (2001). *REal COst Reduction of Door-to-door Intermodal Transport*. Available at: http://www.recordit.org/ (assessed December 2007).

Wiegmans, B. (2003). *Performance conditions for container terminals*. Thesis, Vrije Universiteit Amsterdam.

Zhao, P. and Batta, R. (2000). An aggregation approach to solving the network p-median problem with link demands. *Networks*, vol. 36, pp. 233–241.