Fuzzy ontological model of knowledge representation for the humanitarian response

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Abstract

The article considers the problems of knowledge representation in the context of creating a decision support system for humanitarian aid. To overcome the uncertainty and inconsistency of the data, it is proposed to combine Case Base Reasoning with the ontology of the domain by introducing fuzzy relations and fuzzy inference. The developed fuzzy ontological model allows adapting the solution obtained with the help of Case Base Reasoning by searching for similar fragments in the main concepts of the domain, taking into account the fuzzy relations between concepts. In the process of problem solving, the ontology accumulates knowledge about fuzziness by enumerating the values of the membership function of fuzzy relations. The model can be used for real-time decision making in humanitarian response and for modeling and forecasting risks and resource availability during humanitarian crises.

Keywords

Humanitarian response, case-based reasoning, ontology, fuzzy logic, decision making.

1. Introduction

During the years of full-scale military actions, Ukraine has suffered large-scale destruction, and an estimated 12.7 million people are in need of various types of humanitarian assistance. Increased demands on the speed of response to emergencies require effective solutions based on knowledge representation models derived from the accumulated experience of solving similar problems.

The speed of development and implementation is becoming the most important criterion for the humanitarian response system, so it is important to develop a comprehensive approach to the accumulation and presentation of knowledge that will allow integrating information from various sources and presenting it in a form suitable for decision-making. The use of modern technologies and methods of knowledge representation will reduce the time required to provide assistance during emergencies, thereby saving lives and improving the living conditions of the affected.

The selection of one of the well-known models will limit its use, so the following knowledge representation models can be used in the development of a humanitarian response system [2]:

- an ontological model to represent the basic concepts of the subject area and the relationships between them;
- product model, which allows to obtain a solution through logical inference based on a system of rules, including fuzzy logic;

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- a case database that represents knowledge of previous situations and takes into account the experience of previous decisions; case-based reasoning (CBR) is used to select a case similar to the current situation.

The development of a humanitarian response system requires the integration of information from different sources. The main problem is that the same subject area can be represented by different ontological models. This is due to the use of different systems of concepts and the lack of common terminology. Such ontologies are difficult to compare. Efficiency in solving specific tasks can be used as a comparison criterion.

The purpose of this study is to develop a comprehensive model for representing knowledge about humanitarian assistance processes in the form of a fuzzy ontology that will overcome the uncertainty of data on an emergencies. In order to achieve this goal, it is planned to solve the tasks of establishing a connection between the parameters of the precedent and the concepts of the ontology and their properties to accumulate new knowledge and add fuzzy inference procedures to overcome the uncertainty of the input data.

2. Literature review

A system analysis of global humanitarian response practice [2] has identified an imbalance in emergency response, with maximum attention paid to addressing the consequences of natural disasters, armed conflicts, man-made disasters and pandemics, while preventive measures are overlooked. The future is shaped by big data analytics to gain knowledge that can prevent emergencies or minimize their consequences.

The study of the problems of representing knowledge about emergencies and emergency response processes can be divided into several areas:

- taking into account previous experience by using various modifications of the CBR method;
- development, integration and enrichment of conceptual ontologies of the disaster and/or humanitarian response subject area;
- solving the problem of uncertainty of the basic concepts of the ontology and their properties by developing fuzzy inference procedures.

The use of classical parametric CBR for decision-making in emergencies is insufficient primarily due to the large dimensionality and uncertainty of the parameters of the current situation, as well as their contradictory nature. In [3], the possibility of using temporal precedents to take into account the factor of dynamic changes in the situation is considered, but the problem of incomplete information about the current situation remains unresolved. The ontological representation of the precedent and the development of ontology enrichment procedures [4] allows replenishing the missing data, but does not solve the problem of contradictory parameter values.

The extended CBR has also proven to be quite effective in risk assessment. The issue of predicting possible risks for subway construction is addressed in [5] by combining CBR with an ontology that allows identifying risks using a similarity algorithm integrated with a correlation algorithm. In [6], when developing construction projects, fuzzy CBR is used to build a risk matrix, which is supplemented with linguistic variables, which facilitates the determination of partial similarities between different precedents.

To overcome uncertainty during emergencies, [7] proposes the Empathi ontology, which is aimed at obtaining data from various sources, such as satellite images, sensor data, and witness posts on social media. The ontology describes the conceptual relationships that are important for this area and allows for rapid updating of emergency data.

The ontological approach to workflow management [8] involves the creation of an ontology in the form of a knowledge graph that allows supporting various processes and reasoning. In [9], the fundamental concepts of an ontology that describes a telecommunications network are analyzed, and general concepts for developing ontologies for different subject areas are identified.

The combination of an expert system, fuzzy reasoning, and ontological tools to provide reliable recommendations to students on the next appropriate learning step is proposed in [10]. Fuzzy logic determines the degree of student interest in a particular academic choice, accompanied by an ontological model and a traditional rule-based expert system to compose personalized learning paths. To recommend the next step of learning, the fuzzy logic component together with the knowledge modeled as part of the multifaceted ontology and academic recommendations expressed as semantic rules interact effectively with each other.

A mechanism for working with fuzzy queries for ontologies is proposed in [11]. Converting fuzzy queries to clear ones allows them to be processed using any appropriate modules. The algorithm can be applied to such reasoning tasks as finding fuzzy instances with constraints in a fuzzy ontology. The issue of information retrieval using fuzzy queries is discussed in [12]. Based on the built fuzzy ontology, the most semantically related words for the query are determined in accordance with the fuzzy function of semantic relations, which allows it to be expanded.

In recommender systems, the combination of fuzzy rules and ontology allows creating effective recommendation algorithms for customers [13] by aligning ontologies to make decisions that are more accurate and dynamically generated based on the search context. The travel recommendation system based on context-dependent fuzzy ontology [14] builds a list of recommendations based on multiplicative modeling of various parameters using the maximum hybrid semantic similarity function.

The issue of overcoming uncertainty through the use of fuzzy ontologies, when concepts or their properties take values from some fuzzy set is considered in studies [15-17]. The method of automatic data type learning [15] for fuzzy ontologies based on clustering algorithms increases the efficiency of classification and recognition of fuzzy concepts.

In [16], a fuzzy ontology is used to reduce the variability of the task in the group decision-making process. It is proposed to combine the values of the criteria to reduce their number so that experts can work with them more conveniently. The two-level PN-OWL algorithm [17] is aimed at classifying instances of concepts, with P-rule explaining why an object can be classified as an instance of a concept, and N-rule explaining why it cannot. The final decision is made based on the aggregation function.

In conditions of high uncertainty and inaccuracy of data, type-2 fuzzy ontologies are used, in which the degrees of membership of an element in a fuzzy set are also fuzzy. In [18], the combination of the semantic web of things (SWOT) and type-2 fuzzy logic in smart home technologies is investigated to determine the air quality in a room. Also, ontologies of this type are being actively studied in the medical field. in particular, in [19], the diagnosis of mental health problems is performed using the theory of type-2 fuzzy sets.

Fudge, a tool for creating fuzzy data types developed in [20], aggregates specifications provided by a group of experts. The interface of the software product is implemented with various types of linguistic aggregation strategies, such as convex combination, linguistic OWA, and weighted average. However, the high quality requirements for humanitarian response solutions currently do not allow the use of type-2 fuzzy ontologies, whose conceptual framework is only being formed, and there are no reliable and efficient software implementation tools that allow processing large data sets.

Based on the analysis of the main publications, it can be concluded that CBR has proven itself well in solving problems in this subject area, but it is not sufficient to represent knowledge about emergencies and humanitarian response. To adequately assess risks in order to prevent critical consequences of emergencies, it is advisable to combine several models of knowledge representation, which can be achieved by the integrated use of various modifications of the CBR method, including an ontological approach with the addition of fuzzy inferences.

3. Ontological model of knowledge representation

The structure of a comprehensive model of knowledge representation of the humanitarian response subject area, which includes the integration of cases, ontological and fuzzy product components is being considered.

The use of the CBR method for finding solutions is conditioned by the simplicity of its implementation and by the absence of the need for a complex analysis of the subject area and the construction of logical conclusions. Cases are traditionally represented by the following mapping:

$$Case: Problem \rightarrow Solution, \tag{1}$$

where $Problem$ – situation description, $Problem = \langle pr_1, pr_2, \dots, pr_n \rangle$, $pr_i, i \in \mathbb{N},\ i \in [1, n]$ – a set of parameters that characterizes the situation;

$Solution$ – a decision that is made in the current situation, $Solution = \langle sol_1, sol_2, \dots, sol_m \rangle$, $sol_j, j \in \mathbb{N}, j \in [1, m]$ – components of the solution, can be represented as a pair $\langle parameter, value \rangle$.

The current situation requiring a humanitarian response is also described by a set of parameter values $current = \langle pr_1^c, pr_2^c, \dots pr_n^c \rangle$. To identify relevant cases, the distance between the current situation and each precedent in the database is calculated. Simple metrics have proven to be a good criterion for similarity: Euclidean or Manhattan. The search criterion based on the Manhattan metric with the indicator $\beta = 1$ takes the following form:

$$\min_k \frac{\sum_{i=1}^{n}(\omega_i |pr_i^k - pr_i^c|)}{\sum_{i=1}^{n} \omega_i}, \tag{2}$$

where k – number of cases accumulated in the database;

$\omega_i, i \in [1, n]$ – importance coefficient of the i-parameter.

As a result, the case that best suits the current situation is obtained. In the process of adaptation, the found case is used as an intermediate solution for the current situation

The knowledge-oriented model of case knowledge representation allows to get an adequate solution in cases where all the parameters of the current situation are known, and the solution itself is simple or contains a small number of sequential steps.

Experience shows that in emergency situations, when information about the current state can be contradictory and response time is a critical resource, it is quite difficult to obtain all the parameters necessary for making a decision. Also, the decisions that are made may themselves have a complex structure consisting of a hierarchy of pairs $\langle parameter, value \rangle$, or have more complex relationships between components, such as «cause-and-consequence», associativity, or composition. Also, the situation itself is constantly changing, so it is necessary to have the means to monitor, predict changes in parameters and respond promptly to changes.

In the context of uncertainty, it makes sense to combine knowledge representation cases with other models and supplement them with inference procedures to obtain unknown or conflicting parameter values to form an efficient and effective solution. Data can be enriched by a subject area ontology that reflects the main entities and establishes relationships between them.

An ontological specification is represented by a tuple of the form:

$$O = \langle C, R, F, P \rangle, \tag{3}$$

where $C = \{c_n \mid n \in \mathbb{N},\ n \in [1, |C|]\}$ – a set of concepts of humanitarian response;

$R = \{(c_i, c_j, rt_n) \mid rt \in RT, c_i, c_j \in C\}$, where RT – a set of relationship types;

$F: C \times R$ – is the set of interpretation functions defined by the correspondences between C and R;

P – a set of properties of concepts and relations:

$$P = \{(p_i, e_j) | p_i \in P, e_j \in C \cup R\}. \tag{4}$$

To solve problems in the field of humanitarian response, it is proposed to use an extended specification of the ontological model [4].

The set of relationship types will be considered as

$$RT = \{RT_{CSC}\} \cup \{RT_{RL}\} \cup \{RT_{ASR}\}, \tag{5}$$

where RT_{CSC} — is a partially ordered hierarchical «class-subclass» relationship;

RT_{RL} – a relationship between ontology concepts that is not a hierarchy relationship;

RT_{ASR} — an associative relation for the connection between the case parameters and some property of the ontology concept.

In its turn, an associative relationship is defined as a mapping

$$RT_{ASR}: pr_i \underset{p_k}{\rightarrow} \mathrm{c}_j, \tag{6}$$

where c_j – ontology concept, p_k – property of the corresponding concept.

4. Extension of the domain ontology by fuzzy inference procedures

Ontology in the general sense represents a conceptual formalism that may be insufficient for solving problems in a subject area if some concepts are not fully defined. Some tasks require different interpretations of ontological concepts depending on the context. In this case, the ontology can be supplemented with inference rules based on fuzzy logic. The main component of fuzzy logic is the definition of a membership function, which correlates the possibility of belonging to some fuzzy set with a real number from the interval [0,1].

There are two types of mapping functions: $fref_1$, which define the correspondence of an instance of a given concept to a concept property through an exact value from the interval [0,1]:

$$fref_1: (\, c_i \cup ins_{ij}) \times (p_{ik} \cup Vp_{ik}) \rightarrow [0,1], \tag{7}$$

and $fref_2$ – through some label from a set that is specified in advance:

$$fref_2: (\, c_i \cup ins_{ij}) \times (p_{ik} \cup Vp_{ik}) \rightarrow \{L^K\}, \tag{8}$$

where ins_{ij} – j-th instance of concept i;

p_{ik} – k-th property of the i-th concept;

Vp_{ik} – set of values of the corresponding;

L^K – a set of labels for a concept property, for example, $L^K =$ {Not Enough, Enough, Average, More than Average, Too Much}.

Analogously, the situation when the relation of an instance to a certain concept is fuzzy is considered, i.e. "is as with μ". To describe concepts that are not conceptually defined, the set of fuzzy concepts $C^F = \{c_i^f\}$ is introduced. There are two ways to define membership functions: $fmem_1$, which defines the correspondence of a concept instance through an exact value from the interval [0,1]:

$$fmem_1: (\, \mathrm{c}_i^f \cup ins_j) \rightarrow [0,1], \tag{9}$$

and $fmem_2$ – through some label from the set that is specified in advance:

$$fmem_2: (\, \mathrm{c}_i^f \cup ins_j) \rightarrow \{L^i\}, \tag{10}$$

where L^i – a set of labels to characterize the relation of an instance to a given concept, for example, $L^i =$ {Impossible, Unlikely, Possible, Most Likely, Likely}.

To eliminate the uncertainty of certain parameters, the concept of a set of linguistic variables $V^L = \{V_i^L\}$ is introduced, that correspond to the properties of fuzzy concepts or fuzzy relations. A linguistic variable is represented by a tuple:

$$V_i^L = \langle \beta(V_i^L), T_{V_i^L}, U, G, M \rangle, \tag{11}$$

where $\beta(V_i^L)$ – the name of the linguistic variable;

$T_{V_i^L}$ – is the set of values of the linguistic variable (term set), each of which is a fuzzy value $A^k_{V_i^L}$, $T_{V_i^L} = \{A^k_{V_i^L}\}$;

U – a universal set for a linguistic variable;

G – a fuzzy rule that generates terms of a fuzzy variable;

M – s a semantic rule that corresponds to each fuzzy variable with its value.

For example, the linguistic variable V_1^L is represented as follows:

$\beta(V_1^L)$= "Resource Availability",

$T_{V_1^L}$ = {"Very Low", "Low", "Medium", "High", "Very High"}.

The Universe for the linguistic variable is defined as $U = [0,100]\%$. Figure 1 shows the membership functions of the terms of the linguistic variable "Resource Availability".

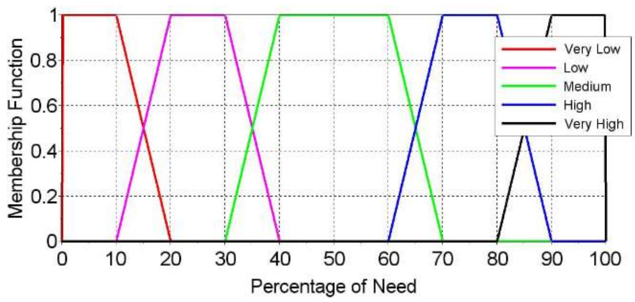

Figure 1: Membership functions of the terms of the linguistic variable "Resource Availability".

The connection of a linguistic variable with a fuzzy ontology is key to representing and processing fuzzy and incomplete information that is typical for the humanitarian response.

Let's consider the extension of the ontological model (3) with fuzzy productive rules in the Mamdani fuzzy inference system, which has the advantage of easy interpretability of inference rules, flexibility when working with fuzzy or contradictory information, the ability to process high-quality data, and ease of implementation. We will represent fuzzy rules by the following constructions:

$$Rule_j: IF\ X_1 = A_1^j\ AND\ X_2 = A_2^j\ AND\ \dots AND\ X_n = A_n^J\ THEN\ Y_j = B_k^j\ (F_j), \tag{12}$$

where $Rule_j$ – j-th rule, $j \in \mathbb{N}, j \in [1, m]$;

$X_1, X_2, \dots X_n \in V^L$ – input linguistic variables, $j \in \mathbb{N}$;

$Y_j \in V^L$ – output linguistic variable;

$A_1^j \in T_{V_1^L}, A_2^j \in T_{V_2^L}, \dots, A_n^j \in T_{V_n^L}, B_k^j \in T_{V_k^L}$ – elements of fuzzy sets for the corresponding linguistic variables;

F_j – weight factor of the j-th rule, $F_j \epsilon [0,1]$, by default $F_j = 1$.

For example, the following rules were used to model the links between threats and possible humanitarian assistance scenarios to make evacuation decisions:

IF ((Distance (Residential_areas, Oil_station) = SHORT) AND (Amount (Fuel, Oil_station) = BIG)) THEN (Risk (Fire) = HIGH);

IF ((Risk(Fire) = HIGH) AND (Amount(Population) = ENOUGH) AND (Probability(Shelling) = MEDIUM)) THEN (Evacuation (Population) = REQUIRED).

An example of a rule that can be used in the absence of power supply and heating:

IF ((Time (Power_outage) = LONG) AND (Amount(Population) = BIG) AND (Time (Lack_of_heating) = MEDIUM) AND (Weather = COLD)) THEN (Installation (Generators) = VERY_NEEDED).

Let's consider fuzzy inference procedures for the case when knowledge about the current situation is inaccurate or some parameters are missing. The fuzzy inference procedure for updating the ontology consists of the following phases:

1. Definition of input and output variables – known (accurate) properties of concepts that will be used to calculate fuzzy properties of the ontology.
2. Input variables phasing – converting clear values of input variables to fuzzy values of linguistic variables in accordance with the values of membership functions of term sets.
3. Aggregation of preconditions in fuzzy productive rules – for each rule (12), the degree of truth of the preconditions is determined. To determine the result of a logical conjunction, it is calculated according to the algebraic product rule:

$$\mu(A_1 \cap A_2) = \mu(A_1) \cdot \mu(A_2), \quad (13)$$

where $\mu(A_1), \mu(A_2)$ – the membership functions of the term sets A_1, A_2 respectively.

4. Accumulation of conclusions of fuzzy productive rules – finding membership functions for the output variables. The values of the conclusions of all rules are represented as fuzzy sets $B_1, B_2, \dots, B_k$, where k – the number of fuzzy productive rules in the rule base.

The final membership functions for each output linguistic variable are found as the union of fuzzy sets according to the algebraic sum rule:

$$\mu(B_1 \cup B_2) = \mu(B_1) + \mu(B_2) - \mu(B_1) \cdot \mu(B_2), \quad (14)$$

where $\mu(B_1), \mu(B_2)$ – the membership functions of the term sets B_1, B_2 respectively.

As a result, we obtain a set of fuzzy sets $B'_1, B'_2, \dots, B'_q$, where q – the number of initial linguistic variables in the system of fuzzy productive rules.

5. Defuzzification of the output variable – obtaining clear values for each output linguistic variable, assigning values to the corresponding properties of the ontology concepts.

To adapt the existing mapping functions (7) – (10) when obtaining new uncertainty estimates after fuzzy inference, we introduce an additional parameter Na – the number of updates of the fuzzy value. After defuzzification, it will be calculated for each fuzzy mapping:

$$f_i = f_i + \frac{f_i^{def} - f}{Na+1}, \quad (15)$$

where $f_i \in \{fref_1, fref_2, fmem_1, fmem_2\}$ – fuzzy display function;

f_i^{def} – result of defuzzification of the output variable calculation in fuzzy output.

The fuzzy ontological model for representing knowledge about humanitarian response is an extension of the ontological model (3):

$$O^{fuz} = \langle C, R, F, P, F^{fuz}, V^L, A \rangle, \quad (16)$$

where F^{fuz} – a set of fuzzy ontology mappings, $F^{fuz} = \{fref_1, fref_2, fmem_1, fmem_2\}$;

A – a set of fuzzy inference rules, $A = \{Rule_j\}$.

The use of model (16) to find a solution consists of the following steps:

1. Search for the most relevant case to the current situation according to criterion (2).
2. Mapping the parameters of the current situation to the ontology according to the relations (6), selecting a fragment of the ontology $O_{cur} \epsilon O$.
3. Updating data on the current situation using fuzzy inference based on rules (12).
4. Adaptation, development and enrichment of O_{cur} according to the rules described in [4].

5. Storage of the obtained solution in the form of a new precedent with updating the ontological model and calculating new values of fuzzy mappings according to (15).

5. Experiment

The models developed in [3] and [4] were used in the experiment. In particular, the data source and the method of reasoning on temporal precedents described in [3], as well as the ontological model and its enrichment rules [4]. The free Protégé framework was used to develop the ontology, and the fuzziness of the ontology was realized using the FuzzyOWL2 plug-in. The fuzzy inference surfaces were built using the SciLAB package, with the involvement of the SciFLT module.

To define the concepts of the ontology, [1, 2] were analyzed and information from other open sources were used. The developed ontology contains about 300 concepts, 400 properties and 150 different types of relations. The top-level concepts of the ontology are related to emergencies, such as Emergency situation, Consequences, Humanitarian aid cluster, Humanitarian aid providers, Resource, Humanitarian aid facilities, Location, Time. Each of the top-level concepts is detailed by a corresponding hierarchy, for example, in Figure 2 shows a fragment of the ontology containing the main components of the top-level concept Humanitarian Aid Cluster and some other concepts, in particular those related to evacuation of the population in case of flood.

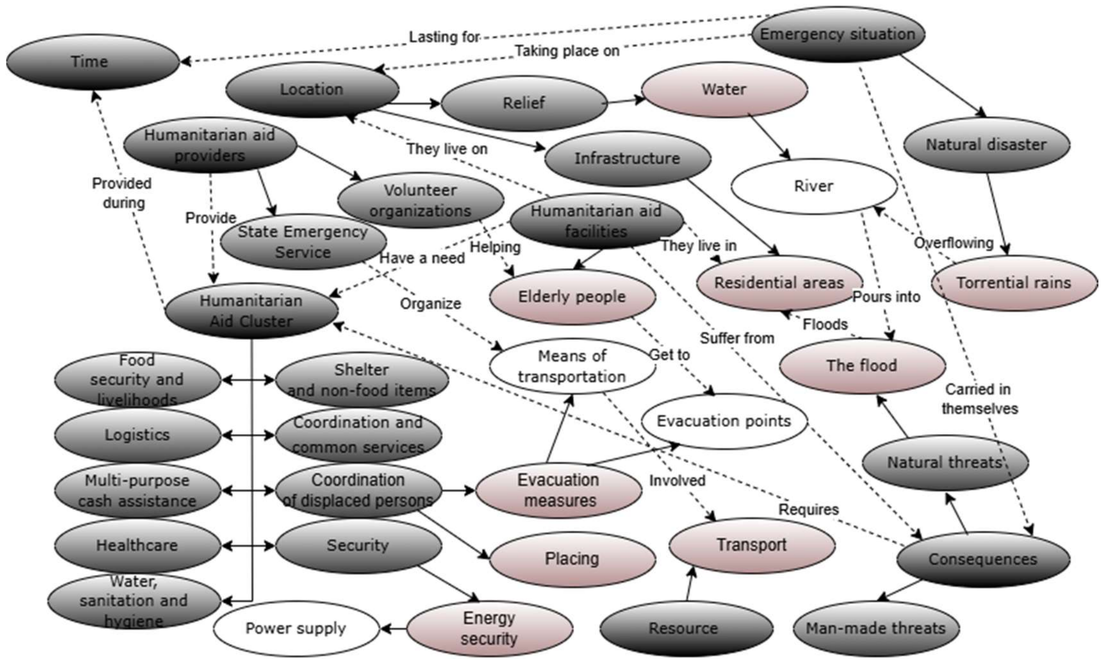

Figure 2: A fragment of the developed ontology.

Fuzziness was introduced into the ontology using the mapping functions (7) – (10). A fragment of the ontological model with fuzzy relationships is shown in Figure 3. Fuzziness was introduced both in the concept classification relations (for example, the concept Environmental pollution has a clear taxonomic relation with the concept Natural threats and a fuzzy taxonomic relation with a membership function of 0.6 with the concept Organizational threats) and in relations that are not taxonomic (for example, the Causes relation between the concepts Release of a hazardous substance and Destruction is fuzzy and is characterized by a membership function equal to 0.2).

To model the decision-making process based on the characteristics of the current situation, the prototype described in [4] was used, extended with the functions of working with linguistic variables, fuzzy inference, and procedures for updating the characteristics of fuzzy relations as a result of fuzzy inference.

The dependence of the classification quality on the number of precedents in the database was analyzed for four cases:

- parametric CBR, the distance between the cases was determined using the Manhattan metric (1) – (2);
- CBR extended with temporal precedents [3];
- CBR extended with an ontological model and ontology enrichment rules [4];
- ontological CBR supplemented with fuzzy inference procedures.

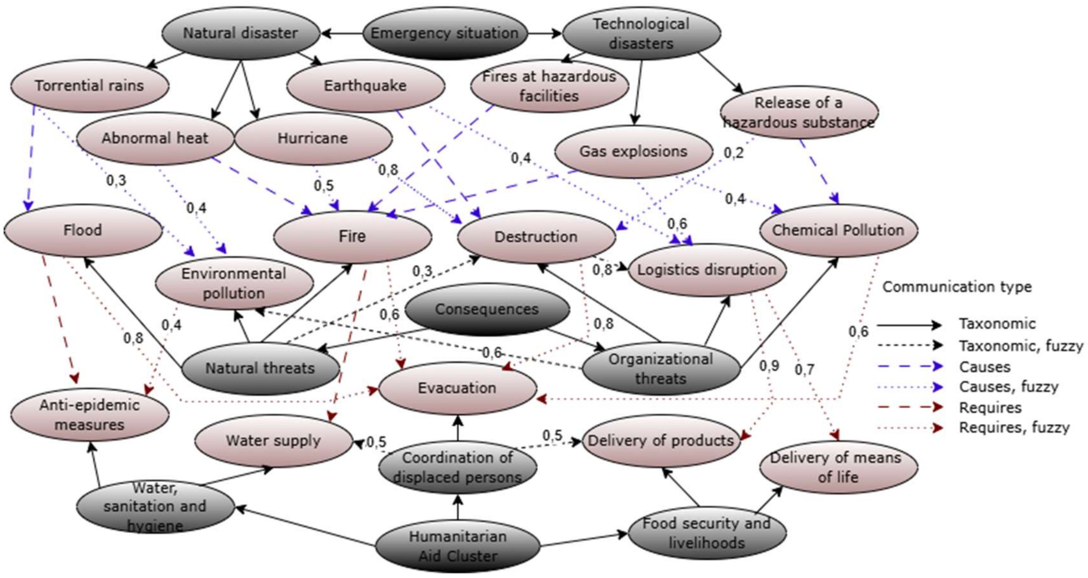

Figure 3: A fragment of the ontology with the addition of fuzzy relations between concepts.

6. Results

Let's consider the use of fuzzy inference methods in the case of uncertainty in the parameters of the current situation, using the example of the assessment of the risk of scarcity of resources, in particular drinking water. The input variables are defined as follows:

$$\beta(V_1^L)\text{= “Resource Availability”;}$$

$$T_{V_1^L} = \{\text{“Very Low”, “Low”, “Medium”, “High”, “Very High”}\},\ U_1 = [0, 100]\%;$$

$$\beta(V_2^L)\text{= “Resource Condition”;}$$

$$T_{V_2^L} = \{\text{“Poor”, “Medium”, “Good”}\},\ U_2 = [0, 1].$$

The linguistic variable “Resource Availability” provides a generalized criterion for the availability of drinking water for the population, which includes both the ability to use open water sources and the ability to organize water delivery, taking into account the availability of appropriate transport and logistical problems. The second input linguistic variable “Resource Condition” characterizes qualitative indicators of resources, such as water quality, the presence of harmful substances in its composition, the efficiency of treatment facilities, and others. Both linguistic variables in the process of phasing are determined by the properties of the Potable water concept of the same name (inheritance scheme Resource → Water → Potable water).

Description of the output variable:

$$\beta(V^L)\text{= “Risk Level”;}$$

$$T_{V^L} = \{\text{“Very Low”, “Low”, “Medium”, “High”}\},\ U = [0,100]\%.$$

The output linguistic variable "Risk Level" represents the risk of losing access to the corresponding resource. The following fuzzy rules were used for the fuzzy inference:

$Rule_1$: IF {Resource Availability IS Very_Low} AND {Recource Condition IS Poor} THEN {Risk Level IS High};

$Rule_2$: IF {Resource Availability IS Low} AND {Recource Condition IS Medium} THEN {Risk Level IS Medium};

$Rule_3$: IF {Resource Availability IS Medium} AND {Recource Condition IS Good}
THEN {Risk Level IS Low};
$Rule_4$: IF {Resource Availability IS High} AND {Recource Condition IS Good}
THEN {Risk Level IS Very_Low};
$Rule_5$: IF {Resource Availability IS Very_High} AND {Recource Condition IS Medium}
THEN {Risk Level IS Very_Low};
$Rule_6$: IF {Resource Availability ISN'T High} AND {Recource Condition IS Medium}
THEN {Risk Level IS Medium}.

The graphs of the membership functions of the input variables and the fuzzy inference surface for the output variable "Risk Level" are shown in Figure 4.

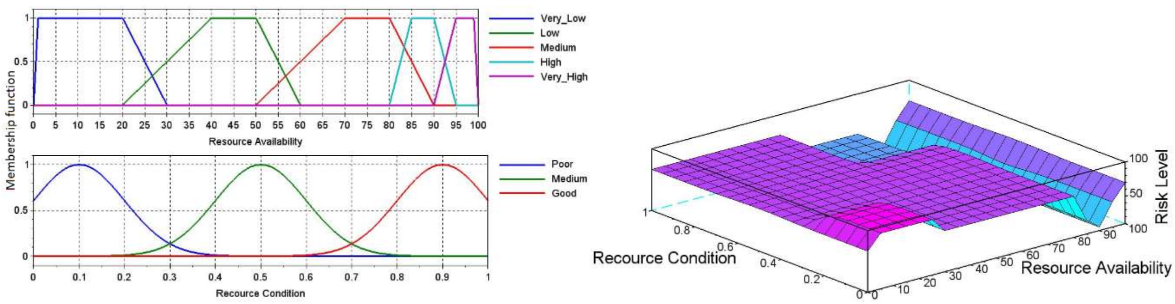

Figure 4: The graphs of the membership functions of the input linguistic variables and the fuzzy inference surface for the output variable "Risk Level".

After defuzzifying the obtained value of the output variable, its result is defined as a parameter of the current situation and is used to find a solution.

The cases developed in [3] were used to evaluate the quality of the classification of the current situation by different variants of the CBR method. For each of them a solution was identified and evaluated by experts as qualitative. The parameters of each case were considered as parameters of the current situation for which the solution was built using different methods. The resulting solution was compared with the one contained in the case. The experimental dependence of the classification quality on the number of cases in the database under conditions of complete information about the situation for different case representations is shown in Figure 5.

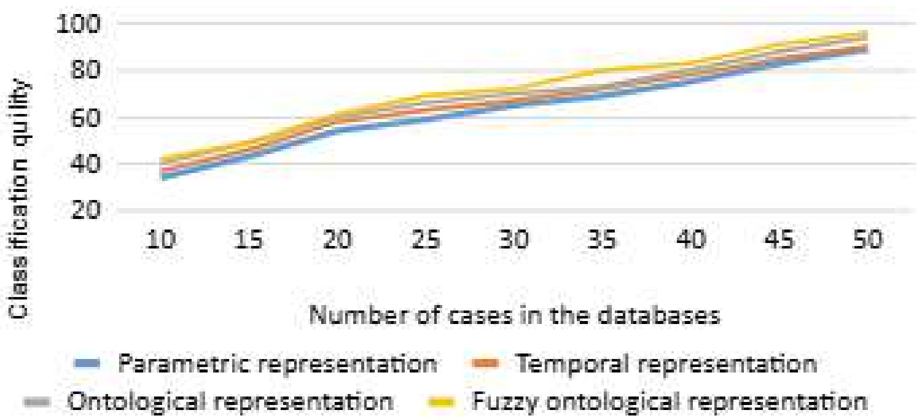

Figure 5: Graph of the dependence of the classification quality of the current situation on the number of cases in the database under conditions of complete information.

To test the behavior of the models under uncertainty, when each new case was added as a characteristic of the current situation, one randomly selected parameter was interpreted as uncertain. For an incomplete case, a solution was also constructed and its quality was determined.

The experimental dependence of the classification quality on the number of cases in the database under conditions of uncertainty is shown in Figure 6.

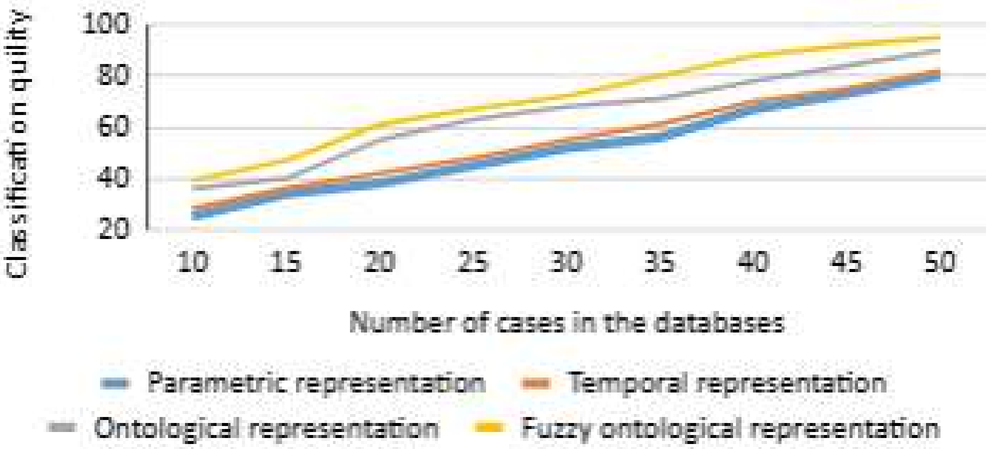

Figure 6: Graph of the dependence of the classification quality of the current situation on the number of cases in the database under conditions of uncertainty.

7. Discussions

As demonstrated in Figure 5, even the classical parametric case representation achieves an accuracy of 89% when populating the database with 50 cases. Each subsequent modification progressively enhances the quality of classification, though the discrepancy remains negligible, at most 5% for the ontological representation augmented by fuzzy inference. It is noteworthy that under conditions of uncertainty (in Figure 5), the ontological representation and fuzzy ontology exhibit enhanced efficacy, with a quality enhancement of approximately 15%.

The ability to adapt to incomplete information about the situation and to find an effective solution is facilitated by vague descriptions of ontology concepts and relationships between them. It should be noted that the uncertainty assessment measure may lose its relevance over time, and that the adaptation of the fuzzy ontology to changes in this measure using formula (15) is uncertain and requires more in-depth experimental verification.

The necessity to accurately specify the membership functions of the terms of a linguistic variable is a well-documented issue, and further research is therefore required to represent a high level of uncertainty in a situation using a type-2 fuzzy ontology [18, 19]. Another promising area is the search for a criterion for assessing the degree of uncertainty of a situation and identifying its levels, which will allow for the selection of the appropriate fuzzy inference procedures.

8. Conclusions

Adapting and extending a simple CBR method with ontological models of the domain and fuzzy knowledge allows to increase the efficiency of decision making in the face of uncertainty and data inconsistency, as well as in the context of solving multi-criteria problems. An experimental study has shown that taking into account fuzziness can improve the quality of classification by up to 15% compared to classical CBR.

Comparison of the properties of ontological concepts and relations between them with linguistic variables allows the use of fuzzy inference procedures to obtain unknown parameters of the situation. The ability to accumulate fuzzy values allows the model to gradually adapt to the dynamic changes in the current situation in the field of humanitarian response.

The developed fuzzy ontological model can be used as the basis of an intelligent decision making system for humanitarian response. Such a system will analyze and predict humanitarian problems, as well as provide the necessary knowledge for decision making in order to prevent the deterioration of the situation in the provision of humanitarian aid to the affected areas and to prevent emergencies in advance.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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