ICCEPM 2022
The 9th International Conference on Construction Engineering and Project Management
Jun. 20-23, 2022, Las Vegas, NV, USA

Automated Prioritization of Construction Project Requirements using Machine Learning and Fuzzy Logic System

Fahad ul Hassan[1]*, Tuyen Le[2], Chau Le[3], K. Joseph Shrestha[4]

[1] *Glenn Department of Civil Engineering, Clemson University, Clemson, SC 29634, USA,* E-mail address: fhassan@g.clemson.edu
[2] *Glenn Department of Civil Engineering, Clemson University, Clemson, SC 29634, USA,* E-mail address: tuyenl@clemson.edu
[3] *Department of Civil, Construction and Environmental Engineering, North Dakota State University, Fargo, ND 58108, USA*. Email address: chau.le@ndsu.edu
[4] *Department of Engineering, Engineering Technology, and Surveying, East Tennessee State University, Johnson City, TN 37604, USA,*. Email address: shresthak@etsu.edu

Abstract: Construction inspection is a crucial stage that ensures that all contractual requirements of a construction project are verified. The construction inspection capabilities among state highway agencies have been greatly affected due to budget reduction. As a result, efficient inspection practices such as risk-based inspection are required to optimize the use of limited resources without compromising inspection quality. Automated prioritization of textual requirements according to their criticality would be extremely helpful since contractual requirements are typically presented in an unstructured natural language in voluminous text documents. The current study introduces a novel model for predicting the risk level of requirements using machine learning (ML) algorithms. The ML algorithms tested in this study included naïve Bayes, support vector machines, logistic regression, and random forest. The training data includes sequences of requirement texts which were labeled with risk levels (such as very low, low, medium, high, very high) using the fuzzy logic systems. The fuzzy model treats the three risk factors (severity, probability, detectability) as fuzzy input variables, and implements the fuzzy inference rules to determine the labels of requirements. The performance of the model was examined on labeled dataset created by fuzzy inference rules and three different membership functions. The developed requirement risk prediction model yielded a precision, recall, and f-score of 78.18%, 77.75%, and 75.82%, respectively. The proposed model is expected to provide construction inspectors with a means for the automated prioritization of voluminous requirements by their importance, thus help to maximize the effectiveness of inspection activities under resource constraints.

Key words: project requirements, construction contracts, natural language processing, fuzzy logic systems, requirement prioritization

1. INTRODUCTION

The contractual requirements in the construction contracts reflect the wishes and expectations of the client towards the final facility. In construction projects, the quality control (QC) staff is responsible for assuring that all requirements in the contract are met in adequately. The assurance of the completion of requirements is crucial to avoid any costly redesign and rework [1]. [2] also found the non-conformance of requirements to be an important reason behind the rework in construction projects. Typically, the QC staff uses the daily progress reports to document the progress and examine the contractor's management, safety, environmental, and design processes in accordance with the requirements. Since the requirements are often described as lengthy text in contracts [1], there is a considerable burden imposed on practitioners to read and prioritize them for evaluating the contractor's procedures. This manual practice of requirement comprehension and prioritization is time-consuming, tedious, and error-prone.

Requirement prioritization is an integral component of the QC process due to the current shortage of inspection resources (budget, time, and manpower) experienced by the state highway agencies [3], [4]. For instance, a 15% reduction in the inspection staff of the Indiana Department of Transportation (INDOT) has been observed just between a gap of 4 years (i.e., 2011 and 2015) [4]. In addition, the increasing complexity and size of the construction projects further demand an increment in the inspection resources and material testing. The prioritization of requirements could be an effective solution to optimize the inspection resources accordingly to their importance and risk levels [5]. However, prioritization is a challenging task since the requirements involve multiple risks (e.g., severity, probability, detectability, etc.) along with different relationships with each risk factor [6]. For instance, a requirement may be of high priority in terms of severity but low priority in terms of detectability. The prioritization requires all risk factors to be considered while identifying the high priority and low priority requirements. Therefore, an effective method is needed for prioritizing the requirements to identify the most critical inspection items.

Previously, a few researchers have attempted to develop frameworks for requirements prioritization [3], [4]; however, the developed frameworks are not generalized, and they are applicable only to a few types of testing requirements. To address this gap, the current study attempts to develop a robust risk-based requirement prioritization model using supervised ML algorithms. The proposed model can predict the risk level of a requirement according to the features present in the requirement text. The model is trained and tested on a labeled dataset produced using fuzzy logic systems.

2. BACKGROUND

2.1. Fuzzy Logic Systems

Fuzzy logic systems are widely used in problems where there is ambiguity or uncertainty present in the values of variables involved in computations [7]. In real-world problems, the decision-makers often face scenarios where they are required to consider multiple factors to reach a decision. However, it is almost impossible to compute the effect of those factors on the potential outcome of a decision, and this usually results in very optimistic or pessimistic decisions [8]. To address such situations, [9] introduced a fuzzy theory that deals with the uncertainty due to vague and incomplete information. A fuzzy set is defined as a class of objects with a degree of memberships [10]. These sets correspond to the fuzzy numbers that indicate the degree of relevance to each object by a membership grade value ranging between 0 and 1 [10]. For instance, a triangular fuzzy number can be represented by (a,b,c) where a,b, and c correspond to the smallest, most promising value, and the largest value for a fuzzy set.

2.2. Fuzzy Failure Model and Effects Analysis (FMEA)

Failure mode and effects analysis (FMEA) is a popular risk measurement tool used in different domains, including construction such as project risk management [8]. In FMEA, a risk priority number (RPN) is computed to determine key risks. This method is used to address several problems, including the prioritization or ranking of objects where the object with the highest RPN value is considered to be the one involving the highest risk. The RPN value is the product of the following three risk factors: (1) severity, (2) probability, and (3) detectability. Here, severity indicates the effects or consequences of a failure of a requirement, probability indicates the likelihood of a failure of a requirement, and detectability corresponds to the possibility of the failure being not detected by the QC team. Generally, the ratings ranging from 1 to 5 are assigned where a value of 5 corresponds to a requirement that is extremely severe, impossible to detect, and very likely to occur.

2.3. Related Studies

Several researchers have attempted to develop requirement prioritization models in different domains to support decision-making. However, the construction domain currently lacks a generalized model for requirement prioritization. One of the initial efforts in the construction domain that aimed to develop a requirement prioritization framework was made by [4]. The authors used the surveys and expert's opinions to introduce a risk-based requirement prioritization model to support construction inspection with limited resources. A total of 333 inspection activities were selected and narrowed down to 126 activities which were prioritized according to the surveys and responses from practitioners. In addition, requirements associated with only four categories, such as earthwork, bridge deck, concrete, and asphalt pavements, were included in the activities list. In another study, [6] also proposed a risk-based prioritization model that can rank the inspection-related requirements according to the consequences and impacts due to the reduced inspection.

Several authors employed fuzzy rule-based systems to prioritize failure modes in other domains. For instance, in mechanical domain, [11] considered risk factors (severity, probability, detectability) as input features which were then processed using the fuzzy rules to compute a fuzzy risk priority number (FRPN). The failure modes were then ranked according to their FRPN values. In another study, [12] implemented the same fuzzy rule-based method to prioritize failure modes for the anesthesia process. The authors compared the performance of two membership functions (MFs), namely triangular and trapezoidal MFs. In the aviation domain, [13] introduced the fuzzy environment-based approach to extend the traditional FMEA method. Four experts were invited to provide ratings for severity, probability, and detectability for failure modes which were then processed using the fuzzy logic systems to rank failure modes for aircraft landing systems.

Undoubtedly, previous studies have provided major contributions towards prioritization of contract requirements. However, the current risk-based construction requirement prioritization models are limited in terms of applicability and scalability as they primarily include a very limited number of requirements mainly in material testing. Given a new project with a new set of contracting requirements, significant time and effort is required for engineers to assess risks of requirement clauses. This manual process of prioritizing requirements is greatly challenging for practitioners. There is currently no scalable technique available that can enable high efficiency in requirement prioritization, particularly for complex construction projects such as infrastructure systems which includes a large set of requirements. Therefore, the current study has attempted to develop a generalized data-driven model that learns risks results from past projects to predict the risk level of new contracting requirements to prioritize them to optimize the inspection resources.

3. METHODOLOGY

This section presents the methodology adopted for the development of the risk-based requirement prioritization model. The proposed methodology is comprised of three steps shown in Figure 1. The first step involved the labeling of the corpus using fuzzy rule-based systems. In the second step, the requirements corpus was pre-processed and classified according to the features present in the requirement text. The classification performance was evaluated in the final third step in terms of precision, recall, and f-score. The details of the three steps are provided below.

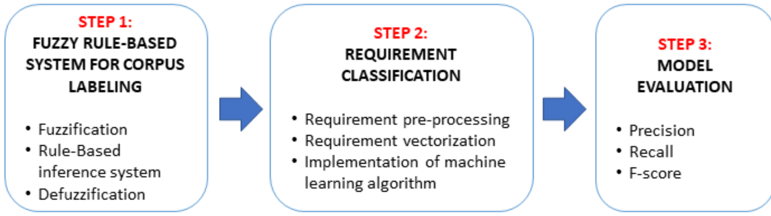

Figure 1. Methodology of the proposed requirement prioritization framework

3.1. Fuzzy Rule-Based System for Corpus Labeling

The first step aims to prepare a labeled dataset using fuzzy logic systems. The reason behind implementing the fuzzy logic was the vagueness and uncertainty in estimating the true values for risk factors such as severity, probability, and detectability. Therefore, it is almost impossible to estimate a precise numeric risk score for a requirement. Fuzzy logic addresses this limitation of vagueness and uncertainty where the crisp input values are fed to the fuzzy model which predicts the fuzzy output values of risk scores, which were later converted into the crisp output risk scores. The steps involved in the fuzzy rule-based systems are discussed below.

3.1.1. Fuzzification

Prior to the fuzzification, an initial labeled requirement corpus including 1331 requirements labeled with numeric values of three risk factors (i.e., severity, probability, and detectability) was prepared. The requirements were obtained from a real design-build (DB) project and labeled by two experts having an in-depth knowledge of construction contracts and inspection. The fuzzification process aims at converting the crisp labels of risk factors into fuzzy sets. The primary step in the fuzzification process is the creation of MF of fuzzy input sets. The major properties of the MF are the number of linguistic terms (degree of risk levels in our study), membership function type (i.e., trapezoidal, triangular, gaussian, etc.), a numerical range of risk factor x (e.g., 100 in our study), and overlap between each MF. The degree of risk levels used in our study are five (very low, low, medium, high, very high), and the type of membership function implemented in this study included triangular, trapezoidal, and gaussian.

3.1.2. Rule-based inference system

A fuzzy inference system combines the fuzzy inputs and rules to produce a fuzzy conclusion. Several fuzzy IF-THEN rules were developed using the expert's judgment and experience in this study. In a fuzzy If-THEN rule, the antecedent part after the IF statement corresponds to the fuzzy input variables, while the consequent part after the THEN statement corresponds to the fuzzy output variable. Each fuzzy IF-THEN rule is expressed as:

IF severity is Low and probability is Low, and detectability is High, ***THEN*** risk is Low.

Since five-degree risk factors were considered along with the number of risk factors equal to three (i.e., severity, probability, detectability), the total number of rules developed in this study was equal to the total number of possible combinations (i.e., 5x5x5 = 125)

3.1.3. Defuzzification

Defuzzification process aims to convert the fuzzy output into the crisp output. In this study, the center of area or centroid defuzzification method was implemented since it was the most commonly used and highest performing method reported in literature. According to the centroid defuzzification method, the output risk score shall correspond to the center of the shaded area shown in Figure 2.

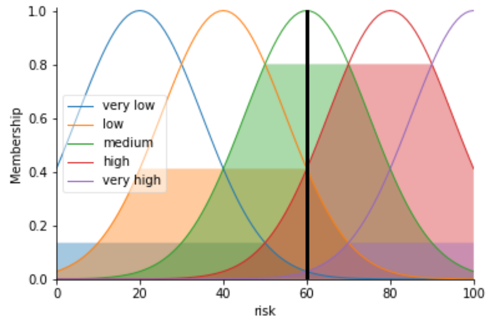

Figure 2. Implementation of centroid defuzzification method

3.2. Requirement Classification

After corpus labeling, the labeled corpus was employed for the training and testing of the classification model to classify the requirements in terms of their risk level or priority level. The sequence of the methods applied for the requirement classification is described below.

3.2.1. Requirement pre-processing

Several natural language processing (NLP) methods were implemented to convert the requirement corpus into an adequate format after removing all unnecessary and noise features. The NLP methods implemented in this study are as follows: (1) Lowercasing converted the requirement corpus into a lowercase format. It helped the model in considering the similar terms "Design" and "design" as one word. (2) Punctuations and stop words removal were applied to remove all punctuations and stop words (such as the, of, am, etc.) from the requirement corpus. It helped in improving the model performance since such noise features did not contribute towards the classification task. (3) Tokenization converted the series of text into individual tokens. This study considered each word, numeric, or a space as one single token. (4) Lemmatization involved the conversion of different grammatical forms of a word (such as design, designed, designs, designing, etc.) into the root form (such as design). For instance, the following high-risk requirement *"LEDs will have a 30-degree viewing angle."* was converted into *['leds', 'will', 'have', '30', 'degree' view', 'angle']* after applying the NLP methods for pre-processing.

3.2.2. Requirement vectorization

Since the computers cannot understand the text in English language, the requirement text is required to be converted into a vector format to feed it as input to the computer for training and testing of algorithms. In this study, the widely adopted Bag-of-words (BOW) method was implemented to convert the text into a vector format. In BOW, each requirement is represented as a vector of N elements where N corresponds to the number of words in the whole corpus. The elements of a vector include the values as either zero or numeric, indicating the absence or presence of a word respectively in requirement text. The numeric values in the vector indicate the weights of the word, which were determined by two methods, namely term frequency (TF) and term frequency-invert document frequency (TF-IDF) methods. The TF method assigns the weights according to the frequency of a word in a requirement statement. However, there are certain domain-specific words that are highly frequent in the requirement text, but they do not discriminate a low priority requirement from a high priority requirement. The weights of such low content words are modified by the IDF factor in the TF-IDF method. The IDF factor scales up the weights of rare discriminating words while reducing the weights of high-frequency low content words.

3.2.3. Implementation of machine learning algorithms

Before implementation of the ML algorithm, the requirement corpus was divided into a training and testing set using the k-fold cross-validation method. In this method, the whole corpus is split into *k* equal sets, and the model is trained *k* times where *k-1* sets are used for the training of the model while the remaining one set is used for the testing. The training process is terminated when all the unique *k* sets are employed as testing sets in *k* iterations. After splitting the corpus into training and testing sets, four ML algorithms were implemented to develop the classification models. Each algorithm has merits and demerits, showing different perfromances on different datasets in different domains [14]. None of the algorithms has consistently outperformed the other algorithms in all domains. Therefore, we tested four most commonly used algorithms in this study to compare their performance. The algorithms included naïve Bayesian (NB), support vector machines (SVM), logistic regression (LR), and random forest (RF). NB is the simplest algorithm that employs the Bayesian theorem considering an assumption that the features include in the corpus are independent. SVM finds the best hyperplane to split the data into unique classes in a high dimensional vector space with the maximum margin. Moreover, LR is a probabilistic algorithm that determines the correlation between the dependent and independent variables to predict the probabilities of different risk levels for the requirements. RF is an ensemble algorithm that trains multiple decision tree classifiers and merges them to develop a final classifier.

3.3. Evaluation

The performance of the proposed classification models was evaluated in terms of three different metrics: precision, recall, and f-score. Precision indicates the number of samples of a class correctly predicted by the model among the total predictions made by the model for that class. The recall represents the number of samples correctly identified by the model from the total number of samples present in the testing set. A trade-off is generally observed between precision and recall. This trade-off is addressed by introducing the f-score metric which is the harmonic mean of the precision and recall. The metrics used in this study are the weighted average of all the classes.

4. RESULTS AND DISCUSSIONS

This section presents the results of the rule-based fuzzy logic systems and the ML-based text classification models. The labeled dataset produced through the fuzzy rules was examined. Following this, the performance of four ML algorithms to classify the requirements in terms of different risk levels was evaluated. The detailed results are discussed in the following subsections.

4.1. Dataset

A labeled dataset is the prerequisite to the development of classification models. In this study, a rule-based approach was used for the labeling of requirements. Five-degree risk levels were considered to construct the rules and fuzzy sets for membership functions. The five degrees of risk levels included very low, low, medium, high, and very high. A total of 125 rules were constructed in the fuzzy logic system. In addition, the triangular, trapezoidal, and gaussian membership functions were applied in this study. The risk scores predicted by the fuzzy rules using different MF shapes were analyzed and compared to identify the unique risk scores, minimum and maximum risk scores, range of risk scores and distribution of different risk levels in the dataset. Table 1 shows the attributes of the datasets produced by the three MF shapes. As shown, the gaussian MF shape produced a better-balanced dataset with a better distribution of the requirements of each category in the dataset. The dataset produced using gaussian MF shape included 42 unique risk scores with a comparatively higher range of 60.41. The minimum number of samples for a category in the dataset produced using gaussian MF is also the highest (i.e., 64). Therefore, this dataset was selected to implement the ML algorithms for requirement classification.

Table 1. Characteristics of datasets produced using different membership function shapes

MF Shape	Unique Risk Scores	Minimum Value	Maximum Value	Difference	Dataset Distribution*
Triangular	21	22.59	75.75	53.16	VL: 67, L: 373, M: 488, H: 387, VH: 16
Trapezoidal	4	22	87.33	65.33	VL: 64, L: 831, H: 429, VH: 7
Gaussian	**42**	**22.27**	**82.68**	**60.41**	**VL: 373, L: 76, M: 670, H: 148, VH: 64**

***NOTE:** VH = very high, H = high, M = medium, L = low, VL = very low

4.2. Classification performance of different machine learning algorithms

In this study, the performance of classification algorithms was evaluated using two different feature weighting methods (i.e., TF and TF-IDF). The results of the classification performance of the four algorithms using two feature weighting methods are shown in Table 2. As shown, the models experienced a reduction in performance when the TF method was replaced by the TF-IDF method for feature weighting. Among the four ML algorithms tested in this study, the RF algorithm achieved the highest performance in terms of precision, recall, and f-score equal to 78.18%, 77.75%, and 75.82%, respectively. The NB and SVM algorithms experienced the highest reduction in precision and recall, respectively. The precision and recall of NB and SVM were dropped by 3.0% and 1.45%, respectively, when TF-IDF method was used for feature weighting instead of the TF method. Generally, the TF-IDF method yields higher performance. However, this study reported a reduction in performance that might be due to the smaller dataset used for the training and testing of the model. The dataset is comprised of a small size of vocabulary or features where the low-frequency features are also discriminating whose removal in the TF-IDF method actually resulted in lower performance.

Table 2. Performance of machine learning algorithms using TF and TF-IDF methods

Machine learning algorithm	TF Feature Weighting			TF-IDF Feature Weighting		
	Precision	Recall	F-Score	Precision	Recall	F-Score
SVM	70.85	70.76	70.01	69.47	69.31	66.28
LR	72.20	72.03	71.60	73.28	73.32	72.71
NB	67.65	65.41	65.93	64.65	65.29	60.33
RF	78.18	77.75	75.82	77.71	76.76	74.34

5. CONCLUSION

The contractual requirements are the wishes and expectations of the owner towards the final facility and these requirements must be verified during the QC process to avoid any costly redesign and rework. The ever-increasing gap between the required and available inspection resources has resulted in the need for finding efficient ways to optimize them. The current study has implemented fuzzy rule-based systems and ML algorithms to develop a model that can prioritize the requirements according to their risk levels. A dataset of 1331 requirements employed for the classification model training was labeled by the fuzzy logic systems. The initial dataset was manually labeled with risk factors, including severity, probability, and detectability. The three aforementioned labels were converted into a single label of risk level for each requirement sample using the fuzzy rule-based systems. The current study tested different fuzzy MF types where the gaussian MF type produced a comparatively well-balanced dataset in comparison with other MF types. In addition, the TF weighting performed better than the TF-IDF weighting method for the majority of algorithms. The highest precision, recall, and f-score of 78.18%, 77.75%, and 75.82%, respectively, were revealed by the RF algorithm with TF weighting methods.

As part of future work, the authors plan to improve the current performance of the model. The ontology-based methods can be implemented to compare their performance with the ML-based methods. Since the ontology-based methods do not require labeling of data, an increment in performance could be expected. However, significant efforts would be required to develop an ontology for such domain-specific problems. In addition, the authors will further develop separate models for different types of projects which may improve the performance of individual models.

REFERENCES

[1] C. Anumba, A. Karim Jallow, A. N. Baldwin, and P. Demian, “An empirical study of the complexity of requirements management in construction projects,” *Eng. Constr. Archit. Manag.*, vol. 21, no. 5, pp. 505–531, 2014, doi: 10.1108/ECAM-09-2013-0084.

[2] S. Assaf, M. A. Hassanain, and A. Abdallah, “Assessment of deficiencies in design documents for large construction projects,” *J. Perform. Constr. Facil.*, vol. 31, no. 5, p. 4017086, 2017.

[3] M. Mohamed and D. Q. Tran, “Risk-based inspection for concrete pavement construction using fuzzy sets and bayesian networks,” *Autom. Constr.*, vol. 128, p. 103761, 2021.

[4] C. Yuan, J. Park, X. Xu, H. Cai, D. M. Abraham, and M. D. Bowman, “Risk-based prioritization of construction inspection,” *Transp. Res. Rec.*, vol. 2672, no. 26, pp. 96–105, 2018.

[5] M. Elmasry, T. Zayed, and A. Hawari, “Multi-Objective Optimization Model for Inspection Scheduling of Sewer Pipelines,” *J. Constr. Eng. Manag.*, vol. 145, no. 2, p. 04018129, 2019, doi: 10.1061/(asce)co.1943-7862.0001599.

[6] A. Mostafavi and D. Abraham, “INDOT Construction Inspection Priorities,” 2012. doi: 10.5703/1288284314669.

[7] C. S. Wu, T. Polte, and D. Rehfeldt, “A fuzzy logic system for process monitoring and quality evaluation in GMAW,” *Weld. J.*, vol. 80, no. 2, pp. 33-S, 2001.

[8] M. Yazdani, M. R. Abdi, N. Kumar, M. Keshavarz-Ghorabaee, and F. T. S. Chan, “Improved Decision Model for Evaluating Risks in Construction Projects,” *J. Constr. Eng. Manag.*, vol. 145, no. 5, p. 04019024, 2019, doi: 10.1061/(asce)co.1943-7862.0001640.

[9] L. A. Zadeh, “Fuzzy sets,” *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965, doi: https://doi.org/10.1016/S0019-9958(65)90241-X.

[10] X. Peng and G. Selvachandran, “Pythagorean fuzzy set: state of the art and future directions,” *Artif. Intell. Rev.*, vol. 52, no. 3, pp. 1873–1927, 2019, doi: 10.1007/s10462-017-9596-9.

[11] Y. M. Wang, K. S. Chin, G. K. K. Poon, and J. B. Yang, “Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean,” *Expert Syst. Appl.*, vol. 36, no. 2 PART 1, pp. 1195–1207, 2009, doi: 10.1016/j.eswa.2007.11.028.

[12] H. C. Liu, L. Liu, N. Liu, and L. X. Mao, “Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment,” *Expert Syst. Appl.*, vol. 39, no. 17, pp. 12926–12934, 2012, doi: 10.1016/j.eswa.2012.05.031.

[13] M. Yazdi, S. Daneshvar, and H. Setareh, “An extension to Fuzzy Developed Failure Mode and Effects Analysis (FDFMEA) application for aircraft landing system,” *Saf. Sci.*, vol. 98, pp. 113–123, 2017, doi: 10.1016/j.ssci.2017.06.009.

[14] F. ul Hassan and T. Le, “Computer-assisted separation of design-build contract requirements to support subcontract drafting,” *Autom. Constr.*, vol. 122, no. October 2020, p. 103479, 2021, doi: 10.1016/j.autcon.2020.103479.