Disaster Resilience Modeling of Municipal Water Supply Infrastructures in the Context of Atmospheric Threats

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ABSTRACT

The resilience of water supply infrastructure (WSI) is of utmost importance as threats to predominantly, although not exclusively, urban WSI may accompany virtually all kinds of natural disasters. In this paper, we present some of the challenges posed by climate change in modeling emergencies in WSIs. Climate change is a global phenomenon that significantly impacts global lifestyle. It is expected that an increase in global temperatures causes sea levels to rise, increases the number of extreme weather events such as floods, droughts, and storms while highly impacting WSI. In this respect, the challenge is to be prepared for the unexpended by modeling various complex scenarios. Only with a multidisciplinary approach at the global, regional, national, and local levels, can success be achieved. We discuss some of the specific challenges posed by climate change in modeling emergencies in WSIs with a case study modeled using EMERTIC. EMERTIC is a software based on AI and scenarios, that is aimed at supporting decision-making at different stages of the Emergency Management cycle.

Keywords

Disaster modeling, urban resilience, water supply infrastructures, climate change, scenarios.

INTRODUCTION

The initial developments within the field of Information Systems for Crisis Response and Management (ISCRAM) can be found in the Emergency Management Information System and Reference Index (EMISARI) system in the Office of Emergency Preparedness (OEP) in the US (Turoff, (2002). EMISARI allowed 200 to 300 users scattered around the US to exercise a coordinated response to crises during the 70s. The principles of EMISARI were revised and extended in the Dynamic Emergency Response Management Information System (DERMIS), which includes a set of generic design principles, in turn providing a framework for the development of flexible and dynamic Emergency Response Information Systems (Turoff et al., 2004). Initial investigations of system design considerations for emergency management decision support were reported by Belardo, et al. (1984). Marovac and Stähly (2001) discuss the general principles of major disaster management decision support systems (DSS). During the last 15 years, a majority of the relevant developments in disaster modeling have been carried out by the ISCRAM community. Their progress has been periodically reported since 2005 in its annual world conference Decision Support Systems and Foresight. We can underline the DSS for creating evacuation strategies in the event of flooding (Windhouwer et al., 2005) or for location planning in disaster areas using multi-criteria methods (Degener et al. 2013), to name a few. Other ISCRAM research relevant for this proposal has been focused on Artificial Intelligence (AI) and DSS, such as intelligent decision support systems for decision making under periods of uncertainty in distributed reasoning frameworks (Comes et al., 2010). We could also reference the research about collaborative scenario modeling for the protection of critical infrastructures (Bañuls et al., 2010); Lopez-Silva et al., 2015; Ramirez de la Huerga et al. 2015; Turoff et al., 2014,2017), climate change-driven disaster resilience (Comes and Van De Walle, 2014; Yang et al., 2015; Turoff et al., 2018) and others. Turoff et al. (2016) provide a systemic interrelation between 16 components of critical infrastructures. These relations may serve as a background for studying optimal resilient structures and for aligning such structures in resilience-oriented DSSs. These ideas are then followed in a special issue of the TFSC journal devoted to increasing resilience for future disasters (Hernantes et al., 2017). We also found recent articles in the ISCRAM community on the resilience of plant water distribution networks (Papion, 2018) as well as emergency event decision support systems at WSI (Che and Liu, 2013; Wang et al, 2020). In this research, AI development trends observed over the past decades, when coupled with recent Earth climate and natural disaster models and confronted with real-life needs, should allow for the creation of intelligent technology solutions to enhance mankind's reactions to natural disasters. This line of research further delves into the effect that climate change can potentially have on WSI. To this end, we raise extreme scenarios with the potential impact on water distribution systems to cities, such as flood or snow droughts, and analyze the level of resilience of drinking water supply and sewage management to such events in cities. To do this, we consider not only the technical aspects but also the interrelationships with other essential services or terrorist attacks. Thus, we want to measure amplifier or cascading effects that service disruptions would yield. In normal contexts, such disruptions would have a low impact. We utilize EMERTIC software to accurately measure these effects of generating scenarios.

This work in progress paper is structured as follows. First, we will analyze disaster modeling issues in WSI. Then, we will introduce the software EMERTIC and a case study of its application in a WSI. We will end with discussions and preliminary conclusions.

DISASTER MODELING IN WATER SUPPLY INFRASTRUCTURES

The resilience of WSI is of utmost importance as threats to predominantly, although not exclusively, urban WSI may accompany virtually all kinds of natural disasters. Contamination of drinking water is a frequent result of flooding, particularly in the case when floodwater persists to stay a long time covering or close to water supply networks. This may result in epidemics and breaks in water pipelines and is a major threat to water reservoirs. Due to the essential WSI service support condition, it is crucial not to simply respond to the emergency but to also recover normal service in the shortest possible time. For example, Hasan et al (2019) apply the reinforcement learning and Markov decision processes to solve a dynamic multi-objective optimization problem by modeling the identification of vulnerable zones concerning water quality resilience in São Paulo, Brazil. The results could serve as a meta-policy selection for city managers.

The WSI resilience problem is closely related to flood protection and mitigation. Floods can damage the municipal water treatment station and flood inundation is often accompanied by the contamination of water. Furthermore, flood prevention infrastructure such as water reservoirs are often combined with water supply facilities. Compared to the general area of natural disaster resilience management, floods exhibit several specificities that show up in their management. First, unlike other kinds of natural disasters that usually occur during a short period, floods can persist for a longer period of time, which increases the importance of flood management DSS. Second, the areas endangered by floods are those close to rivers or seas, so the risk reduction measures can be strictly situated. This is the reason most countries endangered by floods implement flood risk reduction programs (McCallum et al., 2016). Besides, floods can be of mixed, natural, or anthropogenic nature, and natural flood disaster losses can be multiplied by a lack of or false flood mitigating activities and a lack of coordination (Skulimowski, 2019). An important role, in flood emergency management, is played by precipitation and water level forecasting, particularly in a flood-prone region. Therefore, flood-related forecasting problems have been researched by many authors. For example, Wu and Chau (2006), proposed a neural network (ANN) model with parameters tuned by a genetic algorithm that has been applied to a prototype channel of the Yangtze River. Water levels at the Han-Kou downstream station are forecasted with water levels and lead times at the Luo-Shan upstream station. A linear regression model and a conventional ANN+GA model has been compared, revealing the superiority of the newer approach. An application of virtual reality (VR) in a flood control DSS is presented in Ma, Wang, and Zhao (2015). The software incorporates real-time simulation of water flow in the Yellow River, flood disaster assessment, and flood prevention planning. VR interface integrates pattern recognition, communication, multimedia technology, and geographic information systems. It aims to build a digital twin for a Yellow River. Nasim and Ramaraju (2019) point out a major role played by AI technologies in flood-related evacuation and recovery planning. Search and rescue robots (Pransky, 2018) as well as emergency detection with autonomous robots (Skulimowski and Ćwik, 2017) became a feasible alternative to human first responders due to the progress in AI.

Further information about the relations between AI and disaster resilience management can be found in the survey by Saleh and Allaert (2011), who also present two real-life examples of their environmental planning DSS applications in Belgium, including real-time monitoring of water management. According to Abu Bakar and Mohd Hafez (2016), about 60% of disaster management software used AI techniques. The same paper provides a taxonomy of disaster management support with AI methods. AI-supported methods of systems analysis and control, their significance in responding to grand challenges, and future trends are discussed in Lamnabhi-Lagarrigue et al. (2017). Sun, Bocchini, and Davison (2020) study the applications of 26 AI methods such as neural networks, Hidden Markov models, and diverse heuristics in 17 disaster management areas and provide the related bibliographic analysis. As a motivation behind using AI techniques in disaster modeling, the above surveys as well as the papers cited therein mention the growing amount of data that accompany disasters and the need to analyze them in real-time to support the decisions of first responder and management teams. For example, aerial disaster image data can be analyzed automatically with core AI pattern recognition and image understanding techniques, while social network data, such as tweets, require AI-based emotion and causal relation analysis. This is why AI is often used jointly with big data techniques (Shah et al., 2019). In this paper, we use AI-supported EMERTIC, which will be introduced in the next section.

EMERTIC

EMERTIC is a scenario-based simulation software for the management of emergencies based on information and communication technologies. The methodology is based on the construction of scenarios, building different futures, and learning from them. It aims to not only contribute to the constitution of emergency plans but also to participate in the training that these plans require, providing continuous learning that updates both the Emergency Plan and the necessary training. EMERTIC uses AI for detecting critical events and recommending actions based on CIA-ISM algorithms.

Scenario-based Disaster Modeling Scenarios are frequently used in the field of emergency management, especially in the planning process. In an Emergency Plan, scenarios are developed based on significant events that have occurred in the past and need to be updated by accounting for the current conditions. By an *event* we mean a significant change of the state of an object of interest or a change of the value of a predefined relevant indicator (Bañuls and Turoff, 2011; Bañuls, Turoff and Hiltz, 2012). In the field of emergency management, scenario-based planning is also known as contingency planning. This mode of planning is a dynamic process in situations of uncertainty, where scenarios and objectives are evaluated. Managerial, technical actions and structures with possible response systems are defined in order to prevent or improve response to these emergencies. One of the most important contributions of scenario planning to the management of emergencies, often comes from the process itself: the identification of partners, their capacities and resources, the development of a teamwork relationship, and the ability to reach an agreement on the issues, priorities, and responsibilities. Despite the common belief that by using scenarios we can predict the future, we have to account for the uncertain and varying character of the future, being impossible to accurately predict. The uncertainty and complexity of this future drive us to build scenarios with didactic purposes. The aim is not to know exactly what is going to happen, but through the approach of possible futures to learn how to act against them and design appropriate strategies. Through the construction of scenarios, more versions of the future appear, being able to carry out an exhaustive analysis of them and to escape from a linear and closed thought to a more open and dynamic one. Consequently, building additional versions of the future creates more information, so the other advantage is the application of scenarios as a solution and helps to systematize this large amount of information by making it easier to manage and study. Also, it allows us to differentiate between variables that we assume as fixed (with little uncertainty) and those more changing (with a greater degree of uncertainty), cf. (Jordán, 2016). There are numerous techniques to generate scenarios; however, taking into consideration that EMERTIC aims to contribute to planning potential emergencies and disasters, a great range of technical and social factors need to be considered, such as the scenario methods used by EMERTIC to imply a dynamic interacting model. This means that, by controlling the likelihood of the occurrence and non-concurrence of individual events, a variation in outcomes is produced. These results influence the choice between better preparedness decisions, as well as in identifying the best reaction of the modeled environment. Information systems are needed to manage such amounts of alternatives resulting from the dynamic model, as the number of combinations of future events might be very large.

Proposed Methodology

EMERTIC is based on Cross-impact Analysis (CIA)- Interpretative Structural Modeling (ISM) methodology (Bañuls and Turoff, 2011). CIA-ISM can be applied to modeling any emergency. This enables EMERTIC to address a wider audience, improving its flexibility. CIA-ISM contributes to the determination of relationships between events in general, and their impact on final events. By doing so, uncertainty is reduced. CIA resides in the idea that events do not occur independently, but that there are relationships between them, requiring iteration until the estimates correspond with reality. Following this process, subject estimates cause participants to estimate the influence (or causality) resulting from assuming occurrence or non-occurrence of a given event to change the outcome of other events. Analytically, the correlation coefficients (C_{ik}) can be calculated using a variation of the Fermi-Dirac (i.e. logistic) distribution function by asking subjects about the probabilities (P_i) as determined by this relationship:

$$P_i = 1 / [1 + \exp(-G_i - \sum_{i \neq k} C_{ik} P_k)] \quad (1)$$

where:

P_i represents the probability of occurrence of the *i*-th event.

G_i (the gamma factor) is the effect of all (external) events not specified explicitly in the model.

C_{ik} represents the impact of the *k*-th event on the *i*-th event. Positive C_{ik} means it enhances the occurrence of the event, and negative C_{ik} detracts from the occurrence of the event.

A scenario can be mathematically defined as the occurrence of a set of events in a specific order. Conceptually, for a set of events, we can find n! permutations, which is why we have n! scenarios. In EMERTIC, we are able to model whether a threat, atmospheric situations, decision-making, or different results materialize. Although there are many event categorizations, in EMERTIC we will typify them based on when an emergency occurs. In this sense, there can be three stripes. A first stripe places pre-emergency events or initial conditions. This stripe includes events that involve the context of emergency preparedness as well as other aspects over which managers cannot have control. A second stripe is the emergency, the dynamic part that includes events that evolve with the passage of the emergency. In the third stripe, we place the results of the emergency. We will be able to formulate these events based on the range of events in which they occur according to their nature, (Bañuls et al., 2013):

- Dynamic Events (DEi): those events could or could not occur during a determined period.
- Source Events (SEi): they correspond to the assumptions we have mentioned before. These assumptions are events that have occurred before the period that we are analyzing or events that, before that period, have a probability of being true or false.
- Outcome Events (OEi): these are the outcome of the period model, the ones that can be used to measure the results of the modeled system.

Secondly, ISM is used to analyze the complexity of the resulting graph. This different modeling method is applied to the outputs produced by the Cross-Impact Analysis. By implementing the ISM, a linear visualization of the results is created where improvements take place (Bañuls et al., 2013). Once the technical support software for simulations is described in the next section, we will explain the use and application of EMERTIC for emergency modeling in a WSI.

CASE STUDY

In this section, we will report the modeling with EMERTIC on possible emergencies in the first Water Supply Company in Andalusia (Spain). This company manages the direct supply of drinking water in the capital city of Seville and the other 12 municipalities in the area. It provides raw water to 26 additional cities around the vicinity and is also responsible for the public sewage and purification service in this area. Its model consists of a total of 101 interrelated events that are subjected to two classifications during their recording. The first classification takes place according to their origin, as they can be source, dynamic, or result events. Since we are dealing with a WSI, an example of a source event could be the water in a reservoir or a failure of the electricity service. On the other hand, as a dynamic event, referring to those that we can manipulate, we can use a generator as an example. Lastly, as a result event, that is, one that we want to modify, an example would be the supply of raw water. The second classification can be defined by event character, either positive or negative: positive events are those that favor the organization, such as a generator, while negative events could be failures, attacks, or extreme weather events. After implementing the model in EMERTIC, we were able to extract the simplified graph of interrelations from the relationships between the events. In the graph, we can identify the safeguards in green, the internal dependencies in light blue and the external dependencies in dark blue (Figure 1). Once the WSI and both, its external and internal dependencies are modeled, the next step is to analyze the potential diverse impact of various extreme weather conditions caused by climate change on different events of the model. It is important to note that this impact can occur on a set of events at once. For example, extreme snowfall, such as those that have occurred in much of Europe and the US in early 2021 in areas where they are not common, can collapse roads by making it difficult to supply reagents and fuel for electricity and heat generators. They can also pose difficulties in both water collection and distribution, so this impact must be measured in an aggregated form rather than an individual form as traditionally done by risk analysis methodologies.

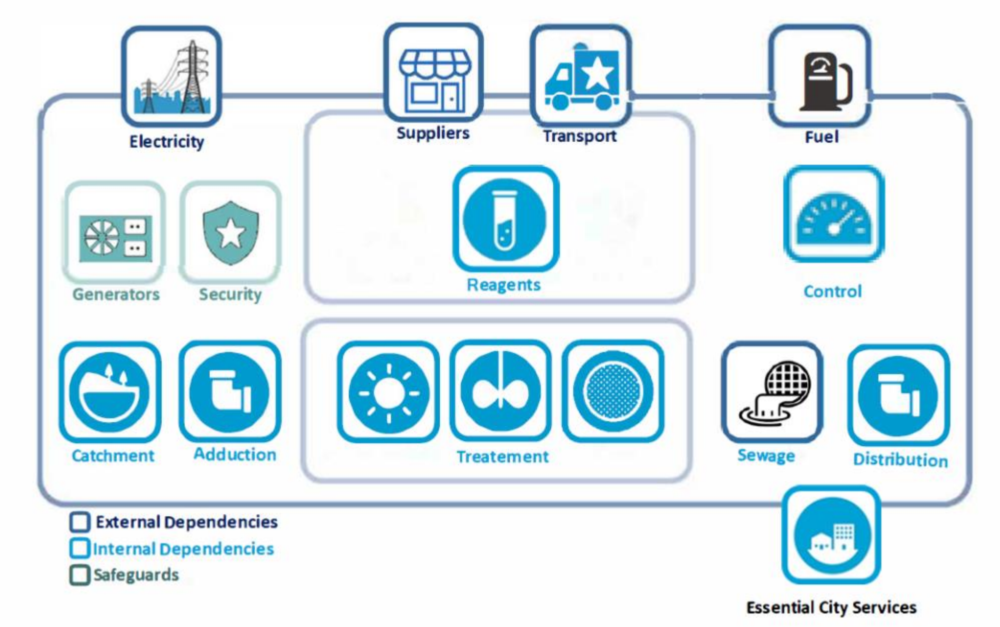

Figure 1. Interrelations map of the WSI

It is important to underline that when working with n=101 events, we are potentially working with $n! \approx 9.42 \times 10^{159}$ scenarios. Traditional scenario calculation methodologies should simulate all of them to calculate probability or the most likely event in certain types of circumstances. This would not be possible because of the number of potential combinations of events. In this sense, the EMERTIC's basic methodology allows us to optimize calculations and detect scenarios as combinations that can put essential services at greater risk. With EMERTIC, we can also monitor weak signals about the occurrence of most risky scenarios to alert well in advance and help decision-making by giving a longer response time.

As a main result, in the Seville WSI case, a set of risk scenarios were detected in climate change contexts. These scenarios are the result of a combination of events that under normal conditions, do not pose a high risk to essential service but when combined and under a climate change context can jeopardize the city's essential services. Each of these scenarios has a series of trigger events and weak signals, which were introduced within the EMERTIC system to be able to perform as an early warning system and to timely respond to them. These notifications, in addition to assuming an early warning, include recommendations of action for each scenario to the relevant personnel of the organization (Figure 2).

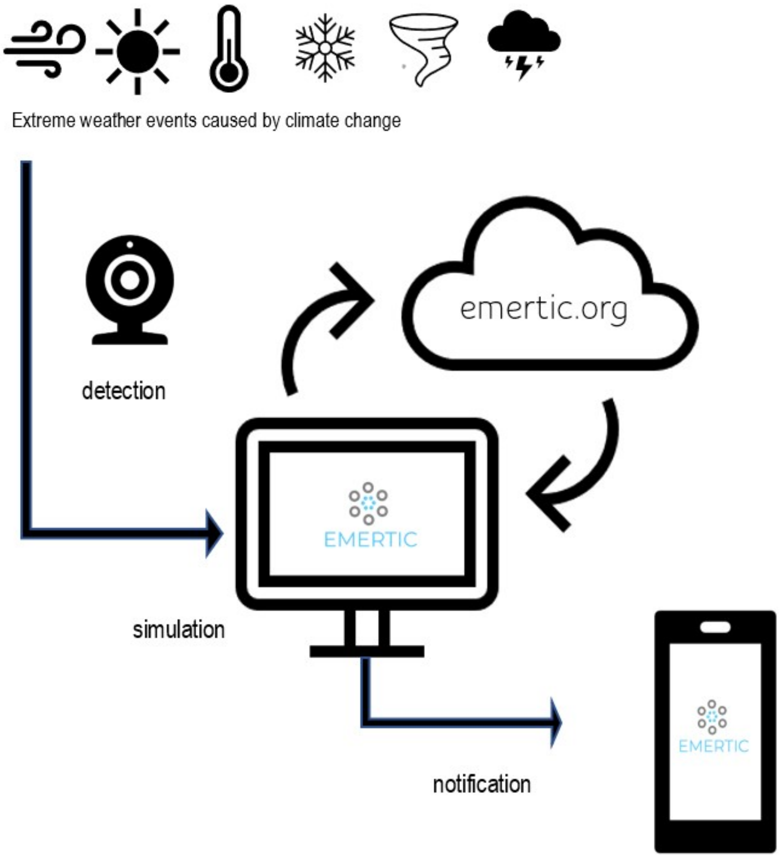

Figure 2. EMERTIC Infrastructure

By implementing the above event model in EMERTIC, and including many such events and relationships between them, it has been possible to carry out highly realistic simulations. Based on the initial results for Andalusia, we aim to develop future disaster scenarios in the context of climate change with potential global impact. These scenarios will serve as the backbone for integrating computer and information technologies with human dimension study to develop AI and other advanced information and communication technology (ICT) tools for continuously assessing climate-driven threats. We will focus on multi-hazard scenarios triggered by climate change and growing atmospheric events. The scenarios will use an integrated view and consider technical, social, organizational, and environmental vulnerabilities.

DISCUSSION AND PRELIMINARY CONCLUSIONS

In this work in progress paper, we have reported the advances in the implementation of EMERTIC software in a large European WSI. The initial results derived from the application of EMERTIC for risk analysis show different types of risk scenarios for the continuity of service in WSI. These include failures in water pipes and pipelines, discontinuity of service in critical suppliers, failures in the control of WSI operation, extreme events caused by climate change, and terrorist attacks. Although, in all such cases, the AI can have different applications for the anticipation of the scenarios in case of the climatic events due to a greater availability of data in real-time. We have found several challenges posed by modeling extreme events' impact on essential services in water and waste treatment infrastructures. At this point, we are working on the response and strategies to these scenarios to close the Emergency Management cycle. That is, our purpose with EMERTIC is to go beyond the preparation and risk analysis phases. Our next steps will be oriented at supporting detection, response, and mitigation. In this way, it is intended to provide a more comprehensive approach to the WSI Emergency Management cycle. In this sense, it is essential to evaluate different strategies to mitigate the possible effects of climate change in WSI under different drought scenarios, extreme temperatures, or extreme coastal phenomena, among other possible adverse atmospheric events. Resources are limited; hence, before executing costly investments, it is very important to analyze their effectiveness in different complex contexts.

We have pointed out the limitations of traditional Risk Analysis due to their lack of measuring interdependencies and cascading effects. This is because these methodologies focus on an individualized analysis of probability or impact for each threat, which, although they can give very low results individually, as a whole, can be catastrophic. Thus, the essential character of cascading risk assessment appears a measurement that these traditional methods are far from being able to provide useful scenarios to be prepared against climate change and build resilient WSI. The causal relationships between events and scenarios can be further modeled with Bayesian and anticipatory networks (Skulimowski 2016), and other causal models.

From our perspective, academics and practitioners need to build an ecosystem of AI tools to respond to different emergency scenarios at various stages. With this approach, based on an ecosystem of solutions, the focus is not on the technology but on the user, and the information they should be given to become aware of the situation and carry out an effective response in each disaster scenario.

Technological developments will be geared towards adjusting information needs to detect, respond to, and manage an emergency. AI tools such as EMERTIC will be required for this purpose. This focus on information and the user is motivated by the fact that despite the multitude of data that is available through open databases, news streams, scientific reports, and published models, we continue to fail to detect the triggering and amplifying events of a disaster situation. We have been able to verify this recently with the COVID-19 pandemic. This is because each emergency is unique, even if it is caused by a common event, such as a flood or an adverse coastal phenomenon. The types of response to emergencies must have the flexibility of being able to give a personalized response to the needs specified by the team and that is why they should not be overly structured. It does not make sense to create a specific emergency management system to deal with each of the infinite scenarios that can occur. Precisely, the concept of resilience is based on the ability of absorption and return to normality in situations in which those affected by an emergency were not prepared. It is for this reason that our future research will be oriented to deploy a fully upgradeable and flexible ecosystem, first developments in AI to support certain emergency circumstances that are fully parameterizable with changing scenarios, cascading, and responding to different scenarios.

This data-centric focus implies four main challenges at the level of information analysis: the first challenge is whether the information sources can be trusted. A second challenge involves the semantic interpretation of the messages, and a third challenge is the interpretation of the message and its contextualization to make sense of an effective response. Finally, a challenge involves providing the system with sufficient capacity for filtering and processing information so that it is not possible to simulate all the possible options, but rather the last one based on the context, avoiding information overload.

Most existing emergency management systems use proprietary data with very inflexible structures and little capacity to anticipate events that have never occurred. Hence, they will not be valid for facing the forecasted climate change challenges. With flexible ecosystems of ICT solutions, we intend to break this barrier using a decentralized and self-managed system, service-oriented, and independent of technological architecture.

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