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# Rapid Generation of Emergency Response Plans for Unconventional Emergencies

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**ABSTRACT** Unconventional emergencies can lead to unforeseen disastrous penalties. Due to their unrepeatable, complex, and unpredictable nature, it is generally hard to establish high-quality Emergency Response Plans (ERPs) for unconventional emergencies, thus posing great challenges for unconventional emergency response. This work proposes a rapid ERP generation approach for unconventional emergencies so as to provide support for emergency decision-making. The generation of ERPs is achieved by exploitation of existing ERPs that contain much emergency response experience. First, a number of ERPs are collected and structurally organized to construct an ERP repository. Then, the applicability of each ERP segment in the repository to a given unconventional emergency is evaluated by a proposed ERP similarity measure and emergency scenario matching mechanism, in which the semantic relevance and the scenario consistency of an ERP segment are taken into account, respectively. Applicable ERP segments are obtained for each section of ERPs, and combined to form a new ERP with the guidance of pre-defined ERP structure. Furthermore, we design an ERP assessment method and perform a case study on the proposed approach which presents encouraging experimental results.

**INDEX TERMS** Unconventional emergency, emergency response plan, emergency scenario, text similarity, text generation.

## I. INTRODUCTION

Emergency Response Plans (ERPs) are a type of important emergency administrative documents that describe pre-specified plans in response to potential emergencies, e.g., typhoons, traffic accidents and epidemic diseases. In general, ERPs not only specify the actions need to be taken to address crisis situations, but also provide essential information about organizations and resources involved in the emergency response process. A well-established ERP can facilitate emergency response officers making a quick decision under complex and urgent situations [1]. Establishing comprehensive ERPs thus has been a key responsibility of emergency administrative agencies of different levels and categories.

Until recently, a variety of ERPs have been created worldwide, mostly based on the experience of handling historical

emergencies. In other words, most existing ERPs aim to provide operational guidance on the response to recurred emergencies. However, emergencies may evolve in an uncertain manner [2], and even interact with one another resulting in chain reactions of emergency events [3]. Therefore, there exist many *unconventional* emergencies that are different from existing emergencies and can lead to unforeseen disastrous penalties [4]. Due to the lack of experience, it is challenging to establish high-quality ERPs for unconventional emergencies.

The management of unconventional emergencies is a challenging issue that has attracted significant attention. There has been much work devoted to supporting decision-making in the unconventional emergency response process. In order to capture the key factors driving the evolution of unconventional emergency events and the interaction between the factors, Zhou *et al.* [2] made a detailed analysis on the evolution processes of 102 unconventional emergencies occurred in 38 megacities. Chen *et al.* [5] studies the

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evolution prediction problem of unconventional emergencies using multi-label machine learning. Since the management of unconventional emergencies generally involves group decision making in which multiple experts may express diverse opinions, Xu *et al.* [6] proposed a conflict-eliminating model to decrease the conflict degree of experts and reinforce the group decision. Domain knowledge has been recognized as an important resource in unconventional emergency decision systems and various ontology knowledge bases for unconventional emergencies have been proposed [7], [8]. In general, most existing work aims to propose theoretical methodologies to tackle particular challenges in the unconventional emergency response process such as evolutionary phenomena of events [2], [5] and conflicts existing among decision-makers [6], [9], [10]. The results achieved, while beneficial to assist decision-making of unconventional emergency response, do not necessarily result in a complete ERP because much more comprehensive information about handling an unconventional emergency should be included in ERPs. Moreover, ERPs currently used in real-world emergency management agencies are mostly in the form of text [11], because natural language is more human-friendly than formalized models [12], [13]. Because of the gap between formalized decision-making models and textual ERPs, the existing theoretical methodologies proposed in the unconventional emergency management literature are hardly to be leveraged to construct textual ERPs straightaway.

To provide more direct guidance in the response process of unconventional emergencies, this work focuses on rapid generation of textual ERPs for unconventional emergencies. An unconventional emergency, although of unique characteristics, can in most cases find its relevant historical emergencies. The experience of treating the relevant historical emergencies is of much value to the response to an emerging unconventional emergency. Taking the unconventional emergency of a traffic accident caused by a typhoon as an example, the ERPs for traffic accident emergencies and typhoon emergencies can be good references to establish the ERP for this unconventional emergency. Following this intuition, we propose a novel approach to generate ERPs for unconventional emergencies based on the massive ERPs established for emergencies already appearing.

The key to our work is to recognize existing ERPs relevant to the given unconventional emergency and then generate a new ERP based on these relevant ones. We approach this issue into three stages. First, an ERP repository is constructed by crawling ERPs published on the Internet by Chinese emergency administrative agencies of different levels. Each textual ERP is structuralized so as to support for similarity analysis in the next stage. Then, by employing state-of-the-art natural language processing (NLP) techniques, the relevance of each segment of ERPs in the repository w.r.t. the given unconventional emergency is quantified. The proposed relevance metric is comprehensive in that both fine-grained semantic similarity and scenario consistency are taken into account. In the last stage, the relevant segments of ERPs are

combined into the ERP for the unconventional emergency. Furthermore, we design an ERP assessment method based on multi-granular fuzzy linguistic modeling, and assess the generated ERPs with a case study of an unconventional emergency decision-making problem.

The rest of the paper is organized as follows. Section II gives a brief introduction of related work. The details of the proposed approach is described in Section III. In Section IV, we demonstrate the validity of the generated ERP through a case study. Finally, we conclude this work with a discussion of future work in Section V.

## II. RELATED WORK

To the best of our knowledge, the problem of generating textual ERPs for unconventional emergency has less been considered so far. Existing studies closely related to our work is Emergency planning.

One traditional way to emergency planning is to build mathematical programming models to integrating various factors in the emergency response process such as emergency scenarios, event duration and resource consumption. For example, Pyakurel and Dhamala [14] developed dynamic contraflow models in continuous time setting for evacuation planning that allow efficient shifting maximum number of evacuees from the disastrous areas to the safe destinations; Zhang *et al.* [15] constructed an optimization model for selecting risk response strategies considering the expected risk loss, risk interdependence and its two directions; Bish and Sherali [16] studied demand-based strategies of aggregate-level staging and routing in evacuation planning by using a linear programming framework.

In order to reuse historical emergency response experience, case-based reasoning has been a popular approach to emergency planning. Fan *et al.* [17] proposed a generalized framework for generating project risk response strategies based on case-based reasoning, which includes case representation, similar case retrieve, historical strategy revision and new strategy generation. In order to establish formalized case description, ontology model is often used to extend the case-based reasoning process [18]–[20]. Afzal *et al.* [21] considered the problem of dynamic emergency response which requires adaptability to changing situation as the incident evolves, and proposed a dynamic composition approach of existing response processes. One drawback of case-based reasoning approaches is that the wide range of information demand of establishing emergency response plans, e.g., organization information and resource information, are hardly satisfied by real world historical cases.

Emergency responses generally involve continuous refining emergency goal tasks into executable tasks according to emergency domain knowledge. Hierarchical Task Network (HTN) [22], as a powerful planning technique for modeling such cognitive process, has been used to solve the emergency task planning problem. For example, Tang and Shen [23] generated a flexible concurrent response action plan of durative actions by integrating HTN planning and

scheduling technologies; Liu *et al.* [24] investigated emergency task planning problems with incomplete initial environment information, concurrent execution and uncertain execution durations based on conditional temporal HTN planning paradigm. More recently, there is work on integrating HTN with case-based reasoning to improve the expression capacity of historical cases at different detail level [25].

Existing work on emergency planning mainly focuses on constructing formalized emergency planning models such as emergency response process models [21], [26], emergency response task networks [23], [24] and ‘strategy-risk’ response ontologies [17], [19], which are still a long way from generating textual ERPs that can be directly used by emergency administrative staffs.

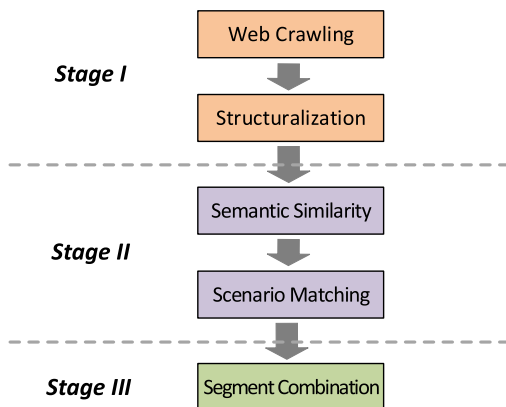


FIGURE 1. The framework of ERP generation.

### III. THE PROPOSED APPROACH

In this section, we present the details of the proposed ERP generation approach. The overall framework, as shown in Fig. 1, comprises three stages: i) ERP repository construction, ii) ERP segment retrieval, and iii) ERP segment combination. Next, we will give the details of each stages.

#### A. STAGE I: REPOSITORY CONSTRUCTION

The aim of stage I is to construct a large-scale of ERP repository that serves as the basis of ERP generation. As opposed to a loose collection of ERPs, the constructed ERP repository essentially provides a structural organization of emergency response information.

##### 1) WEB CRAWLING

In order to construct the ERP repository, we first collect raw ERPs from the Internet. According to the regulations on open government information of China, ERPs for public safety emergencies are a type of official documents that needs to be open to the public, so emergency administrative agencies have disclosed most of the established ERPs through the portal sites of governments. Thus a web crawler is developed to collect raw ERPs from the Internet. In particular, we maintain a URL list of government’s portal sites of provinces and cities in China, then apply the crawler on each portal site to

collect the published ERPs. Beautiful Soup HTML parser<sup>1</sup> is used to extract textual content of ERPs from the crawled HTML documents. Note that we are more focused on special ERPs rather than overall ERPs, as the former provides operational guidance on the response to particular emergencies while the latter only provides principles or frameworks for guiding emergency responses. Thus we only keep special ERPs crawled from the Internet. Finally, our ERP repository is constructed by more than 900 ERPs.

Furthermore, we assign each ERP with a category label. All the collected ERPs are first divided into four groups according to the category of the corresponding emergencies, i.e., natural disasters, accident disasters, public health incidents, and social security incidents. Then, we apply an enhanced *k*-Means clustering algorithm [27] to each group of ERPs to derive a more fine-grained category of ERPs. Finally, 33 clusters are obtained, each taken as the category label of ERPs.

##### 2) STRUCTURALIZATION

Raw ERPs are essentially unstructured as they are presented in textual form. To facilitate further exploitation of ERPs, we structuralize raw ERPs. As a type of formal official documents, ERPs are similar in structure. For example, the ERP shown in Fig. 2 starts from the chapter *General principles* and then provide the information about the *organizational system* performing emergency response, followed by detailed descriptions of the actions taken before (in the chapter *Warnings and Precautions*), during (in the chapter *Emergency response*) and after (in the chapter *Subsequent treatment*) the emergency. In fact, most ERPs have similar discourse patterns as shown in Fig. 2 because approximately fixed types of information are required for handling emergencies, e.g., organizations, resources and graded response actions.

Following this observation, we propose a semi-structured representation of raw ERPs, in which an ERP is organized as a set of inter-related text segments. Taking the textual ERP in Fig. 2 as an example, the corresponding semi-structured representation is shown in Fig. 3.<sup>2</sup> The semi-structured representation is essentially a tree structure that is consistent with the hierarchical documentation structure of ERPs. Each segment corresponds to a unique chapter in the textual ERP and describes a single aspect of the emergency response process.

To derive such a semi-structured representation of ERPs, we develop a number of regular expression rules to split a textual ERP into segments according to the discourse patterns. The segments are then assigned with a set of structure labels, i.e., the primary/secondary/tertiary/quaternary heading and body, which encode the inherent documentation structure of ERPs. With the structure labels, an ERP can be materialized

<sup>1</sup><http://www.crummy.com/software/BeautifulSoup/>

<sup>2</sup>Since an ERP generally has a great length, only parts of the ERP is depicted here.

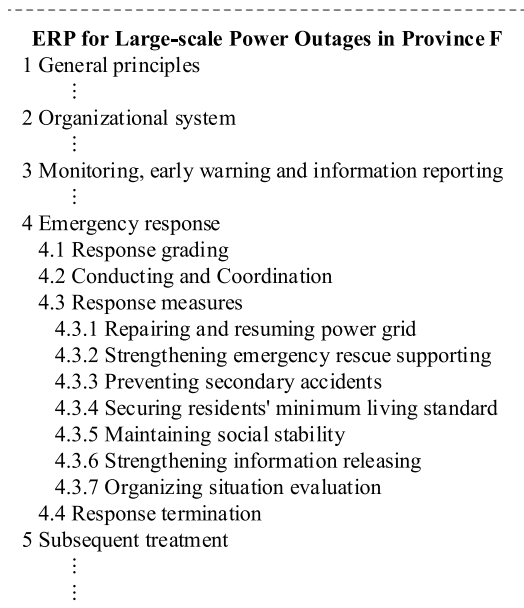


FIGURE 2. An example of textual ERP.

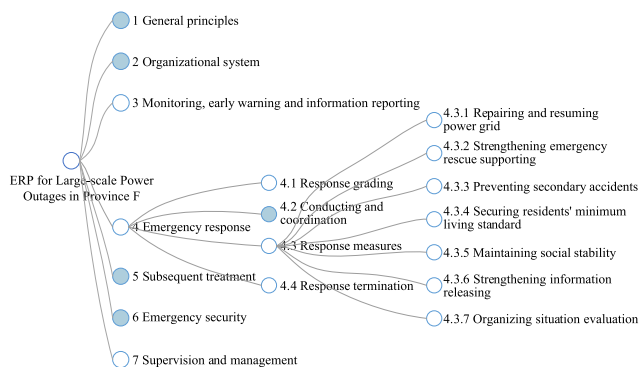


FIGURE 3. The semi-structured representation of the textual ERP in Fig.2.

using XML, due to the fact that XML has become a standard to represent and exchange data with structured semantics [28]. XML is also advantageous in offering flexible extensibility in representing both structured and textual information, which is just the case of ERPs.

Furthermore, we extract emergency scenario information from ERPs that is a determining factor in choosing response actions to emergencies. Emergency scenarios as well as the corresponding response actions are commonly described in ERPs, especially in particular chapters, e.g., response grading and response measures. It is generally hard to extract emergency scenario information from raw ERPs due to the flexibility of natural language. However, the semi-structured representation of ERPs can greatly facilitate the task. In the semi-structured representation, the chapters containing the emergency scenario information can be directly identified, thus narrowing the searching text spans.

In this work, we extract emergency scenario information by applying a classic wrapper-based information extraction approach [29]. The first step is to define the emergency

scenario description template that is capable of generalizing different types of emergency scenarios. According to ‘hazard – bearing body – environment’ emergency modeling framework, we propose the following emergency scenario description template:

*Definition 1:* A scenario attribute template is a tuple  $E = (name, type, \alpha, \beta)$  such that:

- *name:* The name of emergency attribute, in text form.
- *type:* The type of emergency attribute. In this work, we only consider two types of emergency attributes, i.e., bearing body and environment.
- $\alpha$ : The lower bound of the value of the attribute.
- $\beta$ : The upper bound of the value of the attribute.

Taking an emergency scenario description ‘A class I tsunami warning will be issued when a tidal wave of more than 3 meters height is measured at the coastal tide gauge station’ appearing in an ERP as an example, the corresponding formalized attribute tuple could be (tide\_wave, environment, 3,  $+\infty$ ).

*Definition 2:* An emergency scenario template is a set of tuples  $\mathcal{E} = \{E_1, \dots, E_n\}$ . That is, an emergency scenario comprises a number of emergency attributes.

Then, we develop an emergency scenario information extractor based on the Rapier information extraction system [30]. In particular, we manually annotate a number of sentences in the corresponding parts of semi-structured ERPs with the defined emergency attribute template. The Rapier system takes the annotations as input and generates pattern-matching rules that can be used to extract emergency scenario information filling the pre-defined emergency scenario template. For the details, please refer to [30].

### B. SEGMENT RETRIEVAL

The aim of stage II is to acquire good references for handling the given unconventional emergency from the constructed ERP repository. Since ERPs are organized by inter-related text segments, the aim can be achieved by retrieving relevant ERP segments. To be more strict, an ERP segment is said to be relevant if: (1) it is semantically similar to the given unconventional emergency, e.g., both related to similar types of emergencies; (2) its targeted emergency scenario is consistent with that of a given unconventional emergency. To meet these two requirements, we propose a semantic similarity measure of ERPs and an attribute matching mechanism, respectively.

#### 1) ERP SIMILARITY MEASURE

In order to evaluate the semantic relatedness of ERP segments w.r.t. a given unconventional emergency, we propose an ERP similarity measure. In this work, we assume the given unconventional emergency is described using natural language, which is more human-friendly and widely used in real world. Thus the proposed ERP similarity measure essentially calculates a similarity value between two pieces of text.

Text similarity is a fundamental component in many natural language processing tasks [31]. In more recent years, representation learning has been the dominant approach to measure text similarities. The basic idea is to represent natural language units (e.g., words and sentences) in a low-dimensional continuous space which could induce similarity metrics [32], [33]. Following the representation learning mechanism, we represent each ERP segment and the unconventional emergency description as low-dimensional vectors, then calculate the similarity as inner product between the corresponding vectors.

Formally, we denote each ERP segment in the constructed ERP repository as  $T_i = \{t_{i,1}, \dots, t_{i,m}\} (i = 1, \dots, n)$  where  $t_{i,j}$  is the  $j$ -th word in the ERP segment,  $m$  the length of the the ERP segment and  $n$  the number of ERP segments in the ERP repository. Similarly, we denote the unconventional emergency description as  $T_0 = \{t_{0,1}, \dots, t_{0,m'}\}$ . The similarity between  $T_i$  and  $T_0$  is calculated as:

$$\text{sim}(T_i, T_0) = \text{cosine}(\mathbf{v}(T_i), \mathbf{v}(T_0)) \quad (1)$$

where  $\mathbf{v}(\cdot) \in \mathbb{R}^d$  is the vector representation of a text unit.

To obtain vector representation of ERP segments, we first embed the words therein into low-dimensional vector space, then aggregate word vectors. We formally have

$$\mathbf{v}(T) = \text{aggregate}(\{\mathbf{v}(t) | t \in T\}) \quad (2)$$

In particular, fastText [34] is leveraged to learn the word vectors  $\mathbf{v}(t)$ . Compared with traditional word embedding approaches (e.g., word2vec [35] and GloVe [36]), fastText is advantageous in taking into account the morphology of words in the vector representation, as well as its high time efficiency.

In this work, we propose a new word weighting scheme based on smooth inverse frequency (SIF) [37], which has been shown to be very competitive on various semantic textual similarity tasks despite its simplicity. Formally, the SIF word weight is calculated as follows:

$$\text{SIF}(t) = \frac{a}{a + \text{Pr}(t)} \quad (3)$$

where  $a$  is a hyper-parameter and  $\text{Pr}(t)$  the frequency of word  $t$  in the entire ERP repository.

As can be seen from Eq.3, the SIF word weight only takes the inverse word frequency into account, thus likely ignoring other factors valuable for determining the weight of words. When matching ERP segments with a given unconventional emergency description, the category of emergencies needs to be carefully accounted for. In other words, an ERP segment is considered semantically relevant if it is related to similar types of emergencies as the given unconventional emergency. Following this intuition, we extend the SIF word weight as follows:

$$\text{SIF}'(t; T) = \frac{a}{a + \text{Pr}(t)} \cdot \text{IDF}(t) \cdot \frac{\text{Pr}(t; \text{cat}(T))}{\sum_{c \in C} \text{Pr}(t; c)} \quad (4)$$

where  $\text{IDF}(t)$  denotes the traditional inverse document frequency of word  $t$ . Different from Eq.3, the frequency of

word  $t$  is calculated w.r.t. a specified category  $c$  (i.e., one in 33 categories mentioned in Section *Web crawling*), which is denoted as  $\text{Pr}(t; c)$ . Here,  $\text{cat}(T)$  denotes the category of ERP segment  $T$ . Practically, inverse document frequency could decrease the weights of common words, while the third item in the rightside of Eq.4 tends to assign a higher weight to a word when it appearing in ERP segments belonging to its frequently appeared categories. Thus, more informative words can be assigned with higher weight by the extended SIF word weighting scheme.

With the fastText word vectors and the extended SIF word weights, Eq.2 is instantiated as follows:

$$\mathbf{v}(T) = \frac{1}{|T|} \sum_{t \in T} \text{SIF}'(t; T) \cdot \mathbf{v}(t) \quad (5)$$

To reinforce the discriminability of the vector representation, we make a post-processing of the vectors calculated by Eq.5 [37]. In particular, the vectors of ERP segments in the ERP repository calculated by Eq.5 form a matrix:  $M = [\mathbf{v}(T_1); \dots; \mathbf{v}(T_n)]$ . Suppose its first singular vector is  $\mathbf{u}$ , the following transformation is applied to the vectors of ERP segments:

$$\mathbf{v}(T) \leftarrow \mathbf{v}(T) - \mathbf{u} \cdot \mathbf{u}^\top \cdot \mathbf{v}(T) \quad (6)$$

## 2) SCENARIO MATCHING MECHANISM

Semantically similar ERP segments, which can be retrieved according to the proposed ERP similarity measure, do not necessarily be good references for a given unconventional emergency. The attributes of an unconventional emergency scenario are important factors in determining which ERP segments are qualified for ERP generation. Taking a typhoon-related unconventional emergency as an example, the factors to consider include wind speed, tsunami height, etc. In order to obtain scenario-consistent ERP segments, we propose to match the scenario attributes of retrieved similar ERP segments with that of the given unconventional emergency.

Formally, the scenario matching task can be stated as follows: Given emergency scenario templates of an ERP segment and a given unconventional emergency, denoted as  $\mathcal{E}_i$  and  $\mathcal{E}_0$ , respectively, the aim is to derive a matching function:  $\text{match}(\mathcal{E}_i, \mathcal{E}_0) \in \mathbb{R}^+$ . According to the definition of emergency scenario template, the matching function can be decomposed into that between scenario attribute templates as follows:

$$\text{match}(\mathcal{E}_i, \mathcal{E}_0) = \sum_{\substack{E \in \mathcal{E}_i, E' \in \mathcal{E}_0, \\ E.name = E'.name, \\ E.type = E'.type}} \text{match}(E, E') \quad (7)$$

We adopt a graded matching function according to the matching results between the names, types and lower/upper bound of scenario attributes. In particular, we consider four types of matching results which are depicted in Fig.4. For each type of matching result, we specify a constant matching

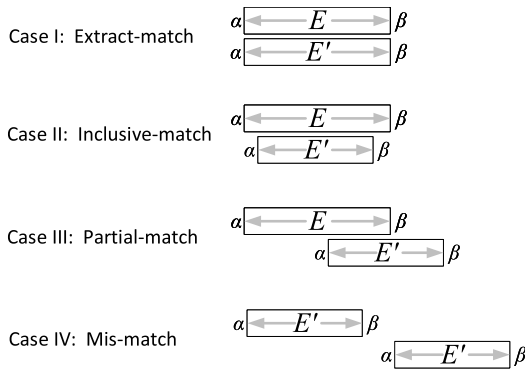


FIGURE 4. The four types of matching results.

score:

$$\text{match}(E, E') = \begin{cases} c_1 & \text{If extract-match} \\ c_2 & \text{If inclusive-match} \\ c_3 & \text{If partial-match} \\ c_4 & \text{If mis-match} \end{cases} \quad (8)$$

It is easy to see that extract-match is the ideal case of scenario matching, whereas mis-match indicates inadaptability of an ERP segment to a given unconventional emergency. Thus the matching scores generally satisfy  $c_0 \geq c_1 \geq c_3 \geq c_4$ .

### C. SEGMENT COMBINATION

The aim of Stage III is to generate an ERP for a given unconventional emergency by combining the ERP segments retrieved in the previous stage. The new ERP is generated following the semi-structured representation of ERPs. In particular, for each chapter in the semi-structured representation, candidate ERP segments are retrieved by taking into account both the semantic similarity and scenario matching results; then the ERP segments retrieved for all chapters are organized according to a pre-specified ERP structure so as to form a new ERP for given unconventional emergency.

Fig.5 illustrates the generation process by taking the chapter *General principles* as an example. First, the semantic similarity score and scenario matching score of each primary ERP segment in the ERP repository w.r.t. the given unconventional emergency description are calculated. The top-2 ERP segments are retrieved as candidates for generating the content of the primary chapter, which is shown on the left side of Fig.5 with the comprehensive scores of 0.90 and 0.89, respectively. Then, the semantic similarity score and scenario matching score of each secondary ERP segment in these two primary ERP segments are calculated similarly. For each secondary chapter specified in the semi-structured representation of ERP, the secondary ERP segment with the highest comprehensive score is taken as the generated content, which is shown on the right side of Fig.5 with the comprehensive scores of 0.84, 0.85, 0.87 and 0.92, respectively. The generation process will continue if to generate tertiary chapters. Here, we terminate the process because only up

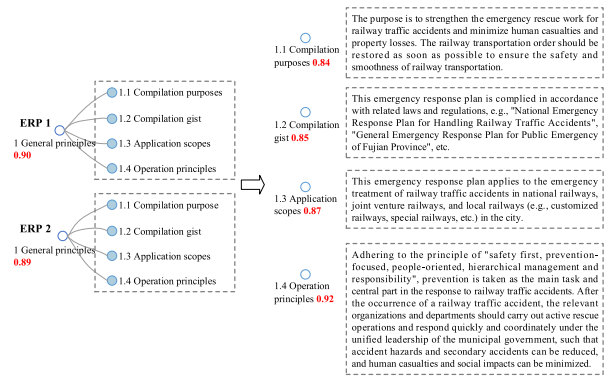


FIGURE 5. ERP generation for the chapter *General principles*.

to secondary chapters are required for the chapter *General principles*. Other chapters of ERP can be generated in a similar way.

## IV. EMERGENCY RESPONSE PLAN ASSESSMENT VIA CASE STUDY

In this section, we empirically assess the proposed ERP generation approach with an example scenario of unconventional emergency. In what follows, we first introduce the real-world case used in our work, then give the details of the ERP assessment methodology, as well as the analysis on the assessment results.

### A. THE REAL-WORLD CASE

We use a railway traffic accident caused by typhoon as the unconventional emergency scenario for case study. The details are provided in Fig. 6. The ERP generated for this unconventional emergency is shown in Fig.7. Here, we only show parts of the generated ERP due to the space limitation.

### B. ERP ASSESSMENT METHOD AND RESULTS

We view the assessment of ERPs for unconventional emergencies as a group decision making (GDM) task [38] in which a group of experts is allowed to express their preferences on a set of ERPs. GDM has been widely exploited in emergency decision making problems in the last decades for its advantage in reducing potential risks of relying on a single decision maker [6], [10], [39]. Following the GDM framework, we formalize the problem of assessing ERPs for unconventional emergencies as multi-attribute & multi-granular fuzzy linguistic GDM, in which the interval-valued 2-tuple fuzzy linguistic model [40] is adopted to represent each expert's preferences on different ERPs, whilst experts' preferences are expressed using their respective linguistic term sets. Before presenting the details of the assessment method, we first give preliminaries on the interval-valued 2-tuple fuzzy linguistic model.

#### 1) PRELIMINARIES

The 2-tuple fuzzy linguistic model is a type of classical linguistic computational model based on the concept of

**Text Description:**

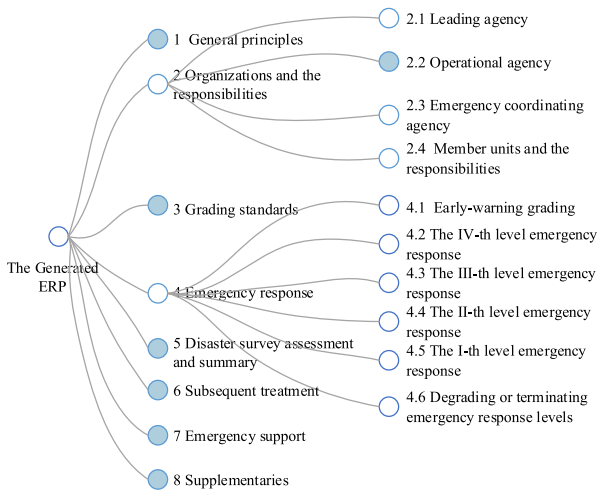
Typhoon S made landfall on the coast of City M in the early hours of the morning. When landing, the maximum wind speed near the typhoon center is 40m/s, and the central air pressure is 960pa. The water increase monitored by 16 tide gauge stations in the coastal area is more than 1.0m. The maximum water increment is 2.19m in Station E, and the highest tide level of the station is 0.03m higher than the local warning tide level. The typhoon caused breakwater, revetment and wharf seriously damaged, and houses in low-lying areas flooded. The typhoon affected about 100,000 people, with at least one dead and one missing.

Due to the heavy rainfall brought by Typhoon S, many landslides occurred in the northern foot of Mountain Z, which caused part of the railway track between Station A and Station B being buried. Furthermore, the lightning stroke accompanied by heavy rainfall caused failures to the catenary system and signal interruption of some lines. Train T hit the landslide and derailed at about 1:15am, making nearly 100 passengers injured. The accident also caused more than 10 trains delayed for more than 5 hours.

**Attributes:**

- Wind speed: 40m/s
- Maximum water increment: 2.19m
- People affected: 100,000
- People died: 1
- People missing: 1
- Passengers injured: 100

**FIGURE 6. The real-world case of unconventional emergency.**



**FIGURE 7. The generated ERP for the unconventional typhoon & railway accident emergency.**

symbolic translation [41]. It has been a popular approach for GDM for its capability of dealing with multi-granular linguistic term sets without any loss of information [42]–[44].

Basically, the 2-tuple fuzzy linguistic model represent linguistic information by means of a linguistic 2-tuple  $(s, \alpha)$  where  $s \in S$  is a linguistic label in the predefined linguistic term set  $S$  and  $\alpha \in [-\frac{0.5}{g}, +\frac{0.5}{g}]$  is a numerical value quantifying symbolic translation. A linguistic term set  $S$  is composed of a set of linguistic terms with odd cardinality. In general, the central term in a linguistic term set represent a judgment of ‘indifference’, while the remaining terms uniformly and symmetrically distributed around the central one [45].

For example, a five-term linguistic set can be given as follows:

$$S = \{s_0 : \text{Poor}, \quad s_1 : \text{VeryPoor}, \quad s_2 : \text{Medium}, \\ s_3 : \text{Good}, \quad s_4 : \text{VeryGood}\} \quad (9)$$

In what follows, we present the definitions of basic concepts on 2-tuple linguistic representation model.

**Definition 3 ([41]):** Let  $S = \{s_0, \dots, s_g\}$  be a linguistic term set and  $\beta \in [0, 1]$  a value representing the result of an aggregation of the indexes of a subset of labels in  $S$ , then the 2-tuple  $(s_i, \alpha)$  that expresses the equivalent information to  $\beta$  is obtained with the function  $\Delta : [0, 1] \rightarrow S \times [-\frac{0.5}{g}, +\frac{0.5}{g}]$  such that:

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} s_i & i = \text{round}(\beta) \\ \alpha = \beta - i & \alpha \in [-\frac{0.5}{g}, +\frac{0.5}{g}] \end{cases} \quad (10)$$

where  $s_i$  has the closest index label to  $\beta$  and  $\alpha$  is the value of the symbolic translation.  $\text{round}(\cdot)$  is the rounding operation.

**Definition 4 ([41]):** With the same notations in Def.3, the equivalent numerical value  $\beta \in [0, 1]$  of a 2-tuple  $(s_i, \alpha)$  can be obtained with the function  $\Delta^{-1} : S \times [-\frac{0.5}{g}, +\frac{0.5}{g}] \rightarrow [0, 1]$  such that [41]:

$$\Delta^{-1}(s_i, \alpha) = \frac{i}{g} + \alpha = \beta \quad (11)$$

In addition to the above transformation functions, a wide range of 2-tuple computational models, e.g., comparison operator, negation operator and aggregation operators, have been developed for the 2-tuple fuzzy linguistic model. For further information, please refer to [40], [43], [45].

Interval-valued 2-tuple fuzzy linguistic model is an extension of 2-tuple fuzzy linguistic model, where the linguistic information is represented by interval-valued 2-tuple variables.

**Definition 5 ([40]):** Given a linguistic term set  $S = \{s_0, \dots, s_g\}$ , an interval-valued linguistic 2-tuple is composed of two 2-tuples, denoted as  $[(s_i, \alpha_1), (s_j, \alpha_2)]$  with  $i < j$ .

Similarly as the 2-tuple computational model, an interval-valued 2-tuple can be transformed into an interval value, and vice versa.

**Definition 6 ([40]):** The interval-valued 2-tuple expressing the equivalent information to the interval value  $[\beta_1, \beta_2](\beta_1, \beta_2 \in [0, 1])$  is obtained with the following function:

$$\Delta([\beta_1, \beta_2]) = [(s_i, \alpha_1), (s_j, \alpha_2)], \\ \text{with } \begin{cases} s_i & i = \text{round}(\beta_1 \cdot g) \\ s_j & j = \text{round}(\beta_2 \cdot g) \\ \alpha_1 = \beta_1 - \frac{i}{g} & \alpha_1 \in [-\frac{0.5}{g}, \frac{0.5}{g}] \\ \alpha_2 = \beta_2 - \frac{j}{g} & \alpha_2 \in [-\frac{0.5}{g}, \frac{0.5}{g}] \end{cases} \quad (12)$$

**Definition 7 ([40]):** The equivalent interval value  $[\beta_1, \beta_2](\beta_1, \beta_2 \in [0, 1])$  of an interval-valued 2-tuple can

be obtained with the following function:

$$\Delta^{-1}([(s_i, \alpha_1), (s_j, \alpha_1)]) = [\frac{i}{g} + \alpha_1, \frac{j}{g} + \alpha_2] = [\beta_1, \beta_2] \quad (13)$$

## 2) THE ERP ASSESSMENT PROCEDURE

Under the GDM formalism, the aim of ERP assessment is to measure the quality of a generated ERP using interval linguistic variables.

**TABLE 1. ERPs generated with different similarity measures.**

ERP	Similarity	Word weight	Word vector
$P_1$ (Baseline 1):	TFIDF-GloVe	TFIDF	GloVe
$P_2$ (Baseline 2):	TFIDF-word2vec	TFIDF	word2vec
$P_3$ (Baseline 3):	SIF-GloVe	SIF	GloVe
$P_4$ (Baseline 4):	SIF-word2vec	SIF	word2vec
$P_5$ (Our):	SIF'-fastText	Improve SIF	fastText

In order to verify the advantage of our proposed ERP generation approach, we construct several variants by employing different NLP techniques for calculating the similarity of ERPs. In particular, we replace the improved SIF word weighting method and fastText used in the proposed similarity measure of ERPs by the conventional TFIDF term weighting schema and word embedding methods (i.e., GloVe [36] and word2vec [35]), respectively. The ERPs generated with different similarity measures are listed in Table 1, in which the first four can be viewed as baselines for comparison and the last one is our generated ERP.

Four experts are employed to assess the five ERPs w.r.t. the following seven indicators [46]:

$$\mathcal{Y} = \{Y_1 : \text{Completeness}, Y_2 : \text{Economy}, Y_3 : \text{Operability}, Y_4 : \text{Cohesion}, Y_5 : \text{Pertinence}, Y_6 : \text{Extensibility}, Y_7 : \text{Clear-Responsibility}\}$$

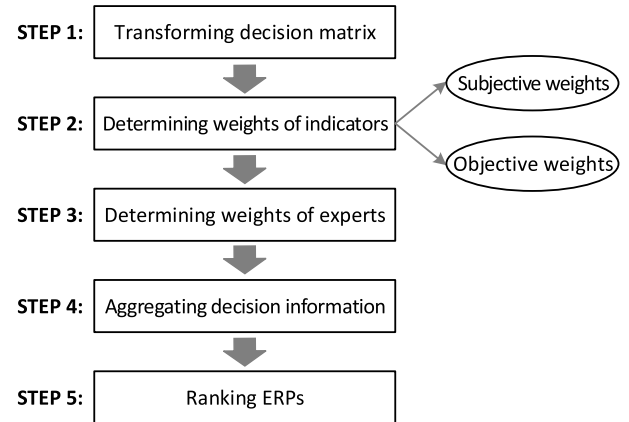
To provide more flexibility of opinions expressing, these four experts are allowed to give preferences to the five ERPs using their respective linguistic term sets as follows:

$$\begin{aligned} S_1 &= \{a_0 : \text{VP}, a_1 : \text{P}, a_2 : \text{M}, a_3 : \text{G}, a_4 : \text{VG}\} \\ S_2 &= \{b_0 : \text{VP}, b_1 : \text{P}, b_2 : \text{MP}, b_3 : \text{M}, b_4 : \text{MG}, b_5 : \text{G}, \\ &\quad b_6 : \text{VG}\} \\ S_3 &= \{c_0 : \text{ERP}, c_1 : \text{VP}, c_2 : \text{P}, c_3 : \text{MP}, c_4 : \text{M}, c_5 : \text{MG}, \\ &\quad c_6 : \text{G}, c_7 : \text{VG}, c_8 : \text{EG}\} \\ S_4 &= \{d_0 : \text{VP}, d_1 : \text{P}, d_2 : \text{M}, d_3 : \text{G}, d_4 : \text{VG}, d_5 : \text{EG}\} \end{aligned}$$

where the linguistic terms ERP, VP, P, MP, M, MG, G, VG and EG denote *extremely poor*, *very poor*, *poor*, *moderate poor*, *medium*, *moderate good*, *good*, *very good* and *extremely good*, respectively.

After reading the five ERPs individually, each expert give its own judgments w.r.t. each of the seven indicators. The decision matrix given by all the experts is shown in Table 2.

Then, the following five steps, as shown in Fig.8, are carried out to determine the most desirable ERP from Table 1.



**FIGURE 8. The procedure of ERP assessment.**

### a: STEP 1: TRANSFORMING DECISION MATRIX

Since the original decision information is expressed using interval linguistic variables, the first step is to represent elements in the original decision matrix using interval-valued 2-tuple variables. Simply, given an interval linguistic variable  $[s, s']$ , the corresponding interval-valued 2-tuple is  $[(s, 0), (s', 0)]$ . The transformed new decision matrix is shown in Table 3.

### b: STEP 2: DETERMINING WEIGHTS OF INDICATORS

The assessment indicators in  $\mathcal{Y}$  may have different importance on deriving the overall assessment conclusion of ERPs and it is hard to pre-specify the weight of each indicator. In the proposed ERP assessment method, both subjective and objective weights [47] are considered. Formally, we denote the  $i$ -th expert's subjective and objective weight on the  $k$ -th indicator as  $w_{i,k}^{(s)}$  and  $w_{i,k}^{(o)}$  ( $i = 1, \dots, 5; k = 1, \dots, 7$ ), respectively.

The subjective weights are derived from experts' specified preference on indicators. In this work, the Analytic Hierarchy Process (AHP) [48] method is employed to determine the subjective weights of indicators. In particular, we first establish the numerical scale of importance values for pairwise comparison as shown in Table 4. Then the four experts give pairwise preference judgments on the 7 indicators. We obtain the overall pairwise comparison matrix and calculate the subjective weight of each indicator as shown in Table 5. For the details, please refer to [49].

In order to determine the objective weights, we propose a deviation-maximization-based method. Intuitively, the optimal weights of indicators are obtained such that the decision deviation over all the indicators is maximized. Following this intuition, let  $r_{j,k}^{(i)}$  ( $i = 1, \dots, 4; j = 1, \dots, 5, k = 1, \dots, 7$ ) denotes the rating score (in terms of interval-valued 2-tuple) given by the  $j$ -th expert on the  $i$ -th ERP w.r.t. the  $k$ -th indicator, its corresponding objective weight is calculated as follow:

$$w_{i,k}^{(o)} = \frac{\sum_{j_1=1}^5 \sum_{j_2=1}^5 d_2(r_{j_1 k}^{(i)}, r_{j_2 k}^{(i)})}{\sum_{k'=1}^7 \sum_{j_1=1}^5 \sum_{j_2=1}^5 d_2(r_{j_1 k'}^{(i)}, r_{j_2 k'}^{(i)})} \quad (14)$$





**TABLE 5. Pairwise comparison matrix and the subjective weights of indicators.**

	Y <sub>1</sub>	Y <sub>2</sub>	Y <sub>3</sub>	Y <sub>4</sub>	Y <sub>5</sub>	Y <sub>6</sub>	Y <sub>7</sub>	Weight
Y <sub>1</sub>	1/1	3/2	3/4	7/5	3/8	6/9	7/4	0.1324
Y <sub>2</sub>	2/3	1/1	4/6	9/4	3/1	1/2	5/8	0.1386
Y <sub>3</sub>	4/3	6/4	1/1	3/7	6/7	5/2	1/4	0.1306
Y <sub>4</sub>	5/7	4/9	7/3	1/1	3/14	5/11	3/1	0.1334
Y <sub>5</sub>	8/3	1/3	7/6	14/3	1/1	3/8	10/7	0.1506
Y <sub>6</sub>	9/6	2/1	2/5	11/5	8/3	1/1	8/15	0.1642
Y <sub>7</sub>	4/7	8/5	4/1	1/3	7/10	15/8	1/1	0.1502

higher weight it is assigned. The objective weights calculated on the decision matrix in Table 3 are shown in Table 6.

**TABLE 6. The objective weights of indicators.**

Indicator \ Expert	Z <sub>1</sub>	Z <sub>2</sub>	Z <sub>3</sub>	Z <sub>4</sub>
Y <sub>1</sub>	0.1101	0.2278	0.2514	0.1278
Y <sub>2</sub>	0.1309	0.1587	0.1184	0.1278
Y <sub>3</sub>	0.1289	0.1241	0.0991	0.1405
Y <sub>4</sub>	0.1773	0.1509	0.1598	0.1864
Y <sub>5</sub>	0.1909	0.1038	0.1345	0.1748
Y <sub>6</sub>	0.1309	0.1308	0.1427	0.1278
Y <sub>7</sub>	0.1309	0.1039	0.0941	0.1150

Afterward, the weight of indicators are obtained by the average of the subjective and objective weights:

$$w_{i,k} = \frac{1}{2} \cdot (w_{i,k}^{(s)} + w_{i,k}^{(o)}) \tag{16}$$

*c: STEP 3: DETERMINING WEIGHTS OF EXPERTS*

Due to the different expertise level of experts in the emergency domain, we also consider the weight of each expert in drawing the assessment conclusion. Similar as the objective weights, we determine the weights of experts by a deviation-maximization-based method.

First, we aggregate the decision matrix in Table 3 along the indicator dimension by considering the weights of indicators and construct a comprehensive decision matrix of all experts. Formally, the comprehensive decision matrix can be written as  $\hat{R} = (\hat{r}_{i,j})_{4 \times 5}$ , with the element  $\hat{r}_{i,j}$  denoting the comprehensive rating score of the  $j$ -th ERP given by the  $i$ -th expert. Using the above notations, the comprehensive rating score is calculated by the generalized interval-valued 2-tuple weighted average (GIVTWA) [43]:

$$\begin{aligned} \hat{r}_{i,j} &= \text{GIVTWA} \left( \{r_{j,1}^{(i)}, \dots, r_{j,7}^{(i)}\}, \{w_{i,1}, \dots, w_{i,7}\} \right) \\ &= \Delta \left( \left( \sum_{k=1}^7 w_{i,k} \cdot \Delta^{-1}(\text{left}(r_{j,k}^{(i)}))^2 \right)^{\frac{1}{2}}, \right. \\ &\quad \left. \left( \sum_{k=1}^7 w_{i,k} \cdot \Delta^{-1}(\text{right}(r_{j,k}^{(i)}))^2 \right)^{\frac{1}{2}} \right) \end{aligned} \tag{17}$$

where  $\text{left}(r_{j,k}^{(i)})$  and  $\text{right}(r_{j,k}^{(i)})$  denote the left-bound and right-bound 2-tuple of the interval-valued 2-tuple  $r_{j,k}^{(i)}$ , respectively.  $\Delta$  and  $\Delta^{-1}$  are the the interval-valued 2-tuple transformation operators in Definition 6 and 7, respectively.

Then, similar to Eq.14, the weight of the  $i$ -th ( $i = 1, \dots, 4$ ) expert is calculated as follow:

$$v_i = \frac{\sum_{j_1=1}^5 \sum_{j_2=1}^5 d_2(r_{i,j_1}, r_{i,j_2})}{\sum_{i'=1}^4 \sum_{j_1=1}^5 \sum_{j_2=1}^5 d_2(r_{i',j_1}, r_{i',j_2})} \tag{18}$$

The weights of experts calculated according to Eq.18 in our case are shown in Table 7.

**TABLE 7. The weights of experts.**

	Z <sub>1</sub>	Z <sub>2</sub>	Z <sub>3</sub>	Z <sub>4</sub>
Weight	0.1101	0.2278	0.2514	0.1278

*d: STEP 4: AGGREGATING DECISION INFORMATION*

The overall preference score of each ERP is obtained by aggregating the decision information while considering the weights of indicators and experts calculated above. Similar to STEP 3, the generalized interval-valued 2-tuple weighted average operator is used. Specifically, the overall preference score of the  $j$ -th ERP is calculated as follow:

$$\text{score}(P_j) = \text{GIVTWA} \left( \{\hat{r}_{1,j}, \dots, \hat{r}_{4,j}\}, \{v_1, \dots, v_4\} \right) \tag{19}$$

*e: STEP 5: RANKING ERPs*

According to the overall preference score of each ERP, we can generate a ranking list of all ERPs in which the top-ranked ERP is considered as the most desirable for the given unconventional emergency.

In order to make a comparison between interval-valued 2-tuple variables, we use the Score Function (SF) and Accuracy Function (AF) of interval-valued 2-tuples. Formally, let  $A = [(s_i, \alpha_1), (s_j, \alpha_2)]$  be an interval-valued 2-tuple, its score function and accuracy function are defined as follow [40]:

$$\begin{aligned} \text{SF}(A) &= \frac{i+j}{2g} + \frac{\alpha_1 + \alpha_2}{2} \\ \text{AF}(A) &= \frac{j-i}{g} + (\alpha_2 - \alpha_1) \end{aligned} \tag{20}$$

Based on the score function and accuracy function, two interval-valued 2-tuples  $A$  and  $B$  can be compared according to the rules listed in Table 8.

**TABLE 8. Comparison rules of interval-valued 2-tuples.**

SF(A) vs. SF(B)	AF(A) vs. AF(B)	Comparison Result
>	> or = or <	A > B
=	<	A > B
=	=	A = B
=	>	A < B
<	> or = or <	A < B

As for our case, the overall preference scores of ERPs as well as their rankings are shown in Table 9.

3) ANALYSIS ON THE RESULTS

From Table 9, it can be seen that the ERP generated by the proposed approach ( $P_5$ ) achieves quite satisfied assessment results, i.e., the overall preference score is better than

TABLE 9. The preference scores and ranking of ERPs.

	Preference score	Ranking
$P_1$	[(MP, 0.0694), (M, 0.0039)]	5
$P_2$	[(M, 0.0480), (M, 0.0992)]	4
$P_3$	[(MG, 0.0191), (MG, 0.1041)]	2
$P_4$	[(M, 0.1183), (MG, 0.0409)]	3
$P_5$	[(G, 0.0823), (VG, 0.0232)]	1

G(good). This validates the feasibility of the proposed ERP generation approach for unconventional emergencies. Furthermore, We can gain more insights from the assessment results:

a: THE IMPORTANCE OF ASSESSMENT INDICATORS

As shown in Table 5 and 6, the seven assessment indicators have approximately similar subjective weights; however, the difference among the objective weights is much more essential. This shows that the indicators are conceived as equally important by most experts, but actually have different discriminability in the experts' preference judgments. This result verifies the necessity of considering subjective weights and objective weights simultaneously.

b: THE IMPORTANCE OF EXPERTS

As shown in Table 7, the weights of the four experts are quite different. In particular,  $Z_3$  has the highest weight while  $Z_1$  the lowest. This is mainly because the more fine-grained linguistic term set used in assessment, the higher weight would be assigned to the expert. In other words, experts are encouraged to provide preference judgments with more fine granularity and discriminability.

c: THE ADVANTAGE OF THE PROPOSED APPROACH

As shown in Table 9, the overall preference score of  $P_5$  is much higher than other ERPs, which indicates that the proposed ERP generation approach can provide the most desirable ERP for handling this unconventional emergency case. To further illustrate the advantage of the proposed approach, we make a more detailed comparison among the five ERPs generated in this case study. In particular, we calculated the preference scores of the five ERPs w.r.t. each assessment indicator, instead of the overall preference scores. To facilitate comparison among different indicators, we transformed the preference scores into interval values by applying the interval-valued 2-tuple transformation function in Definition 7.

The results are shown in Fig.9, in which ERPs and assessment indicators are represented using different shapes and colors, respectively. It can be seen that the preference scores of  $P_5$  (depicted as squares) reside in the upper right of the figure, i.e., are higher than other ERPs. This result provides comprehensive evidence for the superiority of the proposed ERP generation approach. The proposed similarity measure of ERPs can take advantage of category information to locate the more relevant parts of ERPs than traditional measures.

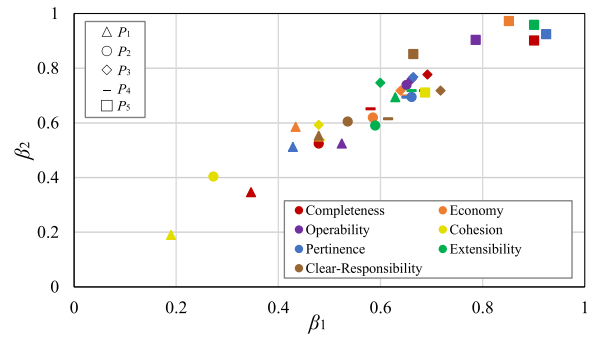


FIGURE 9. Preference scores w.r.t. assessment indicators.

d: LIMITATIONS

From Fig.9 we can also note that in general, the preference scores w.r.t. Cohesion (depicted in yellow) are the lowest among all the assessment indicators. This indicates that the proposed ERP generation framework is not very sufficient in yielding coherent ERPs. The main reason is that the ERP generated is composed of segments from different ERPs. These different segments, although each relevant to the given unconventional emergency, may not necessarily form a smooth ERP. Thus in order to obtain the final ERP for unconventional emergencies, it would be necessary for emergency decision-makers to fine tune the automatically generated ERP. However, the proposed ERP generation approach can provide relevant and organized information for handling unconventional emergencies, thus making emergency decision-makers more efficient at establishing high-quality ERP for the target unconventional emergency.

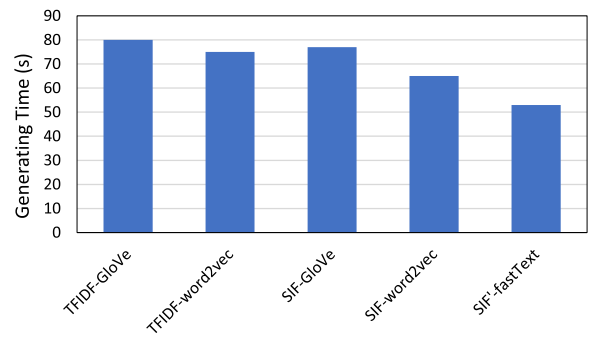


FIGURE 10. ERP generation time.

e: TIME EFFICIENCY

Furthermore, we investigated the time efficiency of the proposed ERP generation approach. Specifically, we recorded the time of generating each of the five ERPs. As can be seen from Fig.10,  $P_5$  takes the least generating time, which indicates the advantage of the proposed approach in time efficiency. The main reason is that fastText is more efficient than Glove and word2vec at calculating word vectors. This advantage of the proposed approach is very desirable since any time delay can result in significant losses in case of emergency situations.

## V. CONCLUSION AND FUTURE WORK

In this paper, a rapid emergency response plan generation approach for unconventional emergencies is proposed. Different from previous emergency management studies, we are focused on generating textual emergency response plans which are more practically used in real world than formalized emergency planning models. There are three key components in the proposed approach: (1) An ERP repository, which provides a structural organization of a large number of ERPs established for historical emergencies, serves as the basis of ERP generation; (2) An ERP segment retrieval engine, including a proposed ERP similarity measure and a proposed emergency scenario matching mechanism, is used to determine which ERP segments in the constructed ERP repository are applicable to the given unconventional emergency; (3) An ERP segment combination method is proposed to organize the retrieved applicable ERP segments into an ERP for the given unconventional emergency.

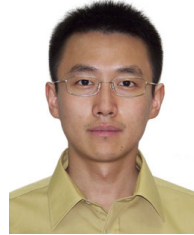
In addition, an ERP assessment method is designed to assess the quality of generated ERPs. In a case study of a typical unconventional emergency scenario, several ERPs are generated by the proposed approach and its variants and presented to experts for judgment. The assessment results show the validity of the proposed methodologies in generating high-quality ERPs.

In the future, we will enhance the components in the proposed ERP generation approach so as to generate ERPs of higher quality. As can be seen from the assessment results, *Cohesion* is the worst-performing assessment indicator of the proposed ERP generation approach. To improve cohesion of the generated ERPs, we will try to measure the cohesion between ERP segments and incorporate it into the ERP segments combination component. Another aspect of the generated ERP that particularly needs improvement is *Operability*. The main reason of the poor performance w.r.t. this indicator is that the constructed ERP repository is quite limited and lack of ERPs containing detailed operational level information for emergency responses. To address this drawback, we will expand the ERP repository by crawling more numbers of ERPs. Furthermore, it is necessary to apply the proposed ERP generation approach to more real world unconventional emergency scenarios and obtain more comprehensive assessment results.

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