IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 8, 2019, accepted January 17, 2019, date of publication January 24, 2019, date of current version February 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2894777

A Method of Emergent Event Evolution Reasoning Based on Ontology Cluster and Bayesian Network

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This work was supported in part by the National Natural Science Foundation of China under Grant 61100133, and in part by the Science Guidance Project of Education Department of Hubei Province under Grant B20101104.

ABSTRACT Comprehensive real-time event information is critical to policymakers during emergency response and decision-making process. However, the development process of the emergent events has great uncertainty, and situational evolutions of emergencies are often difficult to use the fixed reasoning mode to attain. For this reason, this paper proposes a new method based on the ontology cluster for the evolution reasoning of emergency scenarios and extends the sematic web rule language to realize the scenario deduction, which can apply the Bayesian network to perform the conditional probability reasoning. A counterpart modeling and modifying of the Bayesian network optimization process is introduced. Besides, the probabilistic interpretation rules of atom components in context evolution are described with detailed query examples of emergency situation deducting and reasoning. The experimental results show that this approach is efficient in describing and capable of calculating the occurrence possibilities of the emergent events.

INDEX TERMS Emergent events, event scenario deduction, ontology cluster, Bayesian network, SWRL.

I. INTRODUCTION

In recent years, the frequent occurrences of unexpected incidents have caused a huge impact on social and economic normal operation [1]. In the process of dealing with emergencies, decision makers are usually faced with complicated natural and social environment. The analysis of the emergency scenarios evolution can help decision-makers understand the development trend of the event [2], which is of great guiding importance for emergency decision-making. For the sake of automatic association and inference ability of semantic web, many researchers try to use semantic technology and its tools to analyze the emergency trends [3], [4]. However, the current semantic technologies and tools are unable to deal with uncertain information, which disqualifies them to meet the description of evolutional emergency scenarios.

Just as the Web Ontology Language (OWL) based on Description Logics (DLs) has been applied in many fields, one way to overcome this expressive limitation of DLs would be to extend it with probabilistic rules [5]. Reasoning on uncertainty and vagueness data with improved DLP and SWRL gradually becomes a research hotspot [6]. By combining fuzzy dl-programs with Pool's independent choice logic, probabilistic fuzzy dl-programs can express probabilistic rules. While BayesOWL [7], PR-OWL [8], [9] and supplement OWL are useful for representing and reasoning with uncertainty, there is little research about combining probability theory with semantic web rules [10], which are very important for some real-world problems, such as disaster risk evaluations and medical diagnosis.

In this paper, we propose a model for reasoning emergency scenarios based on ontology cluster, and give the counterpart example to illustrate how to design the rule language to describe the evolution of the situational changes. This study extends the classic SWRL language from syntax and semantics, by which the extended scenario evolution rules can not only realize the evolution of language context reasoning, but also achieve similar function as the Bayesian Logic Program to calculate the probability of secondary emergencies [11], as well as to help decision-makers quantitatively analyze the probability of each scenario in emergencies. Besides, the ontology cluster can also facilitate dynamic information exchange between multiple organizations, incorporate human and data resources, as well as improve semantic interoperability and integration. Furthermore, the performance of the inference algorithm for the scene evolution rule sets is realized on the basis of the existing

OWL-DL inference engine [12]. The second section of this paper briefly explains the background and reasons that ontology cluster is needed in scenario reasoning. The third section of this paper introduces how to implement event evolution reasoning by adopting Bayesian network. The fourth section describes how to use the SWRL rule description language to realize the reasoning and query of the emergency scene. The fifth section is the counterpart experiment and evaluation of extended SWRL rules for ontology cluster deduction. And in the last section, we make a concise conclusion. The experiment results demonstrate that the decision maker can analyze the evolution probabilities of the situation in emergency life cycle based on the evolutionary reasoning model and the counterpart rule language algorithms.

II. ONTOLOGY CLUSTER EMERGENCY SCENARIO EVOLUTION DEDUCTION

The current ontology research and application is still at a low level of development, and it is time-consuming and labor-intensive to build large-scale probability ontology. The existing ontology construction methods are usually applied to a specific area, not suitable for emergency deduction and response field. Besides, there are many complicated concepts with property importance and priority in emergencies, which can cause an extra burden on the process of construction or generating comprehensive domain probability ontology with formal reasoning capabilities. There is a great deal of uncertainty in the process of the occurrence and development of unexpected events, so it is necessary to intelligently combine the evolution of multiple event elements in the scenario evolution of a specific event. Construction of emergency scenario evolution ontology cluster is a development trend to establish the evolution relationships between various scenarios and situations, which can help decision-makers effectively implement disposal scheme. As for single event tracking, the academia has relatively wide recognized methods and evaluation standards. Complex emergencies have greater uncertainties and migration status changes. Events develop into different statuses which are often triggered by newly occurred natural hazards, human or technologically caused natural hazards. The potential hazards can be classified by the American Disaster and Emergency Standard [13]. The disposal of emergencies often involves the collaboration of various departments and relates to multiple related factors. To this end, we propose an approach of fuzzy reasoning for emergency scenarios, as described in Figure 1. The correlation between the disaster causing factors depends on both the conditions of the disaster environment and the harm degree of the hazards factors. In order to apply the rule language to realize event scenario evolution reasoning and querying, we designed an emergency scenario reasoning ontology clusters, which depicts the evolution of unconventional emergency situations by causing disaster factors with conditions. C(i), C(j), C(k) are related to the prerequisites for associated disaster factors. We can calculate the possibilities of the event changes in the decision making process.

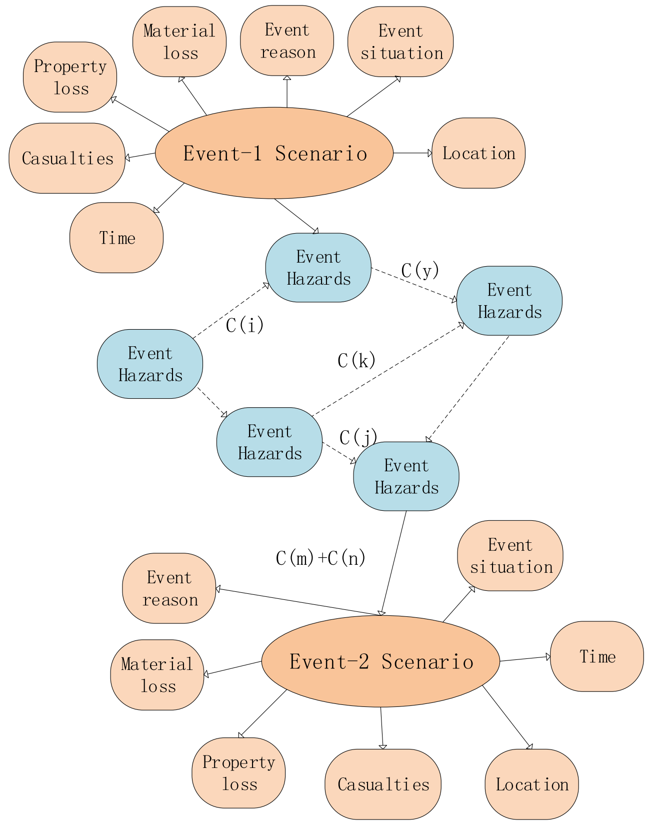
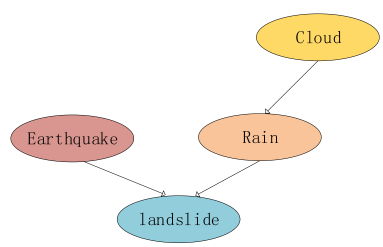


FIGURE 1. A fuzzy scenario reasoning ontology cluster.

III. EVENT EVOLUTION REASONING MODEL BASED ON BAYESIAN NETWORK

A. BAYESIAN NETWORK BASED ON DISASTER HAZARDS

If we generate a directed acyclic graph of event hazards causing factors with the conditional probability from the emergent ontology cluster, a Bayesian event evolution inference model can be constructed. Figure 2 depicts a graph that has four nodes (Cloud, Earthquake, Rain, and Landside). The nodes represent variables, and the edges represent probabilistic dependencies between variables, for example: Landside depends on whether the values of Earthquake and Rain are true. Each node in the graph is probabilistic independent of its descendant node, so we can compute the probability dis-



Cloud	
T	F
0.3	0.7

Cloud	Rain	
	T	F
T	0.6	0.4
F	0.3	0.7

Earthquake	Rain	Landslide	
		T	F
T	T	0.9	0.1
T	F	0.7	0.3
F	T	0.2	0.8
F	F	0.01	0.99

a) DAG b) CPT

FIGURE 2. Bayesian networks and CPT.

tribution of the Figure 2-(a) DAG (Directed Acycline Graph) by adopting means of the local probability. C, E, R, and L represent Cloud, Earthquake, Rain, and Landside respectively and P (C, E, R, L) represent the probability of a state, such as P (C=True, E=True, R=False, W=True). Based on the probabilistic calculation rule, we can obtain:

$$\boldsymbol{P(C, E, R, L) = P(C)^* P(E|C)^* P(R|E, C)^* P(L|R, E, C)} \tag{1}$$

When the parent value is obtained under given conditions, each node is independent of its non-seed nodes. Therefore, formula (1) can be simplified as:

$$\boldsymbol{P(C, E, R, L) = P(C)^* P(E|C)^* P(R|C)^* P(L|R, E)} \tag{2}$$

In determining a probability distribution table, only half of the CPT probabilities need to be determined, while the other half can be obtained by deducing. For example, in order to compute the CPT of Cloud, we just need to determine P (C=True) and then deduce the value of P (C=False) =1-P (C=True). In the practical use of Bayesian network reasoning, a directed acyclic graph is usually constructed by domain experts, and then the conditional probability table is learned from the training data. The training set usually contains a large number of samples and a certain redundancy is needed. However, the practical application of the training set may contain missing values which may be caused by missing samples or the inconvenience of observation variables. In case of missing, the expectation maximization (EM) algorithm can be applied to compute the conditional probability CPT table, as shown in Figure 2-(b) CPT(conditional probability table).

B. DIRECTED SEGMENTATION OF BAYESIAN NETWORKS

A Bayesian network can be composed of directed segmentation links: sequential connection, divergence connection and convergent connection [14].

(1) Sequential connections: Sequential connections ($X_i \rightarrow X_k \rightarrow X_j$) are directed to chain nodes in a sequential structure, where the middle node is referred to the head to tail type. Figure 3-(a) is a Bayesian sequential connection example for an extreme rainfall scenario, extreme rainfall nodes (high level, middle level and low level), intermediate river water rising nodes (high level, middle level and low level) and the tail nodes (flood occurrence or non-occurrence) are in a sequence connection. When the information of the river water level node is unknown, the value of rainfall determines the water level of the river, and the water level of the river also affects the occurrence of flood. In this case, the rainfall node determines the change of river water level and the occurrence probability of flood disaster. But when the river water level height has been at a warning water level, extreme rainfall and flood nodes are blocked under this circumstance.

(2) Divergent connections: Divergent connections are in the form of $X_i \leftarrow X_k \rightarrow X_j$, in which node X_k is called tail to tail node. In the case of unknown intermediate node X_k, the probability change or update will affect the child node

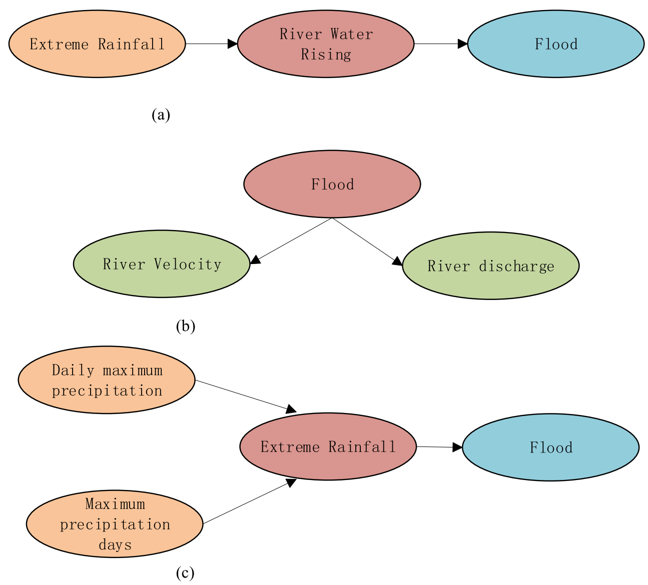


FIGURE 3. Bayesian networks connection examples. (a) A Bayesian sequential connection example. (b) A Bayesian divergent connection example. (c) A Bayesian convergent connection example.

X_i and X_j. However, when the probability distribution of the intermediate node X_k is known, the child node and the parent node are divided. Figure 3-(b) shows the divergent connections between floods (occurring, not occurring), river flow velocity (extreme, medium, and gentle) and river discharge (large, small). If we do not know whether there is a flood disaster or not, according to the velocity of the river flow, we can calculate whether the flood disaster occurs and further determine the flow volume of the river. If it is known that the floods have occurred in an un-recorded extreme situation, there is no need to judge the velocity or volume of the river [15]. The velocity and the discharge volume of the river become independent.

(3) Convergent connections: Directed chains in the form of $X_i \rightarrow X_k \leftarrow X_j$ are called Bayesian convergent connections, in which the middle node is called head to head node. Figure 3-(c) is an example of X_k convergent connection. When there is no extreme rainfall, the daily maximum precipitation nodes and the maximum precipitation day nodes are conditionally independent. When extreme rainfall is known, the maximum daily rainfall and maximum rainfall days are conditional.

C. THE MODELING PROCESS OF BAYESIAN NETWORK

A Bayesian network can be composed of directed segmentation links: sequential connection, divergence connection and convergent connection [14].

Bayesian network modeling is a continuous process, which includes problem definition, node selection, variable definition, data processing, algorithm selection and model improvement [16]. Therefore, the actual network modeling is a repeated refining process and the model needs to be modified continuously to achieve the best evaluation results. The following is a simplified general process of modeling.

(1) Problem definition: the purpose of constructing Bayesian network model should be clear and the domain knowledge must be possessed before the model construction. Besides, relevant domain knowledge is essential to construct a Bayesian network, which depends on how much knowledge are needed for a rational network model and prior probability construction.

(2) Variable selection: the variables correspond to the nodes in the Bayesian network structure, and the number of nodes will have a greater impact on the results of the model. It is necessary to make clear that the more variables are, the higher the accuracy of the evaluation is in constructing Bayesian network models. Selecting effective variables is a very complicated work, which will be affected by many factors, such as the variable selection from different experts' opinions. The expert knowledge often plays a very important role, as experts are familiar with the relative research field and know which variables may have a greater impact on the results.

(3) Variable processing: the processing of data acquisition includes the processing of the missing value, the elimination of singular values and the discretization of data. The Bayesian network based on discrete random variables is efficient to construct and operate.

(4) Network construction: to construct a Bayesian network model, one should not only rely on expert knowledge, but also refer to the different construction method and continuous improvement of the probability distribution of the Bayesian network model.

D. THE MODIFYING PROCESS OF BAYESIAN NETWORK

Emergency decision making often faces limited priori knowledge, so it is necessary to add human-computer interaction and introduce expert knowledge to optimize the structure of Bayesian network. When modifying Bayesian network model, we should communicate with experts in time, detect the logical correctness of the model and solve the practical problems. And there are usually three ways to modify Bayesian networks, shown as in Figure 4 series taking an earthquake emergency scenario evolution as an example.

(1) Adding a new node to the directed path without an intermediate node, as shown in Figure 4-(a).

(2) Adding a parent node to a node without a parent, as shown in Figure 4-(b).

(3) Adding a child node to a node, as shown in Figure 4-(c). Since there is no influence on the causal relation and probability distribution of the existing nodes in the Bayesian network, there is no constraint condition for adding a child node to a parent node.

The decomposition of Bias network node value is a useful way to increase the density of node value, and the combination of node value is the counterpart way to reduce the node value density [17]. Bayesian decomposition network node value can increase the accuracy of the node value, so as to

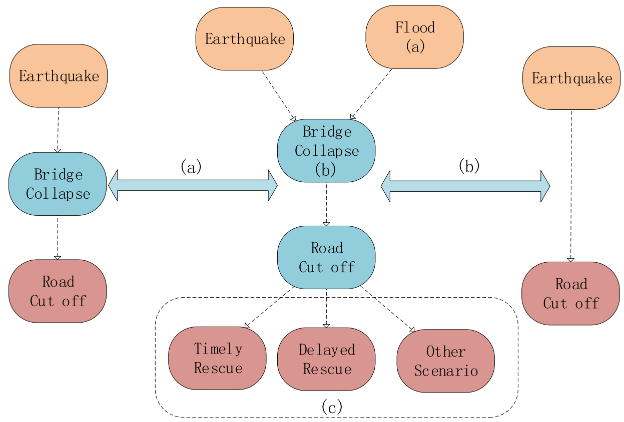


FIGURE 4. Bayesian networks modification examples.

improve the accuracy of Bayesian network model, such as a ''earthquake'' node ranges from {<6,6-8,>8} can be decomposed as {<3,3-4.5,4.5-6,6-8, >8}. Meanwhile, simplifying Bayesian network nodes can reduce node complexity and improve the calculation speed of Bayesian network model. For example, the ''number of casualties'' node range {<10, 10-20, 20-50, 50-100, >100} can be merged into the range of {<50, 50-100, >100}.

IV. SWRL BASED DESCRIPTION LANGUAGE FOR SCENARIO EVOLUTION RULES

A. BAYESIAN NETWORK BASED ON DISASTER HAZARDS

The sematic web rule (SWRL) is a proposed language combining OWL and RuleML, which has the full power of OWL DL at the price of decidability. In most cases, decidability can be regained by restricting the form of admissible rules or imposing suitable safety conditions. In order to enable SWRL to describe the probability of events, this paper adds new notations and syntactic patterns for existing SWRL grammars. Because the conversion between abstract syntax and concrete grammar is too simple to address possibility deduction [18] , this paper uses the abstract symbol as similar as Backus's BNF (Backus-Naur Form) to define the syntax of regular language. In this study, the syntax of the scene evolution rule language is consistent with the existing SWRL grammar. For example, the syntax of atom, i-object, D-object and other components in the context of the evolution rules language are the same as that of the corresponding component in SWRL. Therefore, this paper only lists the syntax of the SWRL specially designed for the scene evolution rule language, which is as follows:

axiom::= rule
rule::= 'Implies(' < URI_reference > {annotation} antecedent consequent ')'
antecedent::= 'Antecedent(' {atom [probability] } ')'
consequent::='Consequent('{atom[probability CPT_path]}')'
probability::= P-variable

Among them, "rule" represents a rule set corresponding to event scenario, "antecedent" is a preceding event of the current event status, and "consequent" is a consequent event of the current event status. URI_reference is an optional item in the existing SWRL language, but it cannot be omitted in the scenario evolution rules. URI_reference will be used as an identifier for the current rule, and the URI_reference value must be determined when the evolution rules are declared to avoid conflict with the defined rules. According to the URI_reference identity, the inference engine can associate the scenario evolution rules with the predefined conditional probability table CPT (Conditional Probability Table). In the scenario evolution rule set, atom may follow P-variable, which means that the probability of occurring is as P-variable defined. The inference engine will calculate the probability of the occurrence of the posterior atom according to the probability table which is defined in advance and the probability of the optional atom. CPT path means the file path and the consequent event probability variables appear in pairs, through which user-defined files can be accessed with a conditional probability table. For example, the possibility of the occurrence of a landslide in the range of an earthquake zone can be described as the following:

$$\begin{aligned}&\text{Mountain}(?m) \wedge \text{Earthquake}(?e) \wedge \text{Rainstorm}(?r)\\&\quad \wedge \text{Affect}(?e, ?m)^{*}\text{em} \wedge \text{Affect}(?r, ?m)^{*}\text{rm}\\&\quad \Rightarrow \text{HasLandslide}(?m, \text{true})^{*}\text{ml@“./DisasterCPTs.xml”}\end{aligned} \tag{3}$$

The counterpart syntax of the context evolution rule language can be expressed as follows:

Implies ('http: //www.whu.edu.cn/Disaster/ LandslideRule')
Antecedent (Mountain (I-variable (m))
Earthquake (I-variable (e))
Rainstorm (I-variable(r))
Affect (I-variable (e), I-variable (m)), P-variable(em)
Affect (I-variable(r), I-variable (m)), P-variable(rm))
Consequent (HasLandslide(I-variable(m), Boolean(true))
P-variable ((ml) './DisasterCPTs.xml'))

In the "./DisasterCPTs.xml" file, the conditional probability table records the probability of a landslide when the optional atom is in a different state. For example, when the earthquake e and rainstorm r both affect the mountain m, the probability of landslide in the mountain m is 0.9. When only the earthquake e affects the mountain m, the probability of the landslide of m is 0.7. After setting the probability of landslides in different situations, the complete conditional probability table can be described in the following form in the "./DisasterCPTs.xml" file.

CPTs('http://www.whu.edu.cn/Disaster/LandslideRule'
Table{HasLandslide(ml)
Case(Effect(e,m) True Effect(r,m) True 0.9) ;
Case(Effect(e,m) True Effect(r,m) False 0.7) ;
Case(Effect(e,m) False Effect(r,m) True 0.6);
Case(Effect(e,m) False Effect(r,m) False 0.01);}

TABLE 1. Probabilistic interpretation of atom components in context evolution rules.

Atom	Explanation
$C^J(x)$	$P(x^I \in C^I)$
$D^J(z)$	$P(z^I \in D^I)$
$Pr^J(x, y)$	$P((x^I, y^I) \in Pr^I)$
$Q^J(x, z)$	$P((x^I, z^I) \in Q^I)$
$sameAs^J(x, y)$	$P(x^I = y^I)$
$differentFrom^J(x, y)$	$P(x^I \neq y^I)$
$builtIn^J(r, z1, \ldots, zn)$	$P((z1^I, \ldots, zn^I) \in D(f))$

B. BAYESIAN NETWORK BASED ON DISASTER HAZARDS

As for fuzzy semantic rule language, Guigno et al. proposed P-SHOQ (D) [19] description logic, which can represent and reason about uncertain knowledge about concepts and instances. BayesOWL makes further the use of the OWL language statement, which increases the description of probabilistic constraints [20]. Because atoms in SWRL not only include OWL description and data range but also contain other components, such as built-in relations, Bayes-SWRL needs more expressive capability than BayesOWL. In this study, The scene in the semantic atom rule language evolution is defined as three tuple I= (ΔI, ΔD, .I), where the individual domain ΔI is a nonempty set of individuals, data type domain ΔD is a nonempty set of data values, .I is an individual interpretation function. More detailed descriptions about OWL DL interpretation can be found in reference [21].

In the scenario evolution rule language, atom interpretation can be defined as two-tuple J= (Δ^J, $\bullet^J$). The non-empty set Δ^J contains various types of atom, $\bullet^J$ can be interpreted as probability function, which maps Δ^J to the value in the range of [0, 1]. Table 1 illustrates the probabilistic interpretation of various types of atom in a scenario evolution rule language. Assuming that C is an OWL DL description, D is an OWL DL data range, Pr is an OWL DL individual valued property, Q is an OWL DL data valued property, f is a built-in relation, x and y are variables or OWL individuals, z is a variable or an OWL data value, and P(F) figures out the probabilistic value when the formula F is real.

When the probability of the posterior atom is calculated by using the scene evolution rule and the conditional probability table, the inference engine of the scenario evolution rule must obtain the probability value of each atom in the rules in advance. There are three methods can be used to obtain the probability value. The first method is to set the probability value of each atom, which is applicable to various types of atom. At this point, the inference engine can be accessed directly. The second approach is to customize the built-in relationship. Because the judgment of this kind of relation is to be accomplished by the user-defined function, the probability that the relation can be calculated by the customer established function. For example, the formula (3) Affect(?e, ?m) can be regarded as user-defined relationship, the probability value of the relationship can be established according to the intensity of the earthquake, the distance between the epicenter and the mountain, the geology of the mountain. The third method is to use the equivalentClass and equivalentProperty relations in the OWL from the results which can be obtained previously in the declaration of the probability value.

In the scenario evolution rules, the key atom is the necessary condition for the establishment of the posterior atom; therefore all key atoms in the rules must be established. If there is a declaration of probability, the probability value must be 1. If there is no probability statement, and then the probability value is default to be 1. Relatively speaking, the latter atoms on the rules of the optional atom requirements are lower, which only need to have statements in knowledge of the library, without the needs to determine whether there is a probability statement. Assuming that R is a scenario evolution rule, R_I is a specific instance of the rule, which means all variables in R have been replaced by OWL instances or values. E_i, O_j and C_k (i, j, k∈N) were key atom, optional atom and posterior atom respectively. The function inABox (a) is used to determine whether the ABox of the knowledge base contains a variable, if so it will return the value of True. Thus, the conditions for the success of the deduction can be shown in formula (4).

$$\forall i(\mathrm{inABox}(E_i) \wedge (E_i^J = 1)) \wedge \forall j(\mathrm{inABox}(O_j)) \tag{4}$$

Once the posterior atom in the decision rule is deducted, the inference engine will calculate the probability value of each atom. Assuming that n is the number of optional R_I in atom, R_I rules among all optional atom are independent of each other, C_m as a result of the performance of a R_I atom, then the scene deduction engine can be calculated by formula) to obtain the probability of C_m.

$$P(C_m) = \sum\nolimits_{X_1,\ldots,X_n \in \{T,F\}} (P(C_m = T|O_1 = X_1, \ldots, O_n = X_n)^* P(O_1 = X_1)^* \ldots {}^* P(O_n = X_n)) \tag{5}$$

In the formula (5), $P(O_j = X_j)$ denotes the probabilistic value when O_j is true or false, the conditional probability C_m on O_j is arranged in the CPT file. The current ABox has declared the earthquake e, rain storm r and mountain m, and the probability of the mountain m affected by earthquake e and rainstorm r is 0.8 and 0.4, respectively. When the above examples are introduced into the formula (5), the rules of the instantiation can satisfy the requirement of deduction, the scenario evolution rule will deduct the possibility of landslide. At this point, according to the "./DisasterCPTs.xml" file in the conditional probability table, the probability of the optional atom value can be calculated from the landslide probability and quantitative description of the event development trend can be further analyzed.

In this paper, we take the WenChuan earthquake for an example to illustrate our deduction process. In order to testify the effectiveness of our method, the scenario ontologies and rules drawn from the historical emergencies were used to deduce the earthquake. Before the task of scenario inference, some instances in the effect area of the earthquake were prepared and imported into the scenario evolution model. Then, Pellet and the algorithm of scenario inference were used to reason out the potential scenarios. The earthquake affected areas have rainfall, the earthquake caused in building collapsed, landslides and other scenarios; landslides can further lead to lake and road damage and other scenarios. The formula (6) describes the evolution of the relationship between earthquakes and rainstorms and landslides. The formula describes the earthquake that may cause the collapse of important buildings. Among them, Affect (e, im) can also be used as user-defined function. According to the level of the earthquake, the location of the building and the epicenter, the probability of building damages can be reasoned.

$$\begin{aligned}&\mathrm{ImportantBuilding}(?im) \wedge \mathrm{Earthquake}(?e)\\ &\quad \wedge \mathrm{Affect}(?e,?im)^*eim\\ &\quad \Rightarrow \mathrm{HasCollapsed}(?im,true)^*imc@\text{"./DisasterCPTs.xml"}\end{aligned} \tag{6}$$

The formula (7) describes a landslide that may cause a river to flow through the mountains, creating a barrier. The Affect (? m,? r), a built function estimates the probability of the river being affected by landslides through the possible volume of the landslide and the width of the river.

$$\begin{aligned}&\mathrm{Mountain}(?m) \wedge \mathrm{HasLandslide}(?m,true)^*ml\\ &\quad \wedge \mathrm{River}(?r) \wedge \mathrm{LATP}(?r,?m) \wedge \mathrm{Affect}(?m,?r)\\ &\quad \Rightarrow \mathrm{BeBlocked}(?r,true)^*rbb@\text{"./DisasterCPTs.xml"}\end{aligned} \tag{7}$$

The formula (8) describes a landslide that could cause damage to the road near the surrounding mountain. All of the scenarios in this article are related to the "DisasterCPTs.xml" file, which means that the file contains all the relevant conditional probabilities of the rules. Affect (?m,? rd) built in function is used to evaluate the probability of the road affected by the possibility of landslide and the distance between the mountain and the road.

$$\begin{aligned}&\mathrm{Mountain}(?m) \wedge \mathrm{HasLandslide}(?m,true)^*ml\\ &\quad \wedge \mathrm{Road}(?rd) \wedge \mathrm{LATP}(?rd,?m) \wedge \mathrm{Affect}(?m,?rd)\\ &\quad \Rightarrow \mathrm{BeDestroyed}(?rd,true)^*rdbd@\text{"./DisasterCPTs.xml"}\end{aligned} \tag{8}$$

The inference engine based on scenario evolution rules can be realized by extending the existing SWRL inference engine. According to the relevant literature, there are three ways to implement SWRL inference engine. The first method is to convert the rule based on SWRL into the first order predicate logic. A typical representative of this method is using Hoolet [21] to extend SWRL the rules, which adopt variables with universal substitution in SWRL, and uses Vampire to verify the compatibility of the axioms. The second method is to convert the OWL DL description in the SWRL into

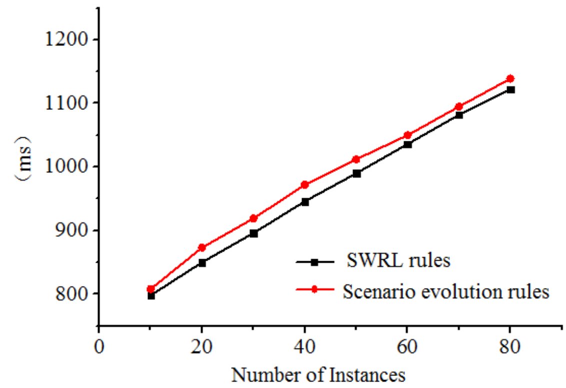


FIGURE 5. Performance comparison between scenario evolution rules and traditional SWRL rules.

rules, and uses the forward inference engine for processing. For example, the Bossam inference engine based on RETE algorithm can be used to inference the knowledge composed of OWL and SWRL [22]. However, the method has obvious some defects and the incompatibility between the description logic and the Horn rules leads to not all OWL DL descriptions can be converted into rules. The third approach is to extend the existing OWL based DL inference engine based on tableaux algorithm, such as Pellet. In view of simplicity and realization, the third methods can cover all the descriptions of the OWL DL. Hence, our research uses this method to combine the probabilistic interpretation and the tableaux algorithm to implement the inference engine.

V. EXPERIMENT AND EVALUATION

In our study, earthquake disaster is taken as an example to testify the deduction abilities of extended SWRL rules. The occurrence of earthquake disasters in different environments usually produces secondary disasters. In the evaluation part, we analyze both the efficiency and application potential of our proposed method.

In order to test the efficiency of the algorithm, it is compared with traditional SWRL rules deduction based on the same statistics, using the same number of rule instances size. Testing environment hardware is under the following configuration: Intel Core i7-3520 processor (4*2.9GHZ, 8GB RAM), the software uses Windows 7 and Java 1.7.0, the inference engine uses a Pellet with open source codes. As there is no complex built-in function in each rule, so we can ignore the influence of the computation time of the built-in function on the inference performance. Figure 5 shows that the number of instances increases from 10 to 80 when the number of rules is five, comparing with the performance of SWRL. The figure illustrates that the computation functions perform better by extending the SWRL scenario evolution rules. Besides, the time-consuming of deduction rate remained linear with increased number of examples.

Our situational information model for emergencies can be formally represented as a four-element ESModel:=<EK, SKR, RK, AK>. Among them, EK (Event Knowledge) stands for the incident knowledge base, in which the knowledge at the event level is described; SKR (Scenario Knowledge Repository) is a set of situation knowledge bases, each of which contains context knowledge, corresponding to certain types of emergencies or event instances. RK (Resource Knowledge) is a resource knowledge base that contains various countermeasures, disaster prevention/mitigation resources, and the relationships between measures and resources. AK (Association Knowledge) is a related knowledge base and describes knowledge across knowledge bases. For example, an emergent E1 causes the occurrence of emergent event E2, which means that the scenario instance has a hazardous impact in the context knowledge corresponding to event E2. Events develop into different status often triggered by newly occurred hazard natural, human or technologically caused, which is classified by the American Disaster and Emergency Standard(NFPA 1600®) [23]. NFPA 1600 standard establishes and maintains crisis management capabilities, which is dedicated to helping users prepare for any type of crisis or disaster resulting from natural, human, or technological events. A set of Events {E1, E2, E3,..., Ei} evolves into a series of status due to the impact of hazards and sometimes one event is simultaneously triggered by multiple hazards as there are associated hazards and secondary hazards, some examples are offered in Table 2. In complicated emergency situations, associated hazards relate to those hazards that go along with the primary hazards and usually happen at the same time, and secondary hazards are the hazards that follow as a result of other hazard events. The composition of the emergency scenario information model is as shown in Figure 6.

TABLE 2. Examples of hazards relationship from NFPA 1600.

Primary hazard	Associated hazard	Secondary hazard
Earthquake	Landslide	Building collapse, Tsunami, Sparry flood
Hurricanes	Cyclone, Flood	Building collapse
Snow	Traffic accidents	Fire accidents caused by heating, Avalanche
Volcano eruption	Earthquake	Forest Fire, Flood, Sparry flood

Figure 6 illustrates the content of each component in the scenario information model and the relationships between them. Clearly, the ESModel model uses a partitioning module to represent local knowledge, with the advantage of being able to reuse knowledge and isolate conflict knowledge. EK is a knowledge base of emergency events based on description logic. It describes the classification of emergencies and the relationship between emergencies. It should be noted that Figure 6 lists only the classification of sub-Events of a certain contingency. SKR contains a number of scenario knowledge

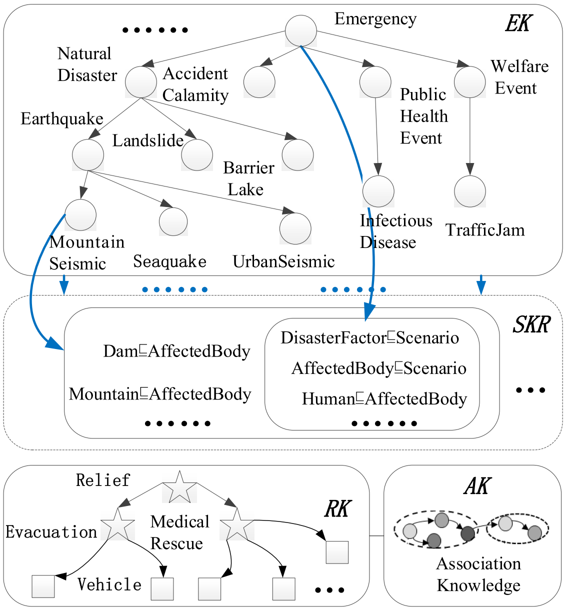


FIGURE 6. **The composition of the emergency scenario information model.**

bases based on description logic. Each type of unexpected event or each instance of an emergency corresponds to a scene knowledge base in SKR. In addition, the inheritance relationship between event classes will have an impact on the corresponding knowledge base scene interpretation, namely situational knowledge base corresponding to sub class events to explain the ''parent'' in the event of situational knowledge. For example, mountain seismic scenario knowledge base should be able to explain the incident scene corresponding to the knowledge base, thus obtains the Mountain Scenario conclusion. Similarly, event instances should also be able to interpret situational knowledge in such events. Similarly, RK is also a knowledge base based on description logic, and uses the various axioms of description logic to describe knowledge about response measures, the relationship between action measures and various resources, which can guide the decision makers to obtain resources according to the countermeasures. The AK library describes the association knowledge among the knowledge bases, and it introduces new formal representations to describe situational knowledge.

In order to realize an efficient deduction, we also developed a Bayes-SWRL reasoning tool by adopting Protégé. Figure 7 shows the analysis result of disaster evolution by using Bayes-SWRL emergency scenario reasoning interface, which can estimate the probabilistic value of secondary and derivative disasters and explain the relationship between the disasters. The preconditions such as mountain and rainstorm are descripted with scaled values and the probabilities of rivers being blocked by the impact of a certain earthquake can be deduced by the Bayes-SWRL reasoning tool using empirical or predefined Bayesian parameters.

By analyzing the earthquake disasters in the mountainous region with our Bayes-SWRL reasoning tool, the key Event scenarios commonly found in mountain earthquakes were

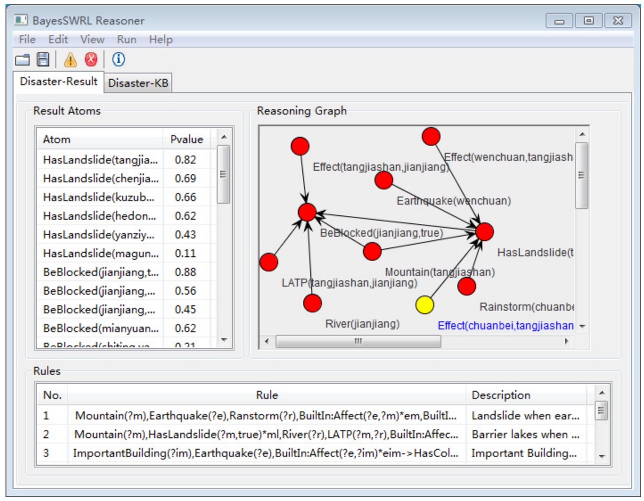


FIGURE 7. **Emergency scenario reasoning interface.**

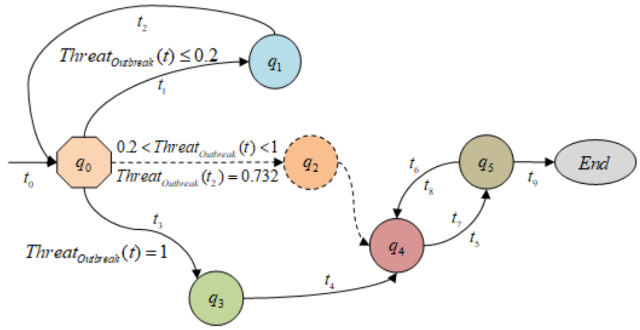


FIGURE 8. **The composition of the emergency scenario evaluation model.**

verified, and their relationships were illustrated in Figure 8 with key event status description in Table 3. Due to the limited rules in our prototype system, it does not list all possible scenarios. For example, when an earthquake occurs, the damage body might also include factories and hazardous facilities within the impact range. As described in Figure 8, people and mountains become disaster-bearing bodies when an earthquake occurs in a mountainous area, and rainfall in the earthquake-stricken areas may further lead to changes in the state of the mountain safety. Mountains will cause a

TABLE 3. **Event status of the earthquake evaluation example.**

Event Status	Status Descriptions
q_0	Initial status: Earthquake
q_1	Disaster Early warning
q_2	Barrier lake \ Flood
q_3	Landslide \ Mudslide
q_4	Building collapse
q_5	Casualties
End	Event disappears

landslide event when some preconditions are met. At this time, the mountain is a hazard factor in the subsequent incident. In our simulation experiment, changes in the state of the disaster-bearing bodies (mountains, rivers and roads) in landslides range can cause scenarios including dammed lakes and traffic jams. Currently, the prototype system is able to analyze specific emergency scenarios when all disaster factors are predefined in Bayesian network with appropriate expert's involvement. We successfully verified its usability in scenario deduction with real cases of ''5.12 Wenchuan Earthquake'' and ''8.3 Ludian Earthquake'' in China.

VI. CONCLUSION

In this study, we propose a new method based on Ontology cluster for the evolution reasoning of emergency scenarios, and extend the SWRL language rules to realize the specific method of scenario deduction, which can further apply Bayesian network to perform conditional probability reasoning according the syntax and semantics of Bayes-SWRL. We extend SWRL rule sets to enable possibility calculation for uncertain event scenarios, through which decision makers can take measures to prevent the occurrence of critical scenarios, deduce the probability of the occurrence of reference scenarios. A counterpart modeling and modifying of the Bayesian network optimization is introduced. At the meantime, probabilistic interpretation of atom components in context evolution rules are described with detailed query examples of emergency situation deducting and reasoning. Consequently, some disaster preventions and reductions can be done ahead of time to decrease losses in the emergency. We will further improve a comprehensive emergency scenario deduction tool by adopting Protégé in our future researches, as well as integrate information from linked open data resources and internet of things to support emergency situation deductions.

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