Emergency management using geographic information systems: application to the first Romanian traveling salesman problem instance

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Emergency Management using Geographic Information Systems. Application to the first Romanian Traveling Salesman Problem instance

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Abstract. The strategic design of logistic networks, such as roads, railways or mobile phone networks is essential for efficiently managing emergency situations. The geographic coordinate systems could be used to produce new *Traveling Salesman Problem (TSP)* instances with *Geographic Information Systems (GIS)* features. The current paper introduces a recurrent framework designed for building a sequence of instances in a systematic way. The framework intends to model real-life random adverse events manifested on large areas, as massive rainfalls or the arrival of a polar front, or targeted relief supply in early stages of the response. As a proof-of-concept for this framework, we use the first Romanian *TSP* instance with the main human settlements, in order to derive several sequences of instances. Nowadays state-of-art algorithms for TSP are used to solve these instances. A branch and cut algorithm delivers the integer exact solutions, using substantial computing resources. An implementation of the *Lin-Kernighan* heuristic is used to rapidly find very good near-optimal integer solutions to the same instances. The *Lin-Kernighan* heuristic shows stability on the tested instances. Further work could be done to better exploit GIS features in order to efficiently tackle operations on large areas and to test the solutions delivered by other algorithms on new instances, derived using the introduced framework.

1. Introduction

Emergency management is a continuous process, aiming at preventing anthropogenic and natural disturbances, designing plans to mitigate their impact, efficiently responding when disasters strike, and recovering to normal state.

Communication procedures are essential in case of disaster. Their proper design could reduce the natural effects and the social costs of an adverse event: clear rules and responsibilities in emergency plans lead to correct assessment and rapid response. For example, the Final Report on the Accident at the Fukushima Nuclear Power Stations describes that the government authorities ” ...fell into a state of confusion at various stages and consequently failed to respond to problems timely or adequately”(Investigation, 2011).

Communication infrastructure is equally important in hazards. A cooperative emergency communication system must be quickly activated and should effectively work until normal communications are re-established. The same Report specifies that ”...the Off-site Center, which should have taken a primary role in accident responses, could not function fully due to failure of communication means and other reasons” (Investigation, 2011). This paper is a contribution towards the proper design of communication infrastructure, in order to efficiently connect specific locations, distributed on a large territory.

When designing communication networks in a specific area, many geographical, ecological and socio-economic characteristics need to be considered. For example, mobile communications require cost-effective ubiquitous coverage for addressing challenges towards 5G standards. The mobile network infrastructure has to be economically designed: the deployment, usage and development costs have equal decision weights as the quality of the services. Some of the main phases of a communication network design are to model in an accurate way the in-situ characteristics and to simulate the normal and abnormal working conditions.

Efficient emergency response is crucial during the first hours. If the communication network is operational, people can signal their presence and an accurate intervention map can be quickly drawn by the rescuers. In dramatic cases, when some persons are physically unable to use their working phones, the mobile network providers could cooperate and offer the exact locations. When the GPS service is not available, it is possible to use Wireless Application Protocol with the Google Maps API (Zacarias et al, 2015). When the cell phone signals are unreachable, it is possible to use the active ad hoc or multihop networks (Asakura, 2013).

If the roads are not operational, then Unmanned Aerial Vehicles (UAVs) can discover people in need and helicopters can be used for assisting and transporting them. Such tours for observation drones, and rescue helicopters or boats must be quickly and efficiently designed. They do not need roads, and they directly reach the points where they are sent. Researchers constructed platforms that can control groups of commercially-available UAVs able to independently and dynamically adjust their on-site behavior (Purta et al, 2013).

In order to efficiently use the software platforms it is suitable to choose techniques that build syntactically correct finite automata models of the component system (Crnkovic et al, 2002; Fanea et al, 2006). Recent methodologies as in (Motogna et al, 2015) could be used to evaluate the quality of the software.

An academic problem that successfully address such real-life situations is the *Traveling Salesman Problem (TSP)*. In its standard formulation, it seeks for the shortest tour connecting all the cities on a map (Lawler et al, 1985; Reinelt, 1994).

Currently, there are many *TSP* variants, modeling real-life situations with high economic and social costs: bottleneck *TSP*, prize collecting *TSP*, multiple *TSP*, generalized *TSP*, etc. (Gutin et al, 2002; Pintea, 2015).

Approaching emergency management through TSP is our choice for this paper, motivated by both the above-mentioned reasons and the previous. Other approaches focus on facility location problems (that is, where to put the rescue center to optimally cover a region) (Toregas et al, 1971; Church, 1974), or on resource allocation problems (how to optimally dispatch the aids from the rescue centers) (Fiedrich, 2000), or both types (Li et al, 2011).

The current work introduces a *Romanian TSP* instance based on *Geographic Information Systems (GIS)* as the first national *GIS-TSP* instance. Two types of situations when several cities are excluded are modeled starting from this instance. A novel framework, designed to model a dynamic situation using a recursive sequence of instances is also introduced. It offers a general and flexible method for systematically derive scenarios starting from a given situation. It generalizes the methods presented in many previous works, but here we focus on its importance for the emergency preparedness: multiple scenarios could be treated and adequate responses could be set up. The framework is illustrated starting from the novel instance; several best solutions for the derived instances are represented as maps based on *GIS* services.

The idea of bridging academic optimization problems with crisis management is approached by many researchers, for example in (Konecny et al, 2010; Showalter et al, 2010). The adaptive governance intends to mitigate the effects of climate change through low-regret adaptive strategies in planning. For example, the European Commission promotes strategic environmental assessment for large-scale trans-boundary projects, as long as changing hazard patterns and changing societal circumstances are new challenges (European Commission, 2013). Our paper is a step towards this goal, as it connects academic Operational Research with modern features of *GIS* services and Environmental Sciences.

The paper is structured as follows. In the *Preliminaries* section the algorithms used for the introduced instances are described; several ways of using *GIS* services in *Operational Research* domain are also shown. Section 3 introduces the first national *GIS-TSP* instance and the novel framework for recursive modification of an instance. Numerical experiments and discussions about their results are detailed in Section 4. Several conclusions and research directions are presented in the last section of the paper.

2. Preliminaries

2.1. Literature preview

To optimally solve a difficult problem is not an easy task. For example, for the NP-hard class of problems it is unlikely that a solving algorithm with polynomial time for worst cases will ever be found. This is why these difficult optimization problems, including Traveling Salesman Problem, are approached using exact, approximate or heuristic methods.

The branch and bound algorithm is used for global optimization for non-convex problems. It was first proposed in (Land et al, 1960). It is interesting that the name of the method first occurred in connection with the TSP (Little et al, 1963). Its basic idea is to maintain a lower and upper bound for the optimal solution, and to exit when the distance between them becomes insignificant. At each step, an efficient and problem-depending method chooses how the solution space is split, decomposes the current problem into several (usually two) problems, computes the corresponding bounds for them, and updates the global bounds (Lawler et al, 1966). As the solution space for each sub-problem becomes smaller, the local bounds are expected to become sharper, and so the gap between the global bounds narrows. Sometimes, the current sub-problem can be eliminated, with consequences in improving the execution time. If its lower bound is greater than the current upper bound, obviously its solution space does not contain an optimal solution.

The cutting plane technique is dedicated to solve mixed integer programming problems using a repeated sequence of relaxations (Gomory, 1960). Once such fast methods for linear programming (as simplex) exist, the first step of the cutting plane approach is to consider a relaxation of the initial problem, by removing the constraint that the variables have to take integer values. If the solution to this problem has integer values for the relaxed variables, then the algorithm stops. If not, a non-integer component of the solution is chosen; a hyper-plane (a Gomory cut) is defined and added to the previous relaxation. The cut detaches the solution (as it is not a solution to the initial problem), but maintains all feasible integer solutions. The algorithm iterates by solving the new tightened relaxed problem.

The cutting plane method was considered impractical so it was integrated into branch and bound implementations with very good practical results (Padberg et al, 1987). The new algorithm, named branch and cut, is currently one of the best exact methods for solving many COPs (Mitchell, 2002). If the problem is large or hard and can not be solved to the optimality, the branch and cut approach can supply very useful lower and upper bounds on the optimal value. The current computing systems and the parallel programming languages allow successful branch and cut implementations for a broad range of complex problems. An example of such demanding problem is treated in (Adulyasak, 2014). Very effective branch and cut approaches are designed for specific problems; for example, symmetric TSP is successfully tackled in (Padberg et al, 1991) by using strong cutting planes from the polyhedral theory. Since 2002 IBM ILOG CPLEX is implementing the concurrent optimization, which allows simultaneously solving a problem by means of multiple algorithms. The version CLPEX 11 includes parallel optimization as a general feature (IBM, 2012).

Traveling Salesman Problem (TSP) can be formulated in terms of graph theory as a minimization problem on a complete weighted graph as in (Padberg et al, 1991): given a complete graph G with vertex set $V = \{1, 2, ..., n\}$, and $\{d_{ij}\}$, $1 \leq i, j \leq n$ its weights on edges, find a least weighted cycle that visits each vertex exactly once.

As exact methods are sometimes computationally expensive for difficult problems, the research community continuously designs and tests heuristic solving methods (Crainic et al., 2009; Pop, 2014; Stoean, 2014). Among constructive heuristics for TSP, we mention successful applications of Genetic Algorithms (Potvin, 1996), Tabu Search (Fiechter, 1994), and Ant Colony Optimization (Dorigo et al, 1997). Several local-search heuristics for TSP involves sub-tour

swaps: *2-opt* or *3-opt* work on a solution and try to improve it by deleting two or three edges and reconstructing the tour in the best way.

One of the best local search heuristic for symmetric TSP is *Lin-Kernighan*; it generalizes the classic *2-opt* and *3-opt* moves as the λ-*opt* move, by considering λ edges from a tour and replacing them with other λ edges such that the total length is shorter. The *Lin-Kernighan* method starts with repeating *2-opt* moves until no improvement is possible, and continues with ascending values of λ in a dynamic way: it decides at each step if it should consider a bigger λ or it should stop. Very recent scientific applications of the method are on modeling wireless sensor networks (Apiletti et al, 2011) and on multi-robot rendezvous for recharging in persistent tasks (Mathew et al, 2013).

Uncertainty of the real systems and the dynamism of life added new characteristics and compounded the difficulty of the TSP. Today there are many demanding versions such as: Probabilistic TSP (Jaillet, 1985), Fuzzy TSP (Crisan et al, 2008), Robust TSP (Montemanni et al, 2007), Online TSP (Ausiello et al, 2001) and Time-dependent TSP (Malandraki et al, 1996).

Comprehensive information on TSP history, data-sets and currently one of the best solver (Concorde, 2011) are maintained on a specialized web-site (Cook TSP, 2005). Very good books including also the state-of-the-art of TSP computation are (Applegate et al, 2006; Cook, 2011). The related software available online at (Czyzyk et al, 1998) is used in Section 4 to illustrate the proposed framework on the new GIS-TSP national data.

2.2. GIS services in Operational Research

The new features of GIS tend nowadays to merge with the academic Operational Research domain. Several GIS commercial packages use heuristic approaches for TSP. For example, Route solver from ArcGIS is proprietary software that has been researched and developed extensively to quickly yield good results (ArcGIS, 2014). The documentation of Esri ArcGIS 10.1 shows that the solver uses Dijkstra's algorithm to find shortest paths. Several heuristics for managing spatial data are discussed in (Wise, 2013). Comparisons between available applications for route planning are made in (Curtin, 2014).

A successful real application for traffic management in case of disaster is the contraflow evacuation on freeways during Hurricane Katrina, which was completed in half of the planned time. Integration of spatio-temporal data into *Database Management Systems (DBMSs)* is at its beginnings. *TerraLib* is an open source package (TerraLib, 2015) for large-scale environmental and economic applications. The *National Atlas of the USA* includes *GIS* and geo-statistic data-sets under a Public Domain license (National Atlas USA, 2015). Other spatial *DBMS*s are: *Oracle Spatial, MySQL, PostGIS.*

Early studies show the efficiency of logistic approaches in emergency transportation for disaster relief in Somalia (Kemball-Cook et al, 1984). Current works explicitly model the disaster relief tour planning as *TSP* (Kirac et al, 2015), or show connections with *TSP* variants, for example with *multiple TSP* in (Wex et al, 2014). From the opposite side, there are many attempts to include *GIS* services into the academic research. Modern *Global Navigation Satellite Systems (GNSSs)* like GPS, Galileo, GLONASS or BeiDou offer accurate location tracking. Broad integration of GNSS into consumer products allows collecting cheap and accessible data for academic use.

For example, in (Nechita et al, 2012) it is presented a Bayesian approach for the assessment of digital risk probability in Romania. The authors consider in (Rodríguez et al, 2012) a benchmark of similar instances from central Spain, and study the influence of the asymmetry on the quality of the solutions. Several bus routes from Zagazig, Sharqia Governorate, Egypt were approached in (Eldrandaly et al, 2012).

3. Proposed Instances and a New Framework for TSP

The current section includes the main novelties of the paper. A new TSP instance based on the major settlements of Romania is introduced. It follows a novel framework to create a sequence of successive instances used to illustrate an emergency management process.

3.1. The First national GIS-TSP Instance

As today the *GPS* coordinates allow intensive computations, accurate positioning and adjustable maps, the data from (Crăciunescu, 2007) were used to build the first *Romanian TSP instance* with orthodromic (great circle) distances. We meant to model one large territory TSP instance in the most correct way, and we decided to use the geodesic distances instead of the Euclidean distances. Realistic data leads to relevant characteristics and complex attributes; for example, car engine emissions could be considered as in (Urquhart et al, 2013).

To our knowledge, this is the first national TSP instance with nodes defined by the geographic coordinates of localities, and great circle distances. All the national instances from (TSP Website, 2014) specified through geographic coordinates use the EUC_2D metric. This is the main contribution of this instance: spreading on a large territory, having more than 238,000 sq km, it is the first that accurately reflects the real distances between its nodes. The need for this specific instances is driven by commercial or open-source packages (Geosphere, 2015; Rossant, 2014; Google Maps, 2015). This instance is used to illustrate the framework introduced in the next sub-section.

From more than 13,000 Romanian human localities, we selected *2950* with administrative autonomy (Romanian Parliament Law, 2001). Their geographic coordinates (pairs of decimal values for latitude and longitude) were transformed to comply with *TSPLIB* format, *GEO* type (TSPLIB, 2013). The first *GIS-TSP* national instance *romania2950.tsp* was set up and is represented in Figure 1.

This new *TSP* instance integrates the geographic coordinates and can be used in all modern applications based on *GIS* services. For example, it is possible to study the temporal evolution of a large territory using Geoinformatics systems and packages. Satellites data could be compared with data collected from the territorial sensors. Ecological, geographical, meteorological or environmental characteristics could be integrated in such modern *GIS-TSP* instances, allowing complex models and accurate predictions at national scale.

The new *GEOM* type introduced for the *World TSP* instance (TSP data, 2009) offers a computational short-cut as it directly handles the geographic coordinates. It allowed us to define the equivalent Romanian TSP instance with geographic coordinates in GEOM norm. The GEOM norm is specifically designed to provide the distances in meters, while the GEO norm uses integer kilometers.
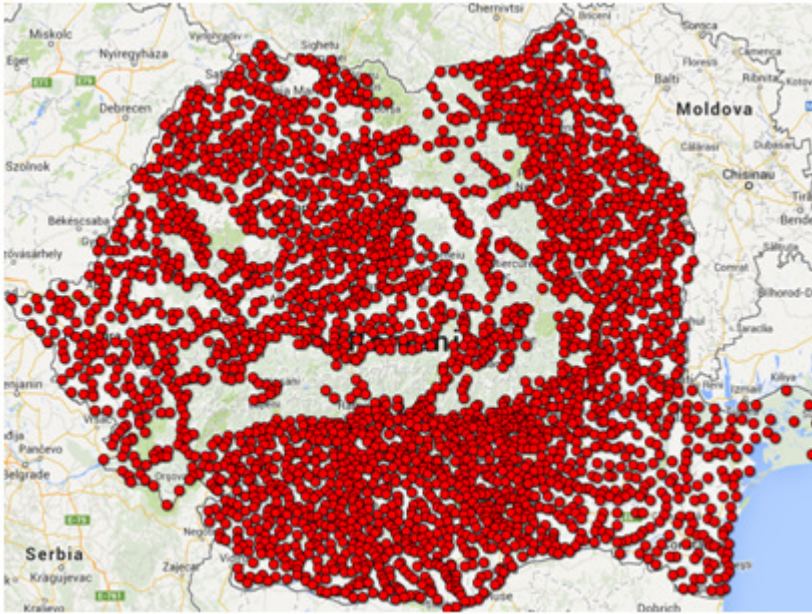
Fig. 1. The new TSP *romania2950.tsp* Romanian instance based on geographic coordinates.

As there are large regions with high node density, we chose to further work with the GEOM version, for higher accuracy.

Both the Romanian instances have the same map (as in Figure 1), only their solutions differ and, of course, their visual representations as well. The *Romanian TSP* link from the *TSP* main page (TSP Website, 2014) provides the detailed page with instances and results; both instances are available on-line for download at (Romania2950.tsp, 2014). There are other attempts in defining TSP instances with geographic coordinates, but none has the real settlements from a country and the orthodromic distance.

For example, the national instances from (TSP Website, 2014) use the EUC_2D norm. In (Rodríguez et al, 2012) the instances are produced by randomly plotting points on the map of Spain. In (Su et al, 2011) random instances on a sphere are used. The researchers' broad interest on such instances led to a new *TSP* variant: *Spherical TSP* or *TSP with spherical coordinates*.

3.2. Introducing a New Framework for TSP

The main TSP data collections currently available (TSP data, 2009; TSPLIB, 2013) consist of sets of independent instances, used to assess the overall performance of a specific solver. But in real life, there are situations when the behavior of a solver on close or dependent instances is important. An example is the need for stable solvers: if two problems are close (in a specific way), then their solutions are expected to be close.

In an industrial process based on stable applications, the technological flow and the production activities for several initial products are designed by computing their exact optimum solutions.

Later on, slightly modified products can be designed using the same technological solutions: the results are expected to have (almost) the same quality. Emergency Management considers also inter-related situations: one geographic area with rapid deteriorating conditions can be modeled by a sequence of pairs of close instances.

To construct a sequence of test instances, a new framework called *ALTER-Framework for TSP (ALTER-FTSP)* is proposed. It is further exemplified from the first national *Romanian GIS-TSP* instance already introduced.

The framework *ALTER-FTSP* uses a method *ALTER* to construct instances based on the recurrence relation (1) where *instance(0)* is an initial instance, *parameters* designates a set of (variable or not) parameters, and $i > 0$.

$$instance(i) = ALTER(instance(i-1),\ parameters(i-1)). \tag{1}$$

The researchers appropriately choose the function ALTER and the parameters. The latter could be dynamically adjusted to tailor the characteristics of specific instances. This framework is general and flexible. It builds a sequence of inter-related instances, controlled by the function *ALTER,* the initial instance and some dynamic parameters. The sequence could be used for diverse investigations. A solver could be tested for behavioral patterns, continuity for example, using these sequences. At theoretical level, the equation (1) allows mathematical investigations, for example convergence or structural stability theorems. From the viewpoint of algorithmic theory, Smoothed Analysis (Spielman et al, 2001) can be done.

The hazard vulnerability and the effectiveness of the response are highly influenced by representative and broad simulations. An example of strategic application of the framework is to include it as a module for generating training situations for spatial decision support systems. A complex control module could replace the basic control parameter set *parameters(i)*. Another example is designing stress tests for the software packages: a battery of complex scenarios can be obtained using this framework.

In operational situations, certified behavioral patterns could allow solution re-usage in case of small modifications. This includes the case when local conditions change due to unexpected events. For example, the 2003 Northeast power outage from USA and Canada was triggered by successive power plants shutdown, dropping in minutes the load with more than 80%. The lack of efficient communication and instant network balance overloaded the energy providers, forcing their automatic disconnection from the grid. Shortly afterwards, the North American power grid lost many nodes. This type of cascade events is suitable for our framework.

The general construction we introduce here brings together many experiments from previous works and correlates with many other methodologies. It is general enough to merge the methods of producing TSP instances starting from an initial set. In (Fischer et al, 2005), new instances are produced only in one step, using two operators: *reduction* and *shake*. In (Ahammed, 2011) a *Lindenmeyer system* is used to construct in one step a new instance by moving a fixed number of nodes in their neighborhood. The same idea of perturbation is presented in (Cohoon et al, 1998).

In general, this framework can deliver a sequence of dependent instances for modeling dynamic TSP. In (Kang et al, 2004) a dynamic TSP with continuous functions for the distances is modeled through a sequence of classic TSP instances with constant distances on all edges.
In (Li et al, 2006) a dynamic elastic operator is introduced for three expressions of dynamism: a node appears, a node disappears, or a node moves. An alternative to our approach is to consider evolving algorithms, that constantly reflect the changes. An example is the Ant Colony algorithms used in (Guntsch et al, 2001).

Other methods for generating instances either produce independent ones, or deliver instances depending on more than one instance. For example, in (Ridge et al, 2008) the authors use a modification of the `portmgen` generator from (Goldwasser et al, 2002) for producing random independent instances with 300, 500 and 700 nodes. In (van Hemert, 2005) the traditional genetic operators *crossover* and *mutation* are used to produce new instances starting from a pool of random instances with 100 nodes. So, the new instance depends on two old ones. The framework we introduce here uses just one instance to derive the next one.

The idea of slight modification is extensively used in Optimization. For example, *Simulated annealing* and *Tabu search* exceptionally accept worse solutions in order to escape from local optimum. Local search is a related paradigm, as sometimes good solutions are close in the search space, forming promising regions. The same idea applied to a different problem is presented in (Crucitti, 2004). The authors evaluate the impact of deleting nodes on the network vulnerability. The extreme case is treated in (Kovács et al, 2015): the most effective way to disrupt a network is investigated.

4. Numerical Experiments and Discussion

To illustrate the $ALTER - FTSP$ framework defined in Section 3.2, we present here two cases. The former models the uncertainty by randomly isolating some localities and dropping them from the instance $romania2950.tsp$. The latter case deterministically excludes the least populous localities. The first case simulates the effect of an adverse event that randomly hits, or multiple errors appeared in a technological network; the second is appropriate in the early recovery phase, when relief dispatching is concentrated in most populous places, or is suited for modeling coordinated, concurrent attacks on networks [1]

4.1. Uncertainty modeling - Case 1

The function $ALTER$ randomly selects and deletes nodes from the current instance and returns a new instance. The process is repeated nine times, so a sequence of nine new TSP instances with fewer nodes is generated. The general equation (1) becomes equation (2) with $i > 0$.

$$instance(i) = Delete\_at\_Random(instance(i-1),\ p), \qquad (2)$$

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[1] The instances are available by request to the authors.

where the function *Delete_at_Random* takes a TSP instance and just one constant parameter p that specifies, as a percentage value, how many nodes are randomly deleted from the input instance and outputs the new instance. We run three such simulations with constant $p \in \{1\%, 3\%, 5\%\}$.

$ALTER - FTSP$ can produce a more complex control on the sequence of instances. For example, the unique parameter p could be a variable, modeling a powerful event that decreases in time: seismic sea waves, floods or nuclear accidents. An increasing series of values for p can model cascade power outages or consecutive earthquakes hitting the same region. The corresponding equation in this case is equation (3) with $i > 0$.

$$instance(i) = Delete\_at\_Random(instance(i-1),\ p(i-1)). \qquad (3)$$

A more general illustration of $ALTER-FTSP$ is based on multiple parameters. Classifications can serve as a supplementary selection criterion. For example the equation (4) with $i > 0$.

$$instance(i) = Delete\_at\_Random(instance(i-1), p(i-1), q(i-1)), \quad (4)$$

where $p(i)$ is the percentage value of the excluded nodes and $q(i)$ is the minimum distance between them. This could be a request for a balanced territorial relief supply.

In our case, driven by equation (2), the exact solutions are obtained using Concorde, a branch-and-cut solver (Concorde, 2011), described in (Gropp et al, 1997). It uses a cutting plan method, iteratively solving linear programming relaxations of the initial instance. We chose the online run, accessible through NEOS server (Czyzyk et al, 1998; Dolan, 2001). The Concorde solver ran for at most four hours on two Intel Xeon processors at 2.2GHz and 64 GB RAM; implicit attributes are used there: CPLEX and fixed seed. The exact solutions were used to assess the results provided by the heuristic method. The *Lin-Kernighan* (Lin et al, 1973) method was chosen as it is one of the most effective heuristic techniques designed for symmetric TSP. The heuristic application was run ten times, and we report here the average and the best values.

Table 1 shows the solutions for the initial instance, with integer distances in meters (GEOM norm). The statistic Relative Percentage Difference (RPD) is computed using the formula:

$$RPD = \frac{Solution - Best}{Best}\%$$

where *Solution* is solution provided by the heuristic method and *Best* is the exact solution. For representing the instances and the solutions, GPS Visualizer, a popular, highly customized and free online tool (GPS Visualizer, 2013) is used.

Table 2 shows the exact solutions and running time in seconds for first nine iterations based on equation (2), using the function *Delete_at_Random* and constant $p \in \{1\%, 3\%, 5\%\}$. The dimension of the current instance, the optimum value (in meters) and the running time (in seconds) are mentioned.

Figure 2 shows an exact solution to *romania2950.tsp* with GEOM norm. Figure 3 illustrates the repeated transformations of the initial instance, showing the nine sets of excluded nodes from the instance *romania2950.tsp* and their visual characteristics when $p = 5\%$. For example, the excluded nodes at the first iteration are represented by green squares. The instance resulted at the 9th iteration, with only 1862 nodes, has the optimum path depicted in Figure 4 (left).

Table 1. The solutions of the *romania2950* instance with the Geographical Norm in meters (GEOM); the results are for the Branch-and-Cut algorithm and the Lin-Kernighan heuristic.

GEOM TSP	Branch-and-Cut Optimal	Lin-Kernighan AVG	Lin-Kernighan MIN
Solution (m)	20338171	20375727.5	20362640
RPD (%)	-	0.1847	0.1203
Time (s)	2852	3.25	2.53

Table 2. Optimum solutions in meters and running time in seconds for the introduced instances using Branch-and-Cut.

Iter	Inst	1% Solution	Time	Inst	3% Solution	Time	Inst	5% Solution	Time
1	2921	20205928	1305	2862	19966083	3619	2803	19730203	9115
2	2892	20095059	2350	2777	19627256	2169	2663	19188050	991
3	2864	19966026	10322	2694	19236971	3487	2530	18661985	321
4	2836	19865204	834	2614	18885027	2944	2404	18163059	2034
5	2808	19742128	326	2536	18594278	7196	2284	17623115	1686
6	2780	19606514	1162	2460	18255359	5933	2170	17096230	9303
7	2753	19498877	1022	2387	17957873	1152	2062	16629320	3909
8	2726	19399992	2751	2316	17626444	4710	1959	16153456	5358
9	2699	19276005	820	2247	17338055	526	1862	15708029	2904

When compared with Figure 2, the path clearly connects fewer nodes, uniformly distributed on the territory.

Figure 4 (right) is a close capture of Eastern Romania, with the excluded nodes and the optimum path connecting the remaining ones. All the sequences manifest irregular solving time for *Branch-and-cut*: there is no decreasing tendency, and no continuity is manifested for consecutive instances. For example, the hardest instance with 2864 nodes is solved in 10,322 seconds. The previous instance is solved in 3250 seconds and the next instance is very quickly solved in 834 seconds. We can state that the running time for a slightly modified instance cannot be predicted (Figure 5).

The results provided by the chained Lin-Kernighan heuristic method for the three sequences of instances are shown in Tables 3-5. The running time values are less than four seconds (Figure 6) proving that the chosen heuristic method is constantly extremely fast.

Figures 7 and 8 illustrate graphical comparisons between statistic RPD(%) minimal solutions and the average solutions of *Lin-Kernighan* heuristic for the three considered instances derived from *romania2950.tsp*. These results show that the average values correlate with the minimum vales, and thus the Lin-Kernighan method proves to be stable on the studied dependent instances.
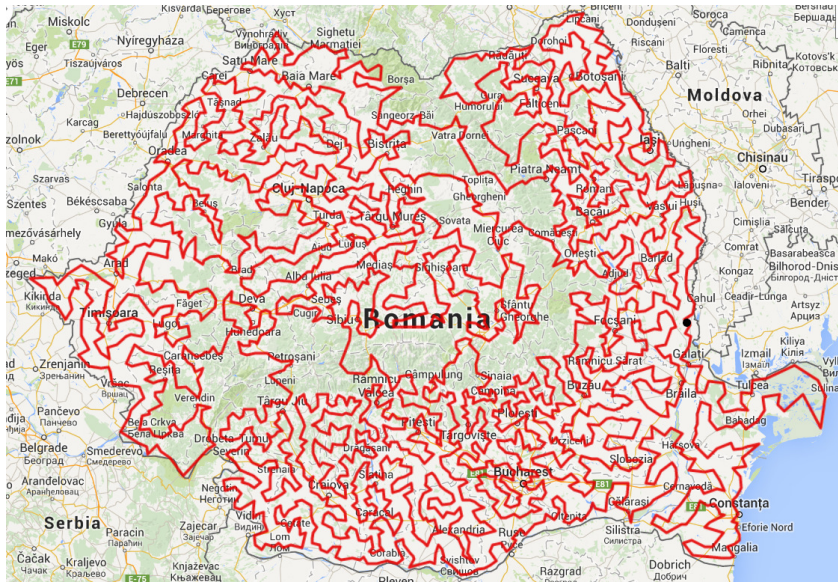
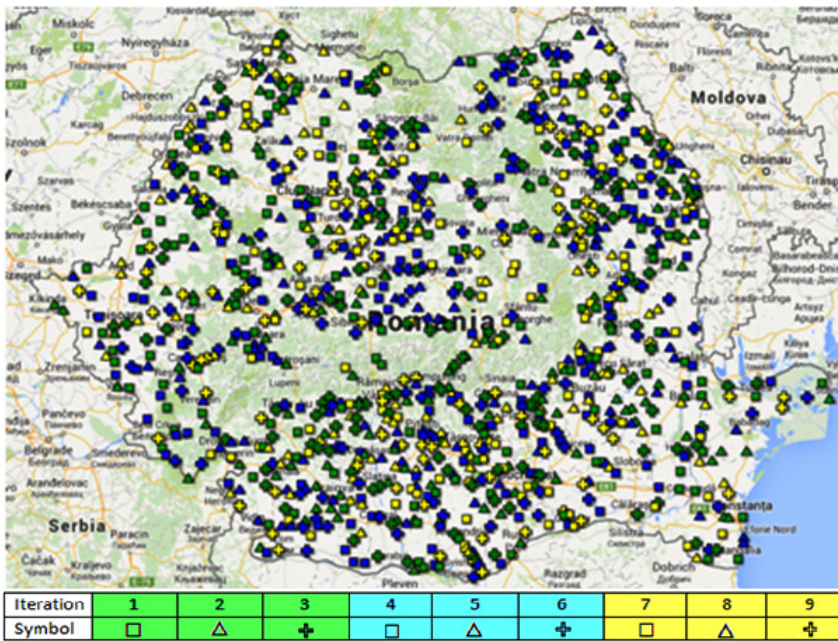**Fig. 2.** An optimum solution to *romania2950.tsp*

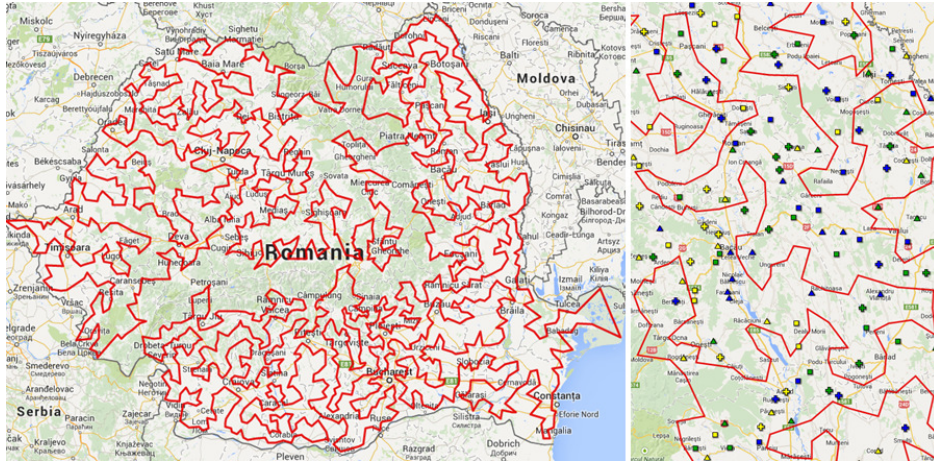**Fig. 3.** The excluded nodes from *romania2950.tsp*, in all iterations, with their symbolic representation, for p=5%.

Fig. 4. One optimum solution to *romania1862.tsp* (left) and a close capture with solution and excluded nodes for *p*=5% (right).
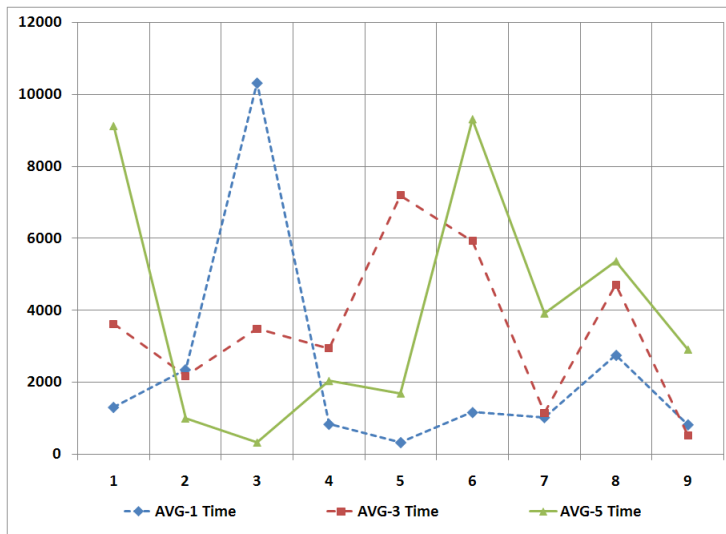

Fig. 5. The average execution time with the *Branch-and-Cut* algorithm on the nine corresponding instances.
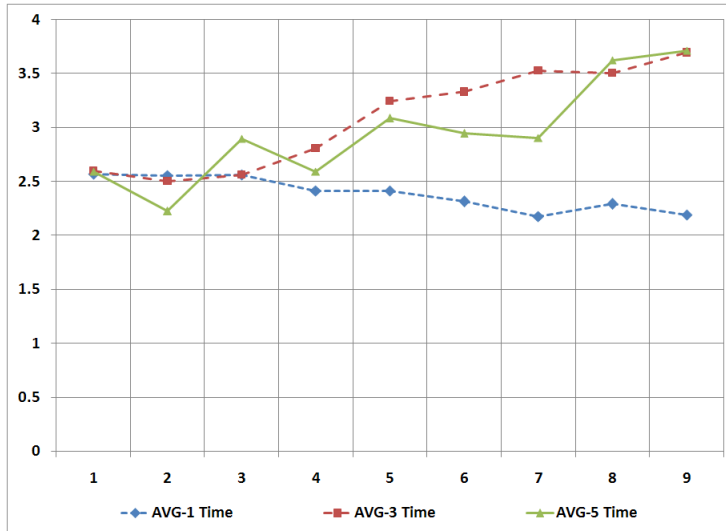
Fig. 6. The average execution time with the *Lin-Kernighan* heuristic on the nine corresponding instances.
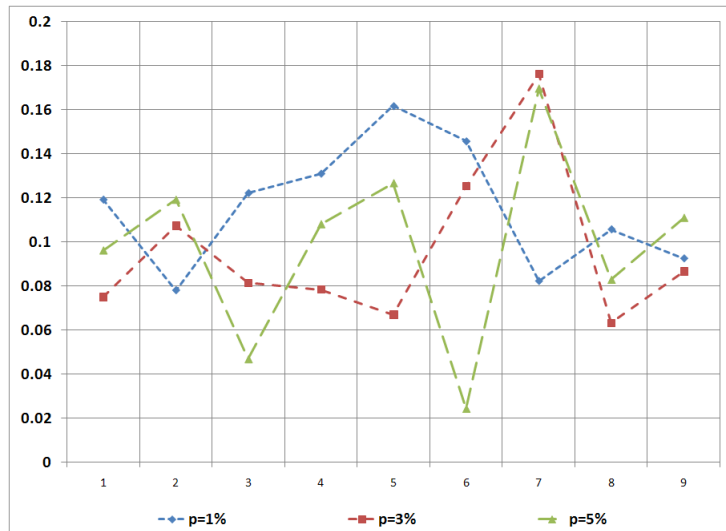

Fig. 7. A graphic comparison between statistic RPD(%) minimal solutions for the *Lin-Kernighan* heuristic on all nine corresponding instances.

Table 3. The results of Lin-Kernighan heuristic after ten runs for the nine considered instances; the percentage of extracted nodes is 1%.

Iter	Inst	AVG Solution (m)	RPD (%)	MIN Solution (m)	RPD (%)
1	2921	20246706.7	0.2018	20230043	0.1193
2	2892	20128245.7	0.1651	20110750	0.0781
3	2864	20007995.9	0.2102	19990449	0.1223
4	2836	19909053.9	0.2207	19891244	0.1311
5	2808	19788311.4	0.2339	19774075	0.1618
6	2780	19644172.8	0.1921	19635096	0.1458
7	2753	19527522.4	0.1469	19514930	0.0823
8	2726	19438145.2	0.1967	19420511	0.1058
9	2699	19308946.7	0.1709	19293860	0.0926

Table 4. The results of Lin-Kernighan heuristic after ten runs for the nine considered instances; the percentage of extracted nodes is 3%.

Iter	Inst	AVG Solution (m)	RPD (%)	MIN Solution (m)	RPD (%)
1	2862	19992830.0	0.1340	19981062	0.0750
2	2777	19664766.8	0.1911	19648316	0.1073
3	2694	19263934.7	0.1402	19252645	0.0815
4	2614	18915476.1	0.1612	18899831	0.0784
5	2536	18620313.8	0.1400	18606727	0.0670
6	2460	18284351.9	0.1588	18278235	0.1253
7	2387	18002802.1	0.2502	17989492	0.1761
8	2316	17655558.4	0.1652	17637597	0.0633
9	2247	17365411.0	0.1578	17353093	0.0867

4.2. Deterministic intervention - Case 2

To illustrate the deterministic control, we imagine below a situation that leads to a complete data-driven node exclusion. We model a targeted network emergency situation on a region with four neighbor counties from Eastern Romania.

Table 5. The results of Lin-Kernighan heuristic after ten runs for the nine considered instances; the percentage of extracted nodes is 5%.

| Iter	Inst	AVG Solution (m)	RPD (%)	MIN Solution (m)	RPD (%)
1	2803	19730203	0.1529	19749199	0.0963
2	2663	19188050	0.1726	19210950	0.1193
3	2530	18661985	0.1406	18670752	0.0470
4	2404	18163059	0.1545	18182716	0.1082
5	2284	17623115	0.2081	17645467	0.1268
6	2170	17096230	0.1299	17100416	0.0245
7	2062	16629320	0.2505	16657541	0.1697
8	1959	16153456	0.1376	16166862	0.0830
9	1862	15708029	0.1693	15725481	0.1111
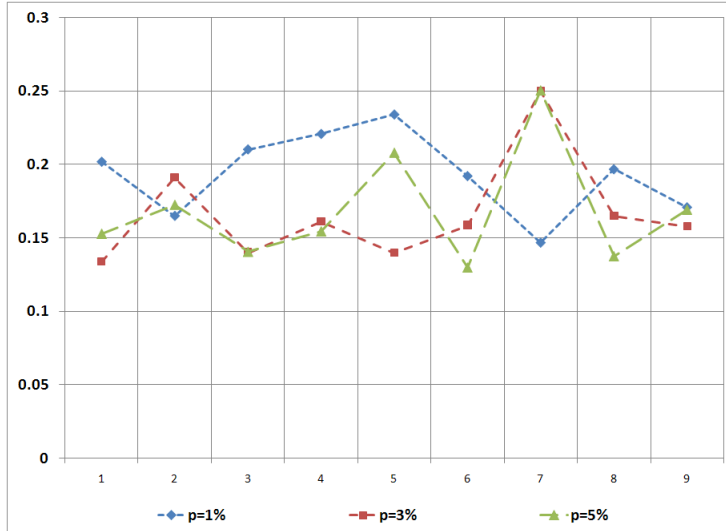
Fig. 8. A graphic comparison between statistic RPD(%) average solutions for the *Lin-Kernighan* heuristic on all nine corresponding instances.
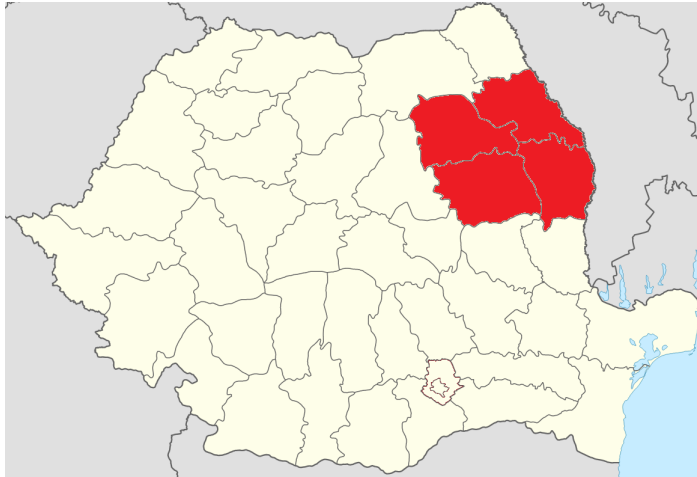

Fig. 9. The area of Targeted Network Emergency Situation. Map from Wikipedia.

The considered region are Bacău, Iaşi, Neamţ and Vaslui, marked in Figure 9. To derive the first set of instances is used equation (5) with $i > 0$.

$$instance(i) = Delete(instance(i - 1), p, pop, asc, area), \tag{5}$$

where p is 1%, and the function *Delete* excludes the $p\%$ least populous localities from the *area* (it uses the values from the column *pop*ulation and deletes the nodes in *asc*ending order).
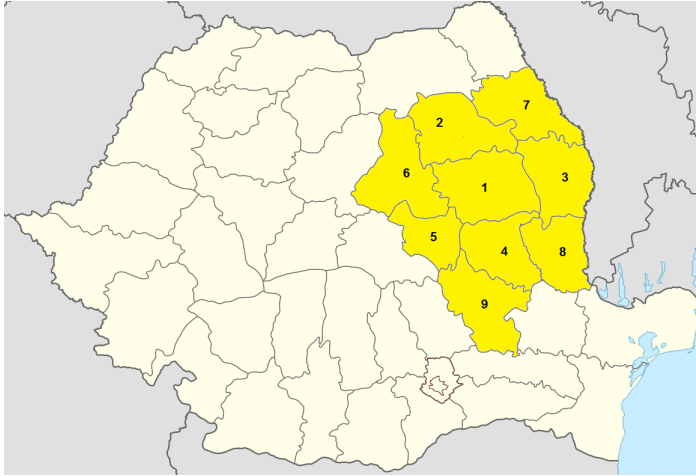
Fig. 10. The area of Regional Network Emergency Situation. Map from Wikipedia.
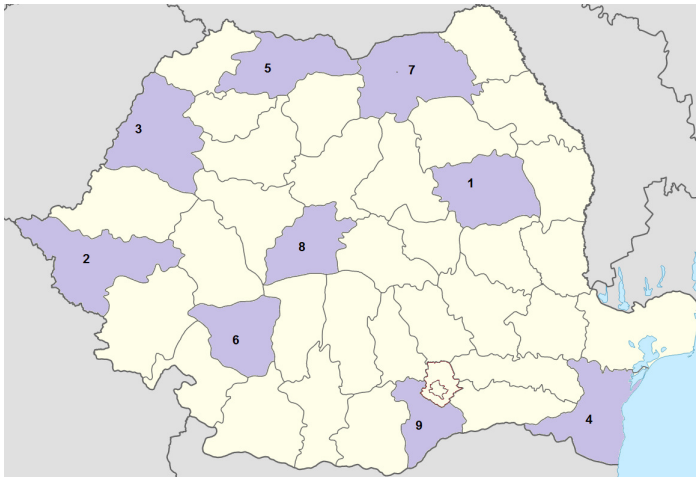

Fig. 11. The area of National Network Emergency Situation. Map from Wikipedia.

We observe that *ALTER-TSP* uses a function with four constant parameters. The exact solution and the Concorde running time are illustrated in the column *Targeted* from Table 6.

In order to introduce a variable parameter it is used equation (6) with $i > 0$.

$$instance(i) = Delete(instance(\text{i}-1), p, pop, asc, area(\text{i}-1)). \tag{6}$$

We made also two more instantiations for our framework: it is designed a regional network attack (from each county shown in Figure 10, in the specified order, the least populous localities were excluded), and a national network attack (the counties and their order for excluding nodes is presented in Figure 11).
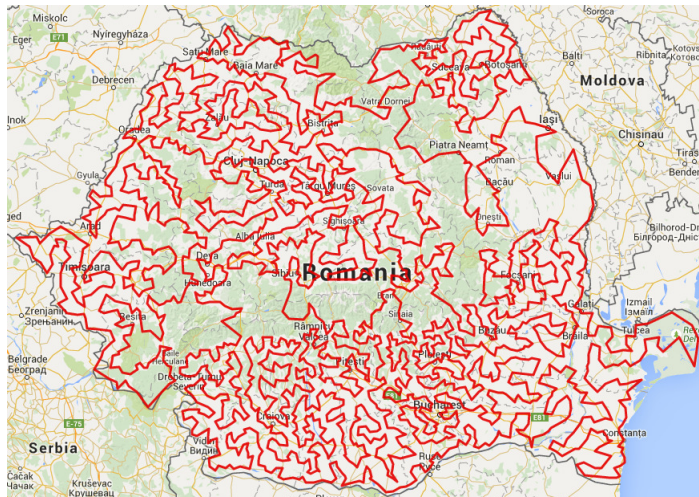
Fig. 12. Exact solution for the instance with 2699 nodes; *Targeted* Network Emergency Situation.

Table 6. The exact solutions and the time for the nine considered instances in *Targeted*, *Regional* and *National* exclusion; the percentage of extracted nodes is 1%.

Iter	Inst	Targeted		Regional		National	
		Solution	Time	Solution	Time	Solution	Time
1	2921	20208799	3156	20192113	1901	20192113	1901
2	2892	20086682	5559	20074178	2410	20013775	2632
3	2864	19971516	11629	19944305	2374	19893760	1671
4	2836	19833281	4220	19836523	11405	19720933	1307
5	2808	19720866	6029	19702054	3828	19589767	707
6	2780	19562158	1700	19568888	2762	19484719	728
7	2753	19400909	7944	19457320	10081	19295968	2187
8	2726	19194571	3878	19310201	1868	19185688	10645
9	2699	19054069	3525	19201192	3945	19056895	10736

The exact lengths and the Concorde running time are presented in the columns *Regional* and *National* from Table 6.

The exact solution to the instance with 2699 nodes from the targeted simulation is presented in Figure 12. The results from Table 6 show again that the exact method we chose does not manifest a predictable execution time. Although we have derived a small number of instances, this result seems to show that the behavior of Concorde on random uniform instances presented in (Hoos et al, 2014) is unlikely to be generalized.

5. Conclusion

This paper has two main contributions. Firstly, it introduces *romania2950.tsp*, the first national GIS-TSP instance with 2950 nodes. The distance between cities is computed using their geographic coordinates, as orthodromic distance. The new instance was recursively modified in order to support an emergency management process and the solutions were compared with the optimum solutions.

Secondly, it introduces a framework to sequentially build instances, starting from an initial one, in order to evaluate a user-defined software metric; here we consider the continuity of the quality of the results delivered by the *Lin-Kernighan* method, when compared to the exact solutions. Our empirical investigation shows that the *Lin-Kernighan* heuristic is stable on the studied instances. The framework is general and flexible, as it can model many real situations.

The aim of this paper is to develop new methods for properly assessing the risks in large-territory, complex networks. For reaching this goal, the two main contributions of this paper (the Romanian GIS-TSP instance and the ALTER-FTSP structure) interfere: the former is the real-word support for the latter. As the real geographic world works in $Space + Time$ dimensions, the instance is a composite network of spatial points, and the framework is a flexible and general description of the network evolution. Thus, they complement each other.

A scenario including uncertainty is presented. This model could be used in Transportation Safety: the randomly broken sensors from a large territory road network have to be inspected after an earthquake by a swarm of drones. Or, during preparedness phase, lots of virtual, randomly generated critical situations could be imagined, and the responses to them could be assessed.

The deterministic scenario presented includes a priority system. It is useful for modeling, for example, top-priority helicopter visits with doctors and supplies to schools and hospitals.

Satellites like *Suomi NPP* transmit global, accurate data on atmospheric, terrestrial and oceanic conditions, helping the forecasters to make early incident announcements. The environmental hazards management systems need to be prepared for cascade severe conditions, and therefore running systematic, theoretic sound simulations and tests would definitely improve the quality of the preparedness. For example, Giovanni Bisignani, IATAs Director General and CEO said in a press release after the 2010 eruptions of Eyjafjallajökull Islandic volcano: "Governments must place greater urgency and focus on how and when we can safely re-open Europes skies. This means decisions based on risk-management, facts and utilizing operational procedures that maintain safety."

More work need to be done in order to test the method on other longer sequences and also to test other solving methods. For example, a stable *TSP* solver could be successfully integrated in touristic GIS applications, as people tend to visit almost the same points of interest. As a generalization, the third dimension could be considered in order to better reflect the Earth conditions. The undersea or the airspace navigation offer many applications needing tridimensional coordinates. One example is the US-European *Jason* series of satellites for ocean altimetry, that can observe now, from an altitude of 1,336 km, water level modifications in the range of few centimeters. Other examples are the celestial missions, or the exploration of the hemispheric craters.

These show that the presented investigation could be used in a broad range of optimization applications.

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