Ontology-Based Decoding of Risks Encoded in the Prescriptive Requirements in Bridge Design Codes

F. Hassan[a] and T. Le[b]

[a]Ph.D. Student, Glenn Department of Civil Engineering, Clemson University, Clemson, SC, USA
[b]Assistant Professor, Glenn Department of Civil Engineering, Clemson University, Clemson, SC, USA
E-mail: fhassan@g.clemson.edu, tuyenl@clemson.edu

Abstract –

Bridge designs are typically governed by a voluminous set of requirements in various design standards and codes. The requirements are aimed at ensuring the structural safety against different environmental risks experienced by a bridge facility during its service life. The requirements provided in the bridge design standards are generally prescriptive in nature that do not explicitly specify the types of risks addressed in them. As a result, the understanding of the risks hidden in the requirement text is solely associated with the individual designer who often lacks adequate training in interpreting the risks addressed in prescriptive requirements. The conventional practice of manual identification of risks encoded in the prescriptive provisions requires much effort, domain knowledge and may include human errors as well. Little attention has been paid towards automated identification of risks encoded in the prescriptive requirements. The paper presents an ontology-based risk decoding model to decode the risks implied in the prescriptive requirements. The risks included the earthquake, flood, wind, fire, vessel collision, blast loading, temperature and overloading. An ontology for conceptualizing the domain knowledge of the eight risks was first developed. The ontology-based decoding model ranks the risks for a prescriptive requirement by measuring the semantic similarity between the requirement and the risk ontology. The model was tested on the AASTO bridge design specifications and evaluated in terms of Spearman, Kendall tau and Pearson rank correlation test. This study is expected to assist the designers in the improved understanding of risks encoded in prescriptive design standards.

Keywords –

Bridge design;Prescriptive requirements; Design standards; Environmental risks; Natural language processing; Deep learning

1 Introduction

Bridge designs are generally carried out in accordance with a set of requirements specified in the design codes and standards [1]. The primary goal behind these requirements is to ensure the structural stability and durability of the bridge against several environmental risks [2]. The major risks experienced by the bridges are flood, earthquake, wind, fire, etc. In order to execute a safe and reliable design, the precise understanding of the requirements is very crucial [1]. The requirements currently available in the bridges design codes are mostly described in a prescriptive manner where the main intention or the objective behind the requirement is not clearly stated [3]. Accordingly, there is a need for an automated framework which can decode the risks hidden in the text of prescriptive requirements.

The accurate decoding of the risks in the prescriptive requirements is very important to produce a design that can enable the safety of the bridge against all hazards or risks [4]. The prescriptive requirements are typically produced by the code writers with years of experience in the industry and research. In addition, a detailed study of the past failures along with the full-scale testing of the proposed models are also performed while designing the prescriptive requirements [5]. The code writers only present the final criteria for the safest designs without providing any information regarding the types of risks considered while developing that criteria. For instance, the prescriptive requirement *"The maximum girder spacing shall not exceed 10½ ft."* may fulfill the design requirements against overloading, earthquake, and flood but may not fulfil the performance required against the fire risk. Another requirement *"The spacing of intermediate bracing shall not exceed 20 ft."* may achieve the goals of flood, wind, and earthquake risks while the fire, temperature and overloading risks may not be mitigated by implementing this requirement. However, such information of the risks is not provided in the requirement text. Since many prescriptive requirements have certain limitations in terms of risks, the implementation of the prescriptive requirements without understanding the risks addressed in them may result in the scenarios where a few risks may be go unchecked in the bridge design [6]. Young engineers in the industry mostly lack the experience and knowledge required for understanding the risks encoded in the prescriptive requirements. The blind implementation of the prescriptive requirements by young engineers without understanding the objectives and performance level implied in the requirement may result in an unsafe design. In addition, since the objectives covered in the prescriptive require are not known, it is difficult in international construction industry to establish an equivalence between two different criteria stated in codes of two different countries [7]. Therefore, a risk decoding model is required that can precisely decode the risks encoded in the prescriptive requirements.

The current body of knowledge lacks methods to address the issue of risks hidden in the prescriptive requirements. To fill the gap, this study has attempted to develop an automated ontology-based risk decoding model using the linguistic methods such as vector space models and ontologies. A detailed ontology covering the domain knowledge of the eight risk categories was first developed. The risk categories included earthquake, flood, wind, fire, vessel collision, blast loading, temperature and overloading. Following this, the trained vector space model and ontology were employed to decode and rank the risks encoded in the prescriptive requirements according to the semantic similarity of the requirement text and the risk ontology.

2 Background

2.1 Risks in bridge design codes

The risks involved in the bridge design are controlled and mitigated by the implementation of requirements available in the design codes [1]. The bridge design codes generally include two types of requirements; (1) prescriptive requirements, and (2) performance-based requirements [8]. The prescriptive requirement only states the acceptable solution without indicating the performance level while the performance-based requirements specifies the performance level required without providing any prescription or solution. The prescriptive requirements can further be classified into two categories. The first category is when the quantitative prescription is explicitly stated, for example, *"The maximum girder spacing shall not exceed 10½ ft."*. The second type is when the relevant code or method is specified to be followed in design, for example, *"The deck overhang shall be designed in accordance with Section 13 of the LRFD Specifications."* Since the goals or intention behind the recommendations in prescriptive requirements are not specified, the young designers often assume that the requirements cover all the risks. However, this is not the case for the prescriptive requirement since prescriptive requirements always have certain limitations as well [4]. The implementation of the requirement for a scenario for which is not designed often results in the failure in achieving the required performance. Therefore, the decoding of the risks is very important to ensure that the requirements are applied to the scenarios for which they are actually designed.

2.2 Text processing using ontologies

Ontologies are the knowledge representation methods widely used to present the domain knowledge shared among different systems [9]. Ontologies are employed to provide the background knowledge in a machine-readable format for the development of several automated systems for text classification, word sense disambiguation, etc. [10]. The representation of knowledge in the form of concepts in ontologies enables the reuse of the ontologies for other systems [11]. Concepts are the domain entities which are represented in a hierarchical form in ontologies. The relationships are used to define the type of connections between the different concepts and sub-concepts. Ontologies can also play a key role in text processing. For instance, the ontologies can be used to represent the features of a text document. The extracted features can then be used to classify or rank the labels using a machine learning algorithm [12]. In addition, ontologies can also be used to represent the domain knowledge of class labels. The developed ontologies of the labels can then be used to analyze the documents followed by the assigning of labels or ranks [13].

2.3 Related studies

Several researchers have studied the limitations pf the prescriptive requirements, however, most studies have been focused on the addressing a few specific limitations such as design hinderance while many other limitations such as absence of risk information in prescriptive requirement have not received the equal attention. For instance, [14] studied the limitation of the prescriptive codes in addressing the fire risk. As a solution, the authors stressed upon the improvement of current prescriptive codes, ensuring their proper implementation along with the promoting the fire education. Another study by [15] highlights the limitations of the prescriptive codes in introducing innovative solutions to mitigate problems associated with the climate change. A five-step solution was provided by the author to control the degradation of environment due to the use of specific materials prescribed in the prescriptive requirements. [16] also addressed the same limitation of hinderance in using alternative methods to improve the project performance in design-bid-build and design-build projects. The study carried out the textual analysis of the performance-based requirements provided in the Swedish design-build contracts.

Prescriptive requirements in the transportation domain also presents the same limitation of disallowing the innovative solutions. Since manufacturers have to follow the prescriptive dimension and weight requirements, they cannot practice new solutions to reduce the road accidents. [17] suggested a performance-based system to address this limitation. The developed regulatory system requires the certification of vehicles as well as operators to meet the approval requirements. [18] highlighted the increase in accidents in Malaysia due to not allowing the new alternative methods in design to prevent the accidents. The author studied the limitations in the prescriptive codes of Malaysia and explored the potential opportunities of improvement by comparing it with the well-established performance-based specifications implemented in Australia. [19] also highlights the limitations of prescriptive requirements in dealing with the complex risks such as blast loading and fire.

Many studies have investigated the limitation of prescriptive requirements in hindering the innovation. However, despite the significant importance, the limitation of prescriptive requirement in specifying the performance level or risk information have not been studied yet. The current study is aimed at developing an automated framework to decode the goals implied in the prescriptive requirements.

3 Methodology

The methodology adopted in this study comprised four major steps illustrated in Figure 1. Firstly, an ontology reflecting the essential semantic knowledge associated with the eight environmental risks was produced. Following this, a vector space model was trained using a domain specific corpus. The third step includes the computation of the semantic similarity scores between the requirement text and the risk categories. After ranking of risks according to the similarity scores, the model was evaluated using different rank correlation coefficients.

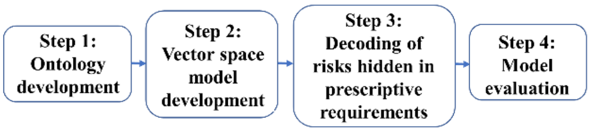

Figure 1. Methodology of the ontology-based risk decoding model

3.1 Step 1: Ontology development

Before development of ontology, the major risks involved in the bridge designs were identified. Upon reading of the relevant published articles, following eight (08) major risks were identified: flood, wind, earthquake, fire, temperature, vessel collision, overloading, and blast loading. A detailed ontology to model all the domain specific knowledge of each of the eight risk categories was developed. The four steps involved in the ontology development are explained below.

1. ***Identification of purpose:*** In the first step, the reason behind the development of ontology was explicitly defined. The ontology developed in this study was aimed to decode the environmental risks hidden in the prescriptive requirements.
2. ***Identification of concepts and sub-concepts:*** The second step involved the identification of all concepts and sub-concepts related to each of the eight risk categories covered in this study. The bridges design codes and published articles were used to identify the concepts and sub-concepts. For instance, ‘liquefaction” and ‘cyclic loading” is related to earthquake, so these concepts were present under the earthquake category in the risk ontology.
3. ***Identification of relations:*** The third step is aimed at defining the relationships between the concepts and sub-concepts in the ontology.
4. ***Ontology modeling:*** Finally, the concepts and sub-concepts were modeled in the protégé tool to produce the final ontology.

Figure 2 illustrates a partial ontology of a risk category “flood’. The ontology of a risk category mainly shows the essential semantic knowledge associated with the risk category in a hierarchical form. As shown, all the sub-concepts below a particular sub-concept provides additional information regarding the upper concept. The higher concepts are the abstract ones while the lower concepts in the ontology provides detailed knowledge of the upper concepts. Each of the eight risk categories has a different number of sub-concepts below it in the ontology depending on the semantic knowledge required to present the risk category.

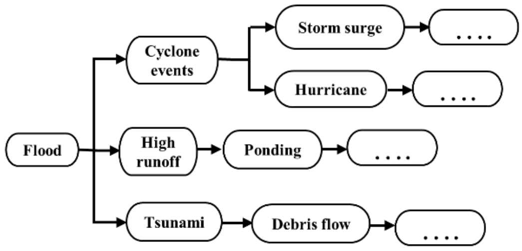

Figure 2. Partial ontology of risk category 'flood'

3.2 Step 2: Vector space model development

Several bridge design codes, standards and the published articles were collected to build a vector space model to learn the semantic meanings of the technical terms used in the design codes. The design codes of ten different state department of transportation (DOT) as well the U.S. DOT was employed to develop the corpus for the training of vector space model. The tables and equations were excluded from the corpus since they are not supported by the natural language processing (NLP) methods. The final corpus used in the training process comprised a total of approximately 1 million words. The domain-specific corpus was pre-processed by implementing the following NLP methods; (1) Lowercasing: The complete corpus was converted into a lowercase format to consider similar meaning words such as "Cracking" and "cracking" as one word. (2) Tokenization: The whole corpus was transformed into a sequence of tokens where a token could be a word, a number or a punctuation. (3) Lemmatization: Lemmatization was performed to convert different grammatical forms of a single word into the root form, for instance, "cracks", "cracked", and "cracking" was converted to the root word "crack".

After pre-processing of the corpus, the wor2vec algorithm was applied to build a vector space model. Both architectures of the word2vec including continuous bag-of-words (CBOW) and hierarchical skip-gram algorithm were applied [20]. Both algorithms have reported comparable performance in the literature [20]. The whole vocabulary in the corpus was presented on a high-dimensional vector space where each unique word holds a unique vector. The distance between the vectors on vector space indicates the semantic similarity between the corresponding words. The training of the vector space model includes the tuning of several parameters such as window size (number of co-occurring words examined in analysing the semantic meaning of a word), vector dimensionality (dimensions of each word vector), frequency threshold (minimum frequency of a word required to include the word in the training process). Different values of the vector dimensionality ranging from 300 to 1200 were tested in this study to determine the optimal value. The window size and frequency threshold considered in all the experiments were 10 and 1 respectively.

3.3 Step 3: Decoding of the risks hidden in prescriptive requirements

The risk decoding approach adopted in this study is the similarity-based. The similarity scores indicating the semantic similarity between the requirement text and the risk ontology were first determined. Based on the similarity scores, the risks encoded in the requirement were ranked in the descending order of relevance. The details of the two steps are provided as follows.

3.3.1 Measurement of the similarity scores

The trained vector space model was employed to compute the similarity score of each term in the requirement and each concept in the ontology. Cosine similarity function was applied for the computation of similarity scores. Cosine similarity computes the angle between the two vectors where a smaller angle shows higher similarity between the corresponding words. The detailed risk ontology and the prescriptive requirement were provided as input to the risk decoding model where the semantic similarity between each word of the requirement and each concept of the ontology were computed using the trained vector space model. After similarities calculation, the similarity values of all terms in a requirement with a specific concept were then summed up to get the total similarity value for the requirement with that specific ontology concept. Since the current study is focused on the decoding of risks which are present at the level 1 of ontology, the similarity scores at the level 1 of ontology are determined by adding the similarity scores of all the concepts below that level 1 concept. Each level 1 concept includes a different number of concepts below it in ontology, therefore, the total similarity values are normalized by the frequency or number of nodes below each level 1 node of ontology. The mean normalized method was applied to compute the total similarity score at the level 1 of ontology. Eq. 1 was used for the computation of mean normalized scores. A total of eight mean normalized scores were obtained where each value corresponds to the total semantic similarity score of the requirement with a specific level 1 concept.

$$mean\ normalized\ score = \frac{\sum_{n=1}^{N}\left(\sum_{t=1}^{T} s_{tc}\right)_k}{N} \tag{1}$$

Where s_{tc} indicates the semantic similarity score of the term *'t'* in the requirement and concept *'c'* in the ontology, *'T'* indicates the total number of terms in a specific requirement, *'N'* indicates the total number of concepts below a level 1 concepts in ontology.

3.3.2 Ranking of the risks

Once the total similarity scores of a requirement with the eight risk factors at level 1 of ontology are calculated, the risk factors are ranked in descending order of relevance. The risk category revealing the highest total mean normalized score was assigned the rank 1 while the remaining categories are ranked from 2 to 8 according to the total similarity scores.

3.4 Step 4: Model evaluation

The risk decoding model was evaluated on a test dataset of 151 prescriptive requirements. The test dataset was manually labeled with the ranks of risks according to the content of the requirement. The performance of the model was evaluated using different rank correlation tests including Spearman, Kendall tau and Pearson rank correlation tests (as shown in Eq. 2-4). The rank correlation value shows the level of agreement between the actual ranks and the predicted ranks. A value of 1 indicates a complete agreement while a value of -1 indicates a complete disagreement between the two sets of ranks.

$$Spearman = r_s = 1 - \frac{6\sum_{i=1}^{n}(x_i - y_i)^2}{n^3 - n} \tag{2}$$

$$Kendall\ tau = r_k = \frac{2}{n(n-1)}(|C| - |D|) \tag{3}$$

$$Pearson = r_p = \frac{n\sum x_i y_i - \sum x_i y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}} \tag{4}$$

where 'x_i' and 'yi' are the ranks of a risk category 'i' in group 1 and 2, 'n' indicates the number of predefined risk categories, 'C' is set of concordant pairs, and 'D' is set of discordant pairs.

4 Results and Discussion

This section presents the results of the experiments carried out to evaluate the performance of the risk decoding model. Two different architectures of the word2vec such as CBOW and skip gram algorithm were used to compute the semantic similarities of the requirement terms and the ontology concepts. For each algorithm, four vector space models were developed using a different value for vector dimensionality ranging from 300 to 1200. The window size and minimum threshold value of 15 and 1 respectively were same in all the experiments.

Table 1 presents the results of the risk decoding model using the CBOW algorithm for the similarity computation. The results show that performance of the model was increased with the increment of vector dimensionality until 900. The performance was decreased as the value of vector dimensionality was further increased from 900 to 1200. The highest spearman, Kendall tau and Pearson correlation coefficient of 0.30, 0.23, and 0.29 was achieved with the vector dimensionality of 900 whereas the lowest spearman, Kendall tau and Pearson correlation coefficient of 0.24, 0.19, and 0.23 was achieved with the vector dimensionality of 300.

Table 1. Performance of the ontology-based risk decoding model using CBOW algorithm for similarity computation

Vector dimensionality	Spearman	Kendall tau	Pearson
300	0.24	0.19	0.23
600	0.29	0.22	0.28
900	030	0.23	0.29
1200	0.26	0.20	0.25

Table 2 presents the results of the risk decoding model using the skip gram algorithm for the similarity computation. The same trend as previously seen with the CBOW was observed with the skip gram as well. However, unlike CBOW, the performance of the skip gram model did not change significantly while varying the value of vector dimensionality. A minor increment has been observed till vector dimensionality of 900, however, a decrease in performance was observed for higher values. The skip gram also revealed the highest Spearman, Kendall tau, and Pearson correlation coefficient of 0.64, 0.51, and 0.63 respectively at the vector dimensionality of 900. Among the two word2vec algorithms, the performance exhibited by the skip gram was almost twice better than that achieved by the CBOW algorithm.

Table 2. Performance of the ontology-based risk decoding model using skip gram algorithm for similarity computation

Vector dimensionality	Spearman	Kendall tau	Pearson
300	0.63	0.51	0.62
600	0.62	0.50	0.61
900	0.64	0.51	0.63
1200	0.63	0.51	0.62

4.1 Model performance for different risk categories

The performance of the model in terms of each risk category was further investigated using the best model of skip gram for similarity computation. Figure 3 shows the mean deviation of the predicted ranks from the actual ranks. As shown, the risk categories such as 'temperature' and 'fire' performed the best among the eight categories. For temperature, the mean deviation of 0.23 shows that the model predicts the correct rank for temperature category most of the times. No risk category exhibited a mean rank deviation of above 2 which proves the adequacy of the model.

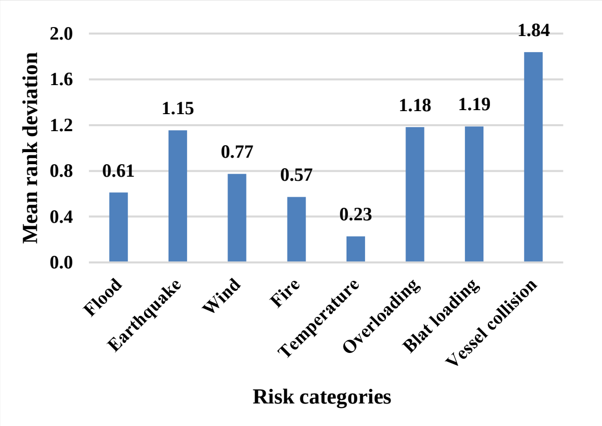

Figure 3. mean deviation of the predicted ranks from actual ranks

5 Conclusion

Bridge design are performed according to the requirements presented in the design codes and standards. However, the requirements are mostly prescriptive in nature where the main objectives or risks addressed in the requirements are not clearly specified. As a result, the designers often face challenges in estimating the limitations and performance level implied in the prescriptive requirements. The study has produced an automated framework using the vector space models and ontologies which can decode the risks encoded in the prescriptive requirements.

An ontology covering the domain specific knowledge associated with the eight risk categories was first developed. In addition, a vector space model was trained on a corpus of approximately 1 million words using the CBOW as well as skip gram algorithm. The model was validated on the unseen prescriptive requirements extracted from the AASHTO bridge design specifications. The experiments revealed that the skip gram algorithm performed better than the CBOW algorithm. The performance exhibited by the skip gram algorithm was double than the performance achieved by the CBOW algorithm. Moreover, the performance was found to be increasing with the increment in the size of word vector dimensions till 900, however, the performance was decreased for higher vector dimensionality values. The overall highest Spearman, Kendall tau, and Pearson correlation coefficient of 0.64, 0.51, and 0.63 respectively was reached by the skip gram model for the similarity computation at the vector dimensionality of 900. Comparing the risk categories, the 'temperature' category performed the best where the model predicted the correct rank in most cases. The model showed the mean rank deviation of 0.23 for the temperature category while the highest mean rank deviation of 1.84 was exhibited by the 'vessel collision' category.

The study has certain limitations in terms of performance. The current model uses the simple mean method to compute the total semantic similarity. In future, the authors will investigate different averaging methods such as weighted average and Bayesian average for the computation of the total similarity scores to examine the improvement in performance. A threshold analysis by setting of a threshold value to exclude the similarity scores of the irrelevant concepts may also improve the performance of the model. In addition, the authors will develop a larger dataset for the training of vector space model to examine if the performance can be improved by using a large dataset.

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