Preprint version of paper now published as https://doi.org/10.1142/S021962202150053X

ONTOLOGY-DRIVEN MULTI-CRITERIA DECISION SUPPORT FOR VICTIM EVACUATION

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Abstract: In light of the complexity of unfolding disasters, the diversity of rapidly evolving events, the enormous amount of generated information, and the huge pool of casualties, emergency responders may be overwhelmed and in consequence poor decisions may be made. In fact, the possibility of transporting the wounded victims to one of several hospitals and the dynamic changes in healthcare resource availability make the decision process more complex. To tackle this problem, we propose a multi-criteria decision support service, based on the Analytic Hierarchy Process (AHP) method, that aims to avoid overcrowding and outpacing the capacity of a hospital to effectively provide the best care to victims by finding out the most appropriate hospital that meets the victims' needs. The proposed approach searches for the most appropriate healthcare institution that can effectively deal with the victims' needs by considering the availability of the needed resources in the hospital, the victim's wait time to receive the healthcare, and the transfer time that represents the hospital proximity to the disaster site. The evaluation and validation results showed that the assignment of hospitals was done successfully considering the needs of each victim and without overwhelming any single hospital.

Keywords: Multi-criteria decision support; Ontology; Victims' evacuation; Disaster response.

1. Introduction

The need to face the suddenness, the complexity, and the chaotic nature of disasters makes disaster response challenging (Devlin, 2006). The key factor for the success of large-scale disaster response is the availability of useful and real-time information to facilitate the decision-making process (Fertier et al., 2020). In fact, emergency responders need accurate and relevant information to be provided in a timely manner in order to allow for appropriate resource deployment and dispatching and to ensure key processes of disaster response, including mass evacuation, are carried out successfully (Bharosa et al., 2009). Emergency responders should work together to ensure the gathering and triage of victims and their subsequent evacuation to an appropriate healthcare institution to receive medical care.

When responding to large-scale disasters, emergency responders (ERs) can be easily overwhelmed by the number of causalities, the rapidly evolving events, and the enormous amount of generated information, and subsequently, poor decisions may be made (Eisenman et al., 2007). As a result, staff and equipment may be sub-optimally used, and victims negatively impacted. The possibility of transporting the victims to one of several hospitals and the dynamic changes in available healthcare resources make the decision process even more complex. Often, the nearest hospitals become quickly overloaded and so can no longer receive new victims. That is to say, the resource allocation is a big challenge for ERs during the operational response phase and it becomes a very complex process especially when it concerns a multi-site response with limited resources. Indeed, feedback from the response to the 11/13 Paris attacks underlined the need to improve victims' evacuation strategies in order to preserve victims' lives (Nahon et al., 2016). Specifically, on the night of the terrorist attacks, and because of a disorganized multi-agency and multi-site response, there were two sites, where victims did not receive medical care (Philippe et al., 2015).

The question therefore naturally arises: How to exploit information and empower decision-making in order to determine the most appropriate hospitals for victims' evacuation on time?

To address this question, we here propose PROOVES (POLARISC Ontology-Based Operational Victims Evacuation Service), an ontology-based multi-criteria decision support service designed to assist emergency responders and improve the process of evacuating victims of disasters. The aim is to find the most appropriate hospital to transfer the victims in terms of the availability of the needed healthcare resources and the rapidity of receiving suitable medical care by ranking the different hospitals from the most appropriate to the less appropriate. Specifically, data that is tagged using the POLARISC Ontology (POLARISCO) (Elmhadhbi et al., 2019) is queried by PROOVES in order to ascertain the healthcare resources, including staffing and equipment, that is needed to meet each given victim's needs. The process of assigning victims to hospitals then depends on the exploitation of the availability of the needed resources, the victim's wait time before receiving medical care, and the hospital's proximity to the disaster site.

PROOVES has been developed within the scope of the existing POLARISC project (for: Plateforme OpérationnelLe d'Actualisation du Renseignement Interservices pour la Sécurité Civile) (Elmhadhbi et al., 2018). As shown in Figure 1, the POLARISC platform is composed of three layers (Elmhadhbi et al., 2020): a user interface layer that offers a real-time operational picture by respecting the graphical charter and color code of each stakeholder, POLARISC mediator that plays the role of gateway between end-user and the core system to provide a suitable representation of the requested information according to ERs' specificities, and the core system that is composed of a knowledge base based on a suite of ontologies elaborated by referring to domain experts and a set of integrated services (PROOVES, etc.) and geospatial resources bases.

This communication describes the proposed multi-criteria decision support service that aims to identify the most appropriate hospital to transfer victims under given conditions. The proposed approach considers the availability of needed healthcare resources and the anticipated rapidity of delivery of suitable medical care. It provides a ranking of available hospitals from most to least appropriate. We present the architecture of the system and a detailed description of the multi-criteria decision support process. This is followed by an evaluation of the proposed service.

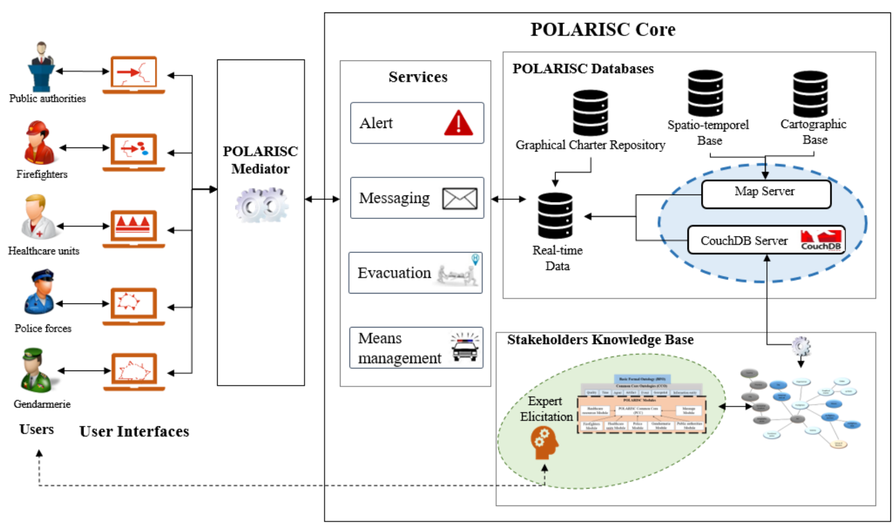

Fig. 1. The global architecture of POLARISC.

2. The victim evacuation process in France

The organization of medical response to large-scale disasters in France is articulated around two interlinked and complementary emergency plans: the NOVI plan and the White plan (Plan Blanc), respectively. The former, which is an updated version of the Red plan*, is the reference plan for on-site mass causality management. The latter is defined as "the implementation of a pre-prepared doctrine to deal with the consequences of a natural, technological or social event causing or likely to cause mass casualties so that the emergency response resources meet the acute increase in healthcare needs" (Lefort et al., 2014). It concerns the process of extracting victims from the affected location, triage of victims, and subsequent healthcare provision in and around the PMA (Medical Advance Post), and resource mobilization.

Figure 2 depicts the process of deployment of the NOVI Plan. Specifically, once the victims are assembled in the victim gathering point (PRV), they receive first aid and they are sorted under the authority of the chief medical officer in order to ascertain who is in most urgently need of immediate care. Victims are classified based on their injury levels, classified as either relative emergency (RE) or absolute emergency (AE). Victims with a relative emergency are transported to the PMA to receive immediate medical care. Those who have an absolute emergency are transported immediately to a hospital. The evacuation resources can be firefighter rescue vehicles, ambulances, helicopters, and so on. Transportation of victims is managed by both firefighter and healthcare units. At the disaster site, this evacuation process is under the command of the medical director, who is known as the DSM (Directeur des secours médicaux) who is an experienced doctor assigned by the healthcare units.

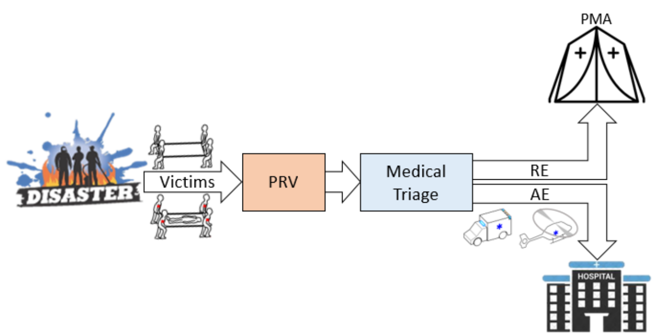

Fig. 2. Process of deployment of the NOVI Plan.

The White plan is used to identify a set of hospitals to which the victims can be transported. It concerns the coordination and organization of the hospitals' activities in responding to the mass causality. It enables preparation of the hospitals for incoming victims taking into account availability of resources such as doctors, nurses, and beds. It consists of a set of procedures designed to guarantee adequate resource mobilization. When the White plan is activated, therefore, each hospital must have an exact schedule of available medical staff and a list of available resources.

To manage the mass causality, the SINUS national system (for: Système d'Information Numérique Standardisé) is used in France to identify and track victims using a bracelet with a barcode. SINUS is a standardized digital identification system composed of three components. First, an information collection application called "ARCSINUS", which enables the input of information and its transmission via laptops and barcode scanners. Second, a central database allows which allows the real-time amalgamation of the information so that it can be provided to all involved emergency responders. Third, an application dedicated to the strategic level of disaster response involved in identifying victims and informing their relatives.

SINUS is used during triage by the DSM to enable the identification of each victim and associated condition using a detailed medical record form as shown in Figure 3. The form contains demographic information pertaining

* https://www.secourisme.net/spip.php?article169

to the victim (if known), their state (absolute emergency “UA” or relative emergency “UR”), their vital signs (heart rate, blood pressure, body temperature), condition, and the projected evolution of the victim’s state, for instance, if it is improving, stabilized, or becoming aggravated. In addition, the DSM specifies the assigned means of transport mean and the hospital to which the victim should be transported.

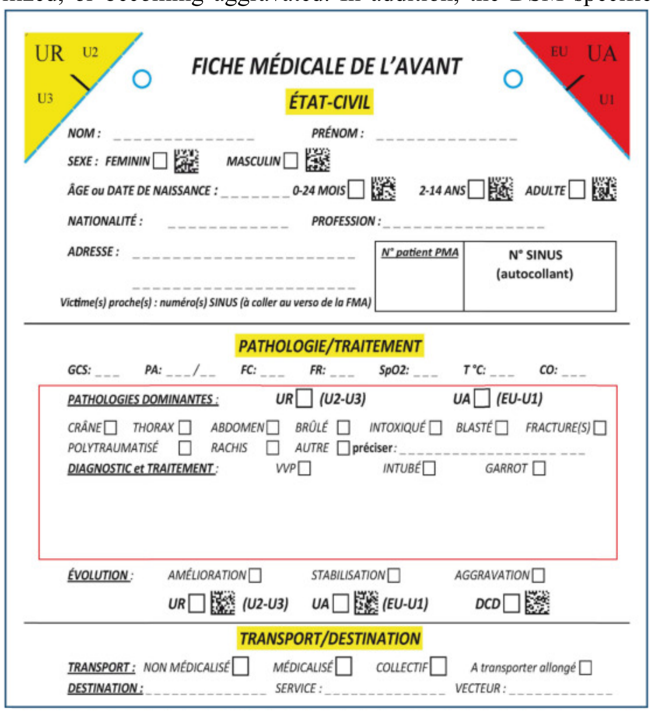

Fig. 3. SINUS: victim’s medical record.

Currently, the choice of the most appropriate hospital is made by DSMs on the basis of their expertise, experience, and taking into account the numbers of victims to be evacuated, as well as with an eye toward not overwhelming the most proximate hospitals. Consequently, the decision-making process may be negatively affected by the lack of adaptation to changing circumstances, difficulties in ascertaining resources available at any given time, and unpredictability of the disaster response process. Emergency responder feedback after the Paris terror attacks suggests the need for considerable improvement in the adopted strategies for hospital assignment (Frattinia et al., 2018). Hence our proposal here: to enhance the process of victim evacuation by means of a decision support service to assist the DSM in making more informed decisions. Our proposal is not to automate the process and remove the discretion of the DSM. Rather, the proposal is to support emergency responders and expand their capabilities.

3. Related works: Victims’ evacuation systems

When disasters strike and victims are created, there is a critical need for appropriate mass causality management. In the literature, different approaches to victim evacuation have been proposed (Caroleo et al., 2018). Most research in this area focuses on two concerns:

(1) When will the victim be evacuated? This issue concerns optimizing the allocation of transport vehicles, finding the best evacuation routes, calculating the shortest paths, and minimizing the transport time.

(2) Where will the victim be evacuated to? This issue concerns managing hospital resource availability according to the nature of each given victim’s injuries.

Our literature review will accordingly be concentrated on research that deals with the topic of victim evacuation during disaster response, considers the issue of healthcare resource availability, and supports the process of choosing most appropriate hospitals.

Benssam et al. (2014) propose the DEvacuS (Dynamic Evacuation System) framework for dynamic evacuation operations that is designed to provide optimal and continuously updated evacuation plans. The DEvacuS system takes into account unpredictability and dynamicity along two dimensions; hospital occupancy per specialty, and condition of transport routes to each hospital. The hospital occupancy can be negatively impacted by different factors, including sudden unavailability of doctors. In addition, the optimality of the shortest path to the targeted hospitals may be affected by road accidents or bridge destruction.

DEvacuS is composed of the following components: a client device, a request dispatcher, a shortest path calculator, and a resolution system. The system uses the specialty required for each given case to search for suitable candidate hospitals. It then calculates the shortest path between the victim triage site and target hospitals. The resolution system then selects the most appropriate hospital by optimizing the ratio between shortest path, occupancy, and load balancing among hospitals. However, DEvacuS selects the most appropriate hospital according to the occupancy in a certain specialty service in a hospital. Thus, it considers hospital load balancing only in terms of available beds.

Muaafa et al. (2014) propose a multi-objective optimization model in order to generate optimal emergency medical response strategies. The proposed model enables identification of the location of healthcare institutions and establishment of strategies to manage evacuation vehicles and determines on this basis how many victims should be evacuated to each identified healthcare institution. The aim of the proposed model is to minimize the response time and cost of the response strategy.

Nouaouri (2010) provides an optimization strategy for hospital human and material resources to enhance victim evacuation. However, the strategy focuses only on surgeons and their scheduling of surgical acts in the operating rooms of available hospitals. Various possible disruptions are considered, including the overflow of surgical care duration, changes in victim prognosis, and insertion of news victim in the scheduling program.

Dain and Nair (2014) present a mixed-integer program that models a resource-constrained triage problem in what is called the Severity-Adjusted Victim Evacuation (SAVE) model. Their work is concerned with how to effectively evacuate victims to different hospitals without overwhelming any single hospital. The SAVE model considers, on one hand, the deterioration condition of the victim's state, and the resource availability and treatment capacity of the hospitals. On the other hand, it considers the availability and capacity of ambulances for victim transport. As concern the availability of resources, the SAVE model focuses only on hospital capacity in terms of the number of unoccupied beds.

Engelmann et al. (2019) propose an ontology that can be used to support the process of determining to which hospitals patients will be allocated. The ontology focuses only on bed availability and it is not evaluated nor used in any real-world scenarios.

Albahri et al. (2018, 2019) propose a smart real-time health recommender framework based on wearable medical sensors for remote healthcare services provision in the context of a telemedicine environment. The aim is to rank the different hospitals and to select the best one for multi-chronic patients. The hospitals are ranked based on their number of available services from the highest to the lowest levels. The empirical evaluation shows the performance of the health recommender framework for hospital selection and how the proposed approach improves the telemedicine environment. However, the focus is only on chronic heart diseases and does not consider the diversity of diseases and emergency levels of each patient.

Most of these contributions study the evacuation problem from a single perspective, thus leaving multiple dimensions of the problem out of the account (see Table 1). In addition to the allocation of beds, the availability of adequate healthcare resources is of utmost importance. Only the availability of medical devices and professionals can ensure that victims are properly treated. Consideration also of victim waits time when is important also in making an optimal decision regarding which victims should be taken to which hospitals.

Table 1. Comparative study of existing victims' evacuation systems

System	Allocation of transport vehicles	Best evacuation routes	Victims needs	Resources availability		Literature
				Beds	Resources	
Ontology-based system	×	×	×	✓	×	(Engelmann et al., 2019)
DEvacuS	×	✓	×	✓	×	(Benssam et al., 2014)
Multi-objective optimization model	✓	×	×	×	×	(Muaafa et al., 2014)
SAVE	✓	×	×	✓	×	(Dain and Nair, 2014)
Optimization model	×	×	×	×	✓	(Nouaouri, 2010)
Smart real-time health recommender framework	×	×	✓	✓	✓	(Albahri et al., 2018, 2019)

4. Toward the selection of an MCDM method

Multi-criteria Decision Making (MCDM) deals with the decision problem of finding consistent and robust solutions given multiple criteria. During the last three decades, MCDM methods have emerged to provide a structured evaluation of decision problems with multiple criteria and to increase thereby the efficiency of the decision-making process (Ishizaka & Nemery, 2013) by promoting the selection of the best solution using given criteria (Köksalan et al., 2011).

To choose an appropriate MCDM method for decision-making concerning victim evacuation, we followed a set of guidelines proposed by Guitouni and Martel (1998).

Guideline G1 holds that one should determine the stakeholders of the decision process and determine whether there is a need to use a group decision-making method. In our context, the healthcare unit members, and more specifically the DSM, are the responsible persons. They ensure the triage of wounded victims, identify the injury of each victim, and selecting the most appropriate hospital. Accordingly, we do not have to consider the use of group decision-making methods.

Guideline G2 holds that one should choose the decision-making cognition that will be used to compare the different alternative approaches, such as pairwise comparison, utility and value function, distance to the ideal point, and so on. The pairwise comparison comes closest to meeting our requirements since it is very similar to the human way of thinking. It involves comparing pairs of criteria by asking how important one criterion is relative to another according to a predefined scale. We think that it is much easier and efficient to compare only two elements at a time. Furthermore, pairwise comparisons are recommended when it is not possible to define a utility function that is complex and time-consuming (De Brito & Evers, 2016).

Guideline G3 holds that one should define the decision problem that the MCDM method should solve. In disaster response, the decision-making process is even more complex and sensitive, since it requires not only reflection on economic and technical issues but also on the consideration of saving human lives. Emergency responders are looking for the most appropriate hospital that provides the required medical resources according to each victim's needs. To this end ranking the different hospitals from the most to the least appropriate is the preferred strategy. In fact, responding to a disaster is a highly complex and time-constrained situation. In cases where emergency responders discover they cannot reach the first-ranked hospital because of a blocked road, they can immediately choose the second hospital without wasting time by running the system one more time. Moreover, the presupposition of this study is that we will support DSMs in their decision-making, and not subvert their role.

Accordingly, it is more reliable to propose a list of ranked hospitals, leaving the final decision to be made by the cognizant DSM. In accordance with the G2, the analytical hierarchy process (AHP) method is chosen, since it alone adopts the pairwise comparison method (Kou and Lin, 2014).

AHP is a multiple-attribute decision analysis technique designed for complex systems that involve various conflicting criteria and alternatives (Saaty, 1990). According to various review studies in the literature (Yu et al., 2021) (De Brito & Evers, 2016) (Kabir et al., 2014) (Zare et al., 2016), it is observed that AHP is the most commonly applied MCDM tool in various research fields due to its simplicity, flexibility, straightforwardness, and comprehensibility. In fact, AHP is able to reduce the complexity of decision-making in a reliable way and to check the consistency of a given proposed approach (Saksrisathaporn, 2015). Moreover, it provides an easily understandable approach for practitioners. Furthermore, one of the major advantages of AHP is that it calculates the measure of the consistency of the pairwise comparison, which can be used to ensure that the final decision rests on consistent judgments (Zhang et al, 2021).

However, the main limitation of the AHP method is that a large number of alternatives and their variation may destabilize the ranking results. In the proposed work, the set of alternatives are fixed by the White Plan from the beginning of the disaster response process. Moreover, the number of activated hospitals is not large, so it will not destabilize the ranking result or slow down the processing time.

5. Ontology-driven multi-criteria decision support service: PROOVES

The DMS is responsible for recommending the hospital to which each victim ought to be transported. The main purpose of PROOVES is to ensure that each victim will be transported to the where they can receive as quickly as possible adequate medical care according to their medical needs. Hospital selection depends on the transfer time to reach the hospital, the availability of the needed medical resources, and the victims' wait time before receiving medical care. The architecture of PROOVES is presented in Figure 4.

To determine where to transport a victim, the DSM responsible for the evacuation team enters the victim's medical record into the SINUS system and submits the request for a search of the most appropriate hospital from the list of hospitals activated under the White plan. To do this, the POLARISC mediator receives the request and then interrogates PROOVES to perform the multi-criteria decision analysis. PROOVES's first algorithm is divided into three steps; 1. resource assignment, 2. availability and 3. wait time calculator, and multi-criteria decision analysis.

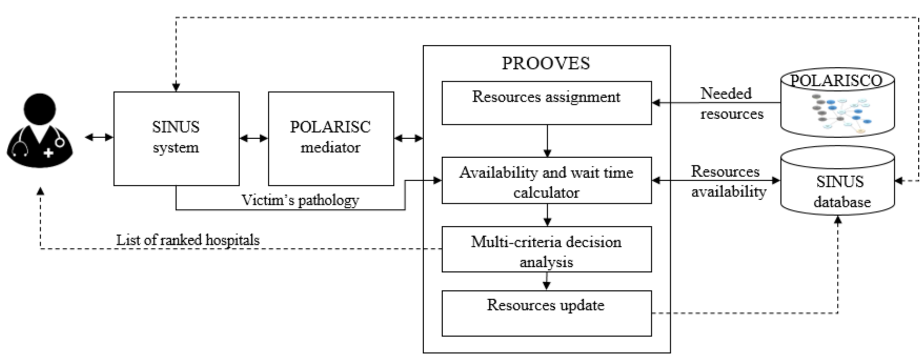

Fig. 4. PROOVES architecture.

Step 1. enables the determination of the needed medical resources and the required staff according to the victim's injury. To do this, the victim evacuation module of POLARISCO is queried and a list of specialized staff and medical equipment is returned in accordance with the submitted injury.

In step 2., the list of activated hospitals is received from the SINUS database as well as the initial resources and the transfer time. The following computation is done for each activated hospital. The arrival time is computed based on the transfer time between the disaster site and the target hospital. Then, the system checks the availability of the different needed resources. If a resource is available, the system calculates the victim's wait time. The availability and wait time calculator is a preprocessing step that prepares the information required to perform the step 3., the multi-criteria decision analysis.

In this step, the list of hospitals is ranked using the AHP method from most to least appropriate according to transfer time, resource availability, and the victim wait time.

Finally, the ranked list is transmitted to the DSM who will make the final decision. Once a hospital is selected, the resource wait time is updated by a second algorithm, so that it can be considered for the next process. Figure 5 summarizes the process of the proposed system.

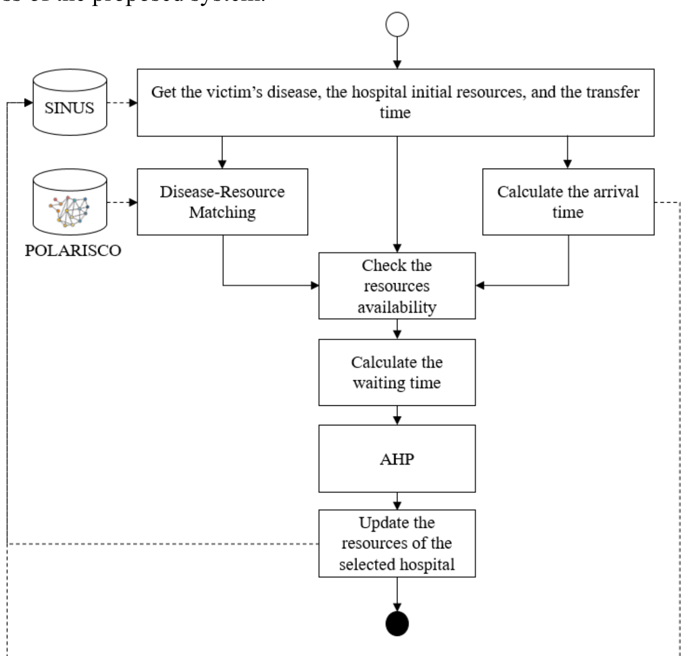

Fig. 5. PROOVES process.

5.1. The healthcare resources module of POLARISCO

In the following, we present in more detail the ontological module of healthcare resources in POLARISCO. This module formalizes the different healthcare resources including hospital staff and equipment, while also providing a categorization of the different possible injuries and associating them with the healthcare resources required to deal with each type of case. This module also defines the victim evacuation process and the participants involved in this process such as healthcare unit members and their roles.

To define this module, we reused the PCC module and the healthcare unit module of POLARISCO. The PCC module uses Basic Formal Ontology (BFO) (Arp and Smith, 2015), which is an ISO standard top-level ontology (ISO/IEC 21838-2), and Common Core Ontologies (CCO) as its mid-level (Rudnicki, 2016). Starting out from there, we tried to reuse existing ontologies as far as possible in order to reduce the modeling complexity and to maximize future data integration. Thus we refer where necessary to existing biomedical ontologies within the OBO Foundry (Smith et al., 2007), which were chosen for their quality, considerable usage, use of common design principles, and compliance with BFO. Figures (8-13) illustrate partial views of the proposed module. In each figure, reused classes are marked with a prefix that marks the source ontology. Classes lacking prefixes were created in POLARISCO *de novo*.

We started by defining the class *injury*. According to the OGMS (Ontology for General Medical Science) (Ceusters & Smith, 2015), an injury is “a disorder that involves some structural damage that is immediately caused by a catastrophic external force”. In fact, OGMS is a BFO-compliant ontology that defines a disorder (for example a broken leg) as a *bfo: material entity*. Accordingly, we reused the two classes disorder and injury from OGMS. OGMS’s coverage domain includes both diseases and their causes and manifestations, as well as diagnostic acts. Its basic axiom is that disorders serve as the material basis for the dispositions which are specific diseases (Ceusters & Smith, 2015). According to (Scheuermann et al., 2009), a disease is “a disposition to undergo pathological processes that exists in an organism because of one or more disorders in that organism”. Accordingly, *cco: disease* is defined by the agent module of CCO as a subclass of *bfo: disposition*.

We reused the Disease Ontology (DO) to provide a standard representation and unified classification of human disease types. DO is an open-source ontology developed initially in 2003 (Schriml et al., 2011) to provides a definition for each disease in order to unify the representation of diseases among various terminologies and vocabularies and to enable their consistent use and application in the biomedical field. The DO semantically captures disease terms used across different vocabularies such as MeSH, NCI’s thesaurus, ICD, SNOMED CT, and OMIM.

In DO, diseases are organized under eight main nodes; disease by anatomical entity (e.g. cardiovascular system disease), disease of metabolism, physical disorder, syndrome (e.g. Wolfram syndrome), genetic disease, disease of cellular proliferation (e.g. cancer), disease by infectious agent (e.g. anthrax), and disease of mental health. Syndromes are defined as “a disease characterized by a group of signs and symptoms that occur together and characterize a particular abnormality”. In POLARISCO, we reused DO’s categorization of diseases as shown in Figure 6.

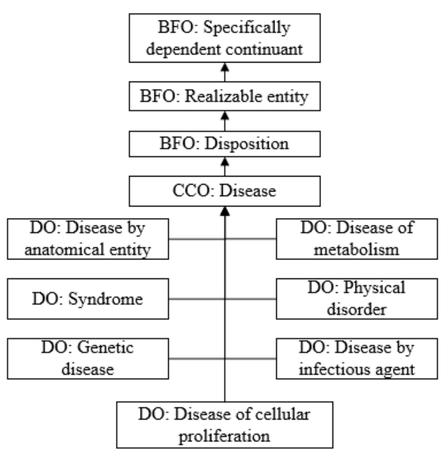

Fig. 6. Classification of diseases in POLARISCO.

To represent healthcare resources, we reused classes from the eagle-i resource ontology (ERO) (Segerdell et al., 2010), a modular suite of ontologies that uses BFO as top-level ontology and reuses the Biomedical Resource Ontology (BRO) (Tenenbaum et al., 2011) in order to represent biomedical resources. In POLARISCO we focus on ERO's instruments module in order to have a means of specifying the medical equipment available in given hospitals. *ero: instrument* is a subclass of *bfo: material entity*. In POLARISCO, we *medical device* as a child of *cco: medical artifact* representing types of resources. It is defined in accordance with (World Health Organization, 2017) as: "An instrument, apparatus or machine that is used in the prevention, diagnosis or treatment of illness or disease, or for detecting, measuring, restoring, correcting or modifying the structure or function of the body for some health purpose". We then defined three types of medical devices. First, the "*diagnostic device"* is any type of equipment or tool used in a hospital for diagnosing a patient's condition (e.g. medical imaging machine, pulse oximetry). Second, "*treatment device*" is any device used to provide therapeutic benefit for a certain disease, for example, to restore the function of affected organs or tissues within the body (for example surgical machines, infusion pumps, medical lasers). Third, a "*life support device*" is any device that aims to maintain the bodily function of a patient (e.g. dialysis machine, incubator). We hereby reused the classes of ERO under "*medical device*" and following the three identified categories, as shown in Figure 7.

Fig. 7. Classification of medical devices in POLARISCO.

Concerning medical staff, the different specialties are already defined as roles in the healthcare units module of POLARISCO as depicted in Figure 8.

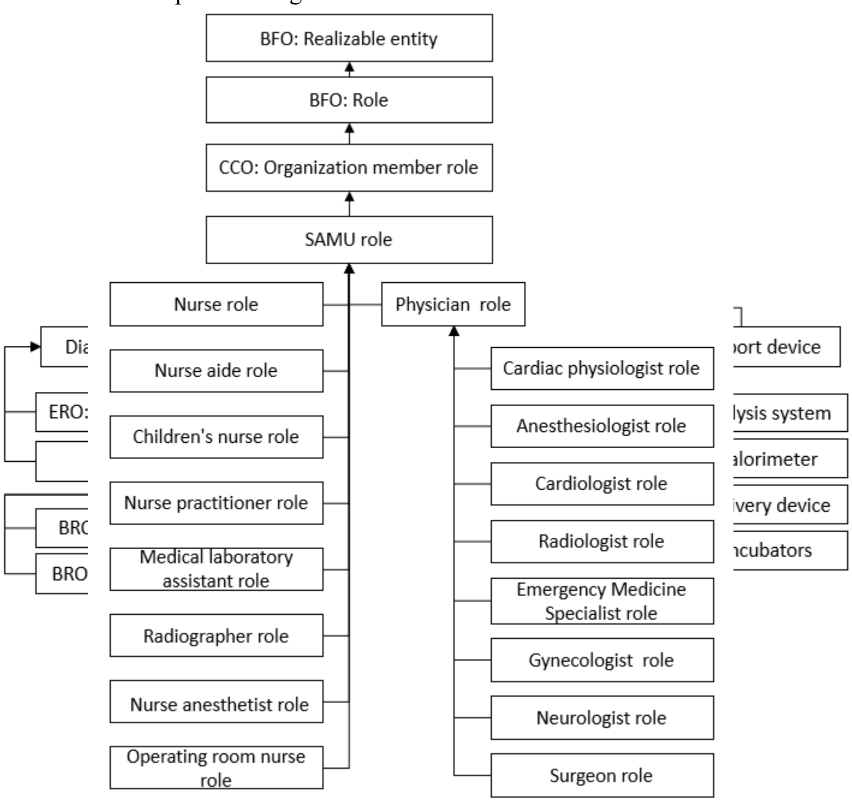

Fig. 8. Classification of medical staff in POLARISCO.

To match diseases and the required resources, we defined an act of treatment as a subclass of *cco: act*. An act of treatment is subdivided into different types; act of nursing, act surgery, and so on. Then, we defined the relationship "needs" to associate each disease with the required act or acts of treatment. Each healthcare unit and each medical device is associated with specific acts of treatment in which it participates. For instance, an act of cardiovascular surgery has participant a cardiothoracic surgeon and an operating room. In fact, a medical device cannot be used without the intervention of specific staff. Accordingly, we linked every act of treatment to a corresponding set of medical devices and the associated staff capable of using them. For instance, to diagnosis a heart disease in a given hospital, the physician needs a cardiac computerized tomography (CT) scan. To perform the latter, both a CT scanner and a radiographer should be available. To highlight the correlation between disease and medical resources, Figure 9 demonstrates an example of the required resources for cardiomyopathy surgery. To realize an act of surgery in terms of specialist physicians, a cardiothoracic surgeon and an anesthesiologist are essential. Concerning the assisting staff, an operating room nurse and a nurse anesthetist are needed. The operating room must be equipped with a defibrillator, anesthesia machines, and so on, where each medical device requires a hospital staff member to operate it.

In fact, in the healthcare resources ontological module of POLARISCO, we defined for each disease only the essential (non-substitutable) medical devices and specialized staff that should be available for effective treatment.

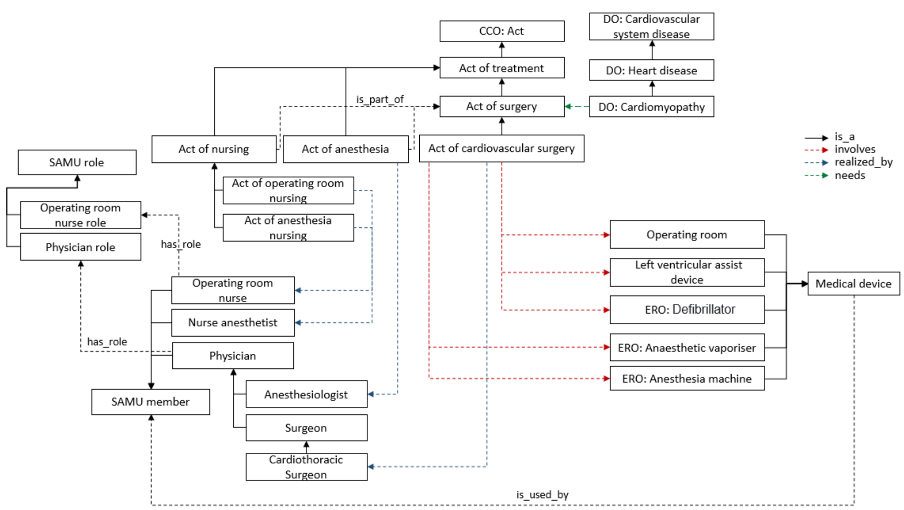

Fig. 9. Examples of the association of healthcare resources to diseases in POLARISCO.

To effectively manage the resource allocation demands over time and to calculate the wait time to receive the required care, we first designate a non-availability duration per act of treatment and second infer the counterpart per resource and staff member. Hence, we define a resource utilization metric that expresses how long a resource is needed to accomplish a certain task. This enables us to answer the question: how many minutes does an act of treatment last? To do this, we used the time module of CCO to represent temporal intervals. Then, to relate each act of treatment to its temporal interval, we defined the relationship "has_duration". For instance, an act of scanning takes thirty minutes (see Figure 10). Since an act of scanning is realized by a radiographer and involves a scanner, we can conclude that the non-availability duration of a scanner and a radiographer are also thirty minutes (which are assumed to account for turnover from one patient to the next).

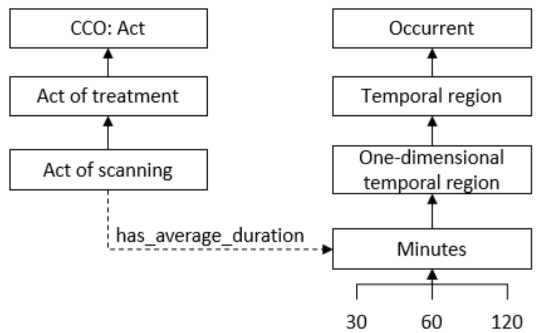

Fig. 1. Example of resource duration of use.

In what follows, we highlight the interaction among the different classes of PCC, healthcare units, and healthcare resource modules. Figure 11 shows a partial view of the whole ontology. An act of evacuation is defined as a subclass of *"cco: act"* in PCC. Both firefighters and healthcare units are responsible for ensuring the evacuation of victims, given that an act of evacuation is ordered by a DSM who chooses the hospital destination and means of transport (for example, ambulance). The DSM is affiliated to the healthcare unit and has role *"DSM role"*. The different healthcare unit members are agent in *pcc: hospital*. Then, in an act of evacuation, a victim is transported to a hospital. Both *"victim"* and *"hospital"* are already defined in PCC as subclasses of *cco: person and cco: artifact*, respectively. Moreover, every medical device is used by a staff and located in a specific hospital.

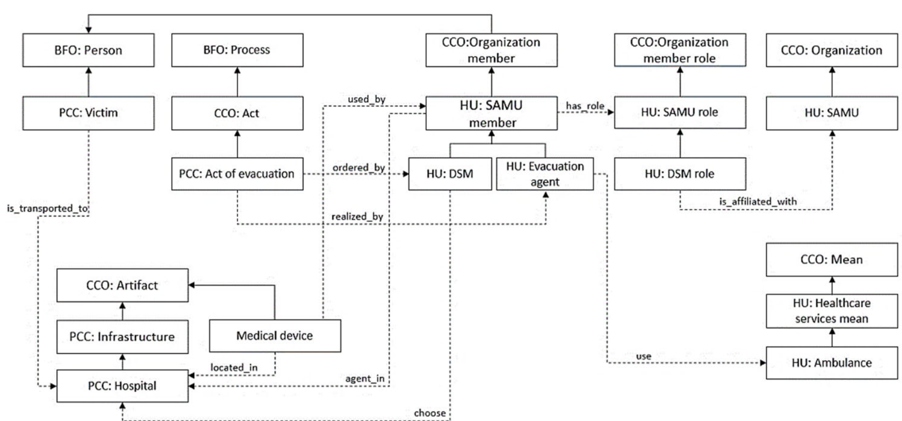

Fig. 2. Interaction among PCC, healthcare units, and healthcare resources modules.

To summarize, the resulting healthcare resources ontological module of POLARISCO is a combination of classes already existing from biomedical ontologies (DO and ERO), classes from PCC and healthcare units module, and classes we specifically created in this module in order to assign for each disease the needed healthcare resources.

5.2. Syntax and definitions

In this subsection, we present a formal definition of the annotations that will be used when elaborating the proposed algorithms. Here:

V is the set of victims to be evacuated where $V = \{v_1, v_2 \dots v_n\}$.

H is the set of activated hospitals by the White plan where $H = \{h_1, h_2 \ldots h_n\}$.

We consider that the triage site is the starting point to query the system for available hospitals to transport the victims.

We consider that the capacity of each transport means is one victim at any given time and that victims are evacuated one by one. We assume also that there is an available transport means to transfer v_i to h_j for each i, j.

t_{hi} is the transfer time needed to transport a victim v from the triage site to the targeted hospital h_i.

We consider t_{hi} a static variable already known and retrieved from the SINUS database.

$t_{arrival}$ is the arrival time at the hospital.

R_{hi} is the set of initial resources of a hospital h_i.

Inj is a set of injuries where $Inj = \{inj_1, inj_2 \ldots inj_n\}$ and inj_i is the injury of a victim v_i. If a victim has different injuries, the DSM inputs only the most urgent one.

R_{needed} is the set of needed resources for an injury inj where:

- $R_{needed}\,(inj) = \{(m_1,s_1), (m_2,s_2) \ldots (m_n,s_n)\}$
- (m_i, s_i) is the ordered pair of medical device and staff that should be available at the same time in a hospital h for an injury inj where:
  - $m_i \in M = \{m_1, m_2 \ldots m_n\}$.
  - $s_i \in S = \{s_1, s_2 \ldots s_n\}$.

$t_{duration}$ is the non-availability duration of a material m or a staff s for a given treatment/patient.

WT_h is the set of wait times of the (m, s) resource pairs to be used in a hospital h, where $WT_h = \{wt_{h1}, wt_{h2} \ldots wt_{hn}\}$

Max_{wth} is the wait time in a hospital h

A_h is the totality of relevant resources available in a hospital h.

RH is the list of ranked hospitals such that $RH \subseteq H$.

5.3. Victim evacuation algorithms

When the injury of the victim is provided to the SINUS system and the search for the most appropriate hospital is initiated, PROOVES proceeds to compute the availability and wait time of the salient resources in order to produce the data needed to perform the multi-criteria decision analysis. This step is done using the first "Hospital ranking" algorithm.

As input, the algorithm requires the victim's injury and the list of the hospitals activated by the White plan and their respective initial resources and transfer times, all of which can be retrieved from the SINUS database. The algorithm then searches for the needed resources in the form of sets of pairs of material entities and medical staff by querying POLARISCO. Afterward, the algorithm checks if the pairs of these resources are available or not for each hospital by examining its list of initial resources. If a pair of resources is available, the number of available resources in this hospital is incremented by one and the algorithm computes the wait time for use of these resources on the basis of the difference between the non-availability duration of each resource and the arrival time of the victim to the hospital. In fact, the system looks for the resource that has a minimum wait time. For instance, both a surgeon and an operating room are needed for a surgery and there are three operating rooms and four surgeons in the hospital (see Figure 12). Accordingly, the system will first, choose the surgeon and the operating room with a minimum wait time. Second, it will select the maximum wait time of the two of them, because one resource cannot be used without the other. It then considers the wait time of the previous victim using the same resource.

Afterward, the transfer time is deducted from the wait time. Once the algorithm has computed the wait time of all available resources, the maximum value is selected.

The transfer time, the availability, and the maximum wait time are the input parameters of the AHP method. Its output is a ranked list of hospitals. This list is displayed to the DSM so that he can make the final choice. The pseudo-code of the "Hospitals' ranking" algorithm is provided in Listing 1. Once the DSM has selected the hospital to which the victim will be evacuated, the system updates the wait time of the resources that will be used to treat the victim using a second algorithm, called "Hospital update". The pseudo-code of the second algorithm is provided in Listing 2.

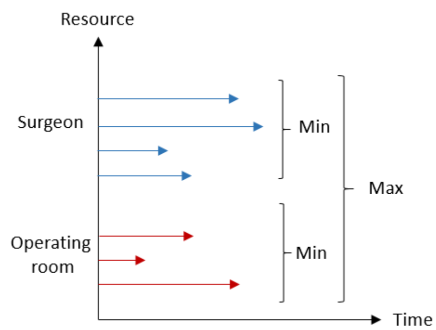

Fig. 3. Example of wait time computing.

To summarize, the two algorithms process eight steps, as shown in Figure 13:

(1) Get the victim's injury.
(2) Query the needed resources of the identified injury from POLARISCO.
(3) Get the hospitals' resources.
(4) Check the resources' availability in each hospital.
(5) Get the transfer time.
(6) Calculate the wait time to use a couple of resources
(7) Rank the hospitals using AHP
(8) Update the resources of the selected hospital.

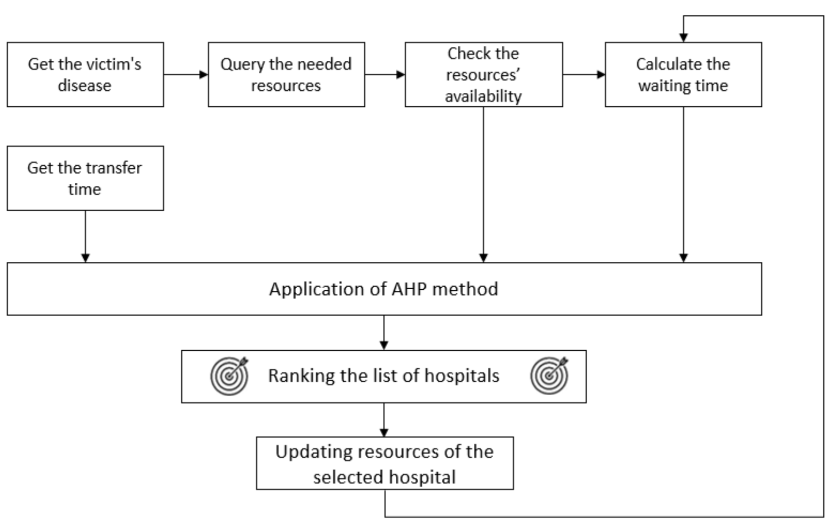

Fig. 4. The different steps of the PROOVES algorithm process.

Algorithm 1: Algorithm Hospitals' ranking

Input :

$V = \{v_1, v_2, v_3 \ldots v_n\}$: Set of victims to be evacuated
$H = \{h_1, h_2, h_3 \ldots h_n\}$: Set of activated hospital
R_{h_i} : Set of initial resources of a hospital h_i
inj: Victim's injury
t_{h_i} : Transfer time to a hospital h_i
$POLARISCO$: The global ontology

Output :

RH: List of ranked hospitals

Variables :

$R_{needed} = \{(m_1,s_1),(m_2,s_2) \ldots (m_n,s_n)\}$: set of the needed resources for a v_i including Staff s and Materials m
A_h: Number of needed resources available in h
$t_{duration}$: non-availability duration of a resource
$WT_h = \{wt_{h_1}, wt_{h_2}, wt_{h_3} \ldots wt_{h_n}\}$: set of resources' Wait time in h_i
Sum_{wt_h}: Sum of the wait time of the needed resources
AVG_{wt_h}: wait time of all the needed resources in h_i
$t_{arrival}$: Arrival time of the victim to the hospital
t: Time period index

begin
  Initialize a list $R_{needed} \longleftarrow \{\}$;
  Initialize a list $WT_h \longleftarrow \{\}$;
  $A_h =$ null;
  $t_{M_h} =$ null ;
  $t_{S_h} =$ null;
  foreach $v \in Victims$ **do**
    $inj \longleftarrow getInjury(v)$;
    $R_{needed} \longleftarrow getResources(d, POLARISCO)$;
    foreach $h \in H$ **do**
      $t_h \longleftarrow getTransferTime(h)$;
      $t_{arrival} \longleftarrow t + t_h$;
      $R_h \longleftarrow getInitialRessources(h)$;
      foreach $(m_i, s_i) \in R_{needed}$ **do**
        if $(m_i \in R_h) \&\& (s_i \in R_h)$ **then**
          $A_h \longleftarrow A_h + 1$;
          $M_a \longleftarrow getAvailableMaterial(h)$;
          $S_a \longleftarrow getAvailableStaff(h)$;
          $t_i \longleftarrow max\{min(t_j | j \in M_a), min(t_j | j \in S_a)\}$;
          if $t_i < (t_{i-1} + t_{duration})$ **then**
            $t_i \longleftarrow t_{i-1} + t_{duration}$;
          $wt_h \longleftarrow t_i - t_{arrival}(v)$;
          $WT_h \longleftarrow push(wt_h)$;
      $Max_{wt_h} \longleftarrow max(WT_h)$;
    $RH \longleftarrow AHP(t_h, A_h, Max_{wt_h})$;
    return (RH);

Algorithm 2: Algorithm Hospitals' update

Input :
$SelectedHospital$ = The hospital selected by the DSM from the list of ranked hospitals RH
$H = \{h_1, h_2, h_3 \dots h_n\}$: Set of activated hospital
R_{h_i} : Set of initial resources of a hospital h_i

Variables :
$R_{needed} = \{(m_1,s_1),(m_2,s_2) \dots (m_n,s_n)\}$: set of the needed resources for a v_i including Staff s and Materials m
$t_{duration}$: non-availability duration of a resource
t: Time period index

begin
find $SelectedHospital$ in H;
foreach $(m_i, s_i) \in R_{needed}$ **do**
$M_a \longleftarrow getMaterial(SelectedHospital)$;
$S_a \longleftarrow getStaff(SelectedHospital)$;
$M_{min} \longleftarrow min(t_i/i \in M_a)$;
$t_{M_{min}} \longleftarrow t_{M_{min}} + t_i$;
$S_{min} \longleftarrow min(t_i/i \in S_a)$;
$t_{S_{min}} \longleftarrow t_{S_{min}} + t_i$;

6. Implementation and use-case evaluation

In the following, we will assess the performance of the PROOVES service using a case study.

6.1 Pairwise comparisons and consistency check

The AHP method will be applied to rank the different hospitals from most to least appropriate. The methodology involves the application of the steps as presented in what follows. It should be noted that the first five steps are applied just once because the criteria weights are fixed by the emergency specialists from the start. Once the consistency of the pairwise comparison has been checked and validated, the alternatives may be analyzed and then ranked.

Step one: Structuring the problem

The problem to be addressed is structured in a hierarchical model, as depicted in Figure 16. Level one represents the goal, level two represents the different criteria to be applied, level three represents the alternative hospitals.

- Goal: Identify the most appropriate hospital to which to transport the victim
- The hospital ranking depends mainly on three criteria:
  - The transfer time (c1).
  - The resource availability (c2).
  - The wait time to receive medical care (c3).
- Alternatives: the possible alternatives are the list of Paris hospitals activated by the White plan when responding to the November 13, 2015 terrorist attacks.

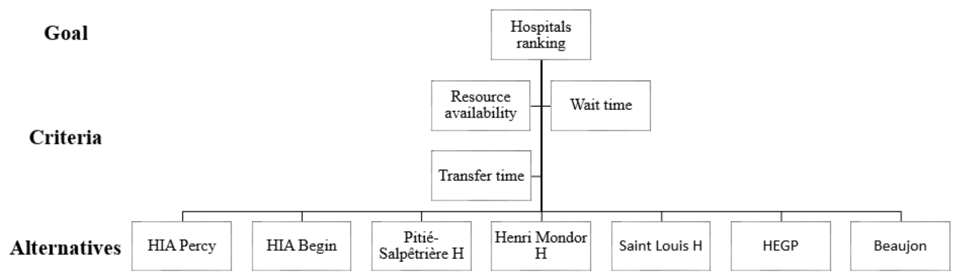

Fig. 5. Hierarchical model.

Step two: Priority calculation

Each criterion is evaluated relative to the others on the basis of a Saaty one to nine scale (see Table 1). The pairwise comparison matrix A is constructed accordingly. The values of the following pairwise comparison are made by emergency specialists and more specifically by the DSM. We see that availability and wait time are more important than transfer time, and that availability is more important than wait time.

Table 2. Pairwise comparison of the different criteria

	Transfer time	Resources availability	Wait time
Transfer time	1	1/7	1/5
Availability	7	1	3
Wait time	5	1/3	1

$$A = \begin{pmatrix} 1 & 0{,}142 & 0{,}2 \\ 7 & 1 & 3 \\ 5 & 0.333 & 1 \end{pmatrix}$$

Step three: Normalization

In order to obtain the weight of each criterion, the sum of each column is calculated (see Table 2). Normalization of the pairwise comparison matrix is then performed by dividing the value of each cell by the sum of the values in the corresponding column.

Table 3. Normalization of the pairwise comparison matrix A

	Transfer time	Resources availability	Wait time
Transfer time	0.077	0.096	0.476
Availability	0.538	0.678	0.714
Wait time	0.384	0.225	0.238

Step four: Priority vector calculation

The weight of the different criteria is computed using the priority vector w that consists of calculating the average of the rows (see Table 3). We can observe from the criteria weight rank that the mentioned preferences are respected.

Table 4. Calculation of the priority vector w

	Transfer time	Resources availability	Wait time	w	Rank
Transfer time	0.077	0.096	0.476	0.073	3

Availability	0.538	0.678	0.714	0.643	1
Wait time	0.384	0.225	0.238	0.282	2

Step five: Consistency check

Before proceeding to the alternatives analysis step, it is essential to make sure that the criteria weights make sense and there is no contradiction in the pairwise comparisons. Accordingly, the system consistency is checked by calculating the consistency index (CI) and the consistency ratio (CR). This feature is generally regarded as one of the most advantageous features of the AHP. To carry out this step, we start by calculating the weight sum vector Aw and the average consistency vector λ_{max}. Then, the CI is determined where n is the number of criteria.

$$Aw = \begin{pmatrix} 1 & 0{,}142 & 0{,}2 \\ 7 & 1 & 3 \\ 5 & 0.333 & 1 \end{pmatrix} \begin{pmatrix} 0.073 \\ 0.643 \\ 0.282 \end{pmatrix} = \begin{pmatrix} 0.22 \\ 2 \\ 0.861 \end{pmatrix}$$

$$\lambda_{max} = \frac{\left[\frac{0.22}{0.073} \quad \frac{2}{0.643} \quad \frac{0.861}{0.282}\right]}{3} = 3.058$$

$$\lambda_{max} = 3.058$$

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{3.058-3}{3-1} = 0.029$$

$$CR = \frac{CI}{RI} = \frac{0.029}{0.58} = 0.05 \leq 0.10$$

Since the value of CR is less than 0.10, we can assume that the judgments are acceptable and consequently that the system is consistent. To apply AHP to rank the different hospitals, their inputs should be computed.

6.2 AHP inputs

We used data from November 13, 2015, terrorist attacks in Paris to test the usability of the proposed approach. We assumed a total of thirty victims that need to be evacuated in an interval of two hours, and seven hospitals, as activated by the White plan. To test the capacity of PROOVES to manage the resource allocation and wait time, we supposed that all the victims have the same injury and subsequently need the same resources. In particular, the victims were diagnosed as having cardiomyopathy and as needing to be transferred to a hospital to receive cardiovascular surgery. First, the system starts by querying POLARISCO to determine the needed healthcare resources. Figure 14 shows the SPARQL query and the obtained results. The needed resources for cardiomyopathy include under staffing: a cardiothoracic surgeon, an anesthesiologist, and an operating-room nurse, and under equipment: an operating room equipped with a defibrillator and an anesthesia machine.

SPARQL query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX ero: <http://www.ontologyrepository.com/CommonCore/Upper/ExtendedRelationOntology#>
PREFIX ao: <http://www.ontologylibrary.mil/CommonCore/Mid/AgentOntology#>
PREFIX polarisco: <http://www.semanticweb.org/linda/ontologies/2018/11/POLARISCO#>
SELECT  ?organization_member_role ?Medical_device
      WHERE {polarisco:Cardiomyopathy polarisco:needs  ?act_of_treatment.
             ?act_of_treatment  ero:realized_by  ?organization_member_role.
             ?act_of_treatment polarisco:involve  ?Medical_device.
             ?Medical_device ao:is_used_by ?organization_member_role }
```

organization_member_role	Medical_device
Operating_room_nurse_role	Defibrillator
Anesthesiologist_role	Anesthesia_machine
Cardiothoracic_surgeon_role	Operating_room

Fig. 6. SPARQL query and results of the needed resources.

Once the needed resources are known, we move to the AHP preprocessing step. For each hospital, the system obtains its resources and then determines the number of needed resources available in the hospital, obtains its transfer time, and calculates the maximum wait time. These computed values represent the inputs to the AHP method (see Table 4).

Table 5. Criteria values of the different alternatives

Alternative	Transfer Time	Availability	Wait time
HIA Percy	50	6	135
HIA Begin	30	6	135
H Pitié-Salpêtrière	20	6	145
H Henri Mondor	45	6	135
H Saint Louis	10	5	155
H HEGP	45	5	135
H Beaujon	40	4	125

6.3 Ranking of alternatives

The next process is repeated until all victims have been evacuated. That is to say, a new request is generated each time a new victim needs to be evacuated. In the following, we explain in detail just one of the tests that need to be applied.

Step six: Alternatives weights

The priority vector is calculated to rank the different hospitals. Table 5 represents the overall priority vector of the different hospitals with respect to the pairwise comparison of the different criteria.

Table 6. Overall priority vector

Alternative	Transfer Time	Availability	Wait time	Somme
HIA Percy	3,65	3,858	38,07	45,578
HIA Begin	2,19	3,858	38,07	44,118
H Pitié-Salpêtrière	1,46	3,858	40,89	46,208
H Henri Mondor	3,285	3,858	38,07	45,213
H Saint Louis	0,73	3,215	43,71	47,655

H HEGP	3,285	3,215	38,07	44,577
H Beaujon	2,92	2,572	35,25	40,742

Step seven: Ranking of alternatives

Table 6 shows the ranking of the different hospitals. The hospital with the highest priority is the most suitable hospital to transport the victim v_i at the time t. These results are displayed to the DSM to make his final decision and choose the hospital destination, which in this case is "*Beaujon Hospital*". Once the choice is made, PROOVES updates the wait times for the hospital resources that will be used.

Table 7. Hospital ranking

Ranking	Alternative
1	H Beaujon
2	HIA Begin
3	H HEGP
4	H Henri Mondor
5	HIA Percy
6	H Pitié-Salpêtrière
7	H Saint Louis

6.4 Discussion

To validate our approach, we compared the traditional process of victims' evacuation during disaster response to the proposed one. Figures 15 and 16 depict the evolution of victim wait times for the needed resources in the different hospitals after the evacuation of thirty victims (thirty scenarios) with and without using PROOVES, respectively.

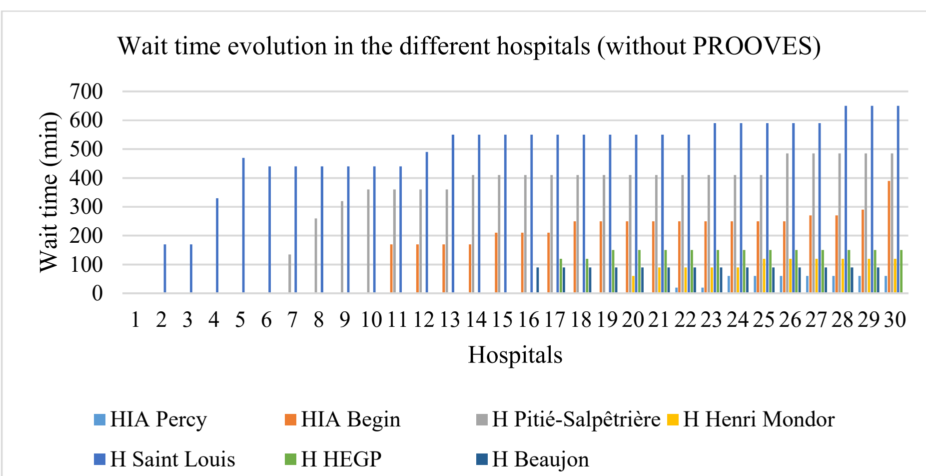

Fig. 7. Results of the wait time evolution in the different hospitals without using PROOVES.

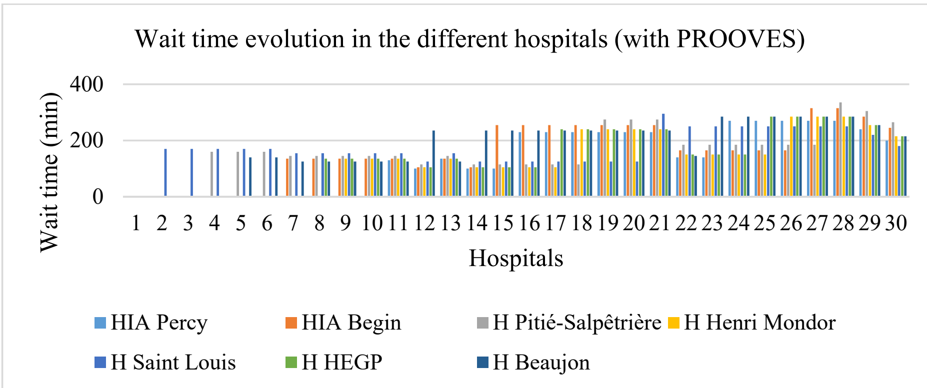

Fig. 16. Results of the wait time evolution in the different hospitals using PROOVES.

In each scenario, a new request is generated each time a new victim is to be evacuated and the system ranks the list of hospitals based on their number of available resources, wait time and transfer time from the highest to the lowest levels, and then updates the wait time of the selected hospital so that it will be considered in the next iteration. Our choice of evacuating victims that suffer from the same injury is made in order to evaluate the system's capability to not overwhelm any single hospital. As is to be expected, we observe that the wait time increases as the number of evacuated victims increases.

The overall comparison between the classical victims' evacuation process, based on stakeholders' experience, and PROOVES during large-scale disaster response shows clearly the superiority of PROOVES. Without PROOVES, the closest hospitals to the disaster site are overwhelmed and their wait time exceeds ten hours compared to the farthest hospitals. This is due to the lack of real-time data related to resource availability. Using PROOVES, the graph shows that the proposed approach outperforms in terms of wait time and the hospital wait time is balanced after almost every ten iterations. Indeed, this is due to the real-time data related to the number of hospitals and also to the number of available resources per hospital and their wait time. These data are exploited and then used to rank the hospitals.

These findings highlight clearly that the victims are transferred to the most appropriate hospital and that is achieved in a balanced manner. This can enhance the reaction to the variation of the wait time, improve the evacuation process from the perspective of the victim, and reflect the operability of the proposed system. Moreover, the application of the AHP for selecting the most appropriate hospital can improve the quality of the results and shorten the decision-making process.

7. Conclusion

The victims' evacuation process must be successfully carried out to ensure the victims' safety. Making the best decision regarding to which hospital a victim should be transported is a very important task. However, decisions regarding the allocation of victims are complex due to the number of criteria that need to be considered. In this work, we have proposed an ontology-based multi-criteria decision support approach for victim evacuation. The provided algorithms enable us to address the dynamic changes in the availability of healthcare resources and wait times. These data are analyzed by the MCDM method AHP in order to rank the list of hospitals from the most appropriate to the least appropriate according to the victim's needs. The AHP consistency analysis and evaluation index reveal that the approach is consistent. Moreover, we provided a comparison between the classical process and PROOVES and showed the advantages of this latter in ensuring a balance between the different hospitals.

The future direction of our work consists of, first, specifying the order in which the healthcare resources should be used to treat the victims. This may lead to increased accuracy in the wait time calculation. Second, the proposed multi-criteria decision support will be more effective if a way can be found to consider an estimate of a victim's survival chances and of how their condition may deteriorate, for such determinations may aid in determining the priorities for evacuation.

Acknowledgment

This research was conducted as part of the POLARISC project. It was funded by the European regional operational program FEDER/FSE Midi-Pyrénés et Garonne 2014-2020 responding to the Easynov2016 call.

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