# Disaster management: an ensemble Multi-Criteria Decision Support System encompassing cascading effects

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**Abstract.** In the last decades, Multi-Criteria Decision Making algorithms have proven to be effective in supporting the decisions of policy makers, especially for what concerns disaster management and a number of other societal challenges. Nevertheless, at the present time none of these tools is able to include in the decision process the evaluation of cascading effects, i.e. the fact that a triggering hazard may cause subsequent catastrophes. Starting from the standard ELECTRE III and ELECTRE TRI algorithms, we propose Decision Support System for disaster management, which takes into account the role of cascading effects and supports the decision maker also in the choice of the best timing for the intervention. The core approach is based on an ensemble algorithm that aggregates the results of an array of possible impact scenarios, conveying a more comprehensive and complete information about the effectiveness of mitigation strategies.

**Key words:** Cascading effects, Multi Criteria Decision Making, Decision Support Systems, Ensemble Methods, Disaster Management

## 1 Introduction

On Friday 11 March 2011, at 05:46 UTC, a magnitude 9.0 undersea earthquake hit the coast of Tohoku, Japan, with the epicenter approximately 70 kilometres east of the Oshika Peninsula of Thoku [1]. Just over an hour after the earthquake, a tsunami flooded Sendai Airport, which is located near the coast of Miyagi Prefecture, with waves sweeping away cars and planes and flooding various buildings. The largest wave in the tsunami arrived approximately 50 minutes after the initial earthquake. The wave was 13m tall and overcame the Fukushima I Nuclear Power Plant's seawall, which was only 10m high. Water quickly flooded the diesel generators, which failed soon afterwards, cutting power to the critical pumps that must continuously circulate coolant water to prevent the fuel rods from melting down. After the emergency pumps ran out, one day after the tsunami, 12 March, the water pumps stopped working and the reactors began to overheat, leading to the largest nuclear disaster since the Chernobyl disaster of 1986. The Fukushima Daiichi disaster shows that natural disasters may be

followed by other natural or technological disasters, creating a chain of disasters coupled with cascading effects. A domino accident is "a cascade of events in which the consequences of a previous accident are increased both spatially and temporally by the following ones, thus leading to major accident."[2]. The analysis of the interactions between disasters acquires an ever increasing importance in the modern society, where technological infrastructures are always more complex and intertwined.
In this paper, we present the main features of a Decision Support System (DSS) that it introduces significant novelties and improvements with respect to the state-of-the-art. The DSS is meant to improve the preparedness, the response capacities and the management of crisis situations induced by natural and technological hazards. In particular, it supports the emergency planners in making the best decisions, highlighting the paramount importance of taking into account the role of cascading effects. The proposed approach is applied to the particular use case of SnowBall, an ambitious FP7 that draws on a multidisciplinary, in-depth analysis of cascading effects as well as on the design and implementation of methods to detect, characterize, predict and anticipate them.
The remainder of the paper is structured as follows: in Section 2 we motivate the methodological choices and introduce the main features of ELECTRE algorithms; in Section 3 we explain how to encompass cascading effects into the decision process and we discuss the ensemble solution; in Section 4 we discuss possible future improvements of the model, with a specific attention to the issue of parameters; in Section 5 we summarize the functioning of the DSS, underlining its innovative features and its potential applications.

## 2 Background

After a thorough analysis of the competing solutions available in literature, the methodological approach chosen to answer the problem of prioritizing a set of intervention strategies according to their expected impact is a Multi-Criteria Decision Making algorithm. Multi-Criteria Decision-Making methods (MCDM) is a branch of a general class of Operations Research models that aims to address complex problems featuring high uncertainty, conflicting objectives, different forms of data and information, multi interests and perspectives (ill-defined problems), and the accounting for complex and evolving biophysical and socio-economic systems [3, 4, 5]. MCDM attempts to unravel complexity in lieu of adding a new layer of simulation and reduces the cognitive effort required to end users (i.e., public decision makers), thus shortening the distance between results generated by the DSS and the real decision scenario. For this reason, MCDM have been extensively used in crisis and disaster management [6, 7, 8, 9]. In general, MCDM methods are framed around four entities (Fig. 1): alternatives (the intervention strategies), criteria (factors taken into account to evaluate the alternatives at stake), performance (outcomes of simulations) and weights (quantitative inputs provided by the user which measure the importance of the criteria according to the DM). The SnowBall DSS thus relies on the simulations tools

| | C1: Number of deaths | C2: Number of injuries | C3: Damage on Grids [€] | C4: Downtime of Grids [h] | C5: Lost buildings | C6: Number of homeless people |
|---|---|---|---|---|---|---|
| **Alternative 1: EvacuationA** | 10 | 12 | 13000 | 9 | 15 | 500 |
| **Alternative 2: EvacuationB** | 15 | 20 | 10000 | 7 | 50 | 800 |
| **Weights** | 0.2 | 0.1 | 0.3 | 0.2 | 0.1 | 0.1 |

**Fig. 1.** Showing the inputs of the MCDM algorithm, divided in alternatives, criteria, performance and weights. The numbers and the criteria are fictive and exemplificative.

developed by the consortium of the project. The tools include a theoretical modelling of cascading effects in natural and technological hazards, the evaluation of the role of the human behaviour during crisis and a specific focus on the coupling between grid infrastructures. These methods are able to quantify, for each alternative mitigation strategy, the performance scores, which constitute the input data shown in Fig. 1. Among the family of MCDM methods which have been shortlisted, one of the most diffuse and popular tool is Analytic Hierarchy Process (AHP) [10]. AHP fits comfortably in circumstances where judgements are the predominant form of input information and has been successfully employed in several situations. Nevertheless, ELECTRE III [11] and ELECTRE TRI [12] have proved to be the most appropriate and close to our purpose. ELECTRE gives high relevance to quantitative impact values obtained from simulations, which constitute the yardstick against which alternative countermeasures have to be selected. It also reduces the cognitive effort required to the end user, for it does not require a pairwise comparison of each criterion and of each alternative relatively to each criterion. It even allows the comparison of the alternatives even if there is not a clear preference for one of the two. More in general, we may say that ELECTRE seems to be able to strike the right balance between user involvement in the configuration of the model and the recourse to quantitative simulated data. A short overview of ELECTRE III and ELECTRE TRI is provided in the following lines.

### 2.1 ELECTRE III overview

ELECTRE is an outranking method that originated in Europe in the mid-1960s and that was first proposed by Bernard Roy [13]. ELECTRE allows decision

makers to select the best choice with utmost advantage and least conflict in the function of various criteria, combining the necessity of involving the user's choices and that of taking into account objective quantitative data coming from simulations. More in detail, the alternatives are ranked on the basis of performance achieved on multiple criteria under consideration, whose importance is assessed by the user during the weight selection procedure.
Subsequently to the pioneering work of Roy of 1968, several versions and improvements of the original algorithm have been proposed, among which we have selected ELECTRE III, because of its improved capacity of dealing with inaccurate, imprecise, uncertain data [11]. The functioning of may be summarized as follows [14]:

- **Alternatives selection**: the DM chooses the list of alternatives to be considered in the analysis
- **Criteria selection**: the DM selects a set of criteria on which the evaluation of the alternatives has to be based
- **Weight selection**: the DM assesses the importance of the criteria by assigning a weight to each one of them, taking into account that the total sum of the weights must be 1
- **Outranking relation**: the algorithm automatically computes a binary outranking relation between the alternatives, i.e. it builds a binary preference relation based on the performance
- **Exploration**: starting from the binary outranking relation, the algorithm computes a global ranking of the alternatives

The procedure requires the DM's involvement in the first three steps and her choices at this stage crucially influence the outputs of the DSS. Although at a first glance this fact may appear as a source of instability and unreliability of the model, in fact this is one of strengths of ELECTRE III, as it represents a way to complement the algorithmic operations with human judgement.

### 2.2 ELECTRE TRI overview

A distinct, yet complementary, perspective is brought by ELECTRE TRI, which is a method conceived for sorting problems [14]. In sorting problematic, each action is considered independently from the others in order to determine its intrinsic value, by means of comparisons to previously defined reference profiles. Therefore, the sorting problematic refers to absolute judgement. It consists of assigning each action to one of the pre-existing categories which are defined by norms, typical elements of the category or international standards. In the framework of the SnowBall solution, ELECTRE TRI helps the DM to compare each of the intervention strategies at stake aimed at mitigating the effects of the disasters with a set of predefined intervention strategies, labelled as class 'A', 'B' and 'C' according to the results they would obtain. From a more technical point of view, ELECTRE TRI requires the definition of a set of reference profiles, then

| | **ELECTRE III** | **ELECTRE TRI** |
|---|---|---|
| **Problematic** | Ranking | Sorting |
| **Judgement** | Relative | Absolute |
| **Results** | Ranking | Class assignment |

**Table 1.** *Comparing the sorting and ranking approach of ELECTRE TRI and ELECTRE III*

each alternative strategy is compared to each of the reference profile, computing an outranking relation. Following this evaluation, an alternative is assigned class 'A' if it outranks the class 'A' profile, class 'B' if it outranks the class 'B' profile and class 'C' if it outranks the class 'C'. This rule is known as "pessimistic assignment", as when an alternative lies between two reference profiles, i.e. it is outranked by the next upper class and it outranks the next lower class, it is assigned to the latter.

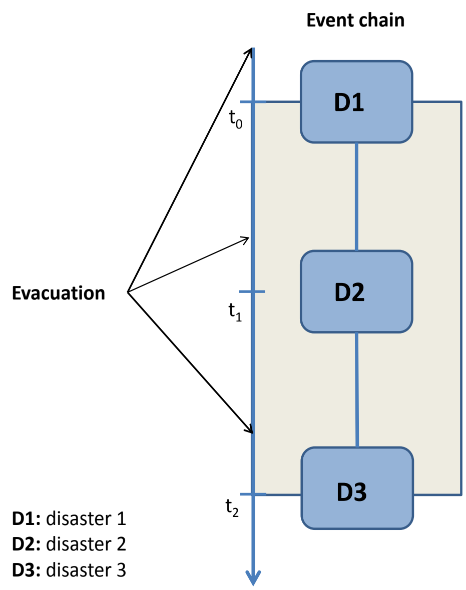
The ranking and the sorting approach, although non equivalent, are not to be intended as in contrast with each other. In fact, they provide two different perspectives meant to support the DM in her decisions. It may be the case that, while the ranking shows a clear winning strategy, none of the strategies is considered to be a top-class option. This result may suggest to the DM that the options at stake are not effective and that she should work to expand the range of possible intervention strategies. On the other hand, it may happen that all intervention strategies deserve a high-class, even if the relative ranking puts them in a low position. A comparison between the two parallel approaches is reported in Tab.1.

## 3 Approach

In this paper, we propose to apply ELECTRE III and ELECTRE TRI to a disaster management system that includes the theoretical evaluation of cascading effects, as, to the best of our knowledge, no similar approach is present in the scientific literature. Furthermore, we combine the ranking and sorting perspective into a single DSS, providing the DM with the possibility of comparing the mitigation strategies with each other and with a set of predefined international standards. Finally, we propose to utilize an ensemble approach to include into the decision process the evaluation of an array of possible impact scenarios and to convey a more thorough and balanced vision of the effectiveness of mitigation strategies. The idea of ensemble learning is to build a prediction model by combining the strengths of a collection of simpler base models. The ensemble approach can be generally broken down into distinct tasks: developing a population of base learners and then combining them to form the composite predictor [15, 16].

### 3.1 Cascading effects

Once we have provided an overview of the ELECTRE algorithm, we can now show how it can be applied to a context where cascading effects are taken into consideration. In general, after a triggering hazard takes place, many possible hazards may follow, with different transition probabilities [17, 18]. For the sake of simplicity, we suppose that the DM intends to consider a fixed hazard chain of three disasters $D1 - D2 - D3$ (e.g. earthquake-tsunami-electric grid failure) and to compare two alternative evacuation strategies with respect to this particular case (Fig. 2). The idea is that a single mitigation strategy may yield markedly different results, according to the time of the intervention. Thus, a single mitigation strategy such as "evacuation" may be split in several different strategies, according to the position assumed in the hazard chain. The motivation is that, even if the mitigation strategy is not changing in its procedures and operations, the impact evaluation differs according to the timing of the intervention, especially considering the role of cascading effects, as evacuating the population before or after a tsunami takes place is dramatically different. Thus, we propose to consider them as different mitigation strategies, evaluated and compared on the basis of their expected impact. After the splitting procedure




| | Crit1 | Crit2 | Crit3 | Crit4 |
|---|---|---|---|---|
| EvacuationA t0 | 10 | 11 | 20 | 18 |
| EvacuationA t1 | 8 | 12 | 19 | 21 |
| EvacuationA t2 | 10 | 11 | 19 | 18 |
| EvacuationB t0 | 11 | 12 | 13 | 20 |
| EvacuationB t1 | 12 | 13 | 17 | 19 |
| EvacuationB t2 | 7 | 10 | 23 | 17 |

**Fig. 2.** Evaluating cascading effects in an event chain. A single mitigation strategy may be considered as an array of mitigation strategies, according to the timing of the intervention. The algorithm thus needs not be modified. The numbers are fictive and exemplificative.

has been carried out, the algorithm can run without any ad-hoc modifications. The produced ranking will therefore allow the decision maker to select the best mitigation strategy-time of intervention pair (see Fig. 3 for an exemplification). Note that it may be the case that not each of the alternative mitigation strategies under consideration can be evaluated at any time of the hazard chain. In fact, some of the intervention strategies may be effective only if applied in a preventive manner, e.g. the retrofitting and the reinforcing of buildings and infrastructures against the effects of an earthquake. Nonetheless, the illustrated procedure is meaningful and useful for most of short-term interventions, aimed at mitigating the consequences of an imminent natural disaster.

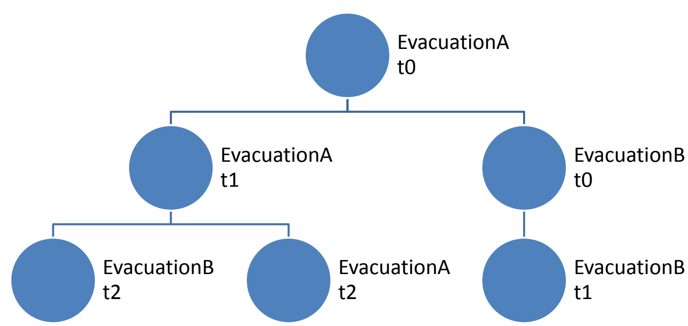



**Fig. 3.** Ranking between the evaluated mitigation strategies (EVC stands for evacuation) considering also the timing of the intervention.

### 3.2 Ensemble solution

Among the MCDM methods, ELECTRE is specifically designed and tailored to deal with uncertainty. This statement stems from the fact that the presence of preference, indifference and veto thresholds is aimed at taking into account the inevitable errors in the performance evaluations, the inherent complexity in comparing heterogeneous criteria and the marked non-linear dependence of the decision on the simulation results [14]. Nevertheless, in most cases (among which the case of our interest) the performance on which the algorithm is based are the results of aggregating procedures over data coming from stochastic simulation, that is means over a large number of runs. What normally happens then is that ELECTRE is fed with the means, thus neglecting the distribution of the data: the decision is made on a hypothetical "average impact scenario". This approach is particularly limiting in the case of natural disasters such as earthquakes, volcanic eruptions, asteroid impacts, landslides and forest fires where the distributions of impact intensities are often represented by fat-tailed, power law-like distributions [19]. A power law distribution $P(x) = \frac{c}{x^{\alpha}}$ has a finite mean if $\alpha > 2$ and finite variance if $\alpha > 3$.[1] Most identified power laws in nature have $2 < \alpha < 3$ and thus have infinite variance: the use of the mean as a performance indicator is therefore not adequate as large fluctuations have a non-negligible probability [20]. This implies that, when the impact simulations are repeated with same initial conditions, they might yield a markedly different "average impact scenario" and the algorithm would then draw different conclusions, thus undermining the reliability of the DSS. In order to mitigate the destabilizing effect of these extreme events and to perform the decision making on an array of possible impact scenarios, we propose to invert the procedure, by applying ELECTRE III to each single matrix of results obtained in each run of the simulation, *before* aggregating them in averages, and *then* aggregating the results of the algorithm (Fig. 4), taking inspiration from ensemble methods. The final step is meant to aggregate a series of ordinal ranking into a unique final ranking. In order to do so, for each alternative, we compute the ranking distribution, by counting the occurrence of the rankings and then calculating the *median* of the distributions, indicator of central tendency for ordinal numbers. The final ranking is thus based on the median of each alternative (Fig. 5). In this way, we apply the algorithm to each possible simulated impact scenario, including the rare extreme events, and not just to the highly variable "average impact scenario" [2]. By means of the DSS, the DM is able to inspect the ranking distributions, which convey a more complete information about the effectiveness of a mitigation strategy. By default, the DSS shows the median ranking, which summarizes in a single number the performance of a mitigation strategy, but the DM may look into the shape of the ranking distributions to ponder her choices. For instance, she may be able to see that a mitigation strategy has a decent median ranking, but highly variable, and opt for a safer, stabler, intervention strategy. Alternatively, she may decide to choose the mitigation strategy that performs worst least frequently, in a risk-adverse perspective, or to endorse the mitigation strategy that performs best most frequently, adopting an optimistic perspective. In addition to the advantage of displaying a more complete information on the performance of the mitigation strategy, we also believe that this method, similarly to most ensemble methods, increase the stability of the decisions to the variability of the input data and we will quantitatively test this hypothesis in a future work.

All the considerations that we have made concerning the cascading effects and the ensemble solution may be applied to ELECTRE TRI without any ad-hoc

[1] $< x >= \int_{x_{min}}^{\infty} \frac{c}{x^{\alpha-1}} dx$ converges only if $\alpha > 2$ and $< x^2 >= \int_{x_{min}}^{\infty} \frac{c}{x^{\alpha-2}} dx$ converges only if $\alpha > 3$

[2] At the price of a higher computational cost, since we run many times the algorithm, instead of only once

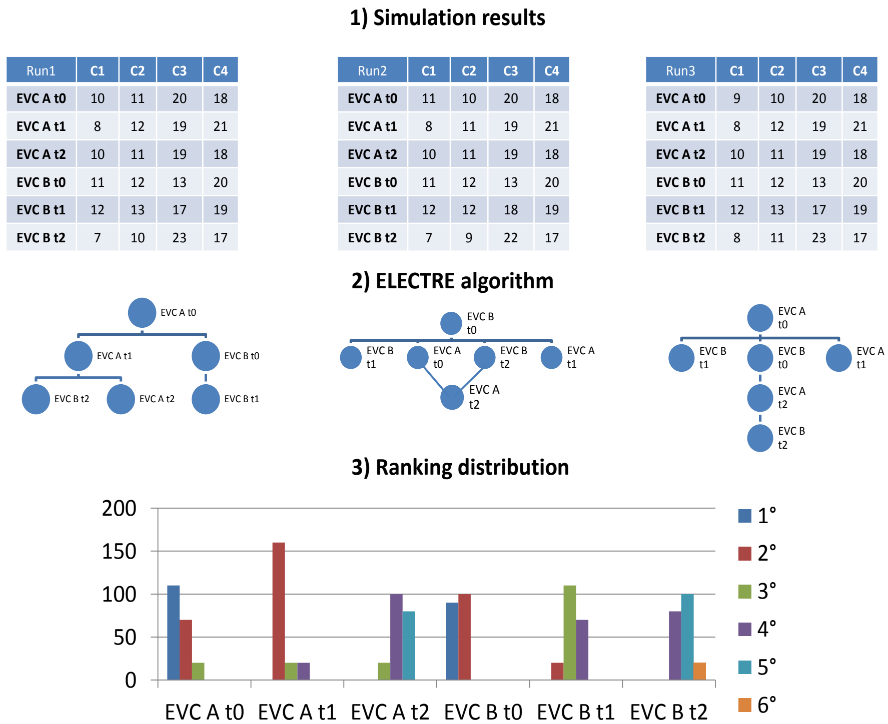



**Fig. 4.** In the standard version, the simulation results are averaged into a unique matrix, on which ELECTRE is run once. The ensemble version works as follows: 1) For each run of the stochastic simulation, an input matrix is produced, results may vary. 2) ELECTRE III is run on each input matrix, obtaining a set of rankings 3) The ranking distribution is computed, i.e. the ranking occurrences for each intervention strategy.

modifications. In Fig. 6 it is summarized the ensemble approach in ELECTRE TRI.

## 4 Future work

One of the most critical aspects of the ELECTRE algorithms is the necessity of manually setting a large number of free parameters, such as preference, indifference, vetos thresholds, without indicating a unique and standard procedure for doing so. In most cases, it is assumed that an expert will pre-configure the algorithm, tailoring it to the usage scenario. This approach is known as "direct elicitation" and it is considered by many as unsatisfactory, as it may involve some degree of arbitrariness [14]. On the contrary, indirect elicitation aims at computing the parameters, instead of explicitly setting them. In this approach,

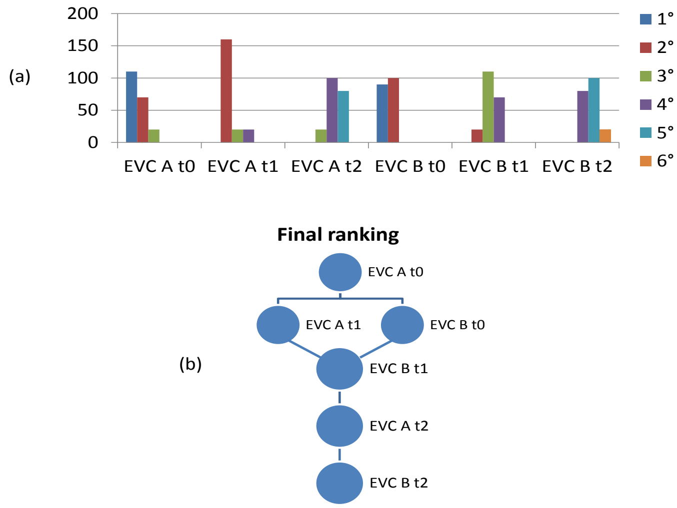



**Fig. 5.** After applying the algorithm to each run of the simulation, for each alternative, the ranking distribution is computed (a). Then, the median is computed for each alternative and the final ranking equals to the median ranking (b).

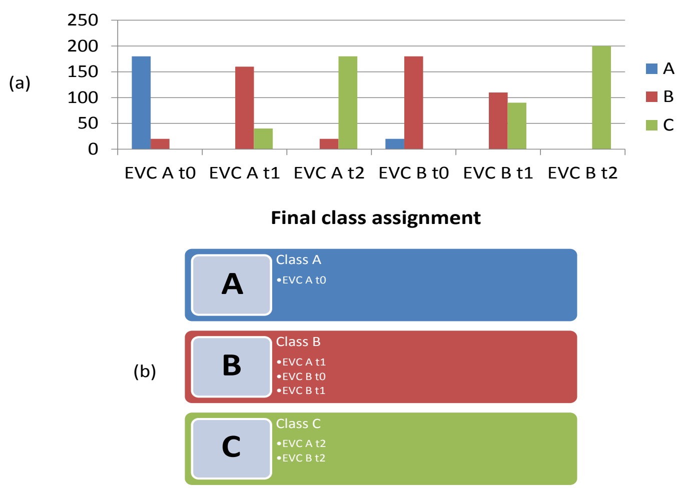



**Fig. 6.** After applying the algorithm to each run of the simulation, for each alternative, the class distribution is computed (a). Then, the median is computed for each alternative and a class assignment is constructed from the median class (b).

the model may be seen as a function depending on a number of parameters, which are determined using a "fitting" procedure on a set of pre-assigned examples, comprehending the inputs and the corresponding outputs. A relevant example of this approach, relative to the case of ELECTRE TRI, is reported in [21]. While promising, this method is computationally demanding. Moreover, even in this case, a major concern may regard the robustness of the model to the determination of these parameters, as estimated parameters always come with an error. In other words, it is highly undesirable to have a model that is sensitive to small variations of its parameters. In [22], the authors use a Monte Carlo Simulation, which share certain features with our approach, but it is performed with respect to the parameters and not to the input data. In order to reduce the computational effort, we will propose to use direct elicitation for the most straight forward parameters and to apply indirect elicitation only to a small subset of parameters. An ensemble method similar to the one that we have developed with respect to initial conditions will be applied with respect to the set of parameters, dealing with the model sensitivity concerns.
Finally, we have provided only a heuristic justification of the advantages of the ensemble approach over the traditional approach. We have argued that our solution would increase the stability of the model with respect to initial conditions and explained why we believe that that is actually the case, but we have not provided quantitative measure to test our claim. In a future work, we will define a measure of stability of the model and we will compare the traditional and the newly proposed ensemble approach.

## 5 Conclusions

We have presented the SnowBall DSS, which is meant to support several decision maker categories (e.g., public decision makers, emergency planners) during the pre-crisis phase in order to improve the effectiveness of decision making processes concerning crisis situations yet to come. To this end, we have proposed a Decision Support System that provides aid in prioritizing a set of alternative intervention strategies. The DSS allows to consider the timing of the intervention as a crucial variable, as cascading effects can dramatically change the situation on the basis of which the strategies are evaluated. The DSS combines the ranking approach of ELECTRE III, which compares the intervention strategies with each other, and the sorting approach of ELECTRE TRI, which compares the intervention strategies with a set of predefined reference profiles. The algorithms require the inputs of the user in the choice of the weights, creating a sense of involvement and making explicit the importance of defining moral priorities. Moreover, the ensemble approach allows to combine the decisions over an array of possible simulated impact scenarios, instead of relying on a single highly variable average impact scenario. The ensemble method may also be seen as a way of raising awareness into the DM, who will be able to visualize the ranking and sorting distribution to better evaluate the effectiveness of the mitigation strategies and to gain actionable insights into the inherent complexity of the decision process.

The DSS has already been tested on the usage scenario of a volcanic hazard in the island of Santorini. A set of mitigation strategies has been selected, a suitable problem structuring framework has been developed, i.e. a structured list of criteria onto which the mitigation strategies are evaluated, on-site measurements have taken place and the DSS has proven its utility on real data obtain from simulated impacts. From a methodological standpoint, it is worth to highlight that the generalizability of the findings will undergo an “acid test” composed by a cohort of additional pilots based on various natural hazards examined in different geographic areas. Therefore, it is important to remark that, although the DSS is explicitly conceived to be a part of the SnowBall project, it can be easily applied and generalized to other contexts and has a general scientific interest. The end user of the DSS will therefore have available a system that relies on top-class algorithms, which combines the ranking and sorting perspective into a unique framework, takes into account the role of cascading effects and offers a more comprehensive picture of the performance of mitigation strategies.

**Acknowledgements**. We acknowledge the support of the SnowBall project, funded by FP7 under the grant no.606742.

## References

1. USGS: Magnitude 9.03, near the east coast of honshu, japan. United States Geological Survey
2. Delvosalle, C.: Domino effects phenomena: definition, overview and classification. In: Proceedings of the European seminar on domino effects, Leuven, Belgium. (1996) 5–15
3. Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H.: Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews **13**(9) (2009) 2263–2278
4. Aruldoss, M., Lakshmi, T.M., Venkatesan, V.P.: A survey on multi criteria decision making methods and its applications. American Journal of Information Systems **1**(1) (2013) 31–43
5. Malczewski, J.: GIS and multicriteria decision analysis. John Wiley & Sons (1999)
6. Li, J., Li, Q., Liu, C., Khan, S.U., Ghani, N.: Community-based collaborative information system for emergency management. Computers & Operations Research **42** (2014) 116–124
7. Kou, G., Ergu, D., Shi, Y.: An integrated expert system for fast disaster assessment. Computers & Operations Research **42** (2014) 95–107
8. Nokhbatolfoghahaayee, H., Menhaj, M.B., Shafiee, M.: Fuzzy decision support system for crisis management with a new structure for decision making. Expert Systems with Applications **37**(5) (2010) 3545–3552
9. Sheu, J.B.: Dynamic relief-demand management for emergency logistics operations under large-scale disasters. Transportation Research Part E: Logistics and Transportation Review **46**(1) (2010) 1–17
10. Dodgson, J., Spackman, M., Pearman, A., Phillips, L.: Multi-criteria analysis: a manual. Department for Communities and Local Government: London (2009)

11. Roy, B.: Electre iii: Un algorithme de classements fondé sur une représentation floue des préférences en présence de criteres multiples. Cahiers du CERO **20**(1) (1978) 3–24
12. Yu, W.: Aide multicritère à la décision dans le cadre de la problématique du tri: concepts, méthodes et applications. PhD thesis, Paris 9 (1992)
13. Roy, B.: Classement et choix en présence de points de vue multiples. Revue française d'automatique, d'informatique et de recherche opérationnelle. Recherche opérationnelle **2**(1) (1968) 57–75
14. Figueira, J., Mousseau, V., Roy, B.: Electre methods. In: Multiple criteria decision analysis: State of the art surveys. Springer (2005) 133–153
15. Friedman, J., Hastie, T., Tibshirani, R.: The elements of statistical learning. Volume 1. Springer series in statistics Springer, Berlin (2001)
16. Opitz, D., Maclin, R.: Popular ensemble methods: An empirical study. Journal of Artificial Intelligence Research (1999) 169–198
17. Gill, J.C., Malamud, B.D.: Reviewing and visualizing the interactions of natural hazards. Reviews of Geophysics **52**(4) (2014) 680–722
18. Tarvainen, T., Jarva, J., Greiving, S.: Spatial pattern of hazards and hazard interactions in europe. SPECIAL PAPER-GEOLOGICAL SURVEY OF FINLAND **42** (2006) 83
19. Malamud, B.D., Turcotte, D.L.: The applicability of power-law frequency statistics to floods. Journal of Hydrology **322**(1) (2006) 168–180
20. Newman, M.E.: Power laws, pareto distributions and zipf's law. Contemporary physics **46**(5) (2005) 323–351
21. Mousseau, V., Slowinski, R.: Inferring an electre tri model from assignment examples. Journal of global optimization **12**(2) (1998) 157–174
22. Tervonen, T., Figueira, J.R., Lahdelma, R., Dias, J.A., Salminen, P.: A stochastic method for robustness analysis in sorting problems. European Journal of Operational Research **192**(1) (2009) 236–242