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A hybrid BIM and BN-based model to improve the resiliency of hospitals' utility systems in disasters

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Abstract

The growing number of disasters in recent years has become a significant threat to hospital buildings' resilience and preparedness. Besides, the stochastic nature of these disasters and the complexity of the hospital building systems exacerbate the difficulty of making appropriate decisions during and after disasters. To address the issue, this research proposes a novel model that utilizes the capabilities of Bayesian Networks (BNs) and Building Information Modeling (BIM). This model helps decision-makers in hospitals and medical centers measure various effects of disasters on utility systems and analyze the consequences of their decisions. The capabilities of the proposed model are tested in the case of a medical gas distribution system in a hospital building. The findings indicate that using this model brings new insights for decision-makers into the effects of an earthquake on the medical gas system of the hospital case. Applying the hybrid BIM and BN model improves the spatial understanding of the utility systems and expedites the hospital team members' response to critical situations.

Keywords: Disaster Management, Hospital Utility Systems, Resilience, Bayesian Networks, Building Information Modeling

1. Introduction

Taking appropriate and timely responses during and after disasters plays a crucial role in preventing human and financial losses (Choi et al., 2018). In recent years, a large amount of capital has been lost in critical infrastructures due to the lack of such timely control measures (Gencer, 2013). Health infrastructures are of particular importance in the socio-economic and psychological recovery of injured people (Mulyasari et al., 2013) and should efficiently provide medical services to its patients in a safe environment for their personnel and equipment (Djalali et al., 2014). Increasing the resilience of a hospital depends on expanding its adaptive capacity by improving the decision-making process during crucial moments (WHO, 2015). Munasinghe & Matsui (2019) have shown that despite the WHO's emphasis on enhancing hospital preparedness for disasters, many are still unprepared. Weaknesses in disaster management in hospitals may include ambiguities in personnel's roles and responsibilities, poor communication, lack of optimal planning, and low-quality training (Paganini et al., 2016). Decision-makers in this discipline often face a shortage of relevant knowledge and experience to deal with unexpected events (Zhou et al., 2018), which can seriously affect the functionality of the whole healthcare system (Fallah-Aliabadi et al., 2020).

Disasters occur at uncertain times and places, with unknown impacts (Lin et al., 2018). Furthermore, the decision-makers usually confront different types of disasters simultaneously with a series of effects requiring proportionate responses (Choi et al., 2018). Uncertainty, diversity, interrelated processes, and a large number of interdependent elements complicate the decision-making process in the healthcare systems during and after disasters (Wachs et al., 2016). Past research has investigated the application of Bayesian Networks (BNs) in disaster management to address the mentioned issues. BNs are powerful tools with probabilistic graphical models based on causal relationships for the decision-making process in high uncertainty situations (Constantinou et al., 2015).

Another controversial aspect of disaster response management is the large amount of data originated from various sources used in the decision-making process. People who are responsible for crisis management are generally under considerable stress to make immediate and effective decisions (Dusse et al., 2016). Concentrating on trivial data and ignoring the proper flow of information due to the extensive data produced can lead to inaccurate conclusions in the disaster (Sarvari et al., 2019). Based on the definition of the National Institute of Building Sciences (NIBS, 2019), "Building Information Modeling (BIM) is a digital representation of physical and functional characteristics of a facility. A BIM is a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle, defined as existing from earliest conception to demolition". In this perspective, BIM can help decision-makers in critical junctures identify and locate problems and determine the hazards through its visual interface (Becerik-Gerber et al., 2012).

This research aims to respond to the current need for expedited decision-making during and after the disasters in the hospital buildings. The proposed model in this research combines the probabilistic inference engine of the BNs with the BIM models to develop a disaster decision support tool for the hospital's utility systems. This work provides new insights for decision-makers in health infrastructures to analyze the probabilistic consequences of disasters and measure the effects of their decisions through a visualized and probabilistic environment. The main focus of this study is the hospitals that remain functional during and after the disaster, but their utility systems might suffer damages, compromising their functionality. First, the literature related to the research topic was studied. Then different parts of the proposed model were identified, and essential information about its implementation procedure was discussed.

To evaluate the applicability of the proposed model, the researchers implemented it on a hospital case in the city of Tabriz in Iran and discussed the results under a simulated earthquake scenario. Finally, the research was concluded by summarizing the contributions, limitations, and future directions.

The remaining part of the paper proceeds in Section 2 by reviewing the related literature. Section 3 explains the proposed emergency disaster management model. In Section 4, a pilot implementation is demonstrated, and the findings are discussed. Finally, Section 5 concludes the research and suggests future study directions.

2. Literature review

2.1 Hospitals in disasters

Achour et al. (2011) surveyed 34 hospital facilities in seven countries following nine earthquakes between 1994 and 2004. Since the regulations have neglected hospital equipment and utility supplies' resilience, they concluded that the utility damage showed a steady trend among all hospitals. Disruptions in the operation of utility systems cause medical supply outages or even evacuation of the building. Kirsch et al. (2010) conducted interviews and field surveys to study the damage to some hospitals following the 2010 Maule earthquake in Chile. Despite negligible structural damage, most of these hospitals could not provide adequate service for up to 7 days after the event due to non-structural damage and utility failures. Despite having redundant systems, many hospitals did not have an effective disaster management plan and faced serious decision-making challenges. Using fault-tree analysis, Jacques et al. (2014) examined the relationship between structural, staff, and stuff failures in stricken hospitals in the 2011 Christchurch earthquake in New Zealand. According to their findings, Christchurch Hospital lost more than 30% of its functionality immediately after the earthquake. This loss of functionality occurred mainly due to damage to non-structural building components and equipment, loss of public services, and breakdowns of transportation and re-supply.

Hospitals are also at risk of losing their functionality in flood-prone areas. In the 2011 Thailand flood disaster, the infrastructures of 561 hospitals were severely damaged. The incident led to severe shortages of resources and hospital staff (Rattanakanlaya et al., 2016). After floods caused by 2012 Hurricane Sandy in New Jersey and New York, some local hospitals lost their functionality for a long time after the accident due to severe damage to electrical systems, emergency and exam rooms, and elevators (Evans, 2012).

2.2 Disaster management efforts in hospitals

Simulating the hospitals for disaster management has been an ongoing and studied topic in recent literature. Simulation can handle high uncertainty and various factors affecting hospitals' performance (Gul & Guneri, 2015). To evaluate different resource allocation plans in the recovery process, Khanmohammadi et al. (2018) used system dynamics simulation to analyze hospitals' performance in the aftermath of an earthquake. Considering the building, staff, medicine, technical systems, and medical equipment in their simulation, they quantified hospitals' resilience to earthquakes. Yi et al. (2010) simulated the hospitals' static and dynamic characteristics in times of crisis, estimating their capacity to respond to the surge in the number of patients. The findings of this study facilitate the disaster management planning of healthcare facilities. Shahverdi et al. (2020) used a discrete event simulation model to investigate the effects of disasters on hospital staff and their physical spaces. This model considers the hospital coalitions after the disasters to assess the joint capacity enhancement in resilience improvement.

Some of the disaster management efforts in hospitals have also focused on improving hospital resilience via mathematical modeling. Using existing data of California hospitals' functionality in previous earthquakes, Yavari et al. (2010) developed a model for predicting hospitals' performance in post-earthquake conditions. In their model, in addition to the hospital's central systems, including structural and non-structural systems, lifelines, and personnel, the impact of external factors such as water and power outages is also considered. With a similar approach, Vugrin et al. (2015) presented a mathematical optimization model to improve hospitals' adaptive capacity in the case of a disruption of infrastructure services. Aghapour et al. (2019) provided a mathematical optimization model for allocating human resources and reconfiguring spaces and physical facilities. This model helps hospital administrators and decision-makers to improve their capacity management programs over time.

Some studies have begun to evaluate the hospital's preparedness for disasters. One attempt in this field was the introduction of the hospital safety index, providing a comprehensive checklist of indices for hospital safety and resilience assessment (WHO, 2019). Implementing this checklist as a diagnostic tool yields useful information on the hospital's strengths and weaknesses, which will lead to the actions to improve their resilience. Lim et al. (2020) used questionnaire-based research among four hospitals in China to conclude that management preparedness has a significant impact on hospital staff's readiness to respond to disasters. They pointed out that two factors of contingency leadership and group integration can play a role in facilitating this relationship.

Analyzing the disaster management efforts in hospitals reveals that most studies in this field have focused on hospital disaster management planning in pre-disaster phases. However, such approaches have failed to address the immediate response management during and after the disasters in the hospitals. Most of these studies have also used simulation and mathematical optimization methods that require a large amount of data collection and often take a time-consuming process to get results. The resilience of the hospital's internal systems has also been the focus of a few researchers. Nonetheless, most studies in this area have been related to predicting hospitals' capacity to respond to increased patients and measuring the resource allocation strategies to increase this capacity.

2.3 Bayesian Networks

A great deal of previous research into disaster management has focused on utilizing probabilistic inference of the BNs. Qiu et al. (2014) built a BN-based model for early warning of crises, facilitating the alleviation process of the crises impacts. In this model, the cascading impacts of disasters were modeled by combining single crisis events. Hu et al. (2015) used dynamic BN's capabilities to analyze disasters' cascading effects among complex and interconnected systems. BNs helped equipment operators to gain a full understanding of the relationships between risk factors, identify the causes of abnormal conditions, and adopt effective corrective measures to deal with them. Wu et al. (2017) used BNs to model probabilistic relationships between the cause and effect of natural gas pipeline network accidents. This model provided a realistic analysis of the consequences and was helpful for decision-makers due to the existing conditional interconnections. Plomaritis et al. (2018) used the BN to probabilistically model the disaster risk reduction actions in coastal areas as an alternative to expensive numerical simulations. Here, the use of BNs reduced the effects of overwash and erosion caused by marine storms. Wu et al. (2020) presented a BN-based model for predicting and assessing damages caused by floods. They modeled the potential connections between different effective parameters through the ontology and quantified the uncertainties through BN.

Incorporating expert knowledge into BNs as a solution to overcome the data paucity has been recently receiving more attention. The BN applications in the literature are mainly mentioned where historical data is available to estimate the conditional probabilities (Uusitalo, 2007). However, BNs are proven to be a suitable tool to incorporate expert knowledge where there is a lack of data for the conditional probability estimations (Kuhnert et al., 2010). Constantinou et al. (2016) incorporated expert knowledge and unstructured data collected from questionnaires in BN development for medical decision-making. This method can structure BNs in cases where historical data is limited or difficult to access. Hossain et al. (2019) developed a BN-based model to quantify the resilience of port infrastructure. Using historical data and interviews with experts, the authors identified potential threats to port infrastructure and defined these infrastructures' capacity to absorb, adapt, and restore from these threats. The expert knowledge and historical data are synthesized into a BN to quantify the mentioned capacities and their interdependencies and estimate the port infrastructure's resilience.

2.4 BIM applications in disaster risk reduction

Research efforts on investigating potential BIM applications in disaster management such as emergency evacuation path planning/finding, indoor localization, fire emergency simulation and analysis, and facility safety management have been carried out in recent years (Gao & Pishdad-Bozorgi, 2019). Wang et al. (2014) proposed a framework that creates two-way communication between the BIM and the users in the evacuation process during a fire and is useful for increasing the users' awareness about the evacuation process. Chen & Chu (2016) automatically determined the best route for rescue operations in a disaster by extracting the building's geometric information from BIM models.

BIM visualization has received particular attention in this research area. Charalambos et al. (2014) estimated the seismic damage to non-structural building systems and displayed it on the BIM model. Visualization of failure modes provided useful insight for non-specialist building owners. Cheng et al. (2017) developed a platform to help decision-makers find fire spots and safe evacuation routes by combining the BIM models' geometry information with the information received from Bluetooth sensors. This study showed that the 3-Dimensional (3D) visualization of BIM could help reduce wrong decisions and the confusion created during the crisis. Providakis et al. (2019) used BIM visualization to build a decision-making tool to assess ground settlement damage to buildings adjacent to underground tunnel workshops.

3. The proposed model

Figure 1 represents the schematic view of the hybrid BIM and BN-based emergency disaster management model for the hospital utility systems. The model architecture is developed in three layers, including user, front-end, and back-end. The user inputs its observations from the crises through the front-end layer, representing the model's interactive interface. An Application Programming Interface (API) is linking the front-end layer to the back-end layer. The back-end layer maintains the stored knowledge and data. In this layer, the observations are translated and transferred into the BN's probabilistic inference engine. Then the system state is predicted using the inference engine. Finally, the probabilistic information turns into the color-coded 3D BIM objects and is presented to the user in the form of a color-coded BIM model.

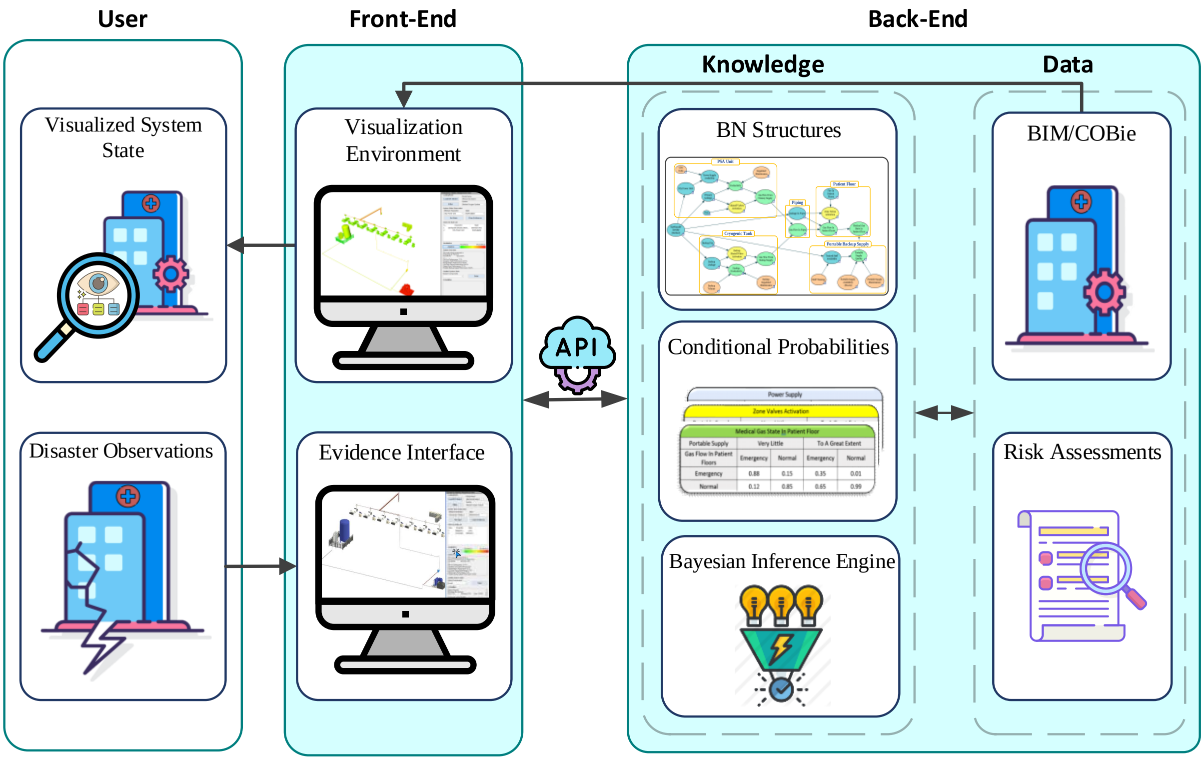


Figure 1. The architecture of the proposed hybrid BIM and BN-based emergency disaster management model

A four-step method is proposed to configure the back-end layer, including 1) System fragmentation, 2) Risk assessment, 3) BN development, and 4) Integration and visualization. Figure 2 represents the configuration steps and their interactions. A detailed explanation regarding the proposed steps is discussed in the following subsections.

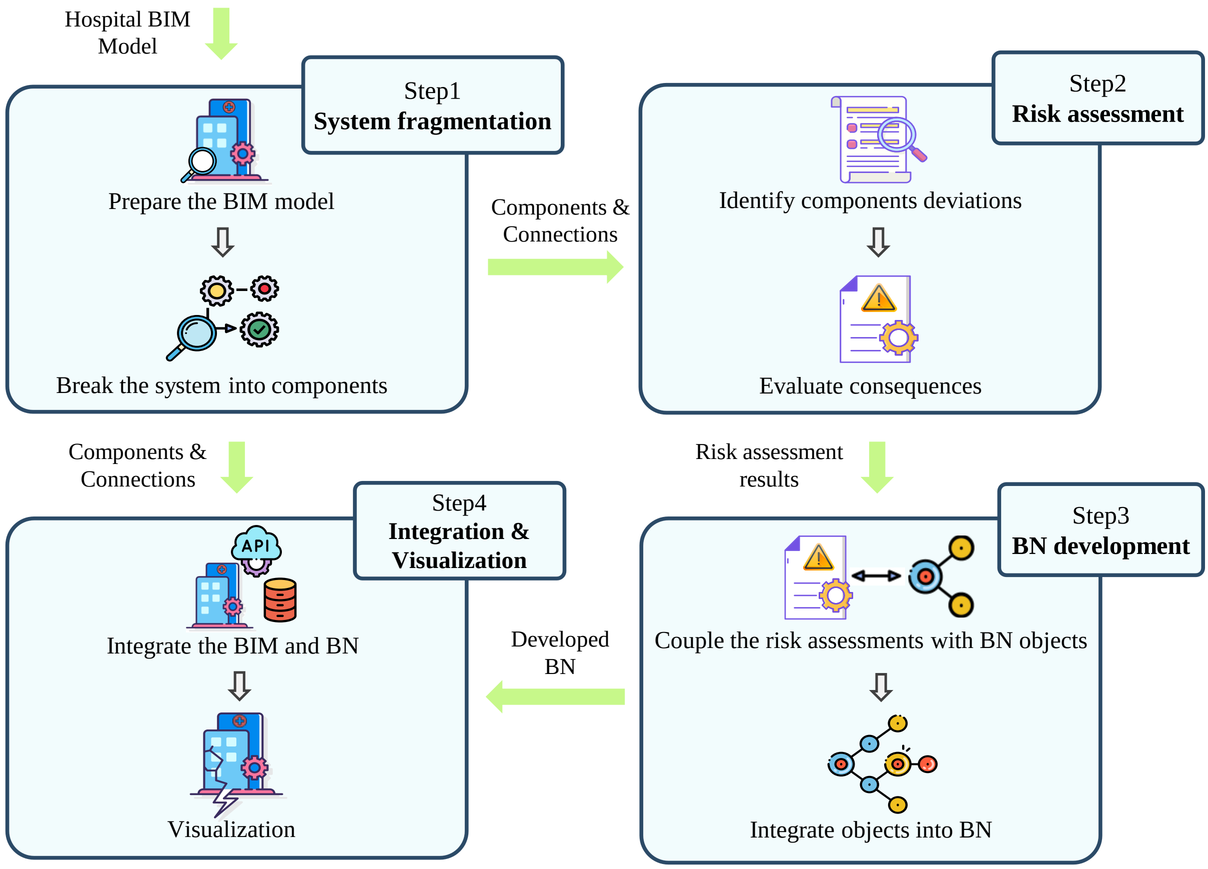


Figure 2. The proposed method to configure the back-end layer of the proposed model

3.1 System fragmentation

The BIM represents the building's components as 3D objects with specified materials and functionality. Therefore, BIM models can provide the risk assessment's requirements by identifying different components' dependencies (Malekitabar et al., 2016). Due to the emergence of the information exchange standards for BIM, engineers can manipulate the collected data in the project's lifecycle. Construction Operations Building Information Exchange (COBie) (East, 2007) and Industry Foundation Classes (IFC) (ISO, 2018) are two standard information exchange formats in the BIM platform. The COBie, represented as a spreadsheet data format, is built based on the IFC to capture and deliver facility management information in a structured manner from an early stage of the construction projects (East, 2007).

In this step, the hospital BIM model is captured as an input. Firstly, the BIM model of the hospital is prepared to incorporate an adequate level of detail, sufficient to contain the target system's functional information. Then, the COBie spreadsheets of the BIM model is utilized to break the target system. For the hospital utility fragmentation, the three sheets of "System," "Component," and "Connection" in the COBie is exploited. *COBie.Component* contains the information of every equipment components installed in the building. *COBie.System* describes how groups of components are organized into relevant categories that deliver specific services to the facility. *COBie.Connection* contains information about the logical relationship between components, which can help the facility managers determine the propagation pattern of any system anomalies (East & Carrasquillo-Mangual, 2012). Here, *COBie.System* helps users recognize the utility systems of the hospital. Then, *COBie.Component* is utilized to fragmentize the target system into components. Finally, *COBie.Connection* is used for recognizing the connections of the components in the target system. The identified components and connections in the target system are used in the following steps as a basis for BN development.

3.2 Risk assessment

The risk assessment starts with "what and how can go wrong?" questions to address the risk factors' identification and evaluate their consequences (Zou et al., 2017). Failure Modes and Effects Analysis (FMEA) has been proven to be a reliable tool to incorporate the identification of the components' potential deviations and evaluate their failure consequences (Wan et al., 2019). Inspired by this tool, two procedures are considered for risk assessment in the disaster management model:

(1) *Deviation identification:* The deviation of the components is a general term used for any deflection of the components or process from an acceptable range of operation (Hu et al., 2015). The target system's fragmented components, identified in Step 1, are

chosen to be analyzed to identify the deviations. Once a component is chosen, the deviations are derived by analyzing its possible deflections from the design intentions.

(2) *Consequence evaluation:* Each deviation should be analyzed considering the identified connections in Step 1 to detect the causes, the probable consequences, and the propagation of the components' deviation in the system.

The two procedures of the risk assessment process are generally conducted based on historical data of the components' failure and the propagation pattern of the failure in the systems during the disaster. However, in the case of data shortage, other sources such as the knowledge of the components' functional criteria available in the scientific literature, design codes, standards, and technical manuals, the post-disaster reconnaissance reports that are focused on the disaster-induced failures and propagation patterns, and the tacit knowledge of the domain experts could be considered as alternative data sources. Utilizing the knowledge of qualified experts can validate and supplement the information obtained from literature or reconnaissance reports for the case under study.

3.3 BN development

In this step, the results of Step 2 are mapped into a BN. Instantiation of the BN is followed in two stages:

(1) *Coupling risk assessments with BN objects:* The BN object refers to the small block of BN structure representing a very generic type of uncertain reasoning (Fenton & Neil, 2018). In this study, the cause-consequence BN object is utilized to model the single component's behavior during and after the disaster. In Figure 3, a schematic view of a typical cause-consequence object is represented. In this type of object, the causal process is represented by the "causes," "events," and "consequences" nodes. Measures for alleviating the effects of "events" and "consequences" are also demonstrated by "controls"

and "mitigations" nodes. Instantiation of cause-consequence objects is performed by mapping each component's deviations, consequences, and mitigation measures to the objects' corresponding nodes. For achieving this goal, the developed technique of mapping FMEA to BN is utilized (Brahim et al., 2019).

(2) *Integrating objects into a complete BN:* The integration of the fully structured BN requires the assembly of the objects. This process is performed by using the identified system fragments in step 1. Figure 3 illustrates the assembly scheme of the BN objects into a fully structured BN. The developed objects reflect the components' behavior in the system; therefore, it is possible to match them with the *COBie.Component* attributes. As represented in Figure 3, the objects' dependencies are derived from the *COBie.Connection*. By linking the objects, the *COBie.System* and the overall BN of the desired system are developed.

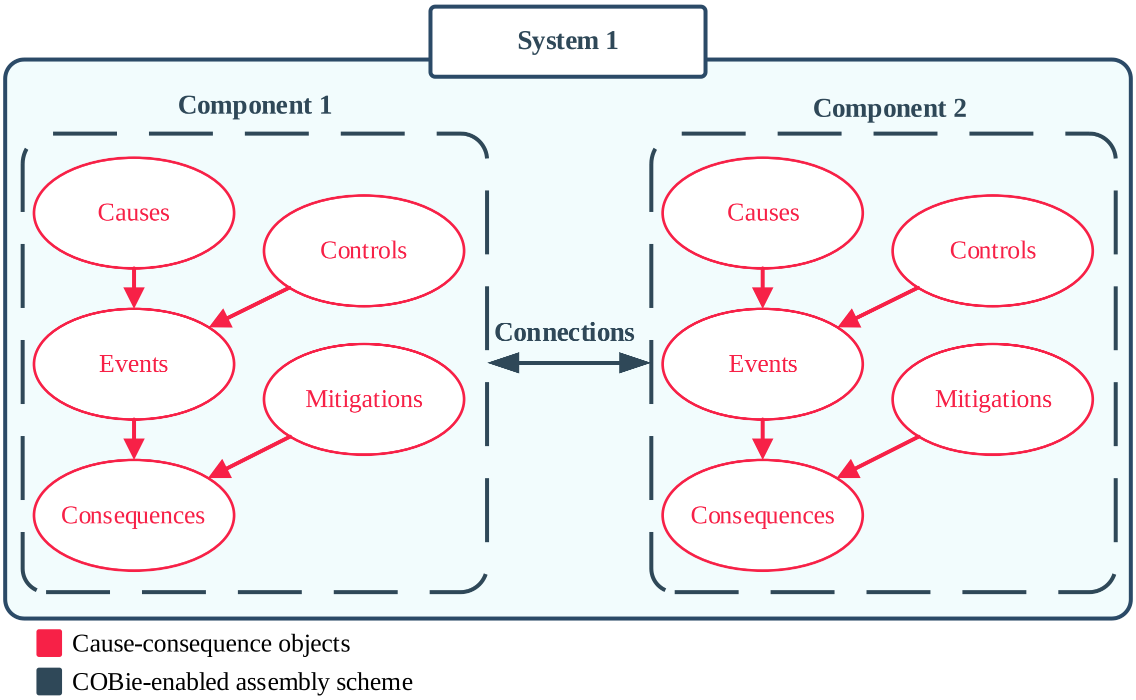


Figure 3. COBie-enabled BN objects assembly

In this step, the overall BN of the target system is structured by assembling the BN objects. Developing the BN from the objects brings the advantages of (i) speeding up the process of

BN development, (ii) increasing the quality of the developed network, and (iii) developing the libraries of objects which could be used for future studies (Fenton & Neil, 2018).

3.4 Integration and Visualization

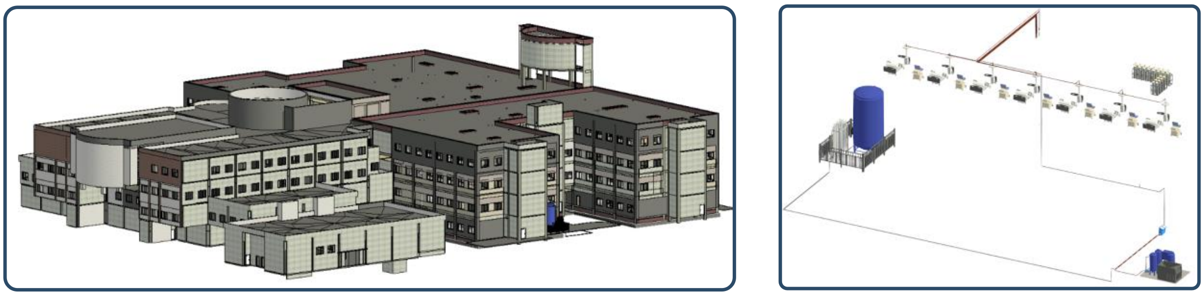
This step integrates the power of BN probabilistic inference and the visualization capability of BIM. The BN probabilistic inference (also known as belief updating) is referred to as the calculation of the probabilities of BN nodes given some observed value of nodes (i.e., evidence) (Pearl, 2014). The probabilistic inference is used for predicting the state of the target utility system given any observations of the disaster events. On the other hand, the visualization capability of the BIM helps decision-makers develop heuristic solutions for managing crises considering the probabilistic outcomes of the BN inference engine. To this aim, an API is developed between the BIM platform and BN software. Here, the identified components of the target system in step 1 are leveraged to map the results of the BN probabilistic inference engine into their respected 3D BIM component. Then, the "3D component" color-coded visualization technique (Motamedi et al., 2014) is implemented by assigning a color to every component to represent their predicted state.

4. Model implementation for the medical oxygen system

The proposed hybrid BIM and BN-based emergency disaster management model was implemented in a general hospital's medical oxygen system to illustrate its applications in the decision-making process during a crisis. The hospital case was located in Tabriz city, in the north-west of Iran. This region had experienced severe earthquakes during the last decade. The area's high seismicity encouraged the research team to develop the proposed model by focusing on earthquake-induced disasters. The medical oxygen delivery system plays a vital role in hospitals' functionality (Achour et al., 2014), and it is identified as one of the most vulnerable systems in the past earthquakes (Dixit et al., 2014). Therefore, the oxygen delivery system of the intensive care unit of the case hospital, as a representative part of the whole system, is selected as the target utility system of this case study. In the proposed model for the oxygen delivery system, the user enters the disaster observations and the mitigation measures into the model and receives the system state's prediction as an output. A detailed explanation of the model implementation is discussed in the following sections.

4.1 Medical oxygen system fragmentation

The BIM model of the hospital is captured as input. Then, the selected oxygen system of the hospital case and its specifications (Figure 4-b) were added to the available architectural 3D BIM model of the hospital (Figure 4-a) to prepare the model for system fragmentation.



(a) Architectural model

(b) Medical oxygen system of the intensive care unit model

Figure 4. Illustration of the developed BIM model of the case hospital

The system fragmentation was conducted for the selected medical oxygen delivery system based on the COBie dataset. For the target system of the case hospital, five principal components were identified with their dependencies. Figure 5 illustrates the identified components and their dependencies. The "PSA Unit" was identified as the primary, and the "Cryogenic Tank" was recognized as the secondary source of the medical oxygen. The oxygen flows from the primary or secondary supply to the "Piping System," which delivers the oxygen to the "Patient Floors." The "Portable Supply" is also added to reflect the portable reserve oxygen cylinders in the hospital wards.

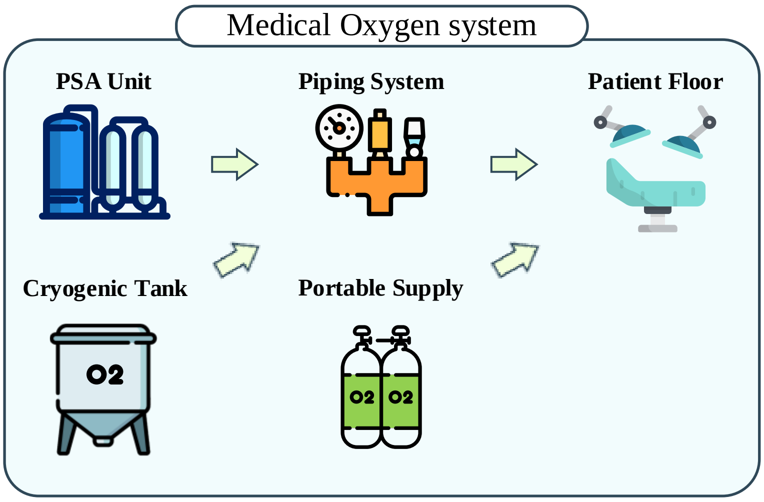


Figure 5. Medical oxygen system fragmentation

4.2 A thorough risk assessment of the oxygen system

In this case study, due to the lack of systematic data collection in the case hospital, the historical data was not reliable to perform the conditional probability estimation algorithms. Therefore, a literature-based risk assessment along with the expert knowledge elicitation was carried out to recognize the components' deviations and their corresponding consequences. The risk assessment procedures of this case study are inspired mainly by the FMEA method. The adopted method covers all the potential deviations and their corresponding possible causes and consequences of the system components. A total of 18 scientific papers, standards, regulations, and guidelines were reviewed for identifying the risks of the target system. Table 1 reflects the achieved results of the literature-based risk assessment.

Table 1. The identified risks for the oxygen delivery system of the hospital

Component	***Failure Modes***	***Causes of Failure***	***Consequences of Failure***	***Mitigation Measures***	***References***
PSA Unit	Outage of power	Failure of the power supply infrastructure Cyberattacks	Oxygen gas system outage	Using the backup power supply	(Li et al., 2013), (Wang et al., 2015); (Adachi & Ellingwood, 2008); (Cao Wang et al., 2019); (FEMA, 2012)
	Leakage	Under-maintained system Excessive ground acceleration	Fire Reduced gas pressure	Regulated maintenance and checking Monitoring the system state via the master panel	(Retamales, 2008); (Blasi et al., 2018); (BCGA, 2006b); (Salah et al., 2018); Experts
	Fire	Faulty wirings	The overall outage of the PSA system	Shutting the main valve off in case of fire	(Manes & Rush, 2020); (BCGA, 2006a); (BCGA, 2006b); (NFPA, 2005)
Cryogenic Tank	Lack of available volume	Misestimation of the oxygen need	Lack of oxygen in the hospital	Estimating the average need Controlling the oxygen level	(BCGA,2006a); (BCGA, 2006b); (NFPA, 2005);
	Leakage from tank	Cracks at the outer and inner surface of the tank Under-maintained system	Lack of pressure Fire	Considering the seismic design codes Regulated maintenance and checking	(Retamales, 2008); (Blasi et al., 2018); (BCGA, 2006b); (Salah et al., 2018); Experts
	Fire	Heating and smoking	The overall outage of the Cryogenic tank	Shutting the main valve off in case of fire	(Manes & Rush, 2020); (BCGA, 2006a); (BCGA, 2006b); (NFPA, 2005)
Piping system	Leakage	Improper pipe connections Excessive sway of the structure	Fire Lack of gas pressure on the wards	Controlling the gas flow and detecting the leak points Using a portable supply	(Retamales, 2008); (Blasi et al., 2018); Experts
Portable supply	Lack of available supply	Misestimation of the oxygen need	Lack of oxygen in wards	Estimating the average need Controlling the oxygen level	(BCGA,2006a); (BCGA, 2006b); Experts
	Misuse of the supply	Lack of trained staff	Hypoxia in patients	Training staff to manage the crisis	(Charney et al., 2015); (Burke et al., 2014); (Yang et al., 2010); (Johnson & Travis, 2006); (Salevaty et al., 2015)
Patient Floor	Fire	Failures of equipment	Exacerbation of fire due to the presence of oxygen	Shutting the oxygen flow in case of fire	(Manes & Rush, 2020); (BCGA, 2006a); (BCGA, 2006b); (NFPA, 2005)
	Medical gas flow outage	Power supply outage Leakage in the pipes Shutting valves due to emergency	Emergency medical situation	Active area alarm panel Monitoring the patients	(BCGA,2006a); (BCGA, 2006b); (NFPA, 2005); Experts

After performing the literature-based risk assessment, the experts' domain knowledge was employed in two stages to tune the risk assessment results with the hospitals' existing arrangement. Two clinical engineering experts with more than ten years of experience were contacted to adjust the "PSA Unit," "Cryogenic Tank," and "Piping" components' risks. A senior nurse was also selected to assess the risks of "Patient Floor." Furthermore, another expert was selected from the disaster management domain for validating the results of risk assessments. The expert assessments were conducted in the form of one to two hours of interactive interviews. In the first stage, the experts were asked about parameters that play a role in the system's behavior. By matching the experts' responses with the identified risks, the required adjustments were made in the risk assessment. In the second stage, the expert knowledge was used to justify the relations of different risk factors and their effects on the system's behavior. For simplifying the process of expert opinion extraction, the indirect elicitation technique of weighting introduced by Kuhnert et al. (2010) was utilized. In this technique, the experts were asked to make comments about the parameters' effects and rank the impacts of parameter variations. Then, the research team evaluated the experts' comments and made the required justifications. Table 2 represents the justifications made to the risk assessment results.

Table 2. Expert's justifications on the literature-based risk assessments

Justification type	***Literature-based assessment results***	***Changes made by Experts***	***Description***
Adding a new risk factor	-	Staff Training	Employees' performance depends on the training they receive. Proper training can help them to stay calm and to increase their productivity during a crisis.
Adding a new risk factor	-	Trained Staff Availability	During an earthquake, escape from the place occurs instinctively, and it is proportional to the intensity of the earthquake. Proper staff training can increase the efficiency of personnel during a crisis.
Changing states of risk factor	Productivity (Poor, Moderate, High)	Productivity (Poor, Good)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Backup Productivity (Poor, Moderate, High)	Backup Productivity (Poor, Good)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Gas Flow From Primary Supply (Poor, Moderate, High)	Gas Flow From Primary Supply (Poor, Good)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Gas Flow From Backup Supply (Poor, Moderate, High)	Gas Flow From Backup Supply (Poor, Good)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Gas Flow In Pipes (Emergency, SlightLack, Good)	Gas Flow From Backup Supply (Lack, Normal)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Gas Flow Inpatient floors (Emergency, SlightLack, Good)	Gas Flow Inpatient floors (Lack, Normal)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Medical Gas State Inpatient floor (Emergency, SlightLack, Good)	Medical Gas State Inpatient floor (Emergency, Normal)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Changing states of risk factor	Portable Supply Quality (Poor, Normal, VeryGood)	Portable Supply Quality (Poor, Good)	Considering the three different states of this risk factor, neither will bring any additional analytical benefits, nor will simplify the risk assessment process.
Adding a new risk factor	-	Leakage In Pipes-Gas Flow inpatient floors	The leakage in the pipes will have a direct effect on the gas flow in the patient rooms
Adding a new risk factor	-	UPS Units	Critical wards are equipped with UPS units, and if the city power goes out, these UPS units can supply the need immediately.
Adding a new risk factor	-	City Power Grid	The PSA units mainly work with the city power grid.
Changing a risk factor	Power supply availability	City Power Supply	Power availability relies mainly on the city power supply, and in case of a power outage, UPS systems could fulfill the needs for a short time.

4.3 The oxygen system's BN instantiation

The collected information of the system risk factors was mapped into the cause-consequence BN objects. The objects were linked using the identified relationships between the components in Section 4.1. The BayesFusion's GeNIe Modeler (BayesFusion, 2020a) was used to develop the BN. Figure 6 represents the overall structure of the BN model.

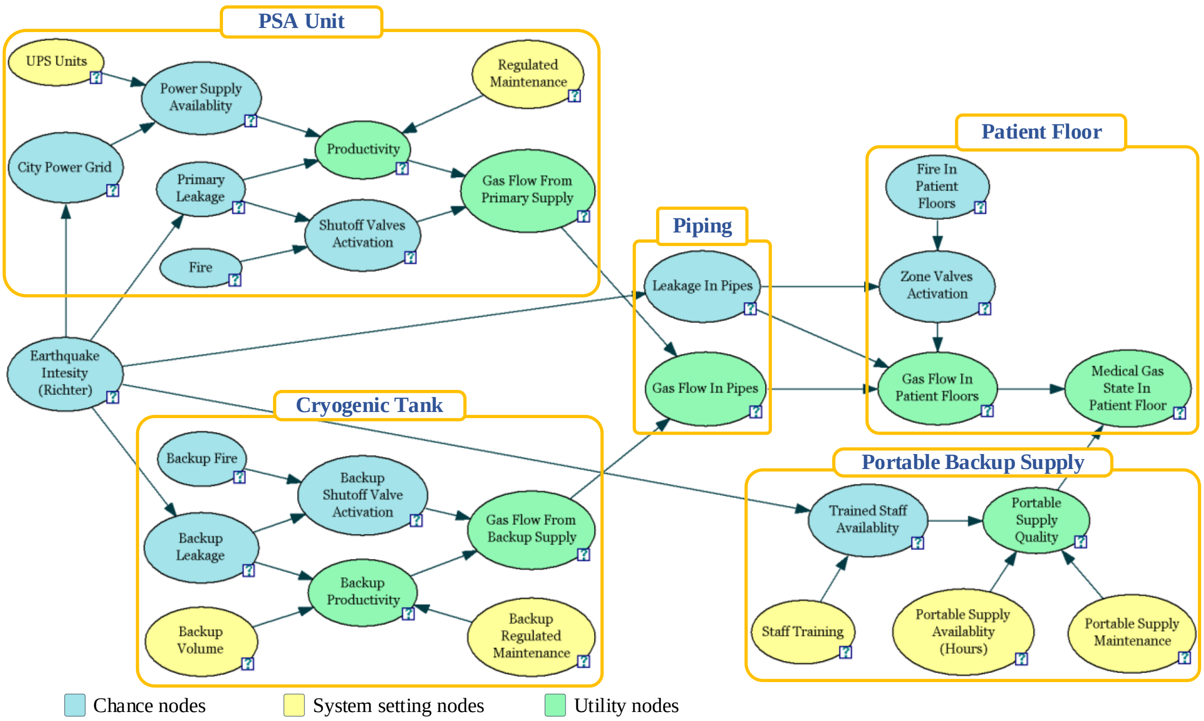


Figure 6. Bayesian Network of the medical oxygen system

The BN nodes were categorized into three groups, including chance nodes, system settings, and utility. The chance nodes express the model's uncertain variables like risk factors, which could be observed at any moment of the crisis. These nodes can also capture the decisions of the managers and working teams. The system setting nodes model the system settings and strategies before disaster hits. The utility nodes express the components' performance according to the disaster observations.

4.4 Model validation

The sensitivity analysis was carried out on all the possible cases to evaluate the effects of input changes on the target node of the "Medical Gas State In Patient Floor." The target node was selected due to its importance in the final result of the BN system. Figure 7 illustrates the impacts of the top ten variables on the target node in the form of a Tornado graph. In the Tornado graphs, different model variables are represented by bars, and the length of bars is interpreted as the magnitude of the variable's impact on the output of the target node (Hosseini & Sarder, 2019).

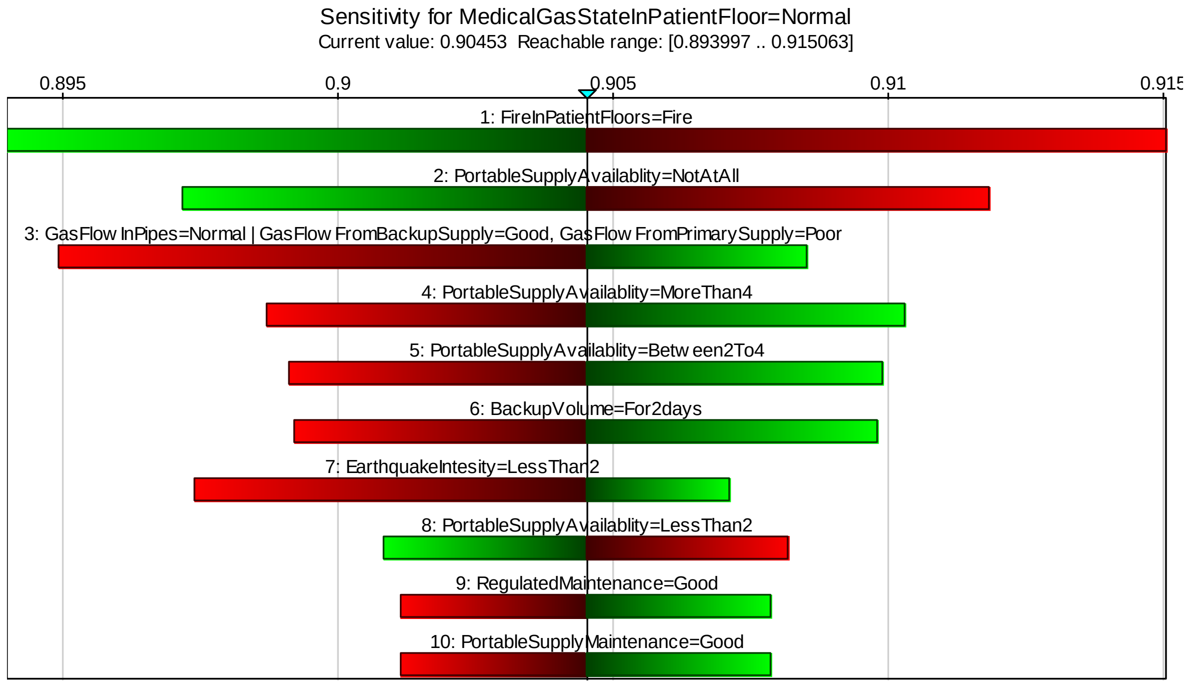


Figure 7. The sensitivity Tornado graph for the normal state of the "Medical Gas State In Patient Floor"

Each bar displayed in Figure 7 represents the impacts of a 30% variation in the value of its respective variable on the target node. The green bars indicate an increase, and the red bars demonstrate a decrease in the value of each variable. For example, the original probability of a normal medical gas state in patient floor is 0.90453, and an increase of 30% in the probability of the "More than 4 hours" state of the "Portable supply availability" variable (see bar 4 in Figure 7), would increase the probability of normal medical gas state in patient floor to 0.9102. On the other hand, a decrease of 30% in the probability of the same bar would decrease the probability of a normal medical gas state in patient floor to 0.8989. In other words, the probability of a normal medical gas state in patient floor ranges from 0.8989 to 0.9102 by 30% variation of the fourth variable plotted in Figure 7. It is concluded that the developed model responds to the slight variations in the input variables in a sensible manner.

4.5 BIM-based visualization

The BN and BIM were integrated by the development of an API in the .NET Framework. The API collects the observed evidence and assigns them to their corresponding nodes on the BN.

Then, it utilizes the SIMLE Engine (BayesFusion, 2020b) for updating the system state. Next, the updated state of each utility node on the BN is matched with its corresponding BIM object. The identified components of the medical oxygen gas system are leveraged to map the BN's probabilistic results on the BIM components. Finally, the results were visualized by reflecting the components' conditions as color-coded 3D objects in the BIM model. The hospital's decision-makers can control the crisis by allocating mitigation measures. The API captures the measures by assigning the values on the nodes that the decision is impacting. Then the model is recalculated to reflect the effects of the mitigation measures on the system.

4.6 A simulated post-earthquake scenario

A post-earthquake scenario of the medical gas system was developed based on available data from past earthquakes to clarify how the model assists the hospital managers in controlling the disaster. The observational data on hospitals' performance in past earthquakes collected by Yavari et al. (2010) and the risk assessment data of the oxygen supply system facing the earthquakes gathered by Deleris et al. (2006) was the source of inspiration for the development of the scenario. The developed scenario is summarized in Figure 8.

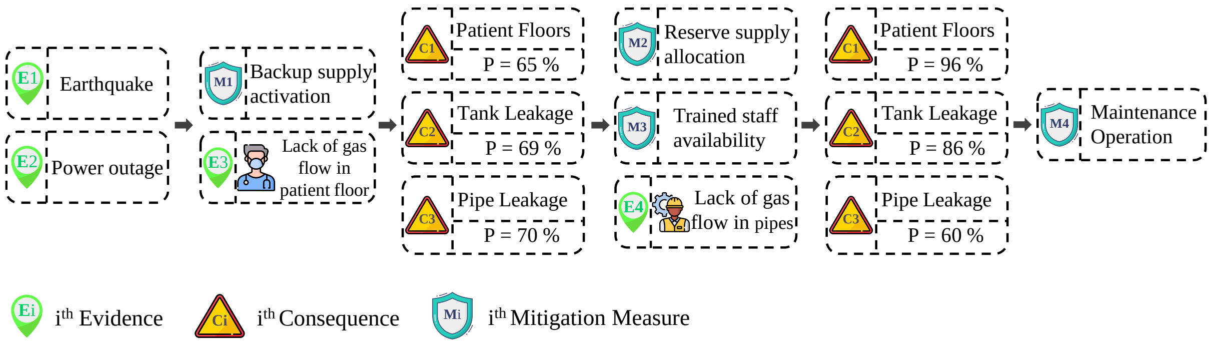
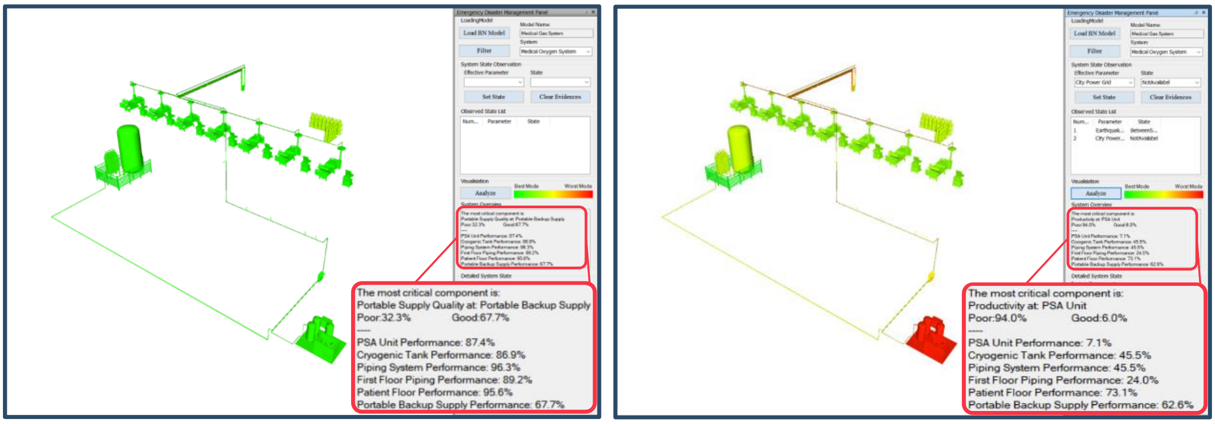


Figure 8. The post-earthquake scenario for the medical oxygen system

In the simulated scenario, an earthquake with a magnitude (M_W) of 5 to 6 occurred (See E1 in Figure 8), ensuing with a power outage in the city (See E2 in Figure 8). In this situation, the PSA Unit will be down until backup power starts to operate, which will take 10 to 15 minutes according to the case hospital's current configurations. During these crucial moments, the cryogenic tank is designed to provide the hospital's demand. To identify the system state, the hospital manager entered the first and second observations into the model by assigning the value on the "Earthquake Intensity" and "City Power Grid" nodes. Figure 9 represents a snapshot of a color-coded model before and immediately after an earthquake (after observing E1 and E2). Although the PSA unit was identified as the most critical component in the system, the backup supply seemed to be able to feed the hospital and fulfill the demand. The red rectangles in Figure 9 illustrate the system overview.



(a) Before earthquake (b) Immediately after earthquake

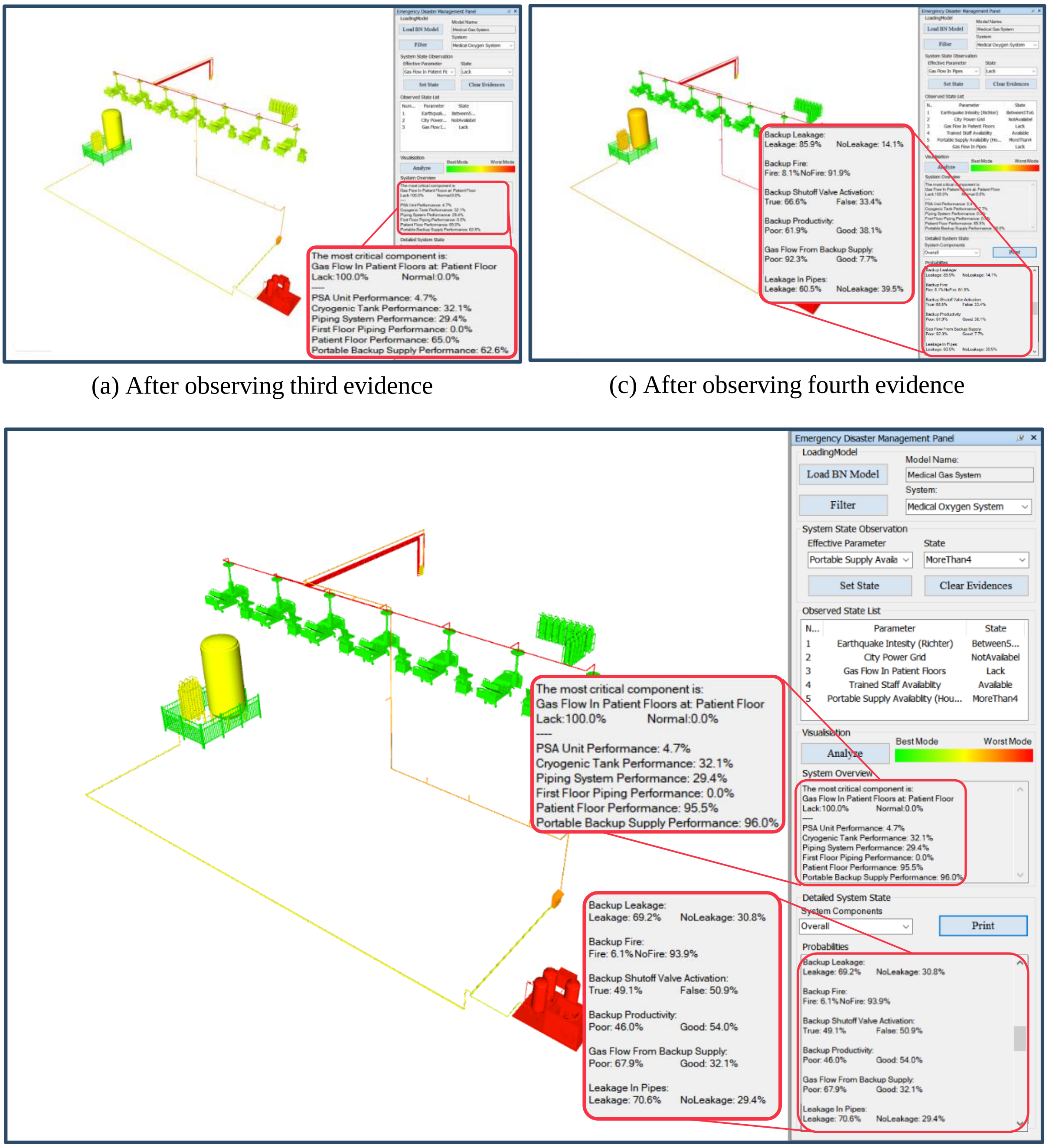
Figure 9. Visualization of the system state before and after a simulated earthquake

Simultaneously, the nurses reported the lack of pressure of the oxygen in the central pipelines (see E3 in Figure 8). The third evidence was entered into the system. The model captures this evidence by assigning the value on the "Gas Flow In Patient Floor" node in the network and runs the inference engine to update the system state considering the new observation. Figure 10-a represents the system state after the new observation, and the red rectangle illustrates the system overview.

By overviewing the system state, the manager identified the critical state of the patient floor (see C1 in Figure 8); therefore, two mitigation measures of calling for the extra portable oxygen supply from the supplier and recalling the trained staff were allocated to control the crisis. The model captures the allocated mitigation measures by assigning values on the "Trained Staff

Availability" and "Portable Supply Availability" nodes on the network. The manager evaluated the mitigations' effectiveness by running the model and observing the updated system state, considering the allocated measures. Figure 10-b represents the system state after performing the mitigation measures. The adopted measures lead to an increase in the "Patient Floor Performance" to 95.5% (see the red rectangle of the "System Overview" in Figure 10-b). Additionally, probabilistic information of the system overview indicated a significant reduction of performance in the "Cryogenic Tank" and "Piping System." The manager analyzed the detailed probabilistic information of the components' states (see the red rectangle of the "Detailed System State" in Figure 10-b) and distinguished the pipe or tank leakage as the two probable consequences (See C2 and C3 in Figure 8).

Hence, the maintenance team was called to conduct diagnosis procedures. The maintenance team used the master alarm panel to check whether the backup supply was feeding the hospital, and a reduction in the gas flow in pipes was detected (See E4 in Figure 8). The fourth evidence was entered into the system. This evidence was assigned on the "Gas Flow in Pipes" node, and then the system states were updated. Figure 10-c represents the system state considering all the observed evidence. As shown in Figure 10-c, the backup supply leakage was more probable than the pipe leakage. Accordingly, the manager decided to request emergency maintenance for the cryogenic tank.



(a) After observing third evidence

(c) After observing fourth evidence

(b) After allocating the measures

Figure 10. Visualization of the system state

4.7 Results and discussion

Based on Figure 7, the occurrence of the fire in the patient floors was recognized as the most disruptive earthquake-induced consequence for the system. Moreover, the portable reserve supply was identified as one of the most sensitive factors that influenced the medical gas state on the patient floors. As it is represented, the bars associated with the reserve supplies are among the highest rank in the Tornado graph (see bars 2, 4, 5, 8, and 10 in Figure 7). This finding implies the importance of the redundancy of the resources in the resilience of the systems. By examining the effect of different variables with respect to their contribution to the medical gas state in patient floors, decision-makers can devise necessary strategies to optimize the resiliency of their systems.

Implementation of the model in the case hospital revealed the model capabilities in emergency management and root cause analysis. Immediately after the earthquake, the performance of the PSA unit was significantly reduced, which was rooted in the city power outage. The PSA units are designed to work with the city power grid, and the outage of power reduced its performance from 87.4% to 7.1% in the simulated scenario. By considering the explicit (i.e., power outage) and implicit (i.e., increased chances of earthquake-induced failures such as pipe or tank leakage) disaster impacts, the proposed model reduced the performance of other components (see the red rectangle of Figure 9-b). The model reduced the patient floor state to 65% by observing the third evidence from the nurses. In this situation, some of the patients might be experiencing hypoxia. The proposed model helped the manager identify the emergency and allocate the measures to control the crisis. The model evaluated the allocated measures to be effective in increasing the patients' status to 95.5%. Moreover, the model's probabilistic information helped the manager conduct a root cause analysis of the performance reduction in the second stage of disaster management. Although the pipe leakage might seem more probable at first sight, the model predicted the same chance of leakage in the cryogenic tank and piping system (see Figure 10-b). By collecting the fourth evidence from the system behavior, the model predicted the tank leakage to be more probable than the pipe leakage (see Figure 10-c). Implementation of the model helped the manager consider the probability of tank leakage, which might be overlooked in the best practices of the case hospital in the same situations.

5. Conclusions

Disasters are threatening societies, and health infrastructures play a vital role in overcoming these threats. The development of a decision support system for facilitating the immediate responses after disasters is a surging demand. This research proposed a novel decision support model by synthesizing the BN and BIM capabilities to respond to the existing demand. The BN's probabilistic capabilities were utilized for analyzing the states of the hospital's utility systems during the disaster. Meanwhile, the object-oriented and 3D visualization capabilities of the BIM was employed to facilitate risk-informed decision making. The proposed model was implemented in a hospital case to investigate its capabilities and demonstrate how it can visually analyze the oxygen delivery system after an earthquake. The proposed model has several distinguishing features that can improve the process of making urgent decisions during a crisis. Integration of the BIM and BN in the model architecture endows the user to visually evaluate the utility system states. Besides the model's capability to simulate the system after disasters, a novel capability is introduced that enables decision-makers to model the system immediately after the disaster. This capability would help the decision-makers investigate different disaster response strategies, assess the effectiveness of viable measures, and allocate the planned strategies optimally. Moreover, the COBie standard is used for constructing BN objects, accelerating the BN structure development, and reducing the burden of the process.

This study is subject to certain limitations. Due to the lack of data about the system behavior during the disaster and the lack of pragmatic solutions to collect such data, the case study limits its scope to the available knowledge in literature and experts' experience. In the case study, the interdependence of systems is neglected, and the scope is limited to a specific utility system. Moreover, the evidence observations in the case study are limited to the operational teams' perception of disaster events. Future research is required to combat the limitations of this study. Further case studies are necessary to develop BN for other utility systems and consider the interdependent relationships of these systems. A systematic data collection method needs to be developed to provide the automated BN instantiation requirement for the hospital utility systems. Moreover, COBie datasets and facility management systems' databases can be leveraged to develop an automated BN instantiation method. Finally, the building facility management systems and equipment sensors' data can be utilized to investigate the disaster observations and update the system state automatically.

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