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5. May 1992

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Abstract. More and more frequently locational planners are faced with the problem of decision making under the condition of *uncertainty*. In this paper a methodological framework is presented for solving Location – Allocation problems, through the application of the multinomial logit model to data derived from the modification of the characteristics of a given network. The study differs from earlier work in two aspects: First, *a utility function*, as a measure of relative attractiveness, is implemented, in order to assign realization probabilities to each alternative scenario. Second, the decisions are made through the utilization of two system–performance criteria. The *expected loss* and the *minimax loss* criterion of the optimal solution of each future scenario generated by the decision maker during the problem–solving procedure of the approach.

1. INTRODUCTION

One of the most important issues in locational planning is to resolve spatial problems, taking into account a set of possible alternatives and their attributes. Planners called to participate in problem solving procedures, are more and more frequently faced with the problem of decision making under uncertainty. This leads to the generation, formulation and evaluation of alternative scenarios, under the assumption that knowledge of the costs and benefits, associated with each scenario, can help the decision maker estimate the adoption probability of each one of them.

Trying to describe the decision making process under the condition of uncertainty, planners have derived various models from the fundamental theory of utility (Von Neumann and Morgenstern, 1947). However, this is only done in terms of maximum utility estimation and adoption of the appropriate scenario (Weisbord, Parcelli and Kern, 1984; Reggiani and Stefani, 1986). This paper aims to show, that through a scenario–based decision making approach of locational planning, improved problem analysis and hence, more robust and sophisticated problem solving procedures can be obtained, since uncertainty and thus limited information, inherent in the non–static problem environment, can cause unpredictable mistakes along any choice procedure of sufficient complexity (de Palma and Papageorgiou, 1991). Consequently, given that in locational planning the locational choices made are generally judged by the 'quality' of the process of decision–making which generated those choices (Densham and Rushton, 1987), improved problem analysis will lead to better locational choices and thus better locational patterns.

We shall consider the case when during the problem solving procedure the planner deals with a set of predefined future scenarios by a decision maker. Beginning with some initial data and defining possible scenarios for the future, he is trying to evaluate all feasible scenarios and their optimal solutions, according to their realization probability in order to improve the quality of his choices. At the beginning of the process he realizes the utility levels of each scenario. His problem then is to examine the performance of each alternative data set of all possible scenarios $\mathscr{S}(\sigma \in \mathscr{S})$, with their relative adoption probability when dealing with his location–allocation problem. In this respect, his decision will be based both on present status and the future scenarios that he imposed. In principle, all that is necessary to solve this problem is knowledge about the potential cost and benefit of each scenario rather than about the utility function of each solution. Intuitively, this process may lead to some improved locational pattern and a more robust service system. In particular, if the decision–maker adjusts only toward the future scenarios and if the above intersection has a single peak, the stationary state of his adjustment process will also maximize utility.

According to this approach, the defined scenarios by the decision maker have fixed cost and benefit attributes, assigned to them through an estimation rule. Hence any given scenario can arise through change combinations of the system's characteristics. Cost and benefit here and thus the alternative attribute values should be understood as cardinal measures of attractiveness in terms of preference elicitation.

We imagine that the decision–maker draws a random network configuration. The planner then estimates the adoption probability of his scenario from the difference between its current status and the future system configuration that would be obtained if the scenario was realized, via the cost and benefit–oriented utility function. He repeats the same procedure for all scenarios and calculates the utilities. The choice environment in which the decision–maker performs those activities is considered to be naturally discontinuous, in terms of scenario generation and specification. Since the change in the network characteristics is assumed to be complex and since it is conditioned by a large number of factors, both known and unknown, changes of the problem environment appear as random events. Within this context the planner makes errors: he is unable to estimate with accuracy the true utility of each scenario and he is subject to framing. Since errors have many causes in a randomly changing environment, the errors made during the scenario formulation process of the approach appear to be independent from one–another. Furthermore, since they are unpredictable, the difference between reality and his perceptions can only be determined by a probability distribution, which serves as a "black box" to summarize complex behavioral aspects of the decision maker. Such ambiguity is deeply rooted in the real world, and it differs from that in the literature concerned with the implications of an uncertain future on rational choice (Drèze 1974).

Our paper consists of the following sections. Section two describes the model and contains its main implications. It introduces the idea of a system being in a state of change and focuses on the generation of future data sets and the estimation of scenario probabilities. Section three examines the approach of scenario–based decision making. In our model, the relevant attractiveness of each alternative scenario is established, as has already been mentioned, via its cost and benefit definition. Section four deals with a numerical example, based on a simple network, consistent with our framework, focusing on how the definition of alternative future scenarios affects the generation of viable alternatives for action by the decision makers. We end this paper with some brief comments, mainly about general locational analysis methodological aspects.

2. THE MODEL

In our model we use the following notation: We consider a network $\mathcal{I}$ of i demand points, with which we associate a demand weight $\mathbf{w}_i$, which is a measure of the importance assigned to the point, and we select a list of $\mathbf{j}$ ($j \leq i$) potential sites to establish an activity. Furthermore, network data reflect the types of the network links in terms of connection quality and related range of travel times. The travel time between site j and point i is denoted $\mathbf{g}_{ij}$, while the associated link type is denoted $\mathbf{k}_{ij}$. Henceforth, $\mathbf{d}_{ij}$ will be the adjusted distance between i and j with

(1) $$d_{ij} = g_{ij} * k_{ij}$$

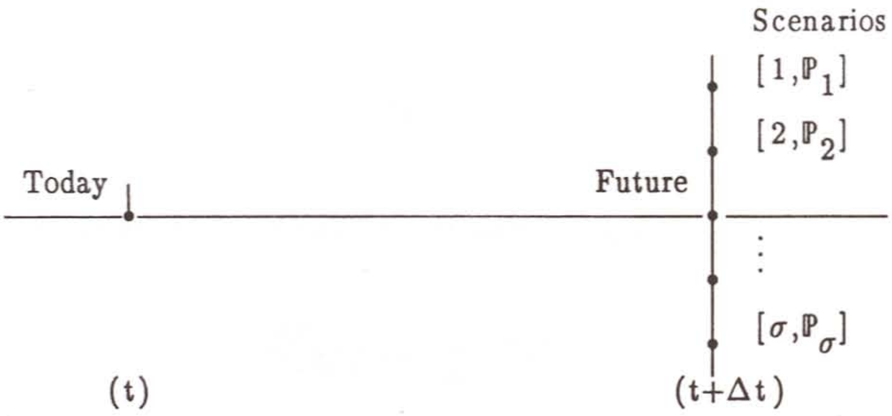
The above network with its set of characteristics that interact within a context of demand and supply we will further on call **a system** and D^t will be the complete data set associated with it. In the given network, the locations of the j facilities and the allocations of them will be defined through the application of a location–allocation model.

In every case, when within the limits of a given system demand is covered by a set of facilities, the **location** of those centers is the compromise between the need for **effectiveness** and **equity** (Koutsopoulos, 1989). The modification of the values of these criteria after a time period calls for adjustments, by the decision makers, which tend to raise the system's decreasing attractiveness.

In terms of retaining a competitive position, planners and decision makers must deal with the uncertainties inherent in the problem environment. This demands, first, the generation of a set of $\mathscr{S}$ $(\sigma \in \mathscr{S})$ alternative possible future scenarios, where $D_\sigma^{t+\Delta t}$ the complete network data set for time $t+\Delta t$ and second, the design of strategies that are viable in the long run considering both the system's current status and future trends. Through the identification of the critical elements that give rise to uncertainty, the next step is to formulate the alternative future scenarios by considering the different possible states these elements may attain.

Ignoring exogenous factors, we consider the system at time **t** which might move to another state at time $\mathbf{t+\Delta t}$. Unable to predict the behaviour of the decision maker with perfect certainty and if the utility measure is directly proportional to the choice probability, we treat the alteration of the system's characteristics as a *random phenomenon* and use probabilities to describe the alteration propensities (Figure 1). Let $\mathbb{P}_\sigma$ denote the *scenario probability*, which is the probability that the system moves towards scenario σ by the end of the change interval $[t,t+\Delta t]$.

Figure 1. The system.



Our choice modeling from a set of mutually exclusive alternatives uses the concept of utility maximization from the field of discrete choice analysis. The principle behind this is that the decision maker is modeled as selecting the alternative with the highest utility among those available at the time the choice is made. Since the estimation and specification of a discrete choice model always successful in predicting the chosen alternatives, by all individuals should be considered impossible, we adopt the concept of random utility (Thurston, 1927). We consider the true utilities of the alternatives random variables, so the probability that a specific alternative is chosen, is defined by the probability that this alternative has the greatest utility from the choice set, which in our case contains all alternatives that are known to the planner during the decision process. The type of choice set that we will focus on in this paper is where the alternatives are naturally discontinuous.

The internal mechanisms utilized by the planner in order to proceed with the available information and finally arrive at a unique choice from a choice set containing two or more alternatives is called a decision rule. In our model the decision rule will be the *utility function*, meaning that the attractiveness of an alternative, which is normally expressed by a vector of attribute values, is reduced to a scalar.

We will approach the decision making process using the concept of rational behavior. In the scientific literature we refer to the term 'rational behavior' based on the beliefs of an observer about what the outcome of a decision rule should be. In general, it means a consistent and calculated decision process in which the decision maker follows his own objectives. Obviously different observers may have varying beliefs and may assume different utilities (Ben–Akiva and Lerman, 1985).

The most difficult assumption to make involves the form of the utility function. In our model, we impose an additive utility function of the following structure:

$$U_1 = -\beta_1 A - \beta_2 B + \beta_3 C \tag{2}$$

when $\beta_1, \beta_2, \beta_3 \geq 0$ are parameters that express the tastes of the decision maker.

3. THE SCENARIO–BASED DECISION MAKING APPROACH

3.1 Realization Probabilities of Scenarios

Time is partitioned into present t and a period of length Δt. At time t we have a network configuration D^t, which is defined by the system's characteristics. On the other hand, the planner defines the set S ($\sigma \in S$) of scenarios for time $t+\Delta t$, which during the interval $[t, t+\Delta t]$ lead to a set S of future network configurations $D_\sigma^{t+\Delta t}$, where $\sigma = 1,\ldots,s$. Changes in the system characteristics through this interval are driven by flows of change and the need for modification and adjustment.

Assumption 3.1: The adoption of a specific scenario σ for time $t+\Delta t$ is associated with its relative *cost* and *benefit* C_σ and B_σ, and respectively with the *Realization* $RLS[\sigma]$ of σ that has the following structure:

$$RLS[\sigma] = -\beta_1 C_\sigma + \beta_2 B_\sigma \tag{3}$$

where $\beta_1, \beta_2 \geq 0$ are the parameters that express the tastes of the decision maker with $\beta_1 + \beta_2 = 1$ and thus

$$RLS[\sigma] = -\beta_1 C_\sigma + (1-\beta_1) B_\sigma \tag{4}$$

The *realization utility* of the scenario σ, defined by the decision maker and adopted at time t, is assumed to be a random variable $RUTIL[\sigma]$ with the following structure:

(5) $$\text{RUTIL}[\sigma] = \text{RLS}[\sigma] + \varepsilon_\sigma$$

where RLS[σ] is the nonrandom systematic component; and ε_σ is the random error term. We may call ε_σ a *scenario–specific error term* because it can assume different values for different scenarios.

We have already explained why the random errors are stochastically independent. If further, they are identically distributed, and if the preference ordering of the decision maker is invariant under uniform expansions of the choice set, then according to Yellot (1977, theorem 6) the random errors are double exponential. Under these circumstances, we can write the random errors as

(6) $$\varepsilon_\sigma = \frac{1}{\mu}\varepsilon \quad \text{for } \mu > 0 \text{ and } \sigma = 1,\ldots,s$$

where $1/\mu$ is the dispersion parameter of ε_σ, and where ε is double exponential with zero mean and unitary dispersion parameter. Then, following Mc Fadden (1974), the marginal adoption probabilities of each alternative scenario are given by the multinomial logit model (ML, Ben–Akiva and Lerman 1985):

(7) $$\mathbb{P}_\sigma = \exp\Big[[\mu\text{RUTIL}[\sigma]\Big]\left(\sum_S \exp\Big[[\mu\text{RUTIL}[s]\Big]\right)^{-1}$$

$$\text{with} \sum_S \mathbb{P}_\sigma \equiv 1.$$

Since errors become smaller for larger μ, this parameter can be interpreted as the ability of the planner to estimate the true utility of a future scenario: larger μ implies larger ability. We also have

(8) $$\lim_{\mu \to 0} \mathbb{P}_\sigma = \frac{1}{s} \quad \text{for } \sigma = 1,\ldots,s$$

$$(9) \qquad \lim_{\mu \to \infty} \mathbb{P}_\sigma = \begin{cases} 1 \text{ if } RUTIL[\sigma] = \max\{RUTIL[v],\ v = 1,\ldots,s\} \\ 0 \text{ otherwise} \end{cases}$$

That is, when there is no ability to estimate the true utility of future scenarios, alternatives are equiprobable irrespectively of differences in their current marginal values; and when the ability to estimate the true utility of the future scenarios is perfect, the best estimation is made with certainty. More generally, the discriminatory power of the decision–maker is reflected on the distribution of the marginal scenario probabilities around alternatives of higher marginal utility. As the ability to estimate the utility of the alternative future scenarios increases so does the discriminatory power, and the distribution of marginal scenario probabilities, until, at the limit, the decision–maker adjusts only toward best alternatives.

3.2 Solution Evaluation Criteria

Let us denote L_σ the optimal solution for the configuration of scenario σ, if this is realized and $z(b,\sigma)$ the value of the objective function if solution L_b is imposed but σ is realized ($b,\sigma \in S$). When S contains more than one scenario, the planner can solve his problem for the s alternative network configurations and then examine the performance first, of each optimal solution $L_\sigma^{t+\Delta t}$ and second, the performance of each configuration if the optimal solution of scenario b is imposed but scenario σ is achieved ($b,\sigma \in S$).

3.2.1 Expected Loss of scenario

At the end of the problem solving procedure for every $b,\sigma \in S$, we can construct a "decision matrix" $[DZ_{b\sigma}]$ whose elements will be $dz_{b\sigma}$, representing the loss in the solution performance of scenario σ if the optimal solution of scenario b is adopted. Consequently, if the realization probabilities of each alternative scenario are known in advance then the planner may proceed with his choice through two different approaches. In the first one, he calculates the expected loss of each scenario E_b which is the summation of the losses $dz[b,\sigma]$ in the objective function if the solution of scenario b is implemented but scenario σ is realized times $\mathbb{P}_\sigma$, which is the adoption probability of σ, for every $b,\sigma \in S$:

(10) $$E_b = \sum_\sigma \mathbb{P}_\sigma dz(b,\sigma) \quad \forall\ b,\sigma\in S$$

and

(11) $$\bar{E} = \min_b \{E_b\}. \quad \forall b\in S$$

3.2.2 Minimization of maximum loss

In the second approach, the planner searches for the solution L_b which minimizes the maximum loss in the objective function of every other alternative scenario σ, when b is imposed but σ is finally achieved. In this regard

(12) $$\bar{z}_b = \min_b\{\max_\sigma[dz(b,\sigma)]\}$$

Dealing with locational planning problems, both in the private and the public sector, requires the selection of the appropriate objective function **(OF)** which in most instances can be expressed in terms of optimization toward the fundamental objectives of the problem to be solved. We thus arrive at the optimization issue of the process and in this regard, we have defined the different data sets that will be utilized by the location–allocation model through the appropriate objective function and the allocation rule. In the next section we present a numerical example. This example, will demonstrate the generation of alternative scenarios by the decision maker and the construction, by the planner, of the decision table mentioned above.

4. A NUMERICAL EXAMPLE

In this section we consider the problem of a planner dealing with a set $\mathcal{S}(\sigma\in\mathcal{S})$ of alternative system configurations for a ten–node network $\mathcal{F}$ (i,j $\in\mathcal{F}$). In this ten–node network and concerning time **t**, data refer to the demand matrix $\mathbf{W}_i^t$, with $w_i > 0$, the straight distance matrix $\mathbf{L}_{ij}^t$ and the connection type matrix $\mathbf{K}_{ij}^t$, with connection types k_{ij} ranging between 1,2 and 3. The straight distances for time t and the link types for time t, t+Δt are displayed in Table 1. The travel time matrix D^t_{ij}, shown in Table 1, can then be written as

$$(13) \qquad [D^t_{ij}] \equiv [L^t_{ij}]\,[K^t_{ij}]$$

Table 1. Straight Distances for time t and Link Types for times t, t+Δt.

From Node	To Node	Straight Distance	t	#1	#2	#3
1	2	10	1	1	1	1
1	6	12	3	1	1	1
1	9	25	3	3	2	1
2	3	11	2	1	2	2
2	5	12	2	1	2	2
3	7	14	3	3	2	3
4	5	6	3	3	2	3
4	6	15	2	1	2	2
4	9	16	3	3	2	3
4	10	9	2	1	2	2
6	9	14	2	1	2	1
7	8	7	2	1	2	1
7	10	18	3	3	2	1
8	10	13	3	3	2	3

Table 2. Distance matrix for time t.

Node	1	2	3	4	5	6	7	8	9	10
1	—	10	32	52	34	36	74	88	64	70
2		—	22	42	24	46	64	78	74	60
3			—	64	46	68	42	56	96	82
4				—	18	30	71	57	48	18
5					—	48	88	75	66	36
6						—	101	87	28	48
7							—	14	119	53
8								—	105	39
9									—	66
10										—

On the basis of the model developed in section two and in terms of scenario definition, the decision maker is enabled to modify both the demand W^t_i and the connection type K^t_{ij} matrices to denote future system configurations. Assume that there are three alternative scenarios $\mathcal{S} = \{1,2,3\}$, for which associated shortest–path distances and demand matrices are shown in tables 3, 4, 5 and 8.

Table 3. Distance matrix for time t+Δt. *Scenario* 1.

Node	1	2	3	4	5	6	7	8	9	10
1	–	10	32	42	34	12	46	53	25	60
2		–	22	42	24	22	36	43	35	54
3			–	50	46	44	14	21	57	32
4				–	18	30	36	43	48	18
5					–	46	54	61	59	36
6						–	58	65	28	48
7							–	7	71	18
8								–	78	25
9									–	66
10										–

Table 4. Distance matrix for time t+Δt. *Scenario* 2.

Node	1	2	3	4	5	6	7	8	9	10
1	–	10	21	40	22	12	35	49	25	58
2		–	11	30	12	22	25	39	35	48
3			–	41	23	33	14	28	46	59
4				–	18	30	55	57	48	18
5					–	34	37	51	47	36
6						–	47	61	28	48
7							–	14	60	53
8								–	74	39
9									–	66
10										–

Table 5. Distance matrix for time t+Δt. *Scenario* 3.

Node	1	2	3	4	5	6	7	8	9	10
1	–	10	32	46	34	24	60	74	60	64
2		–	22	36	24	34	50	64	60	54
3			–	58	46	56	28	42	82	64
4				–	12	30	54	44	32	18
5					–	42	66	56	44	30
6						–	84	74	28	48
7							–	14	86	36
8								–	76	26
9									–	50
10										–

According to assumption 3.1 the adoption of a specific scenario σ at time $t+\Delta t$ is associated with its relevant **cost** and **benefit** respectively C_σ and B_σ where

(14a) $$C_\sigma \equiv C_{w\sigma} + C_{T\sigma}$$

(14b) $$B_\sigma \equiv B_{w\sigma} + B_{T\sigma}$$

In order to calculate the attributes of these variables for each scenario σ, the decision maker imposes some simple *translation rules*:

Translation rule 4.1: The modification of the weights of the nodes from $\mathbf{w}_t$ at time $\mathbf{t}$ to $\mathbf{w}_\sigma$ at time $t+\Delta t$, leads to a *weight-specific* cost $\mathbf{C}_{\mathbf{w}\sigma}$ and benefit $\mathbf{B}_{\mathbf{w}\sigma}$ of scenario σ. Actually,

(15a) $$\text{if } w_\sigma > w_t \text{ then } C_{w\sigma} = (w_\sigma - w_t)/w_\sigma \text{ and } B_{w\sigma} = (w_\sigma - w_t)/w_t$$

(15b) $$\text{if } w_\sigma < w_t \text{ then } C_{w\sigma} = (w_t - w_\sigma)/w_t \text{ and } B_{w\sigma} = (w_t - w_\sigma)/w_\sigma$$

Translation rule 4.2: The modification of the type of the connection between nodes i and j from $\mathbf{T}_t$ at time $\mathbf{t}$ to $\mathbf{T}_\sigma$ at time $t+\Delta t$, leads to a *type-of-connection-specific* cost $\mathbf{C}_{\mathbf{T}\sigma}$ and benefit $\mathbf{B}_{\mathbf{T}\sigma}$ of scenario σ. The smaller the numerical value of the connection type the better it is and thus, the closer the travel time gets to actual distance. On this basis,

(16a) $$\text{if } T_\sigma < T_t \text{ then } C_{T\sigma} = 0 \text{ and } B_{T\sigma} = \left[\frac{w_i + w_j}{2}\right]\left[\frac{T_\sigma - T_t}{T_\sigma}\right] d_{ij}$$

(16b) $$\text{if } T_\sigma > T_t \text{ then } C_{T\sigma} = [T_\sigma - T_t]\, d_{ij} \text{ and } B_{T\sigma} = \left[\frac{w_i + w_j}{2}\right]\left[\frac{T_\sigma - T_t}{T_\sigma}\right] d_{ij}$$

Table 6 displays the expected associated cost and benefit of each alternative scenario, after the implementation of translation rules 4.1 and 4.2 to the three future network configurations.

Table 6. Scenario associated cost and benefit.

Scenario	C_σ	B_σ
1	434	966
2	358	683
3	317	407

Following equations (5), (15a), (15b), (16a), (16b) and after the initialization of factor β_1, which in our case is $\beta_1 = 0.8333$, implying that we are mostly interested in the anticipated cost of the alternative, the associated value of the *Realization utility* **RUTIL**[σ] and the associated adoption probabilities $\mathbb{P}_\sigma$ of each scenario σ, are calculated and shown in Table 8, while Table 7 shows the adoption probabilities of each alternative scenario for the different values of β_1 in the interval [t,t+Δt], while Figure 2 compares the graphical representations of the adoption probabilities of the three alternative scenarios for different values of β_1, throughout the problem–solving approach.

Figure 2. *Plot of* $\mathbb{P}_\sigma$

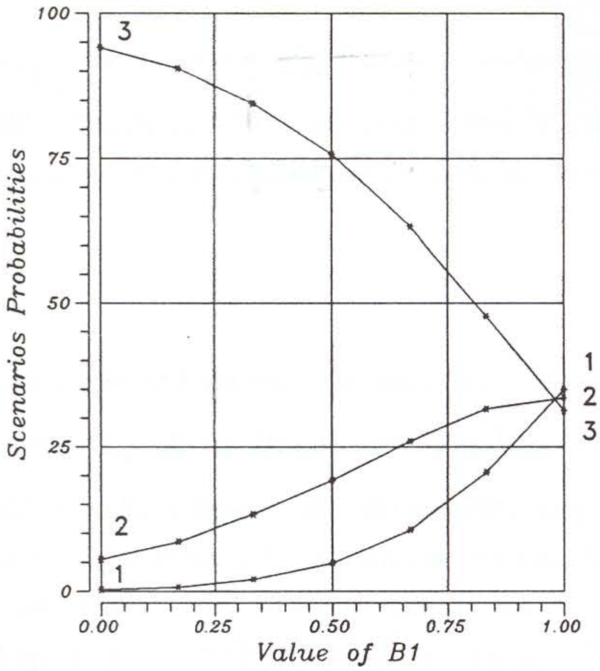


Table 8. Demand for time t and t+Δt.

Node	*t*	*#1* 47.7%	*#2* 31.6%	*#3* 20.6%
1	12	100	70	12
2	24	38	70	24
3	32	32	80	32
4	12	12	12	40
5	16	16	16	40
6	28	28	28	40
7	23	80	23	40
8	22	30	50	50
9	44	44	44	44
10	61	61	61	61

In this example and in order to establish p facilities in p potential locations and supply each node from a subset of the established facilities, we consider a heuristic algorithm which solves the p–median problem (Densham, 1989). By definition, the p–median is a prototype formulation that reflects many realistic locational decision problems. The p–median problem minimizes total distance of demand from the closest of p centers in the system. It can be formulated in the following way:

(17) $$\text{minimize } z = \sum \sum x_{ij} c_{ij},$$

where $x_{ij} = 1$ is the demand node is allocated to facility j, 0 otherwise; and c_{ij} is a metric of interaction that can take various forms including distance, transportation cost, or travel time. In our case, where travel distance minimization is the objective,

(18) $$c_{ij} = w_i d_{ij}$$

where w_i is demand weight of node i, that is the amount of demand to be served at the ith location, and d_{ij} is the adjusted distance from the ith to the jth location, according to equation (13). After proceeding with the analysis of the three alternative scenarios, in which we held constant the number of centers, suppose that p=3 and that three facilities must be located at three nodes of this network, we are able to construct the decision table shown in Table 9. For every proposed regionalization by the location–allocation model we compute the value of the objective function for the optimal solution and the loss in the objective function in the case we adopt the optimal solution of scenario b, but σ is achieved for all b,$\sigma \in$S. Following equations (10), (11) and (12) we fill the Expected Loss and Minimax Loss columns of the table. The evaluation and comparison of the alternatives and the results in our example, shows that scenario #1 has both the minimum Expected Loss and the minimum Maximum Loss for the current problem formulation.

Table 9. Solution Evaluation Table

	Realized Scenario				
Adopted Scenario	#1	#2	#3	Expected	Maximum
#1 ($\mathbb{P}_1$=47.7%)	0	4538	1404	1702	4538
#2 ($\mathbb{P}_2$=31.6%)	3554	0	5406	2841	5406
#3 ($\mathbb{P}_3$=20.7%)	1140	5862	0	2364	5862

Table 7. Scenario probabilities as a function of β_1.

	Alternative values of β_1						
σ	0.000	0.167	0.333	0.500	0.667	0.833	1.000
1	94.1%	90.5%	84.5%	75.8%	63.3%	47.7%	31.3%
2	5.5%	8.6%	13.3%	19.2%	26.0%	31.6%	33.6%
3	0.3%	0.8%	2.1%	4.9%	10.6%	20.6%	35.0%

5. CONCLUDING REMARKS

Uncertainty is inherent in most locational planning situations, due to the dynamic nature of the problem environment and the inability of the planners to predict with accuracy, the exact future system configuration and network specification. Nevertheless, it is exception rather than the rule that such considerations are studied in locational decision problems. In this paper we presented a scenario–based locational planning (SBLP) framework. We deal with the problem of assigning probabilities to each alternative *future scenario* defined by the decision maker, through the application of the multinomial logit model. Still, by no means, we can say that we are able to localize the one and only scenario whose optimal solution is a global optimum. Nevertheless, knowing the nature of locational planning and the problems faced within the context of scenario–based location analysis, we argue, that through the implementation of our model, we can determine a more reasonable decision making process, due to the definition of the utility function as cost and benefit–oriented. Undoubtedly, there are many possible types of change in the problem environment and consequently, a plethora of ways of translating them to cost and benefit and incorporating them in the general framework. In our numerical example, we examined the case when only the weights of the nodes and the types of the connections can be modified through the scenario generation and formulation stages of the approach, bearing in mind that, the overall objective of this paper is to provide insights about methodologies, which can contribute to the solution of locational decision problems in practice, where we believe that there is a strong need for further refinements.

Undoubtedly, according to current trends there is an increasing interest in the ability to operationalize the handling of more complex criteria than we have shown in our example, which can be treated as a *bicriteria model* (that is, incorporating only two criteria), particularly as regards decisions concerning the location of public facilities. Admittedly, it can be forcefully argued that there are no criteria for selecting criteria and in spite of the existing arsenal of algorithms, we believe, that the need for a more sophisticated approach of locational decision making should lead to much more interactive search procedures. More specifically, we refer to systems allowing for interaction among the decision maker, the planner and a computer, which might prove to be able to lead to 'better' locational decisions, being more vital than a 'realistic' location–allocation model. As Krarup and Pruzan stated (1990):

> There is no doubt that locational decision problems focus upon strategic rather than tactical matters, for example where to place schools rather than how to route school buses. That is, the emphasis is placed upon planning and design problems rather than on operational problems. It should be noted however that in practice a locational decision problem can seldom be considered in isolation from other strategic decisions.

Although we deal with a rather simplified case, our approach can be considered as an attempt to provide answers to a limited number of 'what if' questions and furthermore, yields insights into two basic aspects. On the one hand, scenario–based locational planning practically emphasizes on the definition of the utility of possible future states of the system, assessing the relative realization costs and benefits, considering that the visualization and the definition of future scenarios is a very difficult task. On the other, is focusing on the planner's and the decision–maker's attention to the future, as one of great importance, since location decisions require long–term future investments that can be changed only at considerable costs. Consequently, given the importance and possible impact of the systematic evaluation of future uncertainties, we believe, that considerable effort should be placed on the assessment of the expected attractiveness of the system's configuration which, finally, will lead to a more sophisticated analysis of locational planning problems and thus more efficient locational patterns.

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