On Application of Ontology and Consensus Theory to Human-Centric IoT: an Emergency Management Case Study

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***Abstract*—Involving human in the loop of IoT offers numerous advantages to a wide range of applications including emergency management. However, building a collaborative system that is capable of effectively responding to an emergency in timely manner introduces a number of fundamental challenges. It requires effective discovery of crowds for a given emergency and also successful communication of information across discovered crowds of different domains. In addition, the crowds may not agree on a single solution when group decision making is required. Therefore, consensus management such that consensus is achieved in a timely manner is yet another challenge. In this research, we propose a framework that uses ontology-based discovery and data modelling and consensus theory to tackle the aforementioned issues. We demonstrate the efficiency of the discovery and consensus management approach via a case study and set of experiments, respectively.**

I. Introduction

With proliferation of Internet of Things (IoT) applications, humans and things need to operate together more productively. Involving human in the loop, although offers unique opportunities to IoT solutions, is tremendously challenging [1]. This is because in an IoT system, modelling human capabilities and their behaviours and enabling effective communication among them and the information system is a complex task. Therefore, new research is necessary to identify creative solutions for involving human in different IoT applications. To this end, in this paper we focus on such solution for emergency management system as a case study.

Responding to disaster of any kind requires continuous participation of experts from different areas. This requires successful communication of information across people from different domains and likewise across different information systems. One of the major challenges in this context is lack of common understanding between involved experts and machines. For example, a term such as “distress” has a different meaning in information system domain compared to transportation domain. This inadequacy results in miscommunication leading to huge impact including loss of lives. In addition, this heterogeneity makes the symmetric attribute-based matching between requirements and available experts and resources nearly impossible.

Moreover, if we assume experts and volunteers can communicate efficiently, we still have the problem of conflict management. There will be a situation where involved crowds have different opinions on a type of action or solution required to respond to an emergency. This issue is even more challenging to address when crowds are distributed across multiple locations, communication media is not stable, and there is a time constraint on reaching the consensus. Therefore, this research aims at tackling these two major challenges by proposing a framework which uses ontology to overcome miscommunication challenges and utilizes consensus theory to manage conflicts.

To achieve semantic interoperability, the framework uses ontologies for data modeling and reasoning. Such data modeling enables semantic interoperability by providing common specific terminologies that explicitly describe concepts. Hence, it will lead to more efficient management of experts and volunteers who are involved in the process of responding to disasters. This has multiple benefits:

- Enabling effective automated reasoning, and
- Presenting an efficient ontology-based discovery of required crowds and resources that matches a particular disaster.

Moreover, to tackle the problem of consensus management for collaborative emergency response, the framework converges diverse opinions to reach an agreement based on the collaborative knowledge sharing between discovered crowds. To reach the consensus in an emergency when time is a constraint and connections among crowds are unreliable, this research investigates impacts of number of crowds and number of connections among them on convergence time.

The remainder of the paper is organized as follows. First, Section II highlights challenges in human-centric disaster management system by presenting a case study. Then, we describe the proposed architecture along with its components in Section III. Next, in Section IV we discuss the process of ontology design for the system following by a section on our proposed consensus management strategy. Section VI presents experiments which investigate the performance of the system

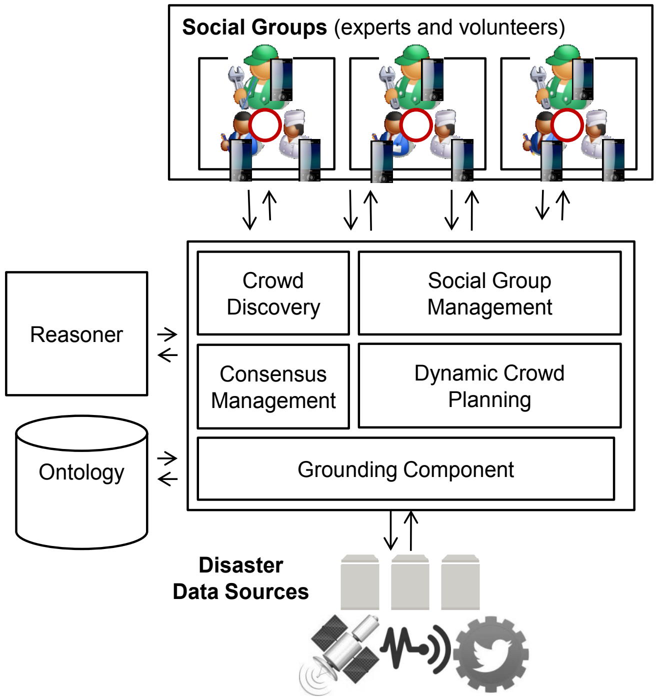


Fig. 1. Architecture's main components that enable effective crowd management in response to disasters.

and Section VII highlights the uniqueness of our approach compared to similar studies. Finally, the paper concludes suggestions on future directions.

II. Motivation Scenario and Challenges

In this section, a case study is described that helps us to demonstrate the effectiveness of the proposed approach. Our case study is a large research facility with a large number of rooms. A researcher is working in one of the rooms. It is late at night and no one is around except few researchers far-off in another rooms in either the same or different buildings. The researcher suddenly starts experiencing a distress (raising blood pressure or abnormal heart beat rate) situation. His smart phone detects that the researcher is in distress. The phone determines the exact room through location-sensing using the Wifi-routers located in the building. The phone then broadcasts an emergency message along with location. The message has to be received by other researchers with necessary skills and access to required resources who can help the researcher. Matching the events requirements to the appropriate experts is the first challenge we face. In addition, the discovered experts might have diverse opinions on how to treat the distress situation e.g., transferring the patient to the nearest medical center by private car, or call the ambulance, or even the choice of medication. However, the time is against them and they need to make a decision as early as possible. How they can converge different opinions to make a decision in timely manner and how reliability of the decision is another challenge to overcome.

III. Architecture

The main goal of the architecture is to simplify management of experts and volunteers who are involved in process of the emergency response. The proposed architecture is depicted in Figure 1 and its main components are described below.

1) **Disaster Data Sources:** Datasets are raw data collected (for example sensors and social media feeds) from data sources and are source of truth. They provide information regarding several aspects of an emergency situation including affected region and the people that occupy it, impacted infrastructure, the severity of damage, and response requirements.
2) **Social Group Management:** This component builds the groups of different experts and volunteers based on:
   a) The type and location of disaster, impacted people and infrastructure information, and
   b) The expertise and volunteer forces available.

   This component is also responsible for building a social group and requires ad-hoc communication systems that people can use through their mobile devices to share data, information, and thoughts in the process of emergency response.
3) **Ontologies:** provide the domain specific emergency response terminologies and is the key element for the success of semantic interoperability and match-making. Furthermore, they use formal semantics to connect machine and human terminologies. We used Web Service Modeling Ontology (WSMO) [2] for describing our ontologies.
4) **Reasoner:** It is used by semantic queries on the ontology. We used Web Service Modeling Language (WSML) reasoner [3] for this component.
5) **Crowd Discovery and Semantic-based Reasoner:** This component receives the disaster information and discovers people that can get involved in a response team. It uses an ontology-based reasoner to improve precision and avoid low recall caused by lack of common understating of concepts and terminologies that have been used to describe the expertise of people, disaster types and response requirements.
6) **Grounding Component:** This component is built to transform semi-structure data from data sources to a semantic model. During the communication of a semantic-level and a syntactic-level, two directions of data transformations (which is also called grounding) are necessary. In this context we are interested in a direction which converts semi-structured data sources to semantic data. We utilize mapping extension offered in grounding package of WSMO that defines how XML instance that is obtained from data sources is transformed to a semantic model. For more detail, refer to our previous research work [4].
7) **Dynamic Crowd Planning:** This component dynamically assigns tasks to experts and volunteers and defines their sequences.
8) **Consensus Management:** In circumstances where all

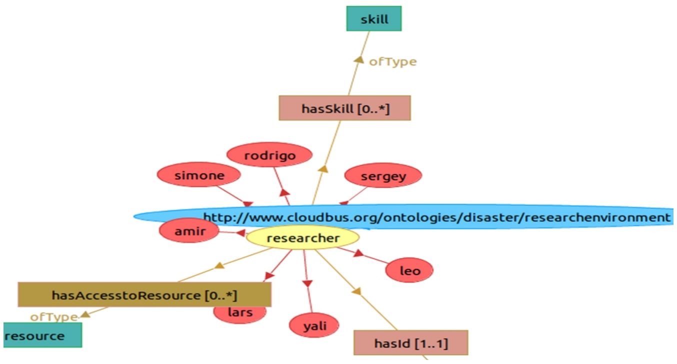


Fig. 2. Researcher concept and its properties and instances.

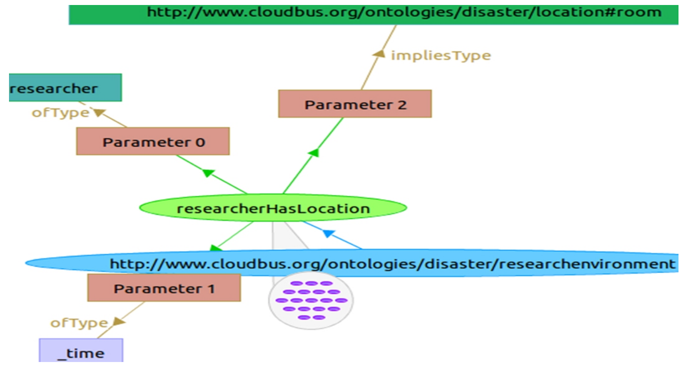


Fig. 3. A WSML relation that links a researcher to a location for a given time.

experts have been asked to collaborate to make a decision on a next action, the consensus process converges diverse opinions to reach an agreement based on the collaborative knowledge sharing between discovered experts. This component guarantees that even with existence of conflicts, a consensus will be reached.

IV. Designing Ontology for Disaster Management System

As mentioned earlier, this research aims at tackling the problem of semantic interoperability between experts or information systems for emergency management systems. We achieve this by developing ontologies that enable semantic interoperability by providing the common specific terminologies that explicitly describe concepts. There are number of advantages [5] to model data via ontology (using semantic-based languages) compared to other methods such as XML, JSON, SQL, etc. This is because these languages do not have the capability of symbolizing subclass relationships. An example of such relationships for our scenario can be defining first aid kits as a subclass of medical resources. With highly-expressive ontology-based language, it is even possible to describe dynamic relationships and in general complex ideas regarding the domain data. For example, to model resources required for an emergency, a dynamic relationship of "an automobile with 4 tires is a car" can be easily modeled with such languages. In Section IV, we elaborate on this and describe how we utilize axiom to provide automated reasoning and build dynamic relationships. To build the data model for the provided scenario, we first require an ontology-based modeling framework and language. We have chosen WSMO [2] that defines a model to describe concepts based on the conceptual design set up in the Web Service Modeling Framework (WSMF). In addition we utilized Web Service Modeling Language (WSML) [3] that consists of logical formalisms, namely, Description Logics, First-Order Logic and Logic Programming, all of which are helpful for the modeling concepts involved in emergency management. WSMO ontologies provide the (domain specific) terminologies and is the key element to achieve interoperability in emergency management.

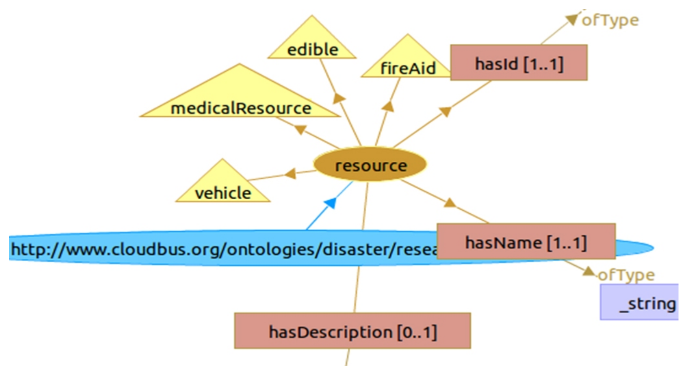


Fig. 4. Concept and sub-concepts related to resources.

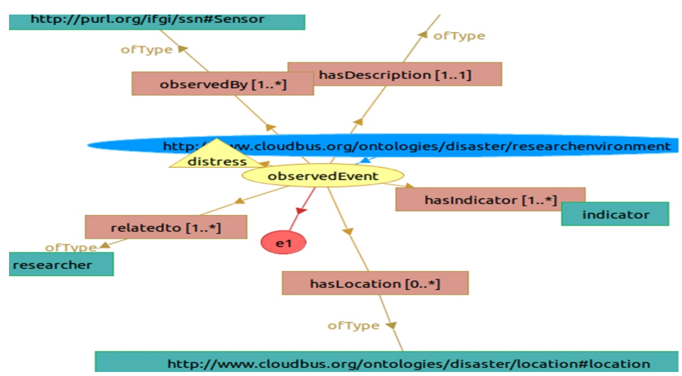


Fig. 5. Concept and sub-concepts related to events.

To develop our ontology, we extend SSN ontology [6] and utilize the conceptual model of disaster management which was developed by Kruchten et al. [7]. The model consists of four categories of concepts as follows:

A. Social Layer

This layer deals with communication and coordination among experts, volunteers, and machines (as depicted in Figure 2). For the given scenario, in this layer we define the concept of human and then sub-concept of researcher. Next, we define concept of skill, which describes capabilities of dealing with distress or disasters. This includes first aid,

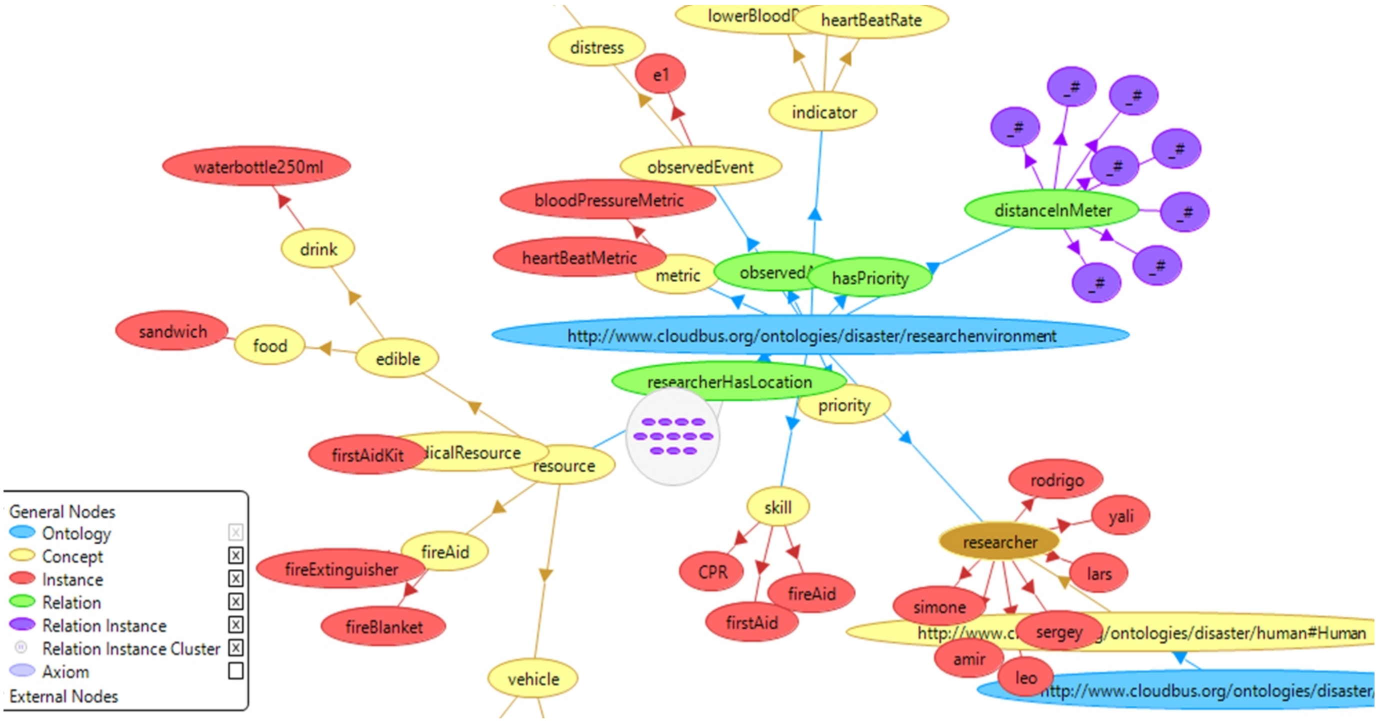


Fig. 6. Overview of the major portion of the developed ontology

CPR, fire aid, etc. Then we associate the skill to the researcher concept. In addition, researcher has access to resources whose concept is defined in other layer. The researcher concept requires more properties which are inherited from the human concept.

B. Location Layer

This layer describes a region and the people that occupy it. In this layer, we define concept of location, its properties and its sub-concepts of buildings, rooms, etc. In addition, we define a relation (as depicted in Figure 3) in WSML named "researcherHasLocation" to link a researcher to a location at a given time. In addition, to model the distance between locations, another relation called distance is created which is a sub-relation of measurement.

C. Resources and infrastructure

For this layer, we require concepts that describe resources required to response to distresses (e.g. medical emergencies). For example as shown in Figure 4, medical resource and vehicle are both sub-concepts of resources. They both have their own sub-concepts and instances which are not shown in Figure 4. Once instances of researchers are being created, we define to which resources (resource instances) they have access.

D. Events and Distresses

This layer describes events such as a disaster and its impact on people. For this layer, we focus on concepts required to model events, metrics, observations, and distresses. As it is depicted by Figure 5, each event is observed by a sensor and is at least related to a researcher and has at least one indicator and a location.

After adding necessary concepts and relations for each layer, the constructed ontology is similar to what is depicted in Figure 6. In the following section, we show how the developed ontology can be utilized for automated reasoning and crowd discovery.

E. Enabling Automated Reasoning

As we mentioned earlier, one of the major motivations behind using ontology for data modeling is enabling automated reasoning. For example, in the aforementioned scenario, it will be very helpful if we can use automated reasoning to spot or mark distresses from other observed events. A sample of such reasoning for the given scenario is presented in Table I, which identifies blood pressure observations as indicator of heart issue if it is above 180 mm. Moreover, similar logical expressions can be defined as axioms to build dynamic relationships as it was explained before. Table II shows two logical expressions and describes how they can help to dynamically add relationships to the developed ontology.

F. Crowd Discovery

In our project context, crowd discovery is the process of searching for crowds of experts whose skills closely match the one required for responding to a distress. For this purpose, we present several types of matching operations based on well-know studies [8], [9] as follows:

TABLE I
AUTOMATED REASONING TO DETECT DISTRESSES.

Query String	Result			
	Row	event	indicator	output
?event memberOf observedEvent and ?event[hasIndicator hasValue ?indicator] and ?indicator memberOf upperBloodPressure and ?indicator[observationOutput hasValue ?output] and ?output ≥ 180 implies ?event memberOf heartIssue.	1	event162432	ubp16	205
	2	event152432	ubp15	195
	3	event122432	ubp	200

- **Exact-Match:** The crowd is matched if its set of capabilities is same as the set of the distress requirements.
- **Subsumption-Match:** The crowd is matched if its set of capabilities is a subset of the distress requirements.
- **Plugin-Match:** The crowd is matched if its set of capabilities is a superset of the distress requirements.

An example of discovery result for subsumption match is presented in Table III where researchers who have either skills of CPR or first aid that are related to a distress of heart type issue are discovered.

V. Consensus Management Process

Once the crowd of experts is formed to make a decision, they should reach a consensus on the next action regarding distress situation. The trust-aware consensus process for the purpose of converging diverse contributions (i.e., opinions) is presented in Figure 7. The involved experts have to pursue the following steps respectively in order to converge to an agreement:

i) Crowds o are interconnected via an established social network, where peers interact with each other based on the existing relationships among them. The interaction network is modeled as a connected digraph, whose nodes, represent the crowds, and its edges reflect the interactions. In the initialization phase, each expert assigns the same trustworthiness level (i.e., $T_{ij} = 0$) to all its connections with other experts.

ii) The consensus process starts over the network, where the discovered experts have different opinions ($x_i(k)$) on how to react to the disaster e.g., finding the nearest medical center.

iii) Each expert begins to interact and send signals to its neighbors to update their opinions based on a trust-aware consensus protocol ($u_i(k)$). In general the idea is to converge to opinion of the most trustworthy peers as described in previous research [10]–[12]. Interested readers can refer to our previous work [12] for further detailed information on consensus protocol.

iv) The trustworthiness of each expert evolves over time. Therefore, a model to update and maintain this trust should be in place. This model works based on the cooperative knowledge sharing between crowd members. The trustworthiness levels between experts are updated based on their collaborations and interaction with other crowds.

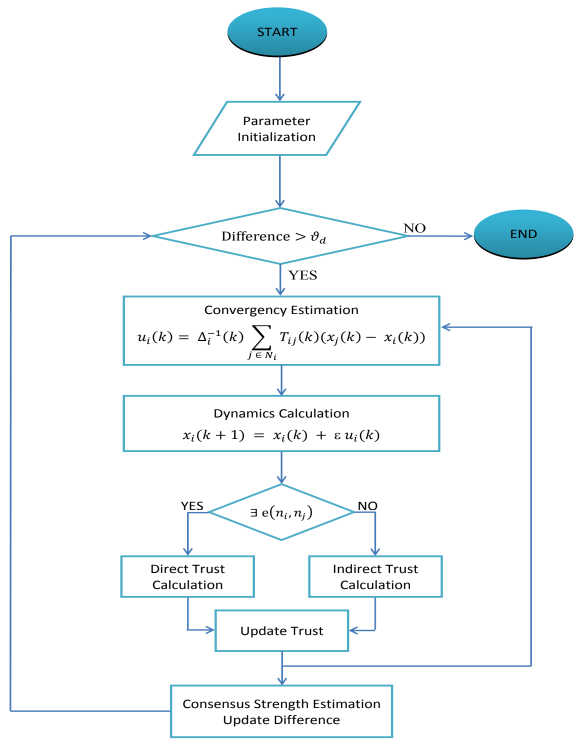


Fig. 7. Consensus Process.

v) These interactions continue until the network reaches a predefined convergence (ϑ_d). In other words, all experts agree on a certain opinion for the next action e.g., shortest route to the nearest medical center. This evaluation is guaranteed by a consensus process that converges to the most trustworthy opinion.

VI. Experimental Results

In this section, we conduct experiments to evaluate the proposed consensus management approach in the context of emergency response. The conducted experiments investigate how number of experts and connections among them in the discovered crowd affect the convergence time. These two factors of convergence time and number of connection are specifically critical in the context of emergency management. The experimental setup is firstly presented. Following this, the conducted experiments are discussed in the next two sections.

TABLE II
AXIOMS AND THEIR FUNCTIONALITIES.

Axioms	Functionality
?x memberOf heartIssue implies ?x [hasSkillRequirenments hasValue CPR, firstAid].	This WSML logical expression dynamically adds skill requirements of CPR and first aid to a distress event if it is a heart issue.
?x memberOf heartIssue and ?y memberOf car and ?z memberOf medicalResource implies ?x[hasResourceRequirenments hasValue ?y,?z].	This WSML logical expression dynamically adds medical resources as requirements for a distress event if it is a heart issue.

TABLE III
CROW DISCOVERY RESULTS.

Row	?distress	?req	?human	?humanskill
1	e1	firstAid	Lars	firstAid
1	e1	firstAid	Amir	firstAid
1	e1	CPR	Lars	CPR
1	e1	CPR	Lars	CPR
1	e1	firstAid	Simone	firstAid

A. Experimental Setup

Three different types of crowd are defined as shown in Equation (1) based on the Density Ratio ($\mathcal{DR}$), the ratio of the number of connections between experts involved in the consensus process to the total number of possible connections among them. The Crowd Type (CT) includes Weakly Connected (WC), Moderately Connected (MC), and Strongly Connected (SC).

$$Crowd\ Type = \begin{cases} WC & \text{if} \quad 10 < \mathcal{DR} \leq 40 \\ MC & \text{if} \quad 40 < \mathcal{DR} < 80 \\ SC & \text{if} \quad \mathcal{DR} \geq 80 \end{cases} \tag{1}$$

In the experiments, we vary the number of experts from 5 to 20 with a step value 5 and vary the type of crowds based on the abovementioned definition. As discussed before, involved experts have diverse opinions to react the distress situation. This diversity necessitates the definition of a difference threshold (ξ), a predefined acceptable difference agreed by all experts to converge their opinions to reach an agreement. Last but not least, the convergence time specifies how fast the involved experts can converge to make a decision to response to the distress situation. It is noteworthy to mention that making reliable decision in the shortest possible convergence time is of paramount importance for emergency response in disaster situations. Table IV presents the experimental parameters and their descriptions.

TABLE IV
DESCRIPTIONS OF SYMBOLS.

Symbols	Description
$\mathcal{N}$	Number of experts
$\mathcal{NC}$	Number of connections
$\mathcal{DR}$	Density ratio
ξ	Difference threshold
$\mathcal{T}$	Convergence time

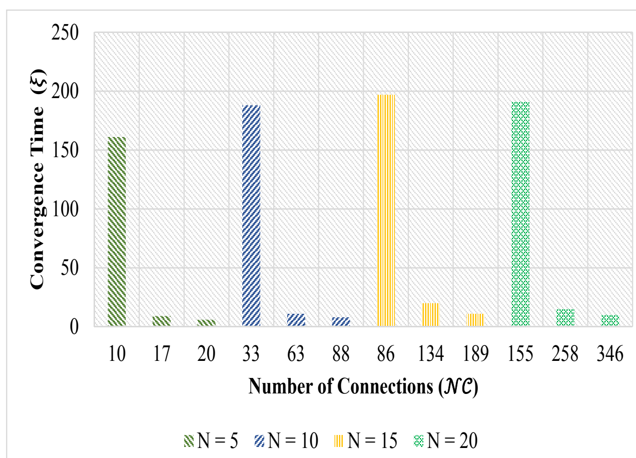


Fig. 8. Impact of number of connections on the convergence time.

B. Impact of Number of Connections

This experiment investigates how increasing number of connections affects the convergence time. For this purpose, 12 different crowds are considered in this experiment that are categorized in four groups in terms of number of experts involved. Each group has its unique difference threshold because of different distributions of the experts opinions. The acceptable convergence time is also supposed to be less than 200 time steps.

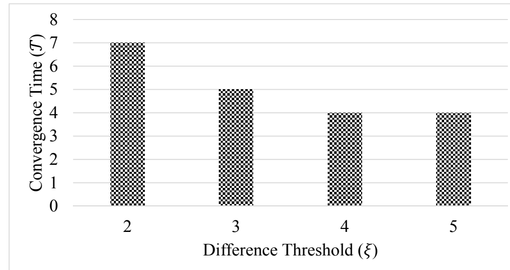
Figure 8 shows that when the number of connections increased from WC to MC and SC crowds, the convergence time is significantly shortened. This reduction is 95.3% in average when type of crowd changed from WC to SC. This observation indicates that, for each set of experts, there is a limit on the number of connections that can be lost during the emergency. If the connections cannot be recovered in such situation, the best action is to decrease number of involved crowds (but keeping the same number of connections) to decrease the convergence time. In addition, this means that when connections are not reliable or there is a limited connectivity, group decision making is not recommended as it may delay the emergency response significantly. Therefore, the result of this experiment (estimating the convergence time based on connectivity) along with information regarding expert availability and reliability of connections helps in more efficient discovery of crowds and delegation of tasks.

C. Impact of Number of Experts

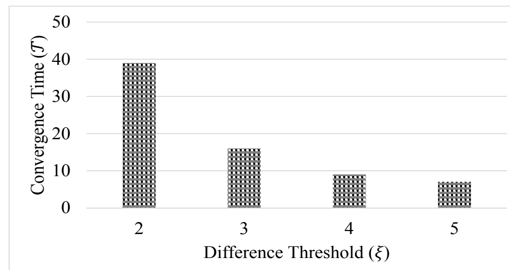
The aim of this experiment is to investigate the effect of the number of experts on the convergence time. In this experiment, the previous MC crowds are utilized and the acceptable convergence time is the same as the previous experiment. However, in contrast to the last experiment that the same difference threshold is used for all crowds to achieve the goal of the experiment. As depicted in Figure 9, increasing number of experts prolongs the convergence time to reach a decision. The speed of convergence time increment accelerates with the increase of number of experts. This increase is more pronounced when smaller values of difference threshold are considered. For example, the convergence time become 673 (time steps) and 1031 (which is beyond the acceptable range) when the crowd includes 15 and 20 experts and the difference threshold is 2. It can be concluded that smaller numbers of experts along with higher values of difference threshold increase the chance of shorter convergence time to reach consensus provided that the discovered crowd is at least MC. This improvement becomes more perceptible with increasing number of experts. This means that in a time-critical situation and when it is essential to involve a large number of crowds in the decision making process, it is recommended to set greater values for the difference threshold. Likewise, in a time-critical situation and when it is essential to make a decision with the minimum difference threshold, the best action is to minimize the number of crowds involved. Similar to the findings of the previous experiment, the information regarding the latency requirement and the minimum acceptable threshold has to pass to the discovery component. Then, it considers the trade-off between number of experts, minimum acceptable threshold, and latency requirement to select appropriate group of crowds.

VII. Related Work

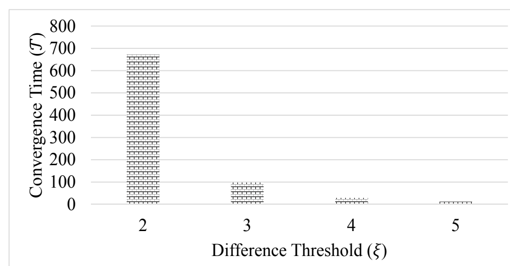
There is a large body of research on information technology systems for managing disasters of all types. These systems have been proposed for different stages of an emergency such as disaster prevention and emergency response. In addition, those systems play different roles in responding to an emergency. Here, we focus on research that helps in emergency response coordination and information integration and communication. As we discussed earlier, the use of ontology and semantic languages improve interoperability across different communities of experts responding to a disaster. Ramanathan et al. [13] developed a multi-level ontology-based modeling approach that enables collaboration across multiple teams of experts and machines in a disaster management scenario. The models are described in Web Ontology Language (OWL) [14], the semantic Web standard for metadata.



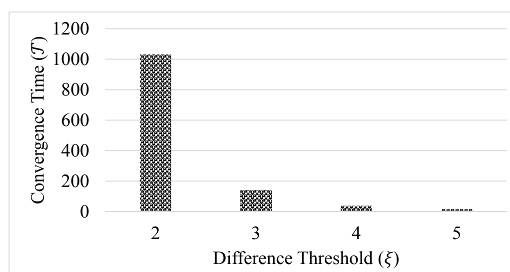
(a) $\mathcal{N} = 5$



(b) $\mathcal{N} = 10$



(c) $\mathcal{N} = 15$



(d) $\mathcal{N} = 20$

Fig. 9. Impact of number of experts on the convergence time.

In addition, there are number of researches [15]–[17] that build ontology (knowledge) of disaster management domain from multiple unstrcutued data sources in a semi-automatic way. Chou et al. [18] created an ontology structure for a disaster management website. This is because Hurricane Katrina has shown the effectiveness of employing a Web site for communication and information management once dealing with natural disasters. The ontology, which is also coded into a Web-based system, was built from multiple web page sources. Similarly, we have proposed a grounding approach [4] for converting unstructured data to ontology. In this research, unlike other researches which only focused on interoperability aspect, we have used ontology and semantic languages for crowd management (expert discovery). In addition, we have shown the advantages of adopting ontology in modeling dynamic relationships in an emergency response system through few examples.

Consensus management is a critical element of all collaborative disaster management system. The importance of consensus process has been discussed in many disaster management researches [19]–[21]. In disaster response, time is too limited, therefore Casse [20] investigated the impact of crowd culture and step-by-step consensus group decision making on consensus time. Likewise, Kapucu [22] discussed the same issue and concluded that a more balanced and similar views in groups of decision makers reduces consensus time during emergency situations. Nevertheless, to the best of our knowledge, none of previous research proposed a concrete solution to consensus management problem that can be utilized when there are both human experts and machines involved in making a decision.

VIII. Conclusions and Future Work

In this paper not only we discussed the interoperability issue in responding to an emergency, but also investigated two fundamental challenges of crowd management. First, the issue of crowd discovery was discussed and is tackled with a semantic-based discovery approach. Next, we provided a solution for reaching a consensus among discovered experts who could not agree on an action for responding to a distress. Based on the obtained results, we can conclude that when the number of connections increases, the consensus time is significantly shortened. In addition, it can be concluded that smaller numbers of experts along with higher values of difference threshold increase the chance of having shorter convergence time to reach consensus. In summary, for our system this means that if (in an emergency) number of reliable connection decreases, it is best to decrease the number of involved crowds (but keeping the same number of connections) to decrease the convergence time.

We plan to investigate crowd formation and composition considering compatibility rules derived from organizations' policies and preferences of users. In addition, another promising research topic is to study algorithms for crowd planning based on disaster priority reasoning, distance from disaster, and resource availability.

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