European Journal of Geography Volume 6, Number 4: 59- 75, December 2015

SCENARIO-BASED LOCATION OF AMBULANCES FOR SPATIOTEMPORAL CLUSTERS OF EVENTS AND STOCHASTIC VEHICLE AVAILABILITY. A DECISION SUPPORT SYSTEMS APPROACH.

Yorgos N. PHOTIS
Department of Geography and Regional Planning, National Technical University of Athens, Greece
yphotis@mail.ntua.gr
Stavros A. SIRIGOS
Department of Planning and Regional Development, University of Thessaly, Volos, Greece
stavros.sirigos@gmail.com

Abstract

Facility location through the utilization of location-allocation models is a scientific field that has been rapidly growing over the last 60 years. Especially in countries where there is an increased need for new infrastructure and services while resources and funding availability is limited, their application in solving respective problems can be effective both in catalyzing needs as well as minimizing required budget and costs. In this context, new models, improved algorithms and alternative methodological approaches have been constantly arising. In Greece, unfortunately, the use of these models is not a common practice in locational projects and studies resulting in relatively limited corresponding experience and research. In this paper we present S-Distance, a stand alone locational analysis and planning support system, initially designed at the Laboratory for Spatial Analysis, GIS and Thematic Cartography in the University of Thessaly, Greece and currently under further development by the GeoCHOROS Geospatial Analysis and GIS Research Group at the National Technical University of Athens, Greece. The operational validity of the proposed system was verified for the location of ambulances in the metropolitan area of Volos and Nea Ionia in Greece.

Keywords: *location-allocation, Spatial Decision Support System, optimization algorithms, EMS*

1. INTRODUCTION

Location planning of a service delivery network is undoubtedly a complicated task. This is mainly due to the fact that the location of service centers and facilities, both in the public and private sector, is tied to decisions relevant to the number of units in the area as well as their characteristics,. These decisions are interrelated and interdependent and thus, spatial, social, political, economic and individual data should be combined and co-examined.

Research in recent years has shown that, contrary to what was assumed until now, especially for densely populated areas, the environment within which location decisions are taken is characterized by uncertainties (Snyder, 2006). Thus, for example, uncertainties have been identified concerning the demand which supply centers have to cover as well as uncertainties related to the transportation network impedance, whether it refers to travel time or cost. At the same time, and given the extensive investment in resources and infrastructures, locational planning policies and decisions are expected to last for a significant period of time.

Therefore, certain predefined problem parameters, which are not defined with certainty during the decision-making process, should be handled as uncertain or random. In this respect, addressing this issue requires a location analysis model, which takes into account the inevitable uncertainty of decisions over time. (Sirigos, 2004).

Aiming to address the growing complexity of locational planning, research, during the last thirty years, has moved towards the design and development of geospatial information systems which will support the relating decision-making process. Such information systems compile and combine methods and techniques from the scientific areas of geoinformation, location theory, regional development and geospatial analysis.

In this paper we present S-Distance, a stand alone locational analysis and planning support system, initially designed at the Laboratory for Spatial Analysis, GIS and Thematic Cartography in the University of Thessaly and currently distributed by the GeoCHOROS Geospatial Analysis and GIS Research Group at the National Technical University of Athens, Greece. The operational validity of the proposed system is verified through the location of ambulances in the metropolitan area of Volos and Nea Ionia in Greece; the location-allocation model that was formulated, optimizes response for the worst case scenario, taking into account the stochastic nature as well as the hierarchical structure of the problem, when considered at the regional or country level. Alternative scenarios are generated based on the expected geographical and temporal distribution of the emergency incidents (demand), the traffic flow variability, the number of available ambulances (supply) as well as the probability of an ambulance being occupied on the time of call.

2. LOCATIONAL ANALYSIS AND PLANNING

Locational analysis and / or planning refers to capturing, modeling, formulating and solving a broad category of problems, which may be best described as siting facility operations and activities in a given area and assigning demand to them in order to build a robust service network. In essence, it constitutes the art and science of mathematically putting things where they should be. The expressions deployment, positioning, and siting are frequently used as synonyms (ReVelle and Eiselt, 2005). In its simplest form, a “services network” is regarded to be a set of generally similar service centres, which are required to meet a certain demand.

To this end, locational planning problems deal with the spatial organization of services, which respectively require the location of centres and the allocation of demand to them, according to specific constraints. A typical location problem is mainly defined by four (4) decision variables: a) the spatial distribution of demand, which is usually located in points (nodes) or paths, b) the nature and the characteristics of the service network, c) the area in which demand has to be allocated and service centres located and d) the metric which denotes (time) distances or the service cost of demand with respect to the locations of the feasible sites (candidate locations) on the study network which is usually reflected to a distance matrix.

2.1. Location - allocation models

Numerous factors play an important role in the modeling of location problems, apart from the basic parameters described above. Such a factor is the objective, which according to the nature of the problem is set by the decision-makers and has to be either minimized or maximized. In several cases, such as ambulance location problems, the primary target is for supply locations to be or get as close as possible to demand. On the contrary, when selecting areas for the location of radioactive waste landfills, geologically stable regions are sought, which will be as far away as possible from densely populated areas.

In their general form, location-allocation models confront the following problem: given the spatial distribution of demand, facilities or service centres must be located and allocation regions must be defined around them in “the best possible way” (Photis, 2014). The “best possible way” is achieved through the optimization of an objective function, according to which profit is maximized or loss minimized depending on the alternative solution configuration. The mathematical foundations of location-allocation problems were set by Pierre de Fermat (1601-1655) and were first applied by Weber (1909) for the definition of a point in the plane that minimizes the sum of the transportation costs from it to n destination points, where different destination points are associated with different costs per unit distance.

2.1.1. Static models

Clinical and statistical data show that if the human brain is deprived of oxygen for more than six minutes, then the probability of survival and continuance of a normal life is less than 50%. Thus, the locational planning process could focus on the minimization of the number of ambulances required, so that all nodes which potentially might represent demand (e.g. residential areas) are within a specific time distance (i.e. six minutes) from the nearest facility or service center (ambulance). This distance is called “covering distance” and the respective location – allocation model formulation is the “set covering”. Respectively, a demand node is considered “covered” when the nearest service center – an ambulance in our example – is located within a distance equal to the covering distance (analogous to the nature of the service). Set covering models have been widely used by a number of authors and researchers for emergency management service and response problems (Photis, 2004).

One of the most common problems associated with the set-covering model is that the solution it proposes, locates more vehicles than the organization’s budget can afford (Daskin, 1995). Specifically, the last ambulances contribute little to the percentage of the demand’s coverage served within the coverage distance, while they increase the service’s provision cost significantly. This fact leads to an alternative target: the maximization of the demand served within a given coverage distance by using a certain number of ambulances. This formulation is known as “maximal covering model” (Church and ReVelle, 1974). In practice, the size of the current fleet this model takes for granted ranges from 1 to the number required for the full coverage according to the suggestion of the set covering model.

Sometimes, the determination of a given covering distance in advance is difficult and sometimes is quite inappropriate. For example, in the examined case of ambulances, the 4-minute covering distance may well be not the appropriate one. A shorter timeline could be substantiated when observing that the countdown for the patient begins with the start of the (serious) medical incident, while the reaction time counts only after the vehicle leaves its base. A considerable time period (several minutes) very often mediates between the medical incident and the activation of the vehicle which will move towards the expected area. This additional time is consumed by the time of the incident’s assignment to a vehicle and information of the crew. On the other hand, further reduction of the covering distance may be impossible due to economical reasons. It would cost much less, instead, if the timeline was 5 minutes or more. In this way, another model is determined: the minimization of the covering distance of the total demand, by using a given number of ambulances (i.e. minimization of the maximum distance). Thus, the set covering’s distance is determined endogenously by the model itself (Daskin, 1995). The above formulation is known as the “P-center model”.

The coverage and center models focus on the systems behavior in the worst case, such is the maximum reaction time, for instance. Moreover, the view that the level of service gradually decreases, while the distance increases, is much more realistic. This observation leads to the fourth basic model with the following formulation: the average time of response (time between points of demand and nearest ambulance) for a given number (P) of vehicles. This model, which is the most classic, is known as “P-median” (Daskin, 1995).

2.1.2. Dynamic and stochastic models

Static models, which were described above, ignore the stochastic (random) nature of demand and the fact that the nearest vehicle may not be available at the time of the call. If the model’s data get characterized as random variables, then results will be random variables as well. In this sense, interest is focused not only on the determination of the average response time (as in P-median model), but also on the function of demand nodes’ distribution. Moreover, demand is as stochastic as travel times are.

Additionally, static models ignore temporal differentiation in the total intensity of calls and the temporal differentiation in the spatial distribution of them. Temporal differentiation of demand implies that use of fixed points may not be optimal; on the contrary, use of mobile (continuously located) ambulances is preferred (Photis, 2004).

Unlike static models, in the dynamic ones ambulance location is examined over time. This means that variable values may be differentiated for each period of time, but in a fixed or predictable way. The object is the optimal service of demand for the total of the examined timelines. On the other hand, in stochastic models, some of the variables are considered to be uncertain. The values they receive are either connected with a possibility distribution function, or are considered to be accidental, or are represented by a set of possible scenarios. In this way, more characteristics which compose the real problem of location are embodied, while the system’s behavior is examined according to variety of non-clearly defined parameters. The main disadvantage of dynamic and stochastic models is that their solving procedure is much more demanding than the one of the static models, while in some of them, due to the nature or/and the number of the variables that compose the uncertainty are practically non-solvable (Grekousis & Photis, 2014).

The issue of service centers’ availability (usually vehicles for dealing emergency incidents) has been the subject of many articles in the relevant literature (Photis & Grekousis, 2012). Daskin (1982 and 1983) extends the maximal covering model so as to take into account the probability that service centers (ambulances in this case) are occupied when demand occurs. In the model of expected maximal covering that results an expected number of service centers is located, in order for the expected demand coverage to be maximized by an available center. In this model, the fact that a center may be occupied is equally possible for all service centers and independent of the existence of already occupied centers. The model of expected maximal covering sets certain restrictions, which many researchers have tried to loosen. For instance, Batta et al. (1989) use results from the “queuing theory” in order to achieve a more realistic representation of reality. The models which **occur** accept the fact that the probability of a center being occupied depends on the probability of another center being occupied too (hence it may have different values). So the interaction between centers that cover common nodes is modeled more accurately. Nevertheless, the models which are obtained are much more difficult to be solved by the expected maximal covering model (Owen and Daskin, 1998).

3. LOCATION ANALYSIS AND PLANNING SUPPORT SYSTEMS

In a highly competitive era, both at international, EU and regional level, location planning cannot be thought of without the necessary methodological and technological tools, which will allow not only the current situation's analysis (quantitatively and qualitatively), but also the production and evaluation of high quality alternative scenarios which will improve the current situation. Besides, the continuous development of computer systems' capabilities and the development of even more powerful and elaborate analysis techniques allow models which were thought to be intractable, be treated successfully.

The international literature on location-allocation models (and general on location analysis) is incredibly rich. However, that knowledge is not concentrated in an integrated system which will help decision-makers in solving location problems. Thus, each researcher has to develop himself the special tools he needs or turn to other, less appropriate, methods and techniques. We hope that this void is going to be filled in by the creation of the *S-Distance* location analysis and planning system, which has been developed since 2001 at the Laboratory of Spatial Analysis, GIS and Thematic Mapping of the Planning and Regional Development, Faculty of Engineering, University of Thessaly (Sirigos, 2003).

3.1 The S-Distance location analysis and planning support system

Locational decision making is a critical and complicated process which in most cases is hampered by the lack of an easy to use support system. In order to deal with the above issue, in this paper we present *S-Distance*, a prototype planning support system for scenario-based location-allocation analysis. The *S-Distance* location analysis and planning system is an autonomous system of location analysis and planning, whose main target is solving location-allocation problems. In its current version, the system is totally functional and has been applied both to standard operational research problems and actual location problems, of small and large scale. The system includes a set of models and powerful location-allocation algorithms which, combined to an effective user interface, interact with the decision-maker guiding him to alternative scenarios of location models.

Using the system, decision-makers are able to diagnose possible spatial problems in the existing service network of the public or private sector, such as the ineffective location of service centers or/and demand distribution to them, in a total area, based on location-allocation models, by using properly social, economical and spatial data. Simultaneously, decision-makers are able to propose optimal positions for locating service centers, alternative positions for reallocating some or all the existing centers and also redistribution of demand to them, wherever this is considered to be necessary and economically feasible.

3.1.1. Functions and capabilities

The *S-Distance* system allows the substantial interaction and contribution of users during the evaluation and determination of final solutions. The user may choose between several basic models and define multivariate models, as well. Solution techniques that have been implemented, include simple heuristic algorithms, powerful meta-heuristic algorithms and optimization techniques as well as combinations of these. Moreover, the user may intervene to all stages of the solution's determination and the individual restrictions, by visualizing and comparing the results directly. This fact is very helpful in understanding the dynamics of a given location problem, while it improves the credibility of the final result. Besides, it should be noted that the *S-Distance* system may (and must) act complementarily with the existing methodologies and location standards, helping, without substituting the competent bodies who are responsible for making decisions concerning location.

The integration of the *S-Distance* system in the procedure of location decision making (both in public and private sector) may contribute in:

- the equal provision and use of public services by the population
- the improvement of sustainability and efficiency of operations and activities, and reduce of a potential nuisance caused by them
- the reduction of cost incurred by annexes that don't function properly due to small demand coverage
- the reduction of time and money wastage for the required movements, and the reduction of unnecessary travel which result from poor location options
- the efficiency improvement in cases of emergency incidents' management and the reduce of the negative consequences that follow that

Indicatively, some of the operations and activities of the public sector may benefit from the *S-Distance* system are:

- the optimal location of utility facilities and services (e.g. libraries, civilians' service centers, polling stations etc.) in order to minimize the average time required to access them by an area's residents
- the optimal location of ambulances, fire trucks, traffic vehicles (respectively of hospitals, fire stations, police stations) in order to minimize the maximum time of their response to emergency situations
- the optimal location of disturbing uses (e.g. landfills, garbage depots, and other polluting activities) in order to minimize both the disturbance of adjacent residents and operating cost
- the optimal location of new school units and the optimal distribution of students according to their capacity and the distance each student covers to reach them

3.1.2 Problem Formulations, models and algorithms

The system's strength lies in its simple albeit efficient (graphical) user interface, which supports an interactive and customizable solution process for the p-median, p-center and maximal covering formulations. Users can easily define, visualize, and compare different scenario-solutions through the utilisation of a set of heuristic methods including greedy and local search procedures, Variable Neighborhood Search and lagrange relaxation.

S-Distance provides detailed monitoring of the solution process, essential in both understanding and exploiting the dynamics of locational planning problems. Decision makers may visualize algorithmic processes on maps, while modifying model variables, algorithm parameters and visualization modes such as allocated shortest network path trees, covered and uncovered demand, (weighted) distance from closest facilities and objective function value improvement. Solution and/or candidate nodes can be graphically altered and compared until the final set of facilities is defined. Global as well as local values of different objective functions are stored in matrix form. Solutions and results can be exported, in order to be further exploited in a GIS or spreadsheet framework.

Multi-objective constraints can also be defined, and a heuristic has been developed for the definition of compromise solutions. All the heuristics in *S-Distance* have been generalized and in some cases significantly improved. Constructive procedures include the standard deterministic Greedy algorithm, slightly enhanced performance-wise, and a fast randomized variant found in [5]. Critical modifications have been made with respect to Maranzana's Alternate Location/Allocation (ALA) algorithm efficiency, following observations by [5]. In addition to the well-studied p-median case ALA has been extended and confronts maximal covering and p-center problems. The Candidate List Search (CLS) heuristic that uses ALA as a sub-algorithm, also proposed by [5], has been altered through the use of precomputed distance strings. Additionally, we have implemented LOPT, one of the two meta-heuristics proposed in [5]. CLS and LOPT have been extended for maximal covering and p-center problems as well. Vertex Substitution (VS) algorithms are also available. More specifically, a simple implementation of the classic Teitz and Bart algorithm is included, which with minor modifications can be applied to any custom objective function.

As for model-specific VS algorithms, a fast local search procedure proposed by [3] has been implemented for the p-median and maximal covering models. For the p-center model, the implemented VS algorithm has been proposed by [2]. The system's VS algorithms are the core of a basic Variable Neighborhood Search (VNS) meta-heuristic, which is able to identify robust solutions in reasonable time. Finally, lagrangian relaxation heuristics have been implemented, partially based on [1] and [4]. By combining the ALA and VS/VNS algorithms for improved upper bounds, they can identify optimal or near-optimal solutions for moderate-sized instances.

4. CASE STUDY: LOCATION OF AMBULANCES IN THE METROPOLITAN AREA OF VOLOS – NEA IONIA, THESSALY, GREECE

As stated earlier, our case study focuses on the location of ambulances in the metropolitan area of Volos and Nea Ionia, Greece. Alternative scenarios are formulated, which are based on the spatial and temporal distribution of emergency calls, the spatial and temporal differentiation of network characteristics, the quantity of ambulances being located and the probability that these ambulances may be busy during an emergency call arrival.

For modeling an emergency incidents network, alternative scenarios are formed; these are based on the spatial and temporal distribution of the expected demand of emergency incidents, the temporal and spatial differentiation of traffic on the road network, the number of the ambulances which are available for locating (offer) and the probability that each ambulance may be occupied at the time of the call (expected offer).

The stochastic maximal expected covering model was chosen for the location (Daskin, 1995), while the coverage distance is determined endogenously by applying a static *P-center* model for each examined scenario. As shown later, modeling a network to address emergency incidents is a complex and demanding procedure, even when the number of the examined variables is quite limited.

4.1 Environmental aspects

The parameters which were considered as most important for solving this specific location problem were: (1) the spatial and temporal distribution of emergency incidents, (2) the road network's characteristics and (3) the number of the available recruited ambulance each time. It was determined that the space of demand distribution and ambulance location is distinguished in nodes, which are defined by the road network of the study area.

Then different periods of time are set, with different parameters' characteristics for each (formed as alternative scenarios). The maximum demand coverage is sought for each period of time. The coverage distance is defined by the optimal range of service that results from a static *P-center* model, so that location's main priority is the optimal behavior of the services network under the worst circumstances. This approach is more appropriate to emergency incidents coverage problems, where even if demand is low, it is considered critical for the service network's effectiveness.

By definition, the basic maximal expended covering model, takes into account the probability that an ambulance may be busy (various values are examined for this probability). Alternative location models are examined at the same time; these result from use of different number of ambulances. On the road network, the existing road categories are divided, and not only bidirectional and one-way traffic directions are counted in, but also levels of nodes and loads service, depending on each one of the ***t*** time periods being examined. Stochastic travel times, in the broad sense of random variables, are not taken into consideration, because this would make the problem quite unsolvable, even in the case of an ambulance (Averbakh, 2003).

Moreover, in the specific application, a simple method was proposed for determining the expected spatial distribution for each period of time; the sample of incidents that were examined was dispersed properly (non-integer dispersion), in the entire space. This method was thought to be fully harmonized with the aim of the system's optimal behavior under the worst circumstances, reflecting demand's intrinsic stochasticity, without ignoring the real position the incidents appear. This specific method will be analyzed extensively shortly.

4.2 Evaluation of the expected demand

One of the main problems that occurs in cases when demand is of stochastic nature but the sample is quite limited, is that nodes with demand equal to 0 are treated equally by covering models; this means that there is no probability for one of these nodes to display demand, whether is located near the recorded incidents or not. On the other hand, even if an area has no demand at all, the consideration that the probability an incident takes place is 0 refers more to an objective of the service center's average response's optimization, than the one of the response in the worst case. Unlike the covering models, center models minimize the maximal range of service and consider that all nodes – in their basic form – may be equally probable to be in demand. However, in this way, the fact that demand is likely to display a specific spatial model is ignored, so the overall system's efficiency is low.

In order to overcome the above problem and ensure the service network's effectiveness in the worst case, without undermining its total effectiveness significantly, we propose a simple method of continuous demand distribution to all network's nodes based on the incidents' sample for each period of time that is examined. The basic consideration is that the probability of a node to be in demand, depends from its distance from all recorded incidents, especially the one ones that take place near.

Specifically, suppose that a set of ***k*** recorded incidents have been distributed to the nodes ***i*** of a network ***G(V),*** where:

Z_i is the number of incidents distributed in each node i

$\bar{d}_{ij}$ $\dfrac{d(i \to j) + d(j \to i)}{2} + 1$ the distance , $\forall\ i, j \in G(V)$

For each node ***i*** of the network ***q*** all nodes ***j*** are classified with $z_j \neq 0$ from the nearest to the most distant one, based on the $\bar{d}_{ij}$ distance's excluding the case of $i = j$. Based on the classification, it presents that the board $\boldsymbol{R_{ij}}$ which for each ***i*** includes the classification order of each node ***j***.

Then for each node ***i*** of the network the following value is calculated:

$$a_i = \varepsilon \cdot z_i + (1-\varepsilon)\sum_{j \neq i} \frac{z_j}{\bar{d}_{ij} R_{ij}} \qquad \text{with} \qquad 0 \le \varepsilon \le 1$$

$\hat{h}_i$ Finally, the value of the expected demand of each node ***i*** is calculated according to the relation:

$$\hat{h}_i = \frac{a_i k}{\sum_i a_i} \quad \text{with the ability to apply} \quad \sum_i \hat{h}_i = \sum_j z_j = k \quad \text{that:}$$

Parameter ***ε*** defines how much demand will be "spread" from nodes with recorded incidents to all network nodes. For $\varepsilon = 0$ the dispersion is complete, while for $\varepsilon = 1$ the initial state occurs, i.e. the expected demand of each node equals with the value of the incidents that are recorded to them, which is now a special case. In the application εt = kt / n was used, for each time period ***t*** of the six that were examined, with ***kt*** being the total of recorded incidents for the respective period of time and ***n*** the number of the network's nodes. In this way, dispersion is inversely proportional to the number of each timeline's incidents. This reflects the view that, regarding the "real" demand distribution, uncertainty gets minimized as the sample's population increases.

On the other hand, the use of the R_{ij} table, instead of simply raising the distance to some power, aims at the reduction of autocorrelation between the network's morphology and the expected distance. Moreover, the median distance $\bar{d}_{ij}$ was calculated based on the length of the network's axis only, without taking into consideration characteristics such as movement direction, load, nodes' service levels, etc., just to minimize the autocorrelation between variables of expected demand and travel cost.

Calculating the expected demand is actually a stage of pre-treating data before the model appliance. Its aim is to guide the maximal expected covering model to solutions which are oriented to the service network's optimization for the worst case, without ignoring distribution and number of recorded incidents in the area. Alternatively, the expected demand could occur from more specialized techniques, such as neural networks.

Concluding this section, the answer to the question, whether population distribution in space should be taken into account as well, is negative, if population data are available from the Hellenic Statistical Service's censuses only. The reasons for this are several and significant. First, it is known that this kind of data is fictional in several occasions, and even if it is acceptable as being representative, it doesn't reflect the population's distribution in space during the day, which is dynamic in nature due to different places of work, residence, commercial and leisure activities and flows provoked during moving form one place to another.

If data of that kind existed (spatial distribution of population during the day), a correlation between spatial distribution of incidents or/and traffic flows on the road network might occur after an analysis. Nevertheless, distribution of emergency incidents themselves is easily measurable and more probationary to a lower planning level, such as a conurbation. The population may possibly be used, in a larger scale, as an indicator for predicting the expected number of incidents with greater security.

4.3 Maximal expected covering model

The model of maximal expected covering was used for locating ambulances (Daskin, 1982, 1983). This formulation's difference is that the coverage distance occurs endogenously according to the problem's data, through the *P-center* model. Moreover, the expected demand's values occur according to the methodology which was analyzed in the previous sub-section. These two characteristics focus on the optimization of the lowest rather than the median efficacy. This is a basic element for the success of an emergency incidents' network, where the adequate coverage of the even most remote areas is considered to be imperative.

Furthermore, the model is analyzed separately for each of the $\boldsymbol{t}$ time periods; each of these may be related to a finite set of alternative scenarios which will define the individual data values (expected demand, number of ambulances, probability that an ambulance may be busy during emergency call, waiting time in the road network, etc.)

4.3.1 Model modulation

The maximal expected covering model may be formulated in a mathematical program form, with each t time period's alternative scenario as follows:

Data

$\hat{h}_i$ = the expected demand in node i

N = the number of located ambulances

q = the average probability that an ambulance may be occupied

d_{ji} = the minimum distance between the candidate center j to the i demand node

D = the optimal value of the objective function of the *P-center* model υποδείγματος for N ambulances

$$\beta_{ij} = \begin{cases} \mathbf{1} & \text{if } d_{ji} \le D \quad \text{(the candidate center } i \text{ covers the } j \text{ node)} \\ \mathbf{0} & \text{if not} \quad \text{(the candidate center } i \text{ does not cover the } j \text{ node)} \end{cases}$$

Decision variables

X_j = the number of ambulances located in the j node

$$Z_{ik} = \begin{cases} \mathbf{1} & \text{if the } i \text{ node is covered at least } k \text{ times} \\ \mathbf{0} & \text{if not} \end{cases}$$

Objective function

$$MAXf_t = \left\{ (1-q) \sum_i \hat{h}_i \left\{ \sum_{k=1}^{N} q^{k-1} Z_{ik} \right\} \right\} \tag{1}$$

Limitations

$$\sum_k Z_{ik} \le \sum_j \beta_{ij} X_j \qquad \forall\, i \tag{2}$$

$$\sum_j X_j \leq N \qquad (3)$$

$$X_j \in \aleph^* \qquad \forall\, j \qquad (4)$$

$$Z_{ik} = 0,1 \qquad \forall\, k, i \qquad (5)$$

The objective function (1) maximizes the expected coverage of the (expected) demand. The probability of a node ***i*** being covered is set equal to (1 - q^n), where n is the number of ambulances that would cover the ***j*** node if they were available. Limitation (2) indicates that the demand in a ***j*** node cannot be covered $\boldsymbol{k_i}$ times, unless if ***k*** ambulances which cover the ***i*** node are located. Limitation (3) requires the location of ***N*** ambulances in a node, at maximum. Finally, limitations (4) and (5) declare the integer values that decision variables X_j, Z_i may get.

It should also be specified that d_{ji} distance, which is included in the model, refers to the ambulance's transition time from the node it is to the node where the incident took place. The time needed for the transition from the demand node to the hospital is not included.

4.3.2 Solution techniques

For the solution of models, meta-heuristic algorithms, well-established in international literature, were used, which were implemented in the *S-Distance* system's environment. The Local Optimization (LOPT) algorithm was used for the *P-center* model (Taillard, 2003), with the proper modification for this specific problem. A variant of the Variable Neighborhood Search (VNS) algorithm was created for the maximal expected distance model (Mladenovic and Hansen, 1997).

Very briefly, the LOFT algorithm breaks the problem to smaller ones, by applying the Candidate List Search (CLS) algorithm to each sub-problem (Taillard, 2003). The CLS algorithm is based on the stochastic replacement of nodes in and out of solution, which gradually gets optimized with use of a simple rotation algorithm (Maranzanna, 1964). The final solutions provided by this algorithm are of quite high quality, especially for a small number of service centers, while its complexity is low.

On the other hand, the VNS algorithm makes stochastic replacements of nodes in and out of the current solution, in order for a second solution to come up, not necessarily better, which comes from a variable subarea of the solution space. The summit replacement algorithm is applied to the new solutions (for which many variations have been proposed). If the objective variation is improved, then this replaces the current one and the variable subarea reduces to minimum. Otherwise, the current solution stays as it is and the variable subarea increases. The classic summit replacement algorithm by Teitz and Bart (1968) was used for the application's needs, which is quite effective for a small number of service centers.

4.4 Methodology application in the Volos-Nea Ionia metropolitan area

NERC, which is based on the new Achillopoulio Hospital of Volos, has about 8 ambulances in its possession, operating in eight-hour shifts of three recruited ambulances. One of these three ambulances usually includes a doctor in its crew and may support life during the route from the place of the incident to the hospital. During the Olympic Games of Athens in 2004, Volos, as being an Olympic city, received additional ambulances covering especially the Panthessaliko Stadium. On this occasion, several staff recruitments took place, bringing the number of recruited ambulances every time to reach four per shift. NERC's personnel admitted that three ambulances are not enough for covering the needs in the conurbation of Volos, Nea Ionia and the surrounding areas.

4.4.1. Data collection

For the application's purposes, data was collected in raw (analog) form from the Volos NERC for the February-August 2004 six-month period. For each recorded incident, only use of place and time that took place was allowed, and not the incident's nature. Thus, all incidents were considered to be equal. In general, in the total of recorded incidents, several of them didn't require calling for an ambulance, while incidents in the centers of Volos and Nea Ionia are more important, according to NERC's personnel.

Incidents are also separated in (a) urgent, which are covered by NERC's ambulances whose base is Volos, (b) urgent, which are covered by ambulances of local health centers and the hospital of Volos is their destination and (c) evacuations, i.e. patients' transfer from the hospital to their homes or transfer of specialized equipment, such as coronary units. Evacuations are predefined and served by special vehicles and personnel. Therefore, these do not affect the network's efficiency. On the other hand, ambulances of local health centers are sometimes occupied, so the incident must be covered by an NERC's ambulance, thus affecting the service network's efficiency.

Given the fact that this specific application focuses on the urban area of Volos and Nea Ionia only, the incidents taken into consideration are only those recorded in that area. Nevertheless, any incidents that take place out of the study area are covered by NERC's ambulances, are considered to contribute to the probability of an ambulance being occupied.

For the road network that was used in the application, there was a distinction between 5 categories of roads and bidirectional and one-way movement direction were also taken into account, service levels of accessible nodes and load, depending on the time period. The final value introduced to the model is the transfer cost (travel time) in seconds per direction for each network link. In general, this approach was based on the General Transport and Traffic Study for the City of Volos (Ministry of Environment, 2008) and on traffic measurements for the period 2001-2003 as well, which were conducted by students of the Planning and Regional Development Department, University of Thessaly.

4.4.2 Modulation of alternative scenarios

The analysis that was conducted after the digitization/geocoding of incidents and the calculation of the expected demand, indicated three important time periods during the day. The incidents were further separated in two time periods and specifically in weekdays and holidays/weekends (see Table 1).

One feature that constitutes the different between weekdays and holidays/weekends is the important increase of incidents that occur outside the study area and are covered by NERC's ambulances based in Volos. This is probably due to the exit of a population's proportion for leisure purposes.

Besides, the time of the call's transition to the ambulance and the evaluation of the traffic's characteristics in the road network, were considered to be the criteria for the separation. Especially for the road network, three situations were defined, which represent two relatively extreme (but not atypical) traffic conditions and an intermediate one.

Then, the maximal expected covering model was solved for each one of the six studied timer periods for number of ambulances N = 3, 4 and 5, while in each one of the eighteen sub-cases the *P-center* model was initially solved for the definition of the coverage distance and then four different values were tested for the ***q*** probability. The probability values were selected in order to differentiate the spatial distribution of proposed solutions. In cases where two time periods shared common road network characteristics, the respective q probabilities remained common.

Table 1. Evaluation of the average probability *q* of an ambulance being occupied, for N=3 ambulances, for each time period (current status)

Time period	**WEEKDAYS**			**HOLIDAYS & WEEKENDS**		
	23:00-7:59	**8:00-13:59**	**14:00-22:59**	**24:00-9:59**	**10:00-16:59**	**17:00-23:59**
Occupied out the study area	3,6 %	4,7 %	3,3 %	2,1 %	7,0 %	6,6 %
Occupied within the study area	8,8 %	27,5 %	20,2 %	6,6 %	16,3 %	12,8 %
Pending situation	87,5 %	67,8 %	76,5 %	91,3 %	76,7 %	80,6 %
q	*0,125*	*0,322*	*0,235*	*0,087*	*0,233*	*0,194*

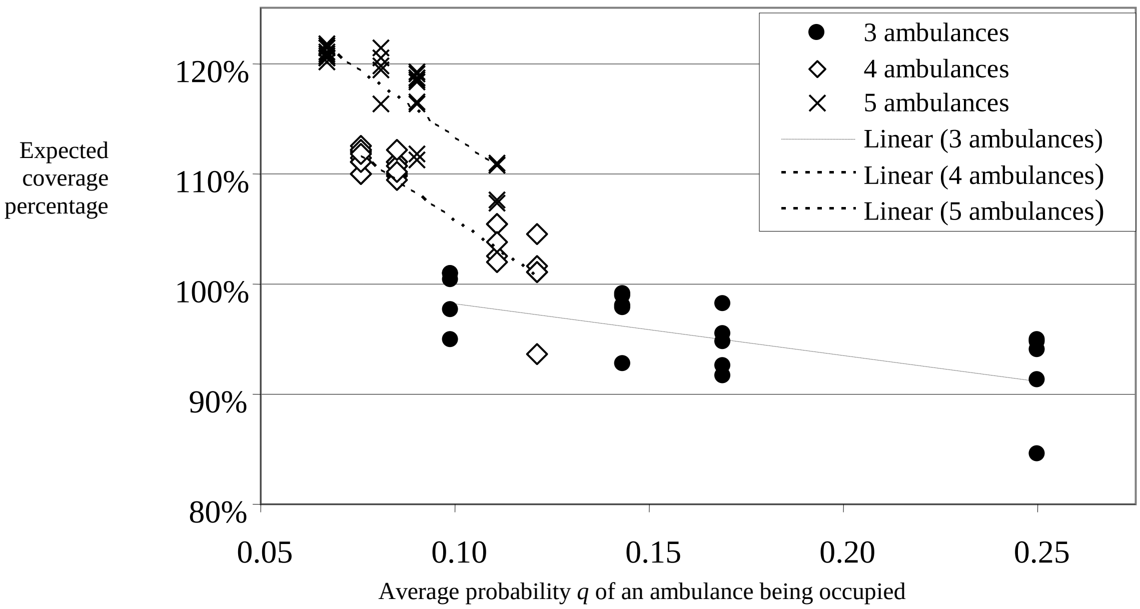


Figure 1. Expected percentage of emergency incidents' coverage, related to the average probability *q*, for a three-minute coverage (each spot is the optimal solution of an alternative scenario)

It must be clarified that the ***N*** number of ambulances and the ***q*** average probability of an ambulance being occupied are parameters interdependent and extrinsic in relation to the model, while in the present application the coverage distance (in seconds) arose endogenously through the *P-center* auxiliary model. Altogether, seventy-two alternative scenarios occurred (ninety with *P-center* solutions).

One of the main goals was, after the optimal solution of the scenarios above, to find intermediary solutions through a third model of minimum regret. Regret which is related to a scenario is calculated by comparing the effectiveness of the optimal location model for the scenario examined with the effectiveness of the location models resulting from the rest of the scenarios, if they were applied to the scenario examined (Owen και Daskin, 1998, Snyder, 2005). Therefore, the use of an objective function for minimizing regret may evaluate a number of robust alternative solutions, based on the optimal values of each initial solution.

5. CONCLUSIONS AND DISCUSSION

The strategic nature of facility location requires methodologies that incorporate, at least up to a certain point, the uncertainties inherent in real world location problems. For example, many real world problems exhibit demand-specific uncertainties and uncertainties linked with transportation costs.

This paper, covered theoretical aspects of static, dynamic and stochastic location-allocation models whilst focused on the case of the location of ambulances in the metropolitan area of Volos – Nea Ionia, in Thessaly, Greece. Alternative scenarios were formulated, which were based on the spatial and temporal distribution of emergency calls, the spatial and temporal differentiation of network characteristics, the quantity of ambulances being located and the probability that these ambulances may be busy during an emergency call arrival.

Furthermore, we introduced *S-Distance*, a Locational Analysis and Planning Support System. *S-Distance* is mainly focused on location-allocation analysis and capable of solving quite large classical discrete and network locational planning problems based on alternative scenarios, taking into consideration a variety of social, economic and geospatial variables and data. Moreover, is a non-commercial Spatial Decision Support System, which incorporates an interactive solution process within a simplified GIS framework. In this paper, is utilized for the location of ambulances in the metropolitan area of Volos and Nea Ionia in Greece; the location-allocation model that was developed, optimizes response for the worst case scenario, taking into account the stochastic nature as well as the hierarchical structure of the problem, when considered at the regional or country level. Alternative scenarios are generated based on the expected geographical and temporal distribution of the emergency incidents (demand), the traffic flow variability, the number of available ambulances (supply) as well as the probability an ambulance being occupied on the time of call.

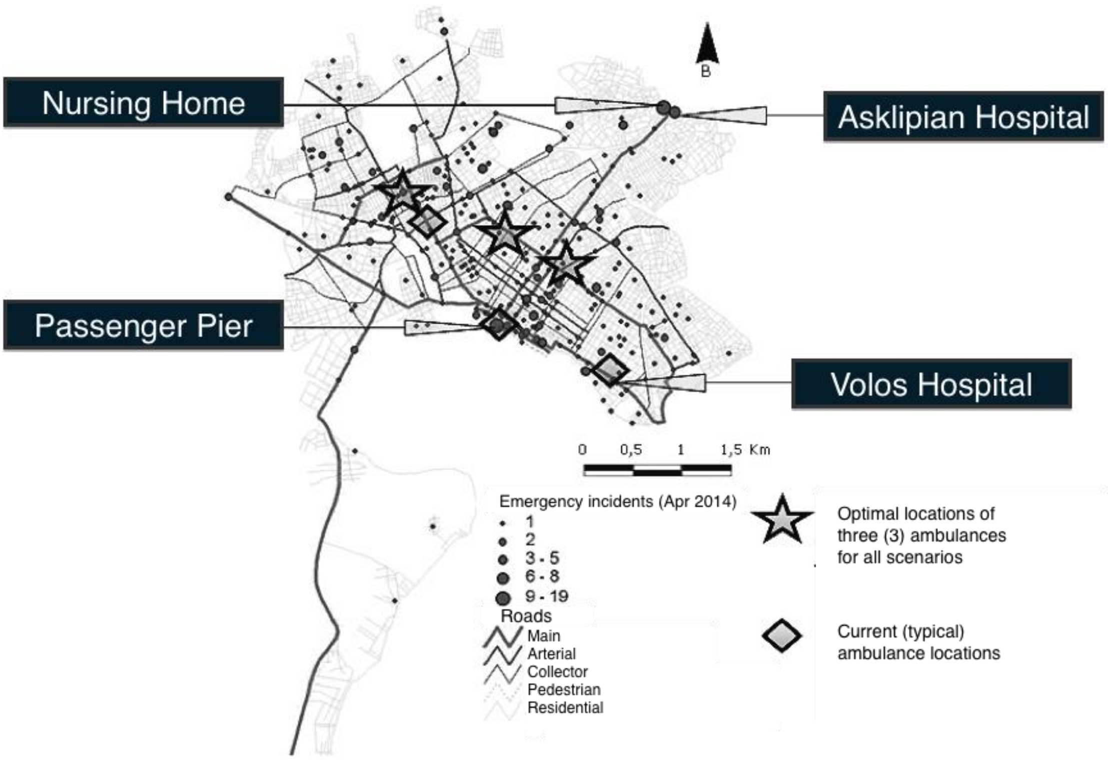
An important finding of our study is that the role of the expected demand was catalytic for most scenarios. This is apparent particularly where the road network, the coverage distance and (in most cases) the $\boldsymbol{q}$ probability are common parameters, with the only difference being the distribution of the expected demand. As shown in Figure 1, for indicative coverage distance of three minutes, the three ambulances are incapable of serving adequately the expected demand.

On the other hand, for the same coverage distance, five ambulances cover the expected demand more than it is needed, regardless of the individual parameters of the alternative scenarios (the same applies, albeit to a lesser extent, for four ambulances, too). Besides, as $\boldsymbol{q}$ probability gradually increased, location models tended to be clustered in nodes which covered the greater demand. This phenomenon is typical of the maximal expected covering model (Daskin, 1983).

The scenarios which theoretically represent more the actual conditions are those where the ***q*** probability is close to the estimated one. Moreover, the quality of scenarios whose individual variables received the worst values (adverse traffic conditions, increased probability of occupied ambulances, expected demand in remote nodes), tended to be higher than the rest of the scenarios. This may apparently be due to the initial selection of optimizing the service network for the worst case.

Nevertheless, the study's results are in contradiction with the existing situation. The location model adopted practically in the study area refers more to the target of optimizing the average performance of the service network, paying close attention to areas where incidents took place more often. A possible cause for this is the greater severity of the incidents recorded in the main part of the conurbation. Another possible case is the available free space that exists in Volos beach for ambulances parking, which applies to a lesser extent in areas identified by the model (example, see Map 1).

Furthermore, factors which were not included in the model, such as roadside parking conditions, could have differentiated the location models which were identified. Finally, the study area is a subset of the broader region covered by the NERC's (National Emergency Response Centre) ambulances, so the two approaches may not be directly comparable. Nevertheless, the methodology proposed, allows its application to a broader study level (e.g. regional).



Map 1. Typical existing situation and indicative optimal location for N=3 ambulances

Within an integrated emergency incidents' management approach, of course, apart from efficient location choices, there is need to balance load of various vehicles, meaning that continuous indulgence and personnel training, proper function and consultation between center and vehicles, proper separation of calls to urgent and incidents that may be dealt locally should be ensured. At the same time, a multi-level service network is required, where personnel of various training levels and capacities will be available, with vehicles of different equipment and capabilities.

REFERENCES

Averbakh I., (2003). Complexity of robust single facility location problems on networks with uncertain edge lengths, *Discrete Applied Mathematics*, 127, pp 505-22.

Batta R., Dolan J.M. and Krishnamurthy N.N., (1989). The maximal expected covering location problem: Revisited, *Transportation Science*, 23, pp 277–87.

Church R.L. and ReVelle C.S., (1974). The Maximal Covering Location Model, *Papers of the Regional Science Association*, 32, pp 101-18.

Daskin M.S., (1982). Application of an expected covering model to emergency medical service system design, *Decision Sciences*, 13, pp 416–39.

Daskin M.S., (1983). A maximum expected covering location model: Formulation properties and heuristic solution, *Transportation Science*, 17, pp 48–70.

Daskin M.S., (1995). Network *and Discrete Location – Models, Algorithms and Applications*, Wiley Interscience Series, New York.

Daskin, M. S. (2000). A New Approach to Solving the Vertex P-Center Problem to Optimality: Algorithm and Computational Results. *Communications of the Operations Research Society of Japan*, 45(9), 428-436. [1]

Dimopoulou, D., Aggelidou, M., Photis, Y.N., (2015). Up to where a city ends. A spatiotemporal imprint of commuting patterns for the ten largest Greek cities, *Proceedings of SSS 2015 - 10th International Space Syntax Symposium*, pp. 68:1-68:20.

Greek Ministry of Environment, (2006). *Transportation analysis for the city of Volos, Athens.*

Grekousis, G., Photis, Y.N., (2014). Analyzing High-Risk Emergency Areas with GIS and Neural Networks: The Case of Athens, Greece, *Professional Geographer*, 66 (1), pp. 124-137.

Hadjichristodoulou, C., Pournaras, S., Mavrouli, M., Marka, A., Tserkezou, P., Baka, A., Billinis, C., Katsioulis, A., Psaroulaki, A., Papa, A., Papadopoulos, N., Mamuris, Z., Tsakris, A., Kremastinou, J., Vakalis, N., Koliopoulos, G., Vontas, J., Dovas, C.I., Tontis, D., Tselentis, I., Tsiodras, S., Photis, Y.N., Papadopoulou, E., (2015). West nile virus seroprevalence in the Greek population in 2013: A nationwide cross-sectional survey, *PLoS ONE*, 10 (11), pp

Maranzanna F.E., (1964). On the Location of Supply Points to Minimize Transport Costs, *Operations Research Quarterly*, 15, pp 261-70.

Mladenović N. and Hansen P., (1997). *Variable Neighborhood Search, a Chapter of Handbook of Metaheuristics*, Technical Report: Mathematical Institute, Serbian Academy of Science, Belgrade. GERAD and Ecole des Hautes Etudes Commerciales, Montreál.

Mladenović, N., Labbé, M. and Hansen, P. (2003). Solving the p-Center Problem with Tabu Search and Variable Neighborhood Search. *Networks* 42(1), 48-64. [2]

Mougiakou, E., Photis, Y.N., (2014). Urban green space network evaluation and planning: Optimizing accessibility based on connectivity and raster GIS analysis, *European Journal of Geography*, 5 (4), pp. 19-46.

Nurković, R., (2015). Contemporary aspects of spatial and urban planning in the Canton of Sarajevo, *European Journal of Geography*, 6 (1), pp. 23-36.

Owen S.H. and Daskin M.S., (1998). Strategic facility location: A review, *European Journal of Operational Research*, 111, pp 423–47.

Papafragkaki, A., Photis, Y.N., (2014). GIS-based location analysis of administrative regions: Applying the median and covering formulations in a comparative evaluation framework, *European Journal of Geography*, 5 (3), pp. 37-59.

Photis Y.N., (2004). *Quantitative methods and techniques in facility location*, University of Thessaly Press, Volos (in Greek).

Photis Y.N., (2014). *Quantitative Spatial Analysis*, Govostis Publishers, Athens.

Photis, Y.N., Grekousis, G., (2012). Locational planning for emergency management and response: An artificial intelligence approach, *International Journal of Sustainable Development and Planning*, 7 (3), pp. 372-384.

Resende, M. G., & Werneck, R. F. (2007). A fast swap-based local search procedure for location problems. *Annals of Operations Research*, 150(1), 205-230. [3]

ReVelle C.S. and Eiselt H.A., (2005). Location analysis: A synthesis and survey, *European Journal of Operational Research,* 165, pp 1-19.

Roşu, L., Corodescu, E., Blăgeanu, A., (2015). Does geographical location matter? Assessing spatial patterns in perceived quality of life in European cities, *European Journal of Geography*, 6 (2), pp. 15-34.

Sirigos S., (2003). *S-Distance: A prototype locational planning decision support system: Models, algorithms and application,* Undergraduate Thesis, University of Thessaly, Volos (in Greek).

Sirigos S., (2004). *Location of facilities and services under uncertainty: Definition of alternative supply and demand scenarios*, Postgraduate Thesis, University of Thessaly, Volos (in Greek).

Snyder L.V., (2006). Facility location under uncertainty: A review, *IIE Transactions*, 38(7), 537-554.

Taillard E.D., (2003). Heuristic Methods for Large Centroid Clustering Problems, *Journal of Heuristics*, 9, pp 51-74

Teitz M.B. and Bart P., (1968). Heuristic Methods for Estimating Generalized Vertex Median of a Weighted Graph, *Operations Research*, 16, pp 955-61.

Weber A., (1909). *On the Location of Industries,* University of Chicago Press, Chicago.