Classification of hazard event via language fractal

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Abstract: HAZOP is a safety paradigm undertaken to reveal hazards in industry, its report covers valuable hazard events (HaE). The research on HaE classification has much irreplaceable pragmatic values. However, no study has paid such attention to this topic.

In this paper, we present a novel deep learning model termed DLF to explore the HaE classification through fractal method from the perspective of language. The motivation is that (1): HaE can be naturally regarded as a kind of time series; (2): the meaning of HaE is driven by word arrangement.

Specifically, first we employ BERT to vectorize HaE. Then, we propose a new multifractal method termed HmF-DFA to calculate HaE fractal series by analyzing the HaE vector who is regarded as a time series. Finally, we design a new hierarchical gating neural network (HGNN) to process the HaE fractal series to accomplish the classification of HaE.

We take 18 processes for case study. We launch the experiment on the basis of their HAZOP reports. Experimental results demonstrate that our DLF classifier is satisfactory and promising, the proposed HmF-DFA and HGNN are effective, and the introduction of language fractal into HaE is feasible.

Our HaE classification system can serve HAZOP and bring application incentives to experts, engineers, employees, and other enterprises, which is conducive to the intelligent development of industrial safety.

We hope our research can contribute added support to the daily practice in industrial safety and fractal theory.

Keywords: hazard event classification; language fractal; deep learning; hierarchical gating neural network; HmF-DFA; HAZOP.

NOMENCLATURE

Notations and Observations

HAZOP Hazard and operability analysis
HaE Hazard event
DLF The proposed hazard event classification model
HGNN The proposed hierarchical gating neural network
HTS Hazard event fractal series
HFS Hazard time series with grey guidance
mF-DFA Multifractal detrended fluctuation analysis
HmF-DFA Hazard-oriented multifractal detrended fluctuation analysis
BERT Bidirectional Encoder Representations from Transformers
CNN Convolutional neural network
BiLSTM Bidirectional long short-term memory
FC Fully connected neural network
GMBC gating mechanism

1. INTRODUCTION

The prosperity and advance of industry are of great significance to the national volume development. Yet, what is urgent is that the complex process system involves miscellaneous materials and large-scale equipment, and frequently operates in extreme environments such as high temperature and high pressure, which is very easy to cause a series of safety accidents, resulting in casualties, economic losses and other disastrous consequences. Fortunately, hazard and operability analysis (HAZOP) can solve the dilemma [1, 2]. As a general industrial safety technique, HAZOP can reveal hazards and serve safety analysis for almost all industries, such as Brazilian waste pickers' cooperatives, sustainable and renewable palm oil industry, biomass supply chain optimization and China fusion engineering test reactor central solenoid model coil heat treatment system, etc., [38-43, 3-5]. In China, HAZOP must be completed for each process that to be put into operation and released [44]. A large number of national policies endow HAZOP with irreplaceable mandatory power [45-47]. Therefore, HAZOP can be a paradigm of industrial safety, and the research on its report is quite promising and necessary.

HAZOP report records the hazards analyzed, as well as the measures and suggestions given for them [4, 6-11]. The hazard with the measure and the suggestion can be called hazard event (HaE), which can be further exploited under natural language processing and artificial intelligence to promote the intelligent development of industrial safety. For example, the classification model of HaE can support experts to explore the process that has not been put into production and assist engineers to launch the determination of decision-making for safety precautions, etc.

\[ HaE = IC \rightarrow D \rightarrow \{ME_1, ME_2, ..., ME_r\} \rightarrow C \rightarrow S \]  \hspace{1cm} (1)

Yet, there is no specific research on HaE classification at present. In order to fill this gap, in this paper, we propose a novel strategy termed DLF for HaE classification via deep learning with language fractal, which mainly has two motivations or perceptions.
1. Inspired by the research of Wang et al., [4] each HaE satisfies the causality of Equ.1, where, \( IC, D, \) \( C \) and \( S \) denote the cause, the deviation, the consequence and the suggestion / measure, respectively. ME refers to middle events that may have multiple. We perceive that HaE is the flow and transmission between these factors, and it follows the propagation path over time, since what it undertakes is the hazard triggered in real conditions and the analysis logic of the expert group. So, we can regard HaE as a kind of time series.

2. Encouraged by linguistics and sociology, we can treat HaE through fractal theory [12], since we realize that each HaE is a combination of words, which is unified in the language system of human beings and society. That is, the meaning represented by HaE is the interaction and semantic arrangement between words, which meets the latent spatial distribution and has self-similarity. Fortunately, some representative studies have confirmed the effectiveness and superiority of fractal theory in processing time and text series features [13-15].

Formally, the proposed DLF enjoys three procedures. First, we manipulate BERT [16] further pre-training to vectorize HaE since HaE contains complicated terminologies and components of different processes, and there are also differences in their language styles. Then, we propose a new multifractal method termed HmF-DFA based on multifractal detrended fluctuation analysis to calculate the obtained HaE vector conditioned on the time series to court HaE fractal series dependent on Hurst exponent. Finally, we design a hierarchical gating neural network (HGNN) to investigate HaE fractal series to accomplish the classification of HaE from severity aspect, possibility aspect and risk aspect. We take 18 processes for case studies. On this basis, we collect HaE for experiments to evaluate our DLF. The experimental results demonstrate that our DLF classifier is gratifying and promising. HmF-DFA and HGNN are effective, and the idea of extending language fractal to HAZOP has received approvals and supports.

Our HaE classification system can serve and heighten HAZOP intelligently and orderly, which can support expert teams to explore new processes, assist engineers to manage emergencies, and facilitate employees to perform routine maintenance. Besides, it can guide other relevant enterprises to conduct safety analysis on industrial processes.

It is feasible and desirable to guide industrial safety through language fractal, which is competent for HaE classification research. Our research can provide a new posture and inspiration for other researchers who are committed to the intelligent development and autonomous perception of industrial safety. The main highlights of this study are as follow.

1. We contribute a novel deep learning model termed DLF for HaE classification via language fractal.
2. We propose a new multifractal method termed HmF-DFA.
3. We design a new a hierarchical gating neural network termed HGNN.
4. Evaluation experiments based on case studies of multiple processes prove the effectiveness and suitability of DLF, HmF-DFA and HGNN.
5. HaE classification system can bring application incentives to experts, engineers, employees, and other enterprises.

Section 2 mainly reviews laws in language, as well as HaE. Section 3 completely illustrates our DLF classifier. Section 4 presents case studies. Section 5 discusses evaluation experiments and analyzes the results. Section 6 records the applications of HaE classification system and future work. Section 7 is the conclusion.

2. RELATED WORK

2.1. Laws in language

Under the influence of grammar, the interaction between words forms the language with specific meaning, which conveys the will, feelings and thoughts of human beings and society. By revealing the laws in words, language itself or some social behaviors can be more profound, such as Zipf law and Heap law.

At present, fractal theory has come into view, as a cutting-edge concept and method, it is being applied and explored in many fields [17-23]. For example, the study [24] has explored the microstructure of cement-based materials and its application in macro performance through fractal theory; the study [25] has constructed a financial evaluation measurement model based on fractal pattern to conduct risk analysis on supply chain finance; the study [26] has analyzed customers’ emotions in hotel reviews through multifractal method; and the study [27] has performed the quantum transmission characteristics in fractal networks by conducting continuous time quantum walks in fractal photonic lattices.

Fractal theory, in a broad sense, reveals the self-similarity between the local and the whole in the objective. Where, the latter can be embodied and deepened through the understanding of the former. In language, the meaning of some text fragments can often express the meaning of the whole text, and may be more accurate, concise and refined, which can reveal the universal connection in language / text from a specific perspective [50].

Menzerath-Altmann law [48] can provide additional support for language fractal. It indicates that the longer a language structure is, the shorter its components are, that is, the part length is a function of the structure length. Another reminder is Hurst exponent [49], which reflects the autocorrelation of time series, especially the long-term trend and memory hidden in the series.

2.2. Hazard event

The hazard event (HaE) analyzed by HAZOP is given three measures [1].

1. Severity aspect. It is classified into five levels according to the degree of consequences caused by HaE, such as property loss and personal injury, etc.
(2) Possibility aspect. It has five levels based on the frequency at which HaE is triggered.

(3) Risk aspect. It enjoys four levels about acceptability that HaE is subjected to actions and preventions, etc.

For example, such a simple HaE, "E-5611104 is abnormal with internal leakage. The blowback gas flows into the medium pressure steam pipe network, causing such serious process hazards as leakage of the heat exchanger body. Add TIC1501 for protection. Suggest that the design unit add a finned tube thermometer at the steam drum to monitor the leakage of carbon monoxide". Its levels under the severity aspect, possibility aspect and risk aspect are #4, #1 and #2 respectively, which indicate that the HaE can cause major accidents, is rarely triggered under the proposed protection, and is moderately tolerated.

Our HaE classification research considers these three aspects. Somewhat related to our research content is the study [11], which applies natural language processing to HAZOP reports, but compared with our paper, it has obvious differences and deficiencies. (1): It fails to consider the possibility aspect and risk aspect, only the severity aspect; (2): Its research object is HaE, only the HaE; (3): It less perceives the HaE. These issues weaken the power of HAZOP in redevelopment.

Note that HAZOP reports protected by property rights are confidential. To a certain extent, our work has brought progress to the transfer and sharing of knowledge.

3. METHODOLOGY

This section is the whole procedure of HaE classification, see Fig.1. First, we obtain HaE from HAZOP reports and vectorize them through further pre-trained BERT. Then, we grab the HaE time series with fractal features through the proposed fractal processing. Finally, we design a hierarchical gating neural network to investigate the HaE fractal series to recognize its classification. Details are as follows.

3.1. HaE Vectorization

This section describes how to vectorize HaE. The input is HaE in text format and the output is HaE vector, see Fig.2.

We get HaE with their own labels from HAZOP reports through document preprocessing such as cleaning and arranging.

Considering that the meaning of the HaE when the equipment is the subject is inconsistent with that when the equipment is the object, for example, the description when the "pressure indicating controller" is the subject often indicates the beginning or ongoing of a hazard, while the description when the equipment is the object is the measures and actions that confront with hazard. In addition, HaE contains complicated terminologies and components of different processes, and there are also differences in their language styles, as well as the wording and phrasing.

Therefore, we vectorize HaE based on BERT that prospers industrial and social language understanding [28-32], which can well capture the semantic information in this topic. Note that BERT is trained from the general domain corpus, without the consideration of the professional domain corpus, and fails to enjoy the prior knowledge in the field of industrial safety. In order to make up for this deficiency, we carry out further pre-
training on the HAZOP corpus through the same two self-supervision tasks as BERT, namely "masked language model" and "next sentence prediction" [11]. In this way, the represented HaE vector is mapped by the elements in HaE dynamically in various contexts, which is more rational and appropriate.

Specifically, first, we preprocess the one-dimensional HaE text \( W = \{w_1, w_2, \ldots, w_n\} \), add the "CLS" mark at the beginning of each HaE to establish the its boundary, that is \( \text{HaE} = \{\text{CLS}, w_1, w_2, \ldots, w_n\} \). Next, each processed HaE is segmented into a series of tokens. Tokens are indexed in the vocabulary provided by BERT to form the token embedding. The position embedding is formed according to predetermined sine/cosine rules. Adjacent sentences are marked with 0 and 1 to form the segment embedding. Then, we straightforwardly pass the sum of the three embeddings into the decoder group of Transformer to generate the HaE vector whose dimension of each word is 768. In this way, each HaE can be mapped into a two-dimensional matrix. We calculate the mean of the matrix as the HaE vector [26].

Now we regard the HaE vector as a class of time series. Fig.3-5 reflect the profiles of some different HaE time series (HTS) under the severity aspect, the possibility aspect and the risk aspect we randomly selected, respectively.

Obviously, regardless of the severity aspect, the possibility aspect and the risk aspect, the HTS from their perspective are close to the noise series whose feathers are not easy to be further detected. In addition, we can notice that in the severity aspect (see Fig.3) and the risk aspect (see Fig.5), the feature amplitude of level #2 is relatively more obvious, and the trend is larger, which is consistent with the status of the industrial system in reality, that is, the medium-scale hazards are more likely to be triggered, while in the possibility aspect, it is level #3 (see Fig.4), we believe that warnings with a slightly higher probability can be paid more attention by the staff, with more precautions reserved. Besides, the amplitudes the highest level among the three are relatively shallow and narrow, perhaps because large-sized hazards are rare. Further, there are some relative similarities among the three in the overall outline, for example, the amplitude of HTS value is the largest when the position is about 200.

Undoubtedly, the potential attributes contained in the HTS are vague and convoluted. It is not easy to directly distinguish the expected differences between their respective levels. Inspired by multifractal methods that have made great achievements in various fields [17-26], we introduce the popular multifractal detrended fluctuation analysis (mF-DFA) [33] to HTS from the perspective of language. Considering that the levels of the three are not evenly distributed (see Section 4), since the higher the level, the rarer the hazard, while the lower the level, the easier the hazard is usually triggered, which brings restrictions to the work of mF-DFA. To alleviate this dilemma, we propose a variant of hazard-oriented mF-DFA termed HmF-DFA to explore the discrimination of different hazards by investigating the implicit self-similarity in nonlinear complex systems.

### 3.2. HmF-DFA

We would like to reiterate our view and assumption that HaE is an arrangement of words, which records the information of hazards in industry. Random changes of word order in HaE may change its meaning, so there is a certain regularity between them, which is reflected in the layout pattern of each word in HaE treated as the HTS, that is, the different spatial patterns composed of words are contained in the HaE fractal set. We follow the operation of mF-DFA to embrace the HaE fractal series from the HTS, as follows.

Given an HTS \( R = \{r_1, r_2, \ldots, r_l\} \) with length \( l \), we calculate its cumulative dispersion series \( D = \{d_1, d_2, \ldots, d_l\} \) as

\[
D_k = \sum_{i=1}^{k} (r_i - R_{\text{mean}}), \quad k = 1, 2, \ldots, l
\]

(2)

to analyze the rhythm of different HaE. Where, \( R_{\text{mean}} \) is the mean value of \( R \). Fig.6-8 show the cumulative discrete series of levels in terms of the severity, possibility and risk, respectively.
the change of position, while a certain degree of data 5 first and then smaller.

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We can slightly reveal the differences between different levels. With the change of position, the relatively least discreteness gradually shifts from the severity level #4 to the severity level #2, and the cumulative discrete value of the former is relatively more concentrated in the former part, while that of the latter is in the rear part. In addition, it can be observed that the dispersion of the possibility level #4 is relatively large, while that of the possibility level #3 is larger first and then smaller with the change of position, and so are the risk level #2 and level #3. In a sense, this can manifest the distance difference between words since the moderate degree hazard is more likely to be triggered, we speculate that that the words it contains are closer in a certain segment, more words are easier to co-exist in the same context, so there are more distance dependencies, at least in the layout and arrangement of language.

To further clarify the features of the three, we slide the cumulative dispersion series D bi-directionally in the way of the sliding window operation, see Equ.3, where s is the length of the sliding window. Therefore, we get 2W, non-overlapping windows, and take \( \phi^t \) to mark the window with serial number n, where 0 < t < s.

\[
W_i = \left[ \frac{1}{s} \right]
\]  

(3)

We notice that each window has its own local trend \( \psi^t \), and the concatenation of all local trends is related to the overall contour of D, which corresponds to the internal self-similarity between the two. The fitting of each \( \psi^t \) is equipped with the least square method. The mF-DFA relishes the detrended HTS \( \delta^t \) by calculating the difference between \( \psi^t \) and \( \psi^t \), but the unbalanced distribution of levels may cause additional conflict to the \( \delta^t \), and the difference between the cumulative dispersion series and its local trend may have undesired changes between different windows, so the HTS may not be well stimulated, and the detrended HTS is weak as expected. To alleviate this deficiency, our proposed HmF-DFA can provide an optimization extension. Specifically, first, we project \( \phi^t \) and \( \psi^t \) onto the plane where Equ.4 is located, one consideration is that Sigmoid function family has a certain degree of data centralization effect [51], and the other is that \( \alpha \) is a scaling index used to homogenize the output, when \( \alpha \) approaches 0, Equ.4 degenerates into a linear function that can hold the original input distribution. Then we perform the difference operation on projected \( \phi^t \) and \( \psi^t \) over the Sigmoid plane. Finally, we restore the difference value calculated thought the inverse function of Equ.4 to accept the detrended HTS \( \delta^t \) under HmF-DFA. See Equ.5, where, \( \sigma^*(\alpha, x) \) is the inverse function of \( \sigma(\alpha, x) \), \( \alpha \) is 0.4 empirically and experimentally.

\[
\sigma(\alpha, x) = \text{sigmoid}(\alpha x) = \frac{1}{1 + e^{-\alpha x}}
\]  

(4)

\[
\delta^t = \sigma^* (\alpha, [\sigma(\alpha, \phi^t) - \sigma(\alpha, \psi^t)])
\]  

(5)

Fig.9-11 illustrate the detrended HTS of all levels under the severity aspect, possibility aspect and risk aspect with four window sizes s assigned 4, 10, 18 and 30 respectively from top to bottom.
Fig. 10: Detrended HTS under the possibility aspect (local fragments).

Fig. 11: Detrended HTS under the risk aspect (local fragments).

Fig. 12: The relationship between $\log(F_q(s))$ and $\log(s)$ in different severity levels.

Fig. 13: The relationship between $\log(F_q(s))$ and $\log(s)$ in different possibility levels.
It can be observed that the HTS becomes relatively clear after being filtered out the trend components of its own evolution, and the three under the detrended are similar as a whole, and the differences of their respective levels are also relatively close, while their local trends change irregularly with the change of position under the interference of different windows. Moreover, with the expansion of the window size, the turns and fluctuations of HTS gradually become frequent on the whole.

$$\sigma^2(s,n) = \frac{1}{S} \sum_{i=1}^{S} (\delta_{in})^2$$  \hfill (6)

The long-range correlation under the representation and behavior of hazard can be revealed by alleviating the non-stationarity in HTS, we calculate the local variance $$\sigma^2(s,n)$$ of HTS dominated by the window size variable and window series number variable with Equ.6, and obtain the fluctuation function $$F_q(s)$$ of HTS, see Equ.7., [52].

$$F_q(s) = \begin{cases} 
\left[ \frac{1}{2W_q} \sum_{s=1}^{2W_q} \sigma^2(s,n)^2 \right]^{\frac{1}{q}}, & q \neq 0 \\
\exp\left\{ \frac{1}{4W_q} \sum_{s=1}^{2W_q} \ln(\sigma^2(s,n)) \right\}, & q = 0 
\end{cases}$$ \hfill (7)

This fluctuation of HTS in logarithmic coordinate system can be more intuitively emerged, and the relationship between $$\log(F_q(s))$$ and $$\log(s)$$ under the three aspects is shown in Fig 12-14 respectively, where $$q = -10, -5, 0, 10, 20$$ for each level of curve from top to bottom in each figure.

The styles of the fluctuation function under the three aspects are similar on the whole, for example, they all have an obvious turning point, especially when $$q$$ is 20, and the trend generally follows the sharp first and then slow, etc., which reflects that the specific level of HaE is often subject to local elements, since the starting point of HaE is often the equipment node with its deviation [2]. Besides, in general, the more diverse the materials invested and the more complex the equipment involved, the higher the severity, the rarer the consequence, and the lower the possibility, etc. For each of the three aspects, the slope of the curve is different and decreases in turn. The above indicates that the HTS has fractal features. The change of the $$q$$ in the same level can ensure that the key of HTS can be highlighted through multifractal methods, so as to win the feature in the fractal sense for recognizing different HaE.

By setting the window to observe the relationship between the fluctuation function of HTS and the size of the window, there is difficulty free in detecting that they meet the power-law in the form of Equ.8 which depends on the $$q$$.

$$F_q(s) \propto s^{H(q)}$$  \hfill (8)

In order to further clearly reflect the difference between the levels under the three aspects, we fit $$F_q(s)$$ by Boltzmann method [53] to obtain their respective fractal-conditioned generalized Hurst exponents, so as to capture their respective fractal features and form the fractal series, see Fig.15-17.

Now, we have depicted the fractal series of HaE (HFS), which are established on their respective vectors under the manipulation of BERT. The HFS is characterized from two different representation perspectives: the semantics of context and the self-similarity of language. Hence, HFS paves the way for subsequent classification exploration. Next, we design a hierarchical gating neural network to investigate HFS.
Fig. 15: Fractal-conditioned generalized Hurst exponents of severity level.

Fig. 16: Fractal-conditioned generalized Hurst exponents of possibility level.

Fig. 17: Fractal-conditioned generalized Hurst exponents of risk level.
### 3.3. Hierarchical gating neural network

We propose a hierarchical gating neural network (HGNN) to investigate HFS (i.e., feature processing), see Fig.18. HGNN is a hierarchical neural network with three types of modules: one is BiLSTM for extracting context features, the other is CNN for extracting text local features, and the last is a gating mechanism for fusing the two kinds of features.

![Fig.18: Architecture of hierarchical gating neural network.](image)

BiLSTM and CNN are classical and popular feature encoders, and their encoding procedure is well known. Please refer to the research [28], and we will not repeat them here. We mainly explain the gating mechanism, as follows.

\[ f_c = BiLSTM(HFS) \]
\[ f_i = CNN(HFS) \]  
\[ \lambda = sigmoid(W_r f_c + b_r) \]
\[ \eta = sigmoid(W_l f_i + b_l) \]  

The fusion between different features can well stimulate the potential of features. For this reason, benefiting from the research [54], we design a gating mechanism termed GMBC to fuse \( f_c \) and \( f_i \).

\[ \psi = \eta \cdot (1 - (1 - \lambda)^2) + (1 - \eta) \cdot \lambda \]  

Finally, the fusion vector \( f_f \) is formed by Eq.12, where, \( \psi + \rho = 1 \).

\[ f_f = \rho \cdot f_c + \psi \cdot f_i \]  

After discussing the GMBC, we expound the operation procedure of HGNN. Details are as follows.

The three feature vectors obtained by the first layer are shown in Eq.13, where the subscript indicates the layer, for example, the subscript "1" indicates the first layer.

\[ f_{c-1}, f_{i-1} = BiLSTM(HFS), CNN(HFS) \]
\[ f_{c-1} = GMBC(f_{c-1}, f_{i-1}) \]  

In the second layer, BiLSTM takes \( f_{c-1} \) as the input, CNN takes the concatenation of \( f_{i-1} \) and the original vector HFS as the input, and their outputs form \( f_{c-2} \) via GMBC, see Eq.14.

\[ f_{c-2}, f_{i-2} = BiLSTM(f_{c-1}), CNN(f_{i-1}, HFS) \]
\[ f_{c-2} = GMBC(f_{c-2}, f_{i-2}) \]  

In the third layer, the input of BiLSTM is the concatenation of \( f_{c-1} \) and \( f_{i-2} \), the input of CNN is \( f_{c-2} \), and see Eq.15 for the three feature vectors.

\[ f_{c-3}, f_{i-3} = BiLSTM(f_{c-2}, f_{i-2}), CNN(f_{i-2}) \]
\[ f_{c-3} = GMBC(f_{c-3}, f_{i-3}) \]  

The operation of the fourth layer is similar to that of the second layer, see Eq.16, where, the fusion feature \( f_{i-4} \) is the concatenation of \( f_{c-3} \) and \( f_{i-2} \).

\[ f_{c-4}, f_{i-4} = BiLSTM(f_{c-3}), CNN(f_{c-3}, f_{i-2}) \]
\[ f_{i-4} = f_{c-4} \oplus f_{i-4} \]  

We leverage a fully connected neural network (FC) to map \( f_{i-4} \) to \( T \) with the dimension of category number, and then employ softmax to predict the classification \( \theta \) from a discrete set of classes for \( f_{i-4} \), see Eq.17.

\[ \theta = \text{argmax}[\text{softmax}(T)] \]  

### 4. CASE STUDIES

We have cooperated with Sichuan Petrochemical, Liaoyang Petrochemical and other enterprises to launch case studies in 18 industrial processes, which are of great significance in clean energy, environmental protection and sustainable development, etc. HAZOP analysis of them is not only a legal obligation, but also an embodiment of social responsibility. The following is a brief introduction to them.

1. 300 T/h solvent regeneration process: It is mainly aimed at sulfur recovery in petroleum refining.
2. 1.2 million T / a heavy oil catalytic cracking process: The main purpose is to produce high octane gasoline fraction and light diesel oil through catalytic cracking of heavy oil.

3. 30 thousand T / a desulfurization and sulfur recovery process: It is mainly used to remove sulfur in acid gas, and realize sulfur recovery.

4. 600 thousand T / a light naphtha isomerization process: The main purpose is to convert light naphtha into isomerized oil.

5. 2.2 million T / a diesel hydrofining process: It is mainly aimed at oil products to achieve desulfurization, denitrification, and solve the problems of chromaticity and storage stability.

6. 0.075 T / h ammonium nitrate to nitrous oxide process: The main purpose is to prepare high purity nitric oxide through the decomposition of ammonium nitrate.

7. 120 thousand T / a sulfur recovery process (from Brunei Hengyi Enterprise): It aims to convert sulfide in toxic sulfur-containing gas into elemental sulfur.

8. 100 thousand T / a sulfur recovery process (from Sichuan Petrochemical Enterprise): Similar to the process #7.

9. 4 million T / a indirect coal liquefaction process: The main objective is to convert coal into liquid fuel with carbon monoxide and hydrogen.

10. 1 million T / a hydrocracking process: Heavy oil is mainly converted into light oil by hydrogenation, cracking and isomerization.

11. 350 thousand T / a polyethylene production process: Ethylene is made into polyethylene by addition polymerization.

12. 8 thousand T / a cis polybutadiene rubber production process: Production of cis-1,4-polybutadiene rubber polymerized from butadiene.

13. 200 T / h acid water stripping process: It is mainly responsible for the treatment of acid water discharged from the refinery.

14. 500 m³ / h water electrolysis hydrogen production process: Water is decomposed by direct current and hydrogen is released.

15. 500 thousand T / a gas fractionation process: It is mainly responsible for converting the waste liquid discharged from the refinery into high-value chemical products.

16. 800 m³ / h natural gas hydrogen production process: Convert natural gas into pollution-free hydrogen.

17. 10 thousand T / a waste liquid desulfurization and sulfuric acid production process: It mainly realizes the production of sulfuric acid from the liquid containing sulfur compounds.

18. 100 m³ / h formic acid to carbon monoxide process: Preparation of high purity carbon dioxide by catalytic decomposition of formic acid.

HAZOP reports under these processes can ensure the universality and authority of experiments and can evaluate our methods well. We collect 5869 HaE with labels from HAZOP reports for each classification aspect through a series of text preprocessing, see Table 1, and randomly assign them into training set, test set and validation set at a ratio of 8:1:1.

| Aspect | Level #1 | Level #2 | Level #3 | Level #4 | Level #5 |
|--------|----------|----------|----------|----------|----------|
| Possibility | 419 | 1760 | 1607 | 1134 | 949 |
| Severity | 1570 | 2732 | 1353 | 170 | 44 |
| Risk | 2902 | 2577 | 335 | 55 | - |

5. EXPERIMENT & ANALYSIS

5.1. Experiment setting

In each trial experiment, the main parameters are consistent. For example, the size of BERT is base, the optimizer is Adam with a learning rate of 1e-5, the epoch of training is 50, and the batch size is 128. We take the average results of 5 repetitions as the evaluation report. According to the convention, the evaluation metrics are F1-score (F1), precision (P), recall (R) [11].

5.2. Trial model

The models used for comparative experiments are:

1. BERT (base#1): The feature vectors generated by BERT are directly transmitted to FC for classification prediction [11].

2. BERT-CNN (base#2): CNN further encodes the feature vectors encoded by BERT, and then decodes them by FC [34].

3. BERT-RAtt (base#3): BiLSTM and Attention jointly act as the encoder for feature vectors, and FC completes classification prediction [11].

4. BERT-DPCNN (base#4): In brief, the feature vectors generated by BERT are encoded by DPCNN, a network composed of multiple isometric-convolution layers and half-pooling operations, and FC implements decoding classification [36].

5. BERT-RCNN (base#5): In brief, BiLSTM and CNN jointly act as the encoder for feature vectors, and FC completes classification prediction [37].

There are two modules in DLF that need to be evaluated, i.e., HmF-DFA and HGNN. The models used for ablation experiments are:

6. BERT-HGNN (DLF#1).

7. BERT-[HmF-DFA] (DLF#2): FC is used for the final classification decoding.

8. BERT-[mF-DFA] (DLF#3): FC is used for the final classification decoding.
9. BERT-[mF-DFA]-HGNN (DLF#4).
10. BERT-[HmF-DFA]-HGNN (DLF#5).

Where, DLF#5 is our complete model; DLF#1 vs. DLF#5 for evaluating the benefit of HmF-DFA; DLF#2 vs. DLF#3 and DLF#4 vs. DLF#5 for evaluating the progress of HmF-DFA compared with mF-DFA; DLF#2 vs. DLF#5 and DLF#3 vs. DLF#4 for evaluating the effect of HGNN.

5.3. Evaluation analysis

Tables 2-4 present all the total classification results of different models under the three aspects respectively, where, "test" means the test set and "val" means the validation set. There are the following major observations.

| Model     | test   | val   | test   | val   |
|-----------|--------|-------|--------|-------|
| base#1    | 81.23  | 78.09 | 85.54  | 82.17 |
| base#2    | 78.46  | 78.06 | 82.04  | 81.69 |
| base#3    | 77.86  | 75.58 | 83.93  | 78.30 |
| base#4    | 76.03  | 73.91 | 77.92  | 76.04 |
| base#5    | 75.82  | 74.91 | 81.78  | 79.69 |
| DLF#1     | 81.12  | 78.59 | 85.57  | 82.62 |
| DLF#2     | 81.55  | 80.67 | 84.99  | 84.86 |
| DLF#3     | 80.84  | 80.87 | 84.27  | 80.88 |
| DLF#4     | 82.46  | 81.95 | 86.36  | 85.70 |
| DLF#5     | **83.04** | **82.75** | 85.99  | **83.83** |

| Model     | P      | R      | F1     |
|-----------|--------|--------|--------|
| base#1    | 69.97  | 69.14  | 70.73  |
| base#2    | 69.44  | 69.22  | 72.54  |
| base#3    | 69.12  | 68.96  | 71.81  |
| base#4    | 69.71  | 68.62  | 72.51  |
| base#5    | **70.62** | **69.31** | 71.90  |
| DLF#1     | 69.66  | 69.69  | 72.56  |
| DLF#2     | 68.90  | 69.88  | **74.31** | **73.88** |
| DLF#3     | 70.38  | 70.25  | 69.89  |
| DLF#4     | 68.59  | 70.16  | 72.52  |
| DLF#5     | 70.45  | **70.41** | 72.52  | **71.35** |

Table 4: Evaluation results (%) under the risk aspect.

| Model     | test | val | test | val |
|-----------|------|-----|------|-----|
| base#1    | 69.48 | 71.51 | 74.33 | 71.97 |
| base#2    | 70.52 | **73.68** | 71.66 | 70.68 |
| base#3    | 70.92 | 69.23 | 70.59 | 73.33 |
| base#4    | 67.34 | 69.97 | 76.75 | 70.19 |
| base#5    | 68.59 | 69.80 | 74.00 | 70.48 |
| DLF#1     | **74.45** | **73.09** | 74.33 | **75.17** |
| DLF#2     | 69.44 | 72.54 | 78.38 | 74.17 |
| DLF#3     | 72.50 | 73.10 | 74.98 | 72.80 |
| DLF#4     | 70.60 | 72.39 | **79.54** | 74.63 |
| DLF#5     | 73.07 | 71.44 | 77.15 | **79.02** |

Fig.19: The total performance gain provided by our strategy in the classification of severity level.

Fig.19: The total performance gain provided by our strategy in the classification of severity level.
Fig. 20: Classification gain for the specific level in severity on the base#1 model comparison group.

Fig. 21: The total performance gain provided by our strategy in the classification of possibility level.

Fig. 22: DLF#5 vs. DLF#1 for evaluating the profit of HmF-DFA.

We evaluate the profit of the proposed HmF-DFA through the performance gap between DLF#5 and DLF#1, see Fig. 22. It can be seen that in three aspects, except for three exceptions, all the evaluations reflect that HmF-DFA has a positive promotion on the DLF classifier. Therefore, HmF-DFA is feasible and effective for HAE's classification duty.

We employ the performance gap between DLF#2 and DLF#3, as well as, that between DLF#5 and DLF#4, to evaluate the progress of HmF-DFA compared with mF-DFA. It can be observed that although a small number of evaluations reflect retrogression, most of them are weak, while other evaluations show that HmF-DFA tends to be more progressive, such as the evaluations under the severity aspect in Fig. 23, and that under the possibility aspect in Fig. 24. Therefore, HmF-DFA is more suitable for HAZOP than mF-DFA and is more conducive to the classification responsibilities of HAE.

Fig. 23: DLF#2 vs. DLF#3 for evaluating the progress of HmF-DFA compared with mF-DFA.

Fig. 24: DLF#5 vs. DLF#4 for evaluating the progress of HmF-DFA compared with mF-DFA.

DLF#5 vs. DLF#2 and DLF#4 vs. DLF#3 used to measure the gain of HGNN. It can be clearly seen that the vast majority of evaluations indicate that HGNN has indeed brought considerable performance gains to the DLF classifier, and it has even improved by more than four percentage points in some evaluations, especially under the aspect of severity.
Undoubtedly, HGNN has greatly enhanced the classification of HaE by DLF.

![Fig.25: DLF#5 vs. DLF#2 for evaluating the gain of HGNN.](image)

![Fig.26: DLF#4 vs. DLF#3 for evaluating the gain of HGNN.](image)

To sum up, our DLF classifier has promising and gratifying aptitudes, greatly ameliorates the classification work of HaE. We explore hazard events based on deep learning from the perspective of language through the concept of fractal, which is novel and profound. We hope our research can contribute added value to the daily practice in industrial safety and provide support for the pioneering of fractal theory.

6. APPLICATION & DISCUSSION

We embed the proposed DLF classifier into HAZOP to serve and support the safety assessment, see Fig.27. At present, HaE classification system can mainly undertake the following preliminary auxiliary applications.

6.1. For the expert group

Assist the expert group to conduct safety analysis on the raw process and support the identification of decision-making. There are large-scale nodes and their intricate objective connections and causalities in the process, hence HAZOP needs to consume a lot of manpower and time in confront new processes, and its analysis efficiency is inevitably flawed. Relievably, the HaE classification system can be used as an auxiliary proofreading to alleviate this embarrassment. Experts can strategically check and review the hazard that the recorded level is inconsistent with the inference given by the HaE classification system during the calibration of analysis results, so as to reduce work costs and potential mistakes caused by human boundedness. Take two preliminarily pre-analyzed HaE (excerpts) that exist on the R-5611101 (a kind of Fischer Tropsch reactor) as cases:

**HaE#1:** There is no or too small flow of deaerated water into the middle section of R-5611101, the temperature of R-5611101 is too high, and the reactor is extremely warm and leaking. In this case, the emergence of ignition source causes fire and explosion, resulting in poisoning and casualties. Execute TI0108-0113-AH, and refine the response time of deaerated water interruption operation.

**HaE#2:** The design of the bottom process of R-5611101 has changed, resulting in the abnormal handing over of maintenance procedure R-5611101, and the treatment at the bottom retains residues. At this time, the recondition and overhaul can cause fire casualties. It is considered to fill the bottom of R-5611101 with ceramic balls, and the handing over activities during the maintenance procedures to record the log that the wax oil at the bottom cannot be discharged smoothly.

Where, the level of \{severity / possibility / risk\} given by experts to them in advance are \{5 / 5 / 2\} and \{3 / 4 / 2\} respectively.

During the review, the HaE classification system first gives its own predictions for these two, then compares the prediction results with the inferences of the experts, and finally, (1) for the hazards with inconsistent comparison results, they are fed back to the experts in the order of the scale of level of severity, possibility and risk given by the experts for review in turn. For instance, the predictions given to HaE#1 and HaE#2 are \{4 / 3 / 3\} and \{4 / 2 / 1\} respectively, which is inconsistent with the inference of the expert group, hence, the two are reviewed in priority, and the priority of the former is higher than that of the latter. (2) For the HaE with consistent comparison results, they are placed in the final unified review, and the order in procedure (1) is also followed. Where, the rationality of the suggestions and the suitability of measures need more rigorous proofreading.

In addition, in the subsequent development of this application, it can also appropriately guide the expert group to make the analysis during the pre-brainstorming to reduce the workload.

Therefore, our HaE classification system can support the expert group to complete the safety exploration for new processes.

6.2. For the engineer

Assist the engineer in dealing with unforeseen hazards. For the process that has been put into production, there are inevitably additional hazards that have not been analyzed by the expert group. Fortunately, engineers can draw support from the HaE
classification system to qualitatively analyze such hazards in advance, and then quickly promote appropriate solutions and aftercare management according to the predicted attributes (severity / possibility / risk) of the hazards. Suppose such a hazard ignored by experts is triggered: a local explosion in the natural gas hydrogen production process. The engineer traces the source of this hazard:

E0102A/B heat exchanger shakes electricity, which makes E0103 corroded, and the converted gas leaks into the shell side of E0103, resulting in the explosion of shell side process after overpressure leakage.

At this time, the HaE classification system can immediately give the attribute \(\{3 / 3 / 2\}\) of the hazard and confirms or modifies it with the understanding of the engineer. After the attribute is approved, HaE classification system implements (also approved by the engineer) the solutions retrieved from the E0103 related HAZOP library of natural gas hydrogen production process that meet or are similar to the attribute \(\{3 / 3 / 2\}\), so as to mitigate the spread and secondary injury of the hazard as quickly as possible, for example, set the normally open vent pipeline and PRV0155A on the deaerator. Meanwhile, relevant suggestions are fed back to the engineer, for example, regularly test the hydrogen concentration at the exhaust outlet on the top of the deaerator and monitor the leakage of E0103.

Undoubtedly, HaE classification system can help engineers to quickly combat unforeseen hazards.

6.3. For the employee

Support the employee to conduct routine work and emergency response. In the daily workflow such as the system maintenance and troubleshooting, with the help of the reminder of HaE classification system, the employee can conveniently adjust the check scheduling according to the type of hazards. Specifically, HaE classification system acts as a medium of information communication, and employees can give priority to eliminating hazards with high possibility level and pay more attention to hazards with strong severity level according to the provided information about potential hazards involved in the unit, etc.

Moreover, in terms of emergency response, it is common for a single deviation factor to cause multiple hazards to be triggered at the same time. Gratifyingly, HaE classification system can participate in the security scheduling of the process, it can sort the urgency of hazards according to the size of their severity level, so as to appropriately and orderly assist employees in making decisions about scheduling on how to deal with multiple hazards.

Accordingly, HaE classification system can facilitate employees to complete their work.

6.4. For other related enterprises

Guide related processes of other enterprises to launch HAZOP. For some small-scale enterprises and independent processes, the received safety analysis is often not exhaustive, since the quality of HAZOP and completeness of HaE are subject to expert teams and processes of different scales. Specifically, for the Claus reactor, the working conditions it faces in different processes may be different, and it interacts with other equipment and materials to trigger different hazards whose diversity and complexity increase with the expansion of the scale of the process. Hence, the Claus reactor is often more likely to be analyzed more thoroughly in large-scale processes, rather than the small-scale processes. In addition, the analysis power of expert teams in different enterprises is also different, which is related to the empirical competence and knowledge reserve of experts. Some small-scale enterprises feebly analyze and collect the hazards related to the Claus reactor as comprehensively as possible.

Therefore, it is necessary for small-scale enterprises to enhance the safety of related processes through the guidance of high-quality HAZOP knowledge [11]. However, HAZOP report is confidential, protected by property rights, and is a scarce resource.

Hearteningly, our HaE classification system absorbs the HAZOP knowledge of a number of large-scale enterprises involving a total of 18 processes, and is competent for this guidance. Its working mode is similar to the first three applications, which will not be repeated here. To a certain extent, our work has brought progress to the transfer and sharing of knowledge.

6.5. Discussion & Future work

From a certain point of view, the effectiveness of the proposed DLF classifier can be attributed to its fusion of different types of features, especially the seemingly profound stimulation brought by language fractal features. It needs to be reiterated that one of the motivations of this paper is that under the compulsion of HAZOP, HaE can be naturally regarded as a kind of time series, so there is an opportunity to explore it through fractal methods. Another note is that No Free Lunch Theorem [56] teaches us that no model can face all practical issues. Similarly, this paper will also face the obstacles in how to migrate it to other classification tasks. In short, our research is promising and meaningful, we hope that it can bring encouragement and inspiration to other researchers.

Future research is mainly committed to two aspects. One is to further optimize the performance of HaE classification system, which can upgrade the user experience. The other is to provide migration and reference for the safety analysis of other types of processes, because our existing HaE classification system is mainly based on the chemical industry, and weakly serve and communicate with other types of industries, such as aviation related industries and civil engineering related industries. So, we need to strengthen and harmonize the audience size and popularity of HaE classification system. Sincerely, we hope that our research can burst out its due value and serve the intelligent progress of industrial safety more comprehensively and orderly.
Fig. 27: Application practice of the HaE classification system. The yellow area, purple area, blue area and green area represent the support that it brings to employees, expert groups, engineers and relevant processes of other enterprises respectively, and process#A, process#B and process#C represent the process under the respective conditions.

7. CONCLUSION

The national volume and industrial development have made HAZOP a leader in industrial safety engineering, especially in China. Therefore, it is meaningful and necessary to study the classification of hazard events (HaE) covered by HAZOP, which has far-reaching significance for the intelligent development and progress of industrial safety. Unfortunately, this topic has not received such attention at present.

In this paper, we propose a novel deep learning based DLF classifier to explore the HaE classification through fractal from the perspective of language, where, this "language" means that HaE composed of words conforms to the language system in human society, and this "fractal" means that HaE meets self-similarity in its meaning, since HaE can be naturally regarded as a kind of time series under the compulsion of HAZOP.

Specifically, DLF classifier has gone through three procedures. First, we manipulate BERT to vectorize HaE. Then, we propose a new HmF-DFA multifractal method to court HaE fractal series dependent on Hurst exponent by calculating the HaE vector which is regarded as a kind time series. Finally, we conceive a hierarchical gating neural network (HGNN) to complete the classification of HaE under three aspects.

We take 18 processes as case studies and conduct evaluation experiments with their HAZOP reports. Experimental results demonstrate that our DLF classifier has promising and gratifying aptitudes, greatly ameliorates HaE's classification work, and the proposed HmF-DFA and HGNN are also feasible and effective.

HaE classification system is beneficial to the redevelopment and enhancement of HAZOP, it can serve the safety and reliability of industry intelligently and orderly. Specifically, it can (1) assist the expert group to conduct safety analysis on the raw process and support the identification of decision-making, (2) assist the engineer in dealing with unforeseen hazards, (3) support employees to conduct routine work and emergency response, and (4) guide related processes of other enterprises to launch HAZOP.

We hope our work can provide additional advance and added value for the daily practice of industrial safety, as well as enlighten researchers committed to fractal theory.

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