A Framework for Locating Logistic Facilities with Multi-Criteria Decision Analysis

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Abstract. Locating logistic facilities, such as plants and distribution centres, in an optimal way, is a crucial decision for manufacturers, particularly those that are operating in large developing countries which are experiencing a process of fast economic change. Traditionally, such decisions have been supported by optimising network models, which search for the configuration with the minimum total cost. In practice, other intangible factors, which add or reduce value to a potential configuration, are also important in the location choice. We suggest in this paper an alternative way to analyse such problems, which combines the value from the topology of a network (such as total cost or resilience) with the value of its discrete nodes (such as specific benefits of a particular location). In this framework, the focus is on optimising the overall logistic value of the network. We conclude the paper by discussing how evolutionary multi-objective methods could be used for such analyses.

Keywords: multi-criteria analysis, logistics, facility location, multi-attribute value theory, multi-objective optimisation.

1 Introduction

Designing logistic networks – involving plants, distribution centres and cross dock terminals – are strategic decisions for industrial companies (Daskin 1995, Ballou 2004, Klose and Drexl 2005, Melo et al. 2009). Locating such logistic facilities in an optimal way is a crucial and frequent decision for manufacturers (Bowersox et al. 2007), in particular for those companies operating in large developing countries which are experiencing a process of fast economic change.

Traditionally, location decisions have been modelled as a network with discrete location alternatives. These models can then be optimised to find the configuration with the minimum total cost. In practice, other intangible factors, which add or reduce value to a potential configuration, are also important in the location choice (Daskin 1995, Klose and Drexl 2005). However, these factors are many times taken into account just exogenously during the analysis.

We suggest in this paper an alternative way to analyse such problems, which combines the value from the topology of a network (such as total cost) with the value of its discrete nodes (such as specific benefits of a particular location). In

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this framework, the focus is on optimising the overall logistic value of the network, considering the criteria that contribute to adding value to the system and the preferences of the company involved in the decision. The framework is presented using an illustrative case, based on the authors' experience in supporting this type of decisions in Brazil.

The paper has the following structure. We start describing the main features present in logistic facility location decision problems and the decision models usually employed for analysing them. We then present the proposed framework. The paper concludes with suggestions for further research on the topic, in particular the use of evolutionary multi-objective methods in this context.

2 The Logistic Facility Location Problem

Decisions involving logistic network design have some specific challenges, which make it extremely difficult to make an informed decision without mathematical modelling and decision support. These challenges are:

- *Systemic properties* : Multi-location decision problems have intrinsic systemic properties, where each topology provides a set of different performances. Examples of systemic properties may be total cost, geographical covering, or resilience. This requires the use of optimisation modelling for analysing the problem.
- *Properties of Elements* : Additionally, nodes in location decision problems have properties that distinguish one from each other. For example, potential sites for an industrial plant could have different levels of performance, such as skilled manpower availability or transportation infrastructure. This would lead to a discrete choice analysis of nodes, without the use of optimisation tools.
- *Multiple Objectives* : When companies are considering location problems, they have a set of objectives they want to achieve. These objectives may reflect concerns about systemic properties of the network (increase profitability, improve coverage, etc.) as well as properties of its elements (availability of skilled manpower, quality of local infra-structure, etc.).
- *Preferences and value trade-offs* : When more than one criterion is involved in the decision, for instance the need to minimise costs versus the wish to have wider coverage (and thus expensive) topology, then there is the need of modelling the company's preferences and trade-offs (e.g. costs versus coverage).
- *Facilitated decision modelling* : The decision process needs to be carefully crafted, as it should allow a consistent and participative decision making process (Franco and Montibeller 2010), where managers are able to negotiate their preferences and trade-offs. It thus should enable decision-makers to "play" with the models (de Geus 1988), assessing the consequences of different topologies and trade-offs and, therefore, an interactive decision tool is required.

We now contrast these problem's features with the existing literature on supporting facility location, which is the subject of the following section.

3 Decision Models for Facility Location Problems

In this section we review first the traditional mono-criterion decision models for facility location suggested in the literature, followed by models that allow the consideration of multiple objectives.

3.1 Traditional Decision Models

Facility location has a long history in the scientific tradition of mathematical modelling (see reviews by Klose and Drexl 2005, and Melo et al. 2009). From this literature, one can conclude that most classical location models in logistics and supply chain management have a single objective function, generally focused on the minimisation of costs (or other surrogate criterion, such as total weighted distance or number of open nodes).

On the other hand, some of those authors caution that location problems in logistics are definitely multi-objective decisions. For instance, Daskin (1995) comments that non-quantifiable objectives and other issues will influence sitting decisions to a great extent, and solutions of a single objective model are optimal in a narrow sense. Klose and Drexl (2005) state that strategic decisions, such as location of logistic facilities, are often multi-objective in nature, and, according to them, the body of literature regarding multiple criteria location models is very limited.

Evidently, in real world interventions, one can construct useful decision location models based on a single criterion, then conduct extensive changes to the model to try to include multiple objective issues (for example, adding a constraint which expresses a minimum level of achievements of a given objective). However, this may prevent decision makers to contemplate radically different, but high-value, topologies. This suggests the use of multiple criteria models for location decisions, which is reviewed briefly below.

3.2 Decision Models Considering Multiple Objectives

The recognition that facility location decisions have an inherent multi-objective nature has led to the development of several approaches for incorporating multiple criteria in the decision models (see Current et al. 1990, Malczewski and Ogryczak 1996 and Nickel et al. 2005).

Here we confine ourselves in briefly describing such models according to a categorisation of benefits which we are proposing. Within this perspective, there are two main types of decision models that incorporate multiple criteria:

- *Topological Benefits* : The more traditional way of incorporating multi-criteria into facility location models is with the inclusion of topological metrics, a subset of the network's systemic properties. Such metrics attempt to reflect the decision-makers' concerns about the topology of the network (e.g. distance between nodes, service coverage, among others). Models including topological benefits employ either goal programming (see Tamiz et al. 1998) or multi-criteria optimisation (see Marler and Arora 2004). Applications using the former approach are, for example, Badri et al. (1998) and Giannikos (1998); and using the latter approach are, for instance, Hugo and Pistikopoulos (2005) and Yang et al. (2007).

– *Nodal Benefits* : Another way of analysing facility location problems is by considering the several benefit dimensions, for each potential site of the network, which the decision-makers are concerned with (e.g., level of infrastructure, availability of labour, among others). Each of these nodes has an intrinsic level of benefits and disadvantages that need to be taken into account in the decision, which are properties of the elements of the network. This type of evaluation can be easily analysed by multi-criteria discrete alternative methods (see Wallenius et al. 2008), where each node is an alternative in the model (e.g. Keeney 1979, Min 1994, Yurimoto and Matsui 1995).

Considering only one type of benefit may be detrimental to the analysis, in our opinion. Methods which include topological benefits lack an evaluation of benefits at the node level and are incapable of dealing with intangible benefits. On the other hand, methods which evaluate nodal benefits do not consider the network structure and, therefore, the benefits that some particular topological layouts may provide. Given these concerns, it is rather surprising that there are a limited number of suggested approaches which try to assess both types of benefits, such as Badri (1999), Cheng et al. (2003), and Farahani and Asgari (2007).

However, none of these approaches mentioned in the former paragraph recognised explicitly the measurement of two distinctive types of benefits, as we are suggesting in this paper. Also, when trying to assess topological benefits, they assumed linear marginal value functions, but this is not always a realistic assumption (Stewart 1996). Furthermore, they did not recognise the importance of facilitated decision modelling when implementing such models in practice. In the next section we are proposing a framework for analysing facility location problems which addresses these issues.

4 A Framework for Using Multi-Criteria Analysis in Facility Location Problems

4.1 The Traditional Optimisation Model

We will consider a multi-criteria, single commodity, capacitated facility location problem (SCFL'), but the framework could be employed for other similar problems. It will be illustrated by a case study inspired on real applications in the food and retail industry in Brazil which we supported, as consultants, in the past. In these problems, a manufacturer has to choose the sites for a number of plants, each one with limited production capacity, to fulfill product demand in different markets (client regions). Traditionally this problem could be analysed using a mono-criterion model (see Aikens 1985, Klose and Drexl 2005):

$$\text{Objective function: } \min C_L = \sum_{i \in I} \sum_{j \in J} c_{ij}\, x_{ij} \; + \sum_{i \in I} f_i\, z_i \tag{1}$$

Subject to:

$$\sum_{j \in J} x_{ij} \le S_i z_i \,, \forall i \in I \tag{2}$$

$$\sum_{i \in I} x_{ij} = D_j \,, \forall j \in J \tag{3}$$

$$x_{ij} \ge 0 \,, \forall\, i,\, j \tag{4}$$

$$z_i \in \{0, 1\} \tag{5}$$

Where: x_{ij} are decision variables (flow between plant i and client j); z_i are decision variable (1, if facility i is established, 0 otherwise); c_{ij} are unit production and distribution cost associated with satisfying client j from plant i; f_i is the fixed cost of plant i; D_j is the demand of client region j; S_i is the capacity of plant i; I,J are sets of candidate sites for plants and clients, respectively. Equation (1) is the mono-criterion objective function, which minimises the total logistic cost (production and distribution) plus fixed costs associated with selected alternatives for a plant site. The constraint set (2) prevents that open plants suffer from violations of their capacities (upper bounds). The constraint set (3) assures that all demand from all clients will be satisfied, while the remaining constraints are the usual non-negativity conditions (4) and binary variable definitions (5).

In our illustration, a food company has to design its logistic network (location of plants and capacity allocation to clients). There are ten alternatives (potential sites) to place factories, chosen from main State capital cities (see Table 1, based on the Brazilian market). Their capacity (3,820 t/year), fixed costs (861,000 US$/year, including investment and overhead for a given production capacity) and variable costs (55.88 US$/t) are assumed to be the same for every alternative. The demand is split between 23 Brazilian States (first column of Table 1) easily accessed by land transportation and concentrated in the State capitals. The demand (last column of Table 1) is calculated as the product of per capita consumption times the State population.

Transportation costs to hauling products from a given factory to a given client region are calculated from actual freight rates and are also shown in Table 1. The optimal solution $c_L{}^*$will find which sites will be opened and, therefore, their location and number, in order to minimise (1). In the following sections we present how this model can be altered in order to consider both nodal and topological benefits.

4.2 Identifying and Measuring Nodal Benefits

A nodal benefit is here defined as a benefit inherent to a specific node and, thus, is concerned about a property of the network's elements. It may be either a tangible or intangible aspect, and nodes (potential sites) may be assessed by any number of criteria. There are several ways of identifying nodal benefits. The analyst could use the existing location literature and select the ones suitable for the particular problem. Or else, the analyst could relate to similar problems and see which benefits were measured in these case studies. A third option is to define tailor-made indices from the client company's objectives. This latter approach is the one that we favour, as it links clearly the company's strategic objectives with the fundamental objectives in locating plants (see Keeney 1992). For example, in the illustrative case study mentioned in the previous section, four nodal benefits could be defined, which would reflect the strategic objectives of the company: *maintenance efficiency*, *planning permission*, *logistic services* and *skilled labour*.

Table 1. Freight Rate from City to State and Demand of Each State

	Cities - Potential Sites										
State	JOV	CUR	SAP	RIO	BHR (US$/t)	GOI	SAL	REC	FOR	SOL	Demand (t)
01) AL	115.32	113.18	98.25	86.81	76.19	85.64	32.69	20.65	43.71	66.28	256.0
02) BA	94.29	92.11	77.22	66.31	55.14	66.59	21.24	41.70	57.37	70.60	1221.0
......	......	......	......	......	......	......	......	......	......	......	......
22) SE	106.41	104.22	89.33	78.21	67.26	77.03	23.77	29.60	48.08	66.40	160.0
23) TO	100.51	96.18	87.22	87.83	72.66	52.41	65.45	79.08	66.66	48.14	104.00

Whatever the method employed to define the set of nodal benefits, the next step is to define an attribute (i.e. a performance index) and assess a value function over its range. For example, in our illustration, the nodal benefit *maintenance efficiency* of a potential city could be measured by the following performance index: 'number of hours required from a breakdown to a full repair' with an associated value function (see Figure 1). For nodal benefits that have a qualitative nature, discrete labels can be defined to represent a given level of performance, as shown in Table 2 for measuring the *logistic services* benefit (for details see Keeney 1992).

If there are several nodal benefits that are preferentially independent of each other (see Keeney 1992), then they can be aggregated using a simple weighted sum. Thus the overall nodal benefit for a given topology can be calculated by:

$$\nu_N = \sum_{p \in P} w_{N_p} \nu_{N_p} \tag{6}$$

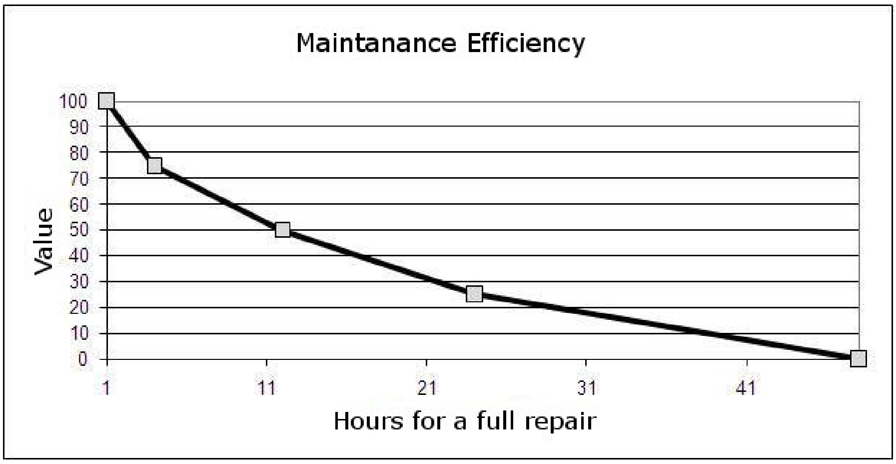

Fig. 1. Marginal value for nodal quantitative benefits - Maintenance Efficiency

Table 2. Marginal value for nodal qualitative benefits - Logistic Services

Value	Description of attribute level
100	Availability of mid-size carriers with a national coverage and high services standards.
75	Availability of mid-size carriers with a regional coverage and high services standards.
50	Few large-size carriers with a national coverage and average service standards.
25	Availability of small-size carriers with regional coverage with high services standards.
0	Few small-size carriers with regional coverage with average services standards.

Where v_{Np} is the partial value on the p-th nodal benefit for this given topology; w_{Np} is the weight of the p-th nodal benefit; P is the set of nodal benefits and $\sum w_{Np} = 1$. Notice that v_N will depend on the number of nodes active, thus:

$$\nu_N = \sum_{p \in P} w_{N_p} \nu_{N_p} = \sum_{p \in P} w_{N_p} \left[\frac{\sum_{i \in I} \nu_{ip} z_i}{\sum_{i \in I} z_i} \right] \tag{7}$$

Equation (7) creates a non-linearity in the objective function. In this paper, we opted for using a direct enumeration method, so a conventional mixed integer linear programming software could be readily used.

4.3 Identifying and Measuring Topological Benefits

Topological benefits are evaluation criteria that assess systemic properties from the network configuration as a whole. Classical mono-criterion location models optimise topological benefits, such as minimising total costs or the weighted distances from clients (a service level surrogate). The same type of criteria is employed in many multi-objective location models, as listed in Current et al.

(1990). In our framework we suggest considering total costs against overall benefits (which can be either topological or nodal), as the former are extremely important in logistic network design. In addition to total cost and geographical coverage, other topological benefits may be employed, such as: number of sites, service area overlap, total system risk, total environmental impact, total quality of service (Badri et al. 1998, Giannikos 1998, Hugo and Pistikopoulus 2005, Farahani and Asgari 2007).

Most methods for measuring topological benefits proposed in the literature use direct measurement of performance (a rare exception is Mirchandani and Reilly 1987) but, again, from a decision analytic point of view, we believe it is important that non-linear value functions are represented in the model, in a similar way as shown in Figure 1.

If there is more than one topological benefit and if these benefits are preferentially independent, then they also can be aggregated using a simple weighted sum. Therefore the overall topological benefit for a given topology can be calculated by:

$$\nu_T = \sum_{m \in M} w_{T_m} \nu_{T_m} \tag{8}$$

Where υ_{Tm} is the partial value on the m-th topological benefit for this given topology; w_{Tm} is the weight of the m-th topological benefit; M is the set of topological benefits and $\sum w_{Tm} = 1$.

4.4 Measuring Preferences for Costs

In the same way as it was done for benefits, we suggest that a value function should be elicited for total logistic costs. Given the large amount of resources typically required in this type of investment, one would expect a non-linear value function, as increases from the minimum cost should be heavily penalised. In practice, we can find the minimum total cost $c_L{}^*$, disregarding the benefits, and then calculate the ratio c_L = cost of the layout/minimum total cost. A value function can then normalise this attribute $v_L = f(c_L)$ (the higher the ratio, the less valuable the solution is, in terms of its overall cost, as shown in Figure 2).

In the illustrative case, component costs are fixed plant costs and variable logistic costs, the latter involving transportation and handling (Table 1). The total logistic costs are calculated by (1). Raw material and manufacturing costs are assumed to be the same for every potential site and thus were not included in the model.

4.5 Defining the Overall Logistic Value Optimisation Model

In our framework, instead of optimising the total cost, as formulated in (1), we suggest a model that maximises the overall logistic value of the network. Thus Eq. 1 is replaced by:

$$Max\, V = w_L \nu_L + w_B [w_N \nu_N + w_T \nu_T] \tag{9}$$

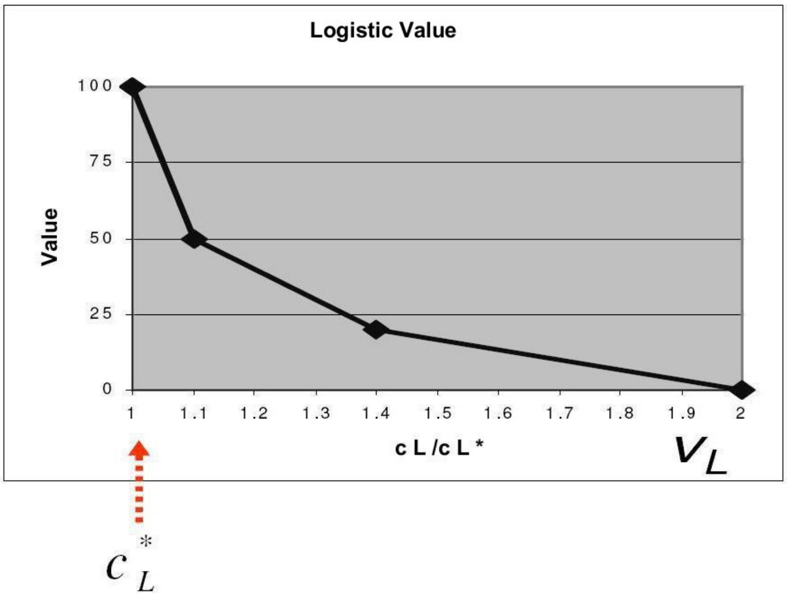

Fig. 2. A value function for total logistic cost

Where V is the overall logistic value of a given topology, w_L is the weight for the logistic cost criterion and w_B is the weight for the logistic benefits (with $w_L + w_B = 1$ and $w_N + w_T = 1$).

4.6 Determining Value Trade-Offs

The next step in our framework is to determine the trade-offs between logistic costs, topological benefits and nodal benefits, represented in (9) by their weights. Defining trade-offs is a crucial step in any important decision involving multiple-objectives, but there are many common mistakes in eliciting them (Keeney 2002), which can lead to meaningless values. For a multi-attribute value model, as the one we are proposing here, trade-offs must be elicited taking into account the ranges of each performance index (for example, in Figure 1, from 1 to 48 hours). Traditionally, trade-offs in multi-attribute value functions are elicited *a priori* from the client, often using the swing weighting method (see Keeney 2002).

We suggest that weights are elicited in phases, i.e., intra-weights w_{N_p} for nodal criteria, intra-weights w_{T_m} for topological criteria, then inter-weights w_N and w_T for nodal and topological benefits, followed by w_L and w_B for cost and overall benefits. In this way, the analyst can reduce the cognitive burden involved in the elicitation (see also von Winterfeld 1999) and help decision-makers think explicitly about the nodal *versus* topological trade-offs, as well as about cost *versus* overall benefits trade-off. Another possibility is to elicit all the intra-criteria weights at once and then infer the inter-weights for benefits from the swing weights allocated to the bottom-level benefit criteria. In any case, once the trade-offs are defined, Equation 9 can be solved to find the configuration which provide the highest overall value.

If the analyst wants to explore different alternatives without *a priori* preference information, for example ranging w_L against w_B in (9), a diagram of efficient solutions can be drawn. Notice, however, that this method does not find all efficient solutions for non-convex fronts (see Marler and Arora 2004). Furthermore, this type of analysis may struggle to convey the results when more than two criteria are considered. That is why we suggest the importance of an interactive visual decision support system in this type of analysis, which is described next.

4.7 Exploring the Solution Layouts

In our experience in supporting this type of decision, location problems require several interactions between analyst and client for exploring alternative solutions. Typically, decision makers want to see an optimal (minimum cost) logistic solution first, in order to anchor their bottom line expectations and start their search for other solutions that provide better benefits within acceptable cost levels. There is, however, an understandable reluctance to explore options which are far from the optimal one, or topologies which are radically different than the optimal one. Furthermore, any analysis that exogenously considers benefits, relying on ad hoc what-if trials, is obviously an inefficient way to explore the solution space. Multi-criteria analysis, on the other hand, allows a more comprehensive evaluation of the benefits in the solution space. It searches for high value solutions, considering the trade-offs between benefits and costs. In this type of approach, visual interactive modelling becomes crucial - the role of the model is to explore different configurations and see how the trade-offs would impact on the topology of the network.

In order to illustrate how such interaction between model and decision-maker may be performed in practice, we have implemented the model described here as an Excel-based decision support system. Changing the weights of cost and benefits leads the model to present a new optimal topology, which is depicted geographically in the map. Figure 3, for example, shows the case where all emphasis is placed on total logistic costs: the network topology can be easily seen on the map, with the different weights shown in the bar graphs. Four sites are opened, appearing as rectangles in the Brazilian map; potential but unused sites are marked as crosses. Different priorities would lead to different layouts, for instance, if all weight were thrown at the benefits then nine plants would be opened. The latter solution maximises network benefits and the topology is therefore quite different than the own shown in Figure 3.

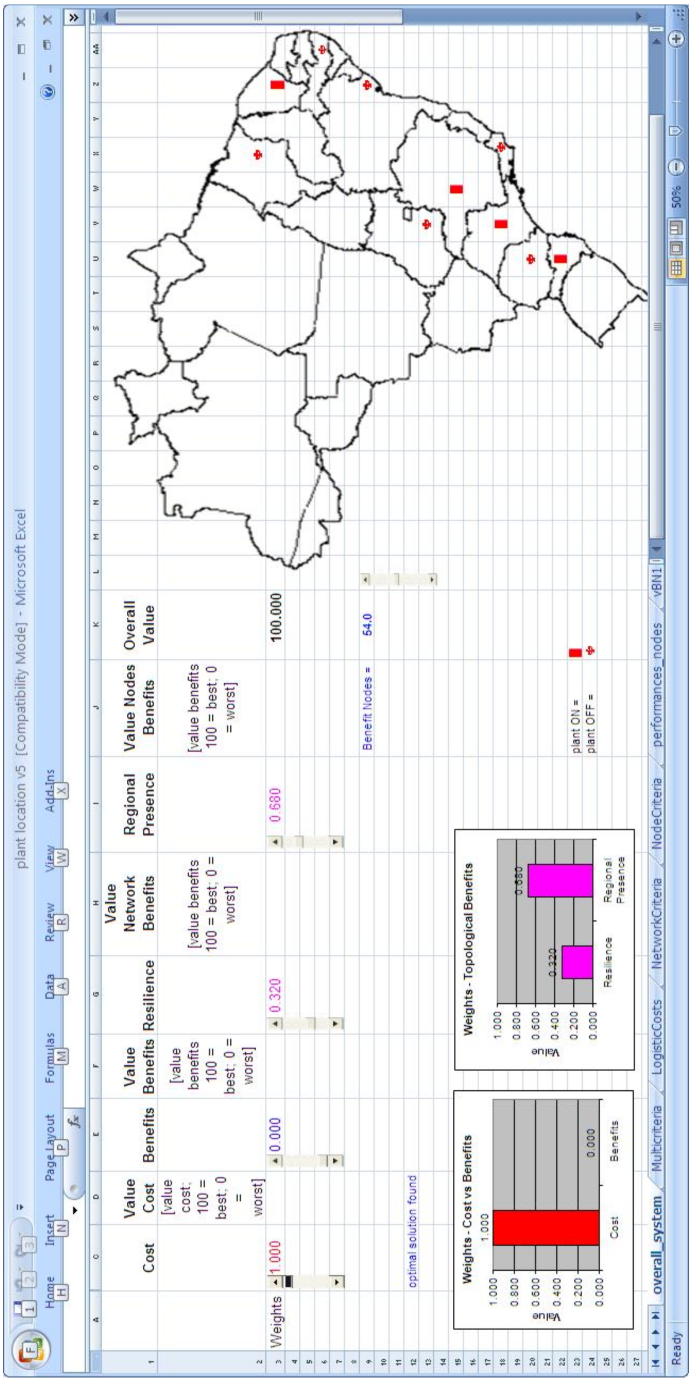

Fig. 3. A visual interactive model for analysing logistic value - All weight on cost

5 Conclusions and Directions for Further Research

This paper proposed a framework for locating logistic facilities with optimisation and multi-criteria value analysis. This was illustrated by an example, based on real data of food companies in Brazil, where a multi-objective single commodity plant location model was developed and implemented as an interactive decision support system. Such an approach may be relevant in complex business environments, such as developing economies, where other considerations beyond total costs are crucial in facilities location (for instance, the availability of infrastructure, technical personnel, logistic services and industrial utilities).

One of the main potential contributions of this paper is to suggest that these issues can be better analysed with a proper categorisation of benefits into topological (network) and nodal (site) types, measured and evaluated in a rigorous way, using multi-attribute value theory. While there is a large literature on multi-criteria facility location, the approach we are suggesting is the first one – as far as we know – that recognises the distinctive role of these benefits and suggests an integrated way of assessing the potential solutions of the network when such benefits are considered. Another potentially relevant contribution is that our framework stresses, within a network optimisation perspective, the relevance of measuring the marginal value of performances and the importance of a proper elicitation of weights in multi-criteria facility location models. Finally, the interactive use of a decision-support system to guide the appraisal of solution, while not new in multi-criteria analysis, is hardly seen in this kind of logistic analysis.

As any decision method, the framework we suggested does have limitations. First, there is a need for the analyst to specify the benefits and elicit value functions and weights for nodal benefits. Second, it is heavy in terms of the computational time required, which could make it less suitable for larger or more complex models. Third, it creates a non-linear objective functions when nodal benefits are considered (i.e. Equation 7). Fourth, it is unable to find solutions in non-convex regions of the Pareto front. There are, therefore, several avenues of further research, as we suggest below.

Non-linearity in the objective function and computational speed. The method we suggested in the paper (running the model for a given number of open plants and finding the number which maximises the overall value, i.e., enumeration) is simple, albeit computationally time consuming. Thus research into ways of making it faster, or solving it directly with the non-linear objective function would be welcomed. Another issue to be investigated is how to find efficient solutions which are not located in the convex front.

We believe that the use of evolutionary methods, as well as other multi-objective meta-heuristics methods (Jones et al. 2002), is an interesting avenue of research for coping with these challenges. There are several levels in which such approaches could be employed. At the first level, one could use a suitable mono-criterion evolutionary method to solve (9), given its non-linear nature.

At the second, and more interesting, level one could employ Multi-Objective (EMO) methods (Deb 2001) for this type of problem. For instance, they could be used to find efficient solutions on the bi-dimensional space v_L versus $w_N \nu_N + w_T \nu_T$ in Equation 9. At a third level, researchers could explore how to deal with the multiple (topological and nodal) benefits of this problem, using EMO methods.

Recent developments in this field, with the incorporation of preferences into EMO methods, as suggested for example by Branke and Deb (2005) and Koksalan and Phelps (2007), may provide an alternative to a full specification of preferences *a priori*. Researchers using EMO could then investigate what is the best way to display the solutions, when multiple dimensions are considered (e.g., performances on multiple topological benefits). They also could identify what type of preference should be provided and how such preferences could be elicited in a decision support system, in a way that is user-friendly and also more efficiently supports decision making. Another avenue of research is using other formulations in (9), for finding efficient solutions located in non-convex regions of the Pareto front, such as the Tchebycheff norms (see Marler and Arora 2004).

Decision Support Systems (DSSs) with visual interaction for logistics. The use of DSSs that have a visual interface with the user and which allow them to "play with the model" (de Geus 1988) could be extended to other decisions in logistics, such as procurement of logistic service operators. More crucially, there is a need for further research into which types of visual interaction are more helpful in these contexts. While such a visual interaction is relatively common now for multi-criteria decision analysis software supporting the evaluation of discrete alternatives, as well as discrete-event simulation software (see Belton and Elder 1994), it seems an aspect under-developed in multi-criteria analysis for logistic problems.

Decision conferencing for facility location decisions. The application of this framework in real business cases would rely on model-based facilitation (Franco and Montibeller 2010) and decision support tools. Research could be conducted on the social outcomes of such interventions (for example, commitment to action, satisfaction of users, etc.). Another issue is how the benefit criteria is structured for a particular problem, for example how concerns about fairness of supply or other social issues could be incorporated in the model.

Concluding, we hope that this paper may further stimulate research on the links between optimisation of logistic problems and multi-criteria decision analysis, particularly with a multi-attribute value perspective. In this context, there are opportunities to use evolutionary multi-objective algorithms, and some open avenues of research were suggested here. We believe that this is a rich area for research and that it may support real-world logistic decisions in a more comprehensive way.

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