Fuzzy logic: A link for behavioral computer simulations of collaboration in emergency management

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ABSTRACT

Emergencies are events that vary in complexity and dynamically shift along different phases of evolution, requiring different types of participants. Emergency management is an interdisciplinary field that involves multiple organizations holding different mandates and structural chains of command. This poses a challenge for collaboration in the way strategic problems are solved at each stage of the emergency, given that they may not follow the traditional normative linear patterns of decision making. To address this query, this work explores the application of fuzzy logic to characterize the problem solving approach used – coordination, cooperation, or collaboration -, with the level of complexity of the emergency and the type of inter-organizational interaction. Of special interest here is the capacity offered by fuzzy logic to operationalize experiences and perceptions of expert emergency managers. Fuzzy logic provides the framework to model these elements under flexible patterns of interaction. In addition, fuzzy logic allows connecting diverse epistemological fields such as behavioural cognitive psychology and management, and linking them to computer sciences and systems engineering. Hence, the results from this paper presents fuzzy logic from a modeling perspective that aims to contribute to achieve an efficient inter organizational emergency management response along the different phases of the crisis, by rendering fuzzy logic models of inter organizational coordination, cooperation and collaboration, which can then be applied to develop behavioral computer simulations. The expected contribution of this document is to facilitate the interaction within and across diverse fields of study involved in emergency management, by translating and interpreting their individual contributions into fuzzy logic models that can inform and complement the interdisciplinary effort.

Keywords: Fuzzy logic, Emergency Management, Collaboration, simulation, multi-organizational problem solving, model, complexity.

INTRODUCTION

Emergencies are events that vary in complexity and dynamically shift along different phases of evolution, requiring different types of participants. Emergency management is an interdisciplinary field that involves multiple organizations holding different mandates and and structural chains of command. This poses a challenge for collaboration in the way strategic problems are solved at each stage of the emergency, given that they may not follow the traditional normative linear patterns of decision making. To address this query, this work explores the application of fuzzy logic to characterize the problem solving approach used –coordination, cooperation, collaboration -, with the level of complexity of the emergency.

Emergency management approaches

There are different approaches to classify emergency management, one of them is a categorization based on the time of the occurrence of the emergency events. In these terms, crisis management studies the onset of an emergency whereas consequence management is responsible for the recovery period [1]. The activities entailed are also different; crisis management is focused on the response of the emergency and it is considered to be reactive, while consequence management deals with the effects in the aftermath of the event [2]. Risk management on the other hand, covers all the stages of the disaster (see Fig. 1), and the control of the crisis is a continuous task [3]. However, each approach possesses strengths and weaknesses.

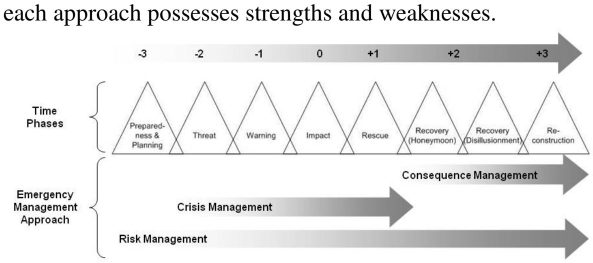

Fig.1. Emergency management approaches by time phase [3]

Event timeline

Emergencies evolve along different phases (Fig.1), each one holding different temporal characteristics [3]. Lemyre et al, [3] characterized each one of this phases as follows: *Preparedness and planning*, focuses on planning and implementing measures to reduce vulnerability. *Threat*, refers to the period previous to an extreme event when there is awareness that such an event may occur. The main activities are focused on information collection and authentication. The *warning* stage is the period previous to an extreme event when the threat is imminent and just about to occur. *Impact*, this phase starts at the moment the emergency is detected. The *Rescue* phase starts after the emergency has been detected and until the authorities declare the end of it; main tasks include rescuing of victims, first aid and evacuation. *Recovery*, during this phase the reestablishment of essential services and cleanout is made. During the *Reconstruction* phase the construction and repairing of infrastructural damages is performed.

Lemyre et al. [4] explain there is an intrinsic dynamical relationship within the activities encompassed along each phase of the crisis, where the only two constants are "*change and movement*". To understand the dynamic evolution of these tasks, Lemyre et al [4], developed a model for problem solving of extreme events, based on two main components: "*situational complexity (complex, complicated or simple)"* and "*inter organizational problem solving approach (collaboration, coordination or cooperation)*", each one of them being modify by multiple factors, such as "*assets (information, resources and power)"* and "*time (stage of crisis)"*.

Interorganizational problem-solving approach

Along the continuum of approaches to problem solving, three different strategies relative to the differential use of information, resources and power had been categorized [4]: *coordination, cooperation* and *collaboration.* In *coordination* the priority is to make an efficient use of resources by avoiding task overlapping, each organization may take decisions independently, and they may only share information. In *cooperation* organizations not only make an efficient use of assets, but also share activities and information. Therefore they have a mild interdependent relationship at different stages of the problem solving cycle. Whereas in *collaboration,* besides of sharing resources, information and activities, organizations may also share power. Therefore the interdependence level is higher, thus both responsibilities and credit are shared.

Situation Complexity

Although the complexity of an event could shift dynamically, there is a continuum ranging from simple to complicated, to complex [4]. In a *simple situation* solutions are known, and each organization can solve it mostly independently. In a *complicated* situation, solutions are also known but the scope of the solution is further than the individual organization's capacity. Whereas in a *complex* situation the solution is mostly unknown, therefore organizations do not have certainty on which actions are more effective to solve the emergency.

Similarly, Scholtens [5] found that as the global complexity of the crisis increases the organizations involved in the response tend to collaborate to solve the manifold challenges faced. In these terms, Lemyre et al [4] in their model pointed out that at every stage of the emergency, there are "*kernels of coordination, cooperation and collaboration*", as well as "*kernels of complexity"* involving "*situations simple, complicated and complex*". This description can be captured by Zadeh's [6, p.310] definition of fuzzy information granulation, where he stated that: "*fuzzy information granulation may be viewed as a human way of employing data compression for reasoning and, more particularly, making rational decisions in an environment of imprecision, uncertainty and partial truth"*. Therefore fuzzy logic offers the possibility to characterize the problem solving approaches for interorganizational emergency response, in terms of the situation complexity along the different phases of evolution of the event.

Fuzzy Logic

Along his "*quest for better models of reality"*, Zadeh [7, p.2774] developed the theoretical basis for fuzzy logic in 1965, where the traditional binary logic was replaced by a multi-valued logic that reflects more closely the human capability of process perception based information, where language and qualitative statements plays a major role [8]. Zadeh [9] explains, that the behavior of very complex or "wicked" systems does not easily admit precise mathematical analysis and this effect increases as the complexity of the system increases. However, an approximate description can be successfully achieved based on linguistic variables and fuzzy algorithms. He envisioned the application of fuzzy logic in research fields where the main roles are played by "*animated systems constituents*", such as psychology, management, medicine, biology and artificial intelligence.

Fuzzy logic and emergency management

The usefulness of fuzzy logic applications is especially well suited to assist in the solution of social problems; of special interest for emergency management is the intricate process of inter-organizational problem solving. In this context, Fedrizzi et al. [10] explained that most of the decision making activities are performed within and across actors, groups or organizations with differing "*value systems"* along the different problem solving stages. For this reason they developed a decision support system to reach consensus based on fuzzy logic principles. Similarly Kacprzyk [11] developed algorithms to represent fuzzy majorities in group decision making contexts. Therefore fuzzy logic has the potential to assist decision makers to deal with complex problems within an environment of uncertainty, and decision support systems based on fuzzy logic can assist in this task [12].

Given the close fit between the interdisciplinary needs and requirements in the emergency management field, and the theoretical and applied capabilities fuzzy logic has to offer, this paper, proposes the use of fuzzy logic in the field of emergency management, to characterize the problem solving approaches for inter-organizational emergency response, in terms of the situation complexity along the different phases of evolution of the event. Although fuzzy logic is not a new theory, the multiple benefits and attributes it provides, have not yet been exploited nor applied in the inter-disciplinary field of emergency management but in a few cases to address information security management problems [13].

Fuzzy logic as a modeling language

Fuzzy Logic is a powerful tool to deal with imprecision and uncertainty, which offers instruments to solve real-world problems. According to Zadeh [7], one of the main legacies of fuzzy logic is its remarkable capability of "*precisiation"* that is the reason why it is highly reliable to represent different models of reality. Another important feature of fuzzy logic is that it can deal with uncertainty "*in terms of imprecision, nonspecific, vagueness and inconsistency*" [14, p. 226]. Likewise Carlssson, Feddrizzi and Fuller [15] pointed out that fuzzy logic can manipulate data and information with unknown statistical uncertainties. In fuzzy modeling, the arithmetic used for inference is based on "*if then rules"*, fuzzy reasoning is an inexact reasoning anchored in partial knowledge [16]. Consequently, fuzzy reasoning is rather qualitative than quantitative [17].

In addition, fuzzy logic offers inference mechanisms that make possible human cognitive processes capabilities to be translated into knowledge based systems [14][8]. Thus in general, the aim of fuzzy logic reasoning is to achieve conclusions from incomplete facts which are produced from experts; Bouchon-Meunier [18] described this as an "*approximation of standard evidence*". As a result, fuzzy linguistic models (FLM) are qualitative descriptions of systems behaviors, sustained on the fuzzy reasoning theory, which is a foundation for the development of expert systems [19]. In this kind of models, traditional equations and numerical symbols are not needed [16].

Moreover, Sugeno and Yasukawa [16] described an expert system as a model build on conclusions obtained from "*observable features"* of the situation under analysis, obtained from experts' qualitative knowledge and experience. Therefore they explain that the design procedure is to build the linguistic rules, to then adapt the fuzzy parameters that bound the linguistic terms involved. The authors mentioned as one possible source of information and data for fuzzy qualitative modeling, observations based on knowledge and /or experience and linguistic data.

Likewise, Chartuvedi [14] describes two methods to outline fuzzy membership functions, classified as direct and indirect methods. In the direct method an expert intuitively designate a membership rating what in his perception portrays more meaningfully the linguistic terms under design. Whereas in the indirect methods, several experts are asked to respond plain probes that indirectly describe the membership function under construction. The answers are then processed via interpolation, curve fitting or through artificial neural networks methods.

Membership function features

In order to understand the designs presented in the results section, a brief explanation of the main characteristics of a membership function developed by Chartuvedi [14] is provided. He indicates that a membership function is a plot that describes how each point from a given *input space* is mapped to a *membership value* (or *degree of membership*) between 0 and 1. The *core* of a membership function is the area of the fuzzy set where there is a complete membership value (see Fig. 2). Meanwhile, the area of a membership function that has any value different from zero is called *support* (Fig. 2). Whereas the *boundaries* are the parts of the membership function that neither have a full membership value nor a zero one (Fig. 2).

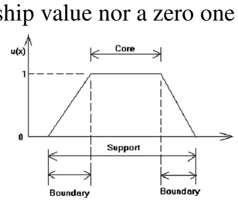

Fig. 2 Core, support and boundaries of a membership function [14, p.251]

A *generalized membership function* [14], is a concept to design membership functions with different shapes. Each generalized membership function has at least four segments of different dimensions holding different positions which can be customized to the design under construction (Fig. 3).

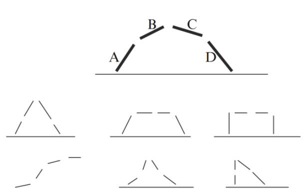

Fig. 3 Generalized membership function, [14, p.252]

Another concept to describe the features of the fuzzy sets is *normality* [14]. A fuzzy set is named as *normal,* if the maximum value of its corresponding membership function is 1, and *subnormal* in any other case.

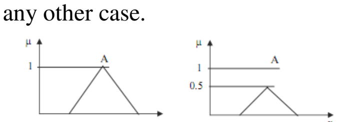

Fig. 4 Normality of a fuzzy set, [14, p.244]

Given the low likelihood of occurrence of emergencies and extreme events, retrospective data collection methods such as interviews, case studies, and other documental sources such as, governmental reports, newspapers, social media feeds and magazines are used to reconstruct the events of major crisis and emergencies. These elements have been recollected and analyzed by several researchers to develop the theoretical foundations for the emergency management field. Within these, outlines for a theory on inter organizational problem solving and decision making during emergencies are still under development and lack empirical evidence., The underlying theoretical logic is not yet fully developed. Nevertheless, there is already enough theoretical elements and material to develop an outline of a fuzzy logic model that enable an approximate representation of the phenomenon.

METHOD

Data collection and materials

The qualitative data to populate the fuzzy logic models was obtained from a series of research articles and reports that portrayed the expert observations and lived experiences from several first responders, governmental authorities, nongovernmental organizations and researchers who had experienced a major crisis, emergency or extreme event. The inclusion criteria for articles were: a multi-organizational environment and an observed effort to achieve collaboration between the organizations involved. After the selection process, three key articles were chosen to design the fuzzy logic models [4] [5] [20].

Membership function design

Within the literature reviewed, preconditions to enable collaboration between organizations during emergencies and extreme events were found. These findings were then related to the phase of the event where they were observed or reported. The design of each membership function aims to characterize the response observed or reported along the different phases of the emergency. The timeline characterization applied is based on Lemyre et al [3], and conform the input space (horizontal axis) within the membership function depiction. The degree of membership values relate the level of interaction experienced by response organizations (vertical axis). Therefore the membership function plot aims to characterize the patterns of problem solving approach used along the different phases of the emergency. This characterization was then classified to the theoretical levels of complexity of the event [4]. Each of the elements were interpreted as linguistic modifiers and outlined as a fuzzy membership function and its corresponding fuzzy sets. Each fuzzy set was setup in a Microsoft Excel spreadsheet as tables of membership values, which enabled the plotting of each membership function using an area type chart. Using these methods we look to acquire a proxy of the general outlines for inter organizational approach to problem solving applied during the different stages of the crisis along the different levels of complexity.

RESULTS

This section shows the design of fuzzy membership functions classified by level of crisis complexity, based on the experience and expert knowledge described in the literature reviewed. First a brief summary of the major literature findings is provided, followed by the set of corresponding fuzzy rules, complemented with a description of the membership values showed in table format, and finally each membership function is graphically presented and discussed.

Simple Crisis

According to the analyses presented by Lemyre et al. [4] from a series of Canadian case studies, within an emergency or major event, there are tasks that can be performed by organizations individually without any interaction with other organizations responding to that particular event. Due to organizations being able to solve the crisis under their own availability of resources, information and mandate. Therefore the pattern observed was a mild coordinated effort mainly around the impact phase of the crisis. Translating these results into a fuzzy logic rule, this can be expressed as:

Rule 1. IF Situational complexity is low, THEN Inter-organizational approach used is LOW COORDINATION.

Table 1 show the membership values during a simple crisis, where a value of 0.3 is assigned to represent a low level of inter organizational coordination in the impact and rescue phases. In a simple crisis the membership values for cooperation and collaboration were set to zero along all the crisis phases.

Table 1. Inter-organizational interaction membership values: Simple crisis.

		Approach to problem solving		
		Collaboration	Cooperation	Coordination
Time phase	Preparedness & planning	0	0	0
	Threat	0	0	0
	Warning	0	0	0
	Impact	0	0	0.3
	Rescue	0	0	0.3
	Recovery	0	0	0
	Reconstruction	0	0	0

The corresponding fuzzy membership function is shown in Fig.5. In this graph, the vertical axis shows the membership function values of inter-organizational interaction (Table 1), and the horizontal axis shows an approximate depiction of the evolution of the timeline of the event. It is worth mentioning that the scale used in the timeline axis, is just an approximation and in any other event it may have different proportions, in other words, each one of the phases of the event may not have the same length and may overlap, this statement is valid for all the membership functions presented in the results section. The membership function shown in Fig. 5 is rendered as a subnormal plot to capture the low level of inter-organizational interaction, given that in a simple crisis the expected level of coordination is low.

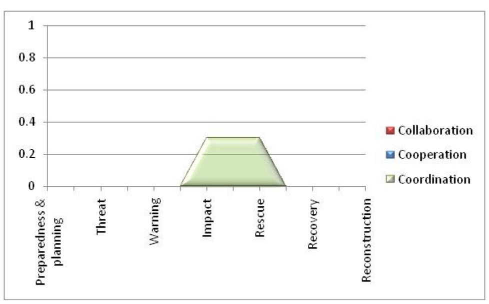

Fig. 5. Membership function for the three levels of problem solving approaches during a simple crisis.

Complicated Crisis

Berlin and Carlstrom [20] found during emergency exercises and simulations in Sweden, four different kinds of inter organizational approaches for emergency response. Parallelism is described as a similar concept to coordination; where each organization works independently from the activities of other response organizations. First initiative, on the other hand, can be classified as inter organizational cooperation, because resources and/or information were shared. Switching is described as another level of cooperation, characterized by a shifting of organizational mandates. Collaboration was barely observed between the response actors. Therefore in their experience, the most frequent pattern of interaction was coordination, followed by cooperation and the less observed pattern was collaboration. However the dynamic interplay of the patterns observed were "*kernels*" of medium coordination and low cooperation around and after the impact stage of the crisis. Translating these results into fuzzy logic rules, these results can be expressed as:

Rule 1. IF Situational complexity is medium, THEN inter organizational approach used is MEDIUM COORDINATION.

Rule 2. IF Situational complexity is medium, THEN Inter organizational approach used is LOW COOPERATION.

In this case, Table 2 shows the inter-organizational interaction membership values during a complicated crisis, where a value of 0.5 is assigned to represent a medium level of inter organizational coordination, and a value of 0.3 to characterize a low level of cooperation, both approaches were identified during the impact and rescue phases. In a complicated crisis the truth values for collaboration were set to zero along all the crisis phases.

Table 2. Inter-organizational interaction membership values: Complicated crisis.

		Approach to problem solving		
		Collaboration	Cooperation	Coordination
Time phase	Preparedness & planning	0	0	0
	Threat	0	0	0
	Warning	0	0	0
	Impact	0	0.5	0.3
	Rescue	0	0.5	0.3
	Recovery	0	0	0
	Reconstruction	0	0	0

The corresponding fuzzy membership functions are shown in Fig. 6. In this graph, the vertical axis shows the inter-organizational interaction membership function values (Table 2), and the horizontal axis shows an approximate depiction of the evolution of the timeline of the event. The membership functions shown in Fig. 6 are rendered as subnormal plots to capture the low and medium levels of inter-organizational interaction, given that in a complicated crisis the level of coordination expected is medium, and a low level of cooperation. In this case, coordination is represented as a precondition to enable cooperation, which in turn may overlap with some coordination activities that may require resource, information and authority sharing between organizations.

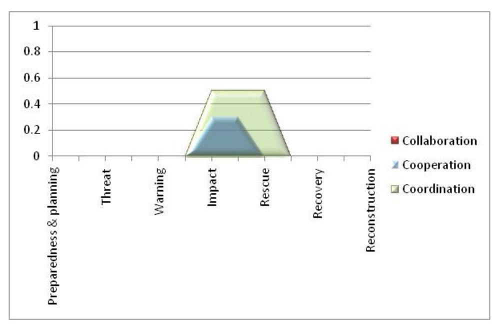

Fig. 6 Membership functions for the three levels of problem solving approaches during complicated crisis.

Complex crisis

In the Netherlands, Scholtens [5] based on field and documental studies for inter organizational emergency response; found that collaboration was only observable when life of people was in danger. That was the only key moment when organizations, had to work jointly and shared resources, information and authority. After this short period of time, the organizations return to work preferably independently. These findings coincide with the observations made by Berlin and Carlstrom [20]. The authors hypothesized that collaboration is not the prefer pattern of interaction, due to the high efforts and costs involved in deploying this kind of response. In this case as well, dynamic interplays or "*kernels"* of coordination, cooperation and collaboration were observed. Translating these results into fuzzy logic rules, these results can be expressed as:

Rule 1. IF Situational complexity is high, THEN inter organizational approach used is MEDIUM COORDINATION.

Rule 2. IF Situational complexity is high, THEN Inter organizational approach used is FAIRLY HIGH COOPERATION.

Rule 3. IF Situational complexity is high, THEN Inter organizational approach used is HIGH COLLABORATION.

For complex crisis, Table 3 shows the membership values of inter-organizational interactions interpreted from the literature descriptions. Inter organizational coordination was set up to a value of 0.5 to represent a medium level. Cooperation was assigned a value of 0.7 to characterize a fairly high level of inter-organizational interaction; both approaches were identified during the impact and rescue phases. On the other hand, collaboration was set up to a value of 1, to represent the high level of inter organizational interaction needed during the life-danger period of the impact phase of a complex crisis.

Table 3. Inter-organizational interaction membership values: Complex crisis.

		Approach to problem solving		
		Collaboration	Cooperation	Coordination
Time phase	Preparedness & planning	0	0	0
	Threat	0	0	0
	Warning	0	0	0
	Impact	1	0.7	0.5
	Rescue	0	0.7	0.5
	Recovery	0	0	0
	Reconstruction	0	0	0

The corresponding fuzzy membership functions are shown in Fig. 7. In this graph, the vertical axis shows the inter-organizational interaction membership functions values (Table 3), and the horizontal axis shows an approximate depiction of the evolution of the timeline of the event. The coordination and cooperation membership functions shown in Fig. 7 are rendered as subnormal plots to capture the medium and fairly high levels of inter-organizational interaction. Notice that the pattern described for collaboration is a normal triangular membership function, with slopes so steep that its shape recalls a Dirac's function. As in the former case, both coordination and cooperation are represented as preconditions to enable collaboration. In the impact phase of the crisis patterns of dynamic interplays between collaboration, coordination and cooperation are shown.

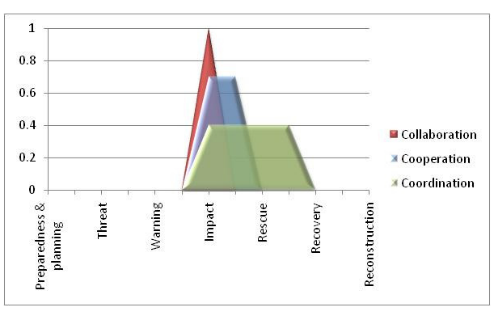

Fig. 7 Membership functions for the three levels of problem solving approaches during complex crisis.

Very Complex Crisis

In the analysis presented by Lemyre et al [4] from a series of case studies of international major events and disasters, the 2003 SARS case stands out, due to the high level of international collaboration involved to overcome the extreme complex challenges faced. In this case as well, the main danger was the lost of hundreds of lives related to the high power of viral transmission, and the uncertainty related with its treatment and prevention. Therefore collaboration was observed over an extended period, because the impact phase was geographically extended as well.Translating these results into fuzzy logic rules, these results can be expressed as:

Rule 1. IF Situational complexity is very high, THEN inter organizational approach used is MEDIUM COORDINATION.

Rule 2. IF Situational complexity is very high, THEN Inter organizational approach used is FAIRLY HIGH COOPERATION.

Rule 3. IF Situational complexity is very high, THEN Inter organizational approach used is HIGH COLLABORATION EXTENDED.

For very complex crisis, Table 4 shows the inter-organizational interaction membership values interpreted from the literature descriptions. Inter organizational coordination was set up to a value of 0.5 to represent a medium level along the impact, rescue and part of the recovery phases. Cooperation was assigned a value of 0.7 to characterize a fairly high level of inter-organizational interaction during the impact and rescue stages. Finally, collaboration was set up to a value of 1, to represent the high level of inter organizational interaction needed during the extended life-danger period of the impact phase of a very complex crisis.

Table 4. Inter-organizational interaction membership values: Very Complex crisis.

		Approach to problem solving		
		Collaboration	Cooperation	Coordination
Time phase	Preparedness & planning	0	0	0
	Threat	0	0	0
	Warning	0	0	0
	Impact	1	0.7	0.5
	Rescue	1	0.7	0.5
	Recovery	0	0	0.5
	Reconstruction	0	0	0

The corresponding fuzzy membership functions are shown in Fig. 8. In this graph, the vertical axis shows the membership functions values (Table 4), and the horizontal axis shows an approximate depiction of the evolution of the timeline of the event. The coordination and cooperation membership functions shown in Fig. 8 are rendered as subnormal plots to capture the medium and fairly high levels of inter-organizational interaction. Collaboration, on the other hand, is portrayed as a normal trapezoidal membership function. And as in the former complex case, both coordination and cooperation are represented as preconditions to enable collaboration. During the extended impact phase of the crisis, patterns of dynamic interplays between collaboration, coordination and cooperation are shown.

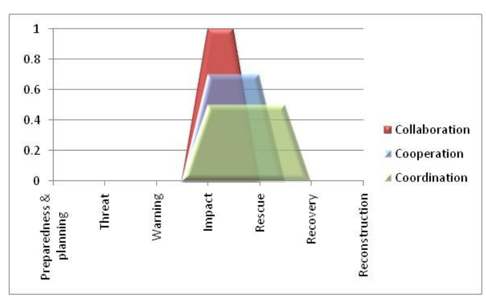

Fig. 8 Membership functions for the three levels of problem solving approaches during very complex crisis.

DICUSSION

The fuzzy logic models presented here are first attempts to characterize inter-organizational patterns of interaction and response during emergencies based on fuzzy rules. The characterization presented explored the inter-organizational approach for problem solving – coordination, cooperation, collaboration -, and related it to the level of inter-organizational interaction experienced by organizations in the response of the event along the different phases of the disaster, according to the level of complexity of the emergency. Of special interest here is the capacity offered by fuzzy logic, to operationalize experiences and perceptions of expert emergency managers. These fuzzy logic models can eventually help to populate expert knowledge data for computer behavioural simulations and expert systems, by offering basic low cost instructions to build on more complex algorithms. The fuzzy logic models can also be applied in situations where experimentation is a challenge for data collection. Although neither optimal nor comprehensive, the models portrayed provide an approximate description of inter-organizational problem solving patterns along different levels of crisis complexity. These models provide a graphical depiction of the literature results descriptions, which potentially could bring forth more precise or complete models that fit better the phenomena based on qualitative analogies.

Next steps will include refining, tuning up and validation of the fuzzy models to assess their external validity. Future steps will also include the development of fuzzy models of variables such as inter-organizational sharing of information, resources and power; inter-organizational inter-dependencies along the different phases of evolution of disasters and featuring of organizational resilience by organizational background. All of these models could eventually provide outlines to develop expert systems to assist in the field of emergency management. The first step is presented here using fuzzy logic as a mediator linking epistemologically differing fields, such as social and computer sciences by enabling the representation of degrees of human rationality bounded by vagueness.

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