Journal of Civil Engineering and Management
ISSN 1392-3730 / eISSN 1822-3605
2018 Volume 24 Issue 4: 301–317
https://doi.org/10.3846/jcem.2018.3072

EXAMINING ASSOCIATION BETWEEN CONSTRUCTION INSPECTION GRADES AND CRITICAL DEFECTS USING DATA MINING AND FUZZY LOGIC

Chien-Liang LIN[1], Ching-Lung FAN[2*]

[1]*Department of Construction Engineering, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan*
[2]*Institute of Engineering Science and Technology, National Kaohsiung University of Science and Technology & Department of Civil Engineering, the Republic of China Military Academy, Kaohsiung, Taiwan*

Received 08 August 2017; accepted 15 May 2018

Abstract. This paper explores the relations between defect types and quality inspection grades of public construction projects in Taiwan. Altogether, 499 defect types (classified from 17,648 defects) were found after analyzing 990 construction projects from the Public Construction Management Information System of the public construction commission which is a government unit that administers all the public construction. The core of this research includes the following steps. (1) Data mining (DM) was used to derive 57 association rules which altogether contain 30 of the 499 defect types. (2) K-means clustering was used to regroup the 990 projects of two attributes (defect frequency and original grading score of each project) into four new quality classes, so the 990 projects can be more evenly distributed in the four new classes and the correctness and reliability of the following analyses can be ensured. (3) Finally analysis of variance (ANOVA), fuzzy logic, and correlation analysis were used to verify that the aforementioned 30 defect types are the important ones determining inspection grades. Results of this research can help stakeholders of construction projects paying more attention on the root causes of the critical defect types so to dramatically raise their management effectiveness.

Keywords: data mining, association rules, fuzzy set, critical defects, construction quality management, inspection grades.

Introduction

The total output value of Taiwan's construction industry was approximately NT$403.7 billion in 2016, accounting for 2.28% of Taiwan's GDP. Public construction accounted for 46.8% (approximately NT$189.0 billion) of the aforementioned total output value, indicating its substantial contribution to the overall economic development of Taiwan.

In practice, the construction quality of a project is generally measured by the types and frequencies of defect discovered and recorded in the quality inspection checklist. Defects are not only the focus of quality management but also a performance index of construction project.

According to Webster's Dictionary (1828), defect is defined as "a lack of something necessary for completeness, adequacy, or perfection". In the academic study, error, fault, failure, defect, quality deviation, non-conformance, quality failure and snag are the words to describe construction defect (Mills *et al.* 2009; Georgiou *et al.* 1999; Love 2002; Macarulla *et al.* 2013). Nonetheless, from the truth that there are denotational variations among these words, it is better understood that both the research's and the proprietor's management perspectives can affect the definition of defect.

A defect is defined by SS-ISO (1987) as an error of not performing regulated requirements. Watt (1999) defines defect as a failing or shortcoming in the function, performance, statutory or user requirements of a building, and might manifest itself within the structure, fabric, services or other facilities of the affected building.

The two definitions of defect from SS-ISO (1987) and Watt (1999) are integrated into one in this study: a defect is an error of not performing regulated requirements, creating a failing or shortcoming in the function, performance, statutory or user requirements of a building, which might manifest itself within the structure, fabric, services or other facilities of the affected building. The reason the

*Corresponding author. E-mail: *u0315916@nkfust.edu.tw*

integrated definition is used in this study is that it is more in accordance with the system conditions which regulate Taiwan's public construction defects, i.e., as in the content and registered standards in the mechanism of public construction inspection.

The quality of public construction in Taiwan was frequently criticized and contested before. To uphold the quality of public construction, since 1993, Taiwan has implemented a three-level public construction quality management system, consisting of (1) quality control system (Level 1, administered by contractors), (2) quality assurance system (Level 2, administered by procuring units), and (3) public construction inspection (Level 3, administered by competent authorities). In this article, construction inspection refers to the Level 3 construction quality management implemented by the public construction quality audit team assigned from either the central or the local government.

A public construction quality audit team is a committee consisting of 2–3 members of specialists or scholars and they inspect quality of public construction projects according to the related law, regulation, contracts and predefined quality audit guidelines. When performing inspection, the quality audit team visits and walks through the construction site, performs inspections, listens to briefings, checks relevant documents, and finally hosts a quality audit meeting. During the meeting, the committee notifies both the procuring unit and contractor of the discovered defects and gives the project team an opportunity to explain. After the meeting, the committee summarizes the inspection records and determine the scores and inspection grades.

The construction inspection grading system is graded into four quality ratings. They are: S (Grade S, 90–100), A (Grade A, 80–89), B (Grade B, 70–79) and C (Grade C, <70). The final score of the inspections is decided by calculating the average of the raw sum of the scores added together from each committee member's original ones.

Since the implementation of construction inspection mechanism in Taiwan, numerous inspection records of public projects have been accumulated. The inspection content is divided into four categories: Quality Management System (Defect Code 4.00, 113 defects), Construction Quality (Code 5.00, 356 defects), Construction Progress (Code 6.00, 10 defects), and Planning and Design (Code 7.00, 20 defects). All inspection records of the inspection grades, scores, defect codes, and defect details are completely released by the procuring units in the Public Construction Management Information System (PCMIS).

Therefore, the high inspection grades and scores generally indicate that the inspected project achieves excellence on quality management system, high construction quality, progress management, and planning and design. By contrast, receiving a "C" grade means a loss of the contractor's reputation as well as the future opportunities of undertaking public construction projects. Worse still, if a serious defect happens, then those responsible for it will be punished, and the construction site manager will be replaced, or the contractor have to pay punitive damages as a fine for the cause of the defect. Not only that, the loss will also make a profound impact on the project executive team.

However, the correlations between inspection grades and defects and the influential power of particular defects are associated with construction quality and costs; these correlations are worthy of further investigations and analyses.

Cheng *et al.* (2015) believed that in the construction industry, defective building works will lead to time and cost overruns in the project, and disputes may arise among the construction participants in the construction and management stages, and also that, as of today, not a single analysis model is able to sufficiently retrieve useful information from the database of building defects.

Thus, it is evident that although there is plenty of useful information in the database of building defects and the big data warehouse, there is a lack of related research findings and concrete analysis results on the application of the database to preventing defects, reducing their items and number and improving construction quality.

Based on the above, this study examined the construction inspection database of the PCMIS through data mining (DM) to discover association rules among the copious data regarding construction defects. In addition, this study applied fuzzy sets to further identify critical defects and sorted them by importance before proposing suitable management strategies and solutions. The methods used in this study and the research purposes are as follows:

- Association rules. The prime purpose of an analysis of defect association rules is to explore the probability of the associations and dependence (simultaneously) among the defects, so as to create links between the defect types.
- Cluster analysis. In this study, it is found that in the inspection grading system the sample sizes (defect frequencies) of Grade S (taking up 0.6%) and Grade C (0.2%) are apparently smaller than those of Grade A (77.1%) and Grade B (22.1%) (see Table 1). At the time if the researcher went on to conduct significance tests, then the problem of unbalanced date would be created, i.e., even though there existed a huge difference, no statistically significant difference would happen because of the smaller sample sizes of the groups (Pallant 2013). In order to secure the correctness and reliability of the statistical results by mitigating the sample size differences between different inspection grade groups, this study conducted the cluster analysis on the inspection grades and defect frequency and regrouped and redefined the samples in the new grading system, in which four grades are classified: Class 1 = 1, Class 2 = 2, Class 3 = 3 and Class 4 = 4 (see Table 2).
- Analysis of Variance (ANOVA). In the ANOVA setting, the defects are tested to see if the elicited data meets the criteria for homogeneity of variance hypothesis; the data is then used to analyze whether

Table 1. Construction inspection grading system

Inspection grades	Score	Project number
S	90–100	6 (0.6%)
A	80–89	763 (77.1%)
B	70–79	219 (22.1%)
C	<70	2 (0.2%)
Total		990

⇒

Table 2. New grading system in cluster analysis

New grades	Cluster analysis	Project number
Class 1	1	458 (46.3%)
Class 2	2	135 (13.6%)
Class 3	3	303 (30.6%)
Class 4	4	94 (9.5%)
Total		990

there is an apparent difference ($p < 0.05$) between different grades as well as between different types of defect. In the study, the ANOVA was applied to analyze the associated defects and the significance in the new grading system; if both defect association and significance exist, then the defect is a critical one.

– Fuzzy logic. Linguistic variables are established in the fuzzy sets to infer relative importance between those critical defects; the input variables are defect frequency, effect size (Eta) and score, and the output variable is importance.

This study uses an integrated model of association rules and fuzzy logic with the aim, firstly, of exploring useful rules and valuable knowledge among the defects from the large amount of the inspection data, and secondly, of reasoning relative importance between the critical defects and securing its impact on the inspection grades. On top of that, the integrated analysis model with the analytical items of inspection grades and critical defects is able to provide the construction executive team with ideas of creating an effective defect prevention action plan to boost construction quality and improve performance management, which in turn is the realization of an effective construction cost-saving measure.

1. Literature review

1.1. Data mining

Data Mining (DM) is the computational process of uncovering hidden events and valuable information and identifying implicit association rules through data classification, estimation, forecasting, association, clustering, and description. This technique deduces structured patterns to perform prediction, taxonomy, or identification of similarities between databases to help decision makers understand the associations between various data, to predict patterns, and to develop comprehensive managerial decisions (Berry, Linoff 1997).

DM is a powerful technique with great potential to discover hidden knowledge in large data sets (Xiao, Fan 2014). In recent years, DM has drawn increasing attention from industries such as banking and financial services, retail, health care, telecommunication, and antiterrorism (Maimon, Rokach 2010). In addition, DM has been applied in the construction industry to analyze structural defects in bridges (Cheng, Leu 2011).

Various DM techniques have been employed to solve a variety of problems, and appropriate DM techniques can ensure favorable outcomes. Particularly, association rule mining (ARM), one of the most famous DM techniques, was originally used to analyze purchase behavior in supermarkets where rules identified which products customers tended to purchase together. ARM was rapidly applied in marketing and is also known as market basket analysis (MBA).

In recent years, association rules have also been employed in various fields of the building industry, e.g. occupational injuries in the building industry (Liao, Perng 2008), building project disputes (Chou *et al.* 2016), building energy operational performance (Xiao, Fan 2014), and occupational accidents in construction sites (Cheng *et al.* 2010; Amiri *et al.* 2016; Li *et al.* 2017).

ARM algorithms include Apriori (Agrawal, Srikant 1994), FP-Growth algorithm (Han *et al.* 2000), Eclat algorithm (Zaki 2000), and Itemset-Tidset tree algorithm (Zaki, Hsiao 2005). These algorithms were developed to uncover frequent itemsets in large databases (Hong *et al.* 2008; Le *et al.* 2012; La *et al.* 2014; Van *et al.* 2014).

Previous studies have applied ARM to construction defect analyses. For example, Cheng *et al.* (2015) proposed a genetic algorithm-based approach that incorporated a hierarchical concept of construction defects to discover useful information in a construction defect database and to identify relationships between these defects. Lee *et al.* (2016) used ARM to quantify causality between defect causes and utilized Social Network Analysis (SNA) to identify indirect causalities among defects in concrete.

In addition, Aljassmi *et al.* (2014) developed the Project Pathogens Network (PPN), a new method to acquire the complex mechanisms of defect generation and quantify their pathogenic capacities in accordance with their positions within the network of the sequential events that lead to defects. Still, some other researchers (Ilozor *et al.* 2004) analyzed the interconnections between key house defects by using SPSS to find and establish the patterns or sequences hidden behind them.

Some previous studies have examined the causes and origins of construction defects (Atkinson 1999; Josephson, Hammarlund 1999; Love, Edwards 2004; Sommerville

2007; Aljassmi, Han 2013; Forcada *et al.* 2013a; Aljassmi *et al.* 2016; Shirkavand *et al.* 2016); some others have classified defects by type (Love, Irani 2003; Chew 2005; Karim *et al.* 2006; Mills *et al.* 2009; Ahzahar *et al.* 2011; Forcada *et al.* 2013b).

However, these studies are limited in the statistical data analyses of defect classification and defect cause distribution; the statistical methods used in them are not capable of automated data explorations. Consequently, no construction executive teams can benefit much from their restricted helps.

Additionally, most of the past researches revolved around the cause-effect relationship of what causes the defects, with their limitations being on the vague explanation of the relationship; traditional quantitative analysis methods are not capable of recognize the root causes of the defects, either. Accordingly, the complex pattern leading to the causes is hard to comprehend.

Association rules can reflect relationships between the causes of defects and the executions of concurrency and, through managing the defects of high lift value, they can also reduce the possibilities of other associated defects coming into being. That being said, the importance between the defects remains unknown when large amounts of defect data need to be dealt with, resulting in ineffective key managements and a lack of defect prevention strategies. Consequently, construction quality cannot be enhanced effectively.

1.2. Fuzzy theory

Several studies have solved construction problems through the fuzzy theory. For example, Chae and Abraham (2001) combined the neural networks and the fuzzy logic to examine various types of defect in sanitary sewer pipes. Sinha and Fieguth (2006) proposed a new neuro-fuzzy classifier that combined neural networks and concepts of fuzzy logic for the classification of defects by extracting the image features of the buried segmented pipes.

Vieira *et al.* (2015) proposed a model to predict the service life of painted walls, using a Takagi–Sugeno fuzzy model. In this model, the influential fuzzy variables of paint degradation include when it was painted, its type, the height of the building, the direction the wall is facing, the degree of moisture of the exposed wall, and the condition of the protected coated surface. This model can properly describe the wall surface degradation and predict the service life of the building being analyzed as a sample.

In addition, other studies have applied fuzzy theory to neural networks, expert systems, and cluster analysis to evaluating road defects and testing the characteristics of the road structures (Cheng 1996; Koduru *et al.* 2010; Amadore *et al.* 2014).

2. Research methodology

This study retrieved construction inspection records from the PCMIS. A total of 990 projects from January 2003 to October 2016 were collected for analysis, in which 17,648 defects out of 499 types were found. This study has mined and analyzed the associations of various defects, i.e., the degree of different defect types happening concurrently, and has established a set of association rules of defect.

There are five major stages in this study and its research framework is shown in Figure 1. The steps are described as follows:

1. Stage 1 (Association rule mining): This study constructed the association rules among various inspected defects to identify associated defects.
2. Stage 2 (Cluster analysis): With regard to bringing closer the sample sizes of the inspection grades to the utmost, the cluster analysis of the frequencies and grades of the defects is implemented to create the new grades (Class 1 = 1, Class 2 = 2, Class 3 = 3 and Class 4 = 4) and then to calculate Eta values from the analysis of the two variables: individual defect and new grade.
3. Stage 3 (ANOVA): This study conducted ANOVA on the association rules of defect to obtain the statistical significance of associations between the defects and grades. When the defects were both associated and significant, they were classified as critical defects.
4. Stage 4 (Fuzzy logic): The important value and sequences of the critical defects obtained in Stage 3 were compared according to IF-THEN preconditions, and fuzzy variables were configured according to the defect frequencies and scores retrieved from the construction inspection database and the effect sizes calculated in Stage 2.
5. Stage 5 (Correlation analysis): To test the correlation between critical defects and their inspection grades, this study conducted a correlation analysis to evaluate the correlation between the important value (IV) of the critical defects and the newly assigned levels in the cluster analysis.

This study established an analytical model of inspection grades and critical defects to provide construction supervisors and contractors with a solution for managing construction defects. This analytical model is crucial on the management of construction quality as well as the saving of construction costs.

The details and formulas of the theories and methods used in this study, including association rules, cluster analysis, ANOVA, and fuzzy sets, are explained in the following subsections.

2.1. Association rules

Analyzing association rules allows researchers to define the concurrence degree of the variables according to the association frequency and dependent items among the defect items (or products).

This study configured the support and confidence indices of defects according to the defects and frequencies discovered during the construction inspections, and subsequently the strength of lift of each rule was calculated. The objective of these concepts was to screen key association rules, ensure the associations among defects, and

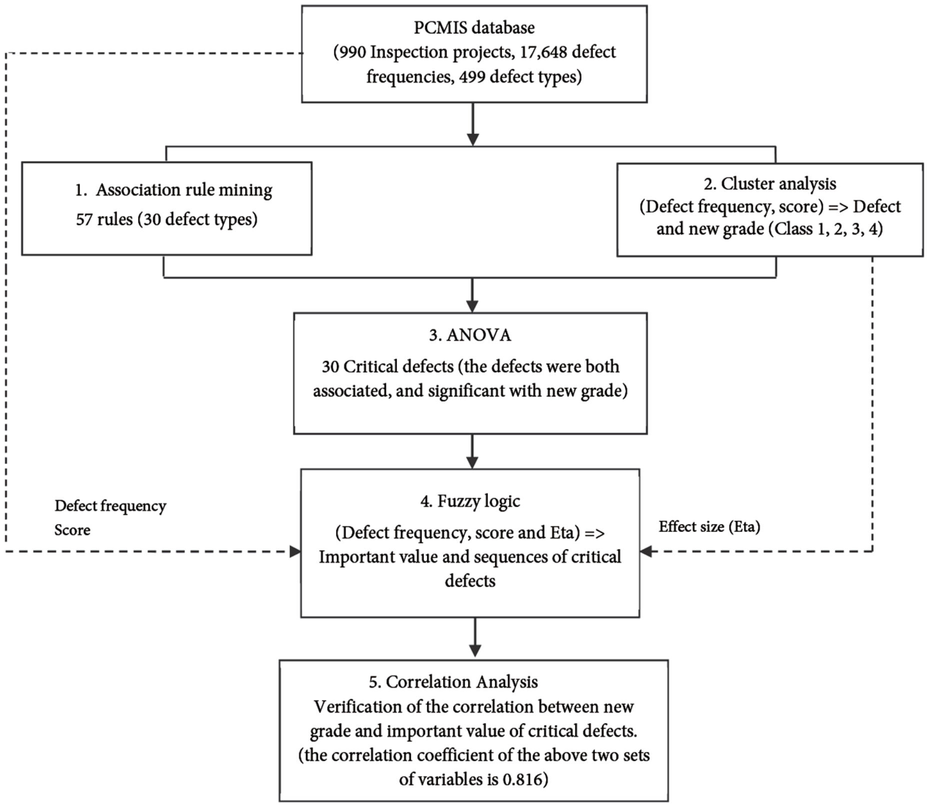

Figure 1. Research framework

analyze the strength of each association rule. The formula of a confidence index can be described as follows (Zhang, C., Zhang, S. 2002):

$$\text{Confidence: } A \rightarrow B = \mathrm{P}(A \cap B) / \mathrm{P}(A). \tag{1}$$

Confidence indicates the probability of event *A* causing event *B*. During the calculation, the sample size is not considered; only the association between events *A* and *B* (i.e., the probability that both events *A* and *B* occur in juxtaposition) is determined. Even though the sample data features an extremely large quantity of data with millions of transactions and thousands of variables, confidence is still an applicable index:

$$\text{Support: } A \rightarrow B = \mathrm{P}(A \cap B). \tag{2}$$

Support is generally expressed by percentage ranging from 0% to 100%. Support can be regarded as how frequently events *A* and *B* occur in juxtaposition. However, the drawback of this index is that an extremely large dataset with a large number of variables tends to establish association rules with low support values (Cohen *et al.* 2001). In addition, the support values of association rules within a single dataset are extremely similar in general (Aguinis *et al.* 2013). Therefore, the relative strength levels of the association rules cannot be judged solely by support. In summary, support should only be regarded as a reference for association rule screening; the selection should be mainly based on confidence and lift:

$$\text{Lift: } A \rightarrow B = \mathrm{P}(A \cap B) / \mathrm{P}(A) \times \mathrm{P}(B). \tag{3}$$

If events *A* and *B* are independent from each other (i.e., no correlation exists), then the denominator is the probability of event *A* multiplied by that of event *B*, and on the other side, the numerator will be the joint probability of events *A* and *B* if they occur simultaneously (i.e., correlated). According to the above formula, when the numerator and the denominator have similar values (i.e., lift ≥1.0), it means events *A* and *B* are associated with each other. As a matter of fact, previous studies have frequently used lift as a reference for screening association rules (Baralis *et al.* 2011). When lift is ≥1.0, events *A* and *B* are correlated; when lift is <1.0, events *A* and *B* are not correlated (i.e., the probability of the numerator is smaller than that of the denominator).

Support represents the likelihood of an event occurring, and is defined as the proportion of support for decision variables appearing in the database where a higher proportion denotes a higher degree of support, while confidence is the degree of credibility obtained using this association rule (Chou *et al.* 2013). Moreover, lift is a measure of the dependence and correlation between the antecedent and the consequent (Xiao, Fan 2014).

This study uses cases (Table 3) to shed light on Apriori algorithm and how support, confidence and lift values are calculated; the process is shown below:

– Support {Defect 1} = Defect 1 / all Defects = 4/8
  In Table 3, the support of {Defect 1} is 4 out of 8, or 50%.
– Confidence {Defect 1 → Defect 2} = Defect 1 and Defect 2 / Defect 1

Table 3. Defect statistics (for example)

ID	Defect 1	Defect 2	Defect 3	Defect 4	Defect 5	Defect 6	Scores
Project 1	1	1	1	1	0	0	70
Project 2	1	1	1	0	0	0	76
Project 3	1	1	0	0	0	0	82
Project 4	1	0	0	0	0	1	88
Project 5	0	1	1	1	1	0	68
Project 6	0	1	1	0	1	0	78
Project 7	0	1	0	0	1	0	85
Project 8	0	0	0	0	1	1	90

Note: 1 represents a defect occurrence, 0 represents no defect.

$$= \frac{\text{support}\left\{\text{ Defect 1, Defect 2 }\right\}}{\text{support}\left\{\text{ Defect 1 }\right\}} = 3/4 .$$

The confidence of {Defect 1 → Defect 2} is 3 out of 4, or 75%.

$$= \frac{\text{support}\left\{\text{ Defect 1, Defect 2 }\right\}}{\text{support}\left\{\text{ Defect 1 }\right\} \times \text{support}\left\{\text{ Defect 2 }\right\}} =$$

$$\frac{3}{4 \times 6/8} = 1.$$

– Lift {Defect 1 → Defect 2}
The Lift of {Defect 1→ Defect 2} is 1.

2.2. Cluster analysis

Cluster analysis, also known as affinity grouping, is a kind of unsupervised analysis. It divides data into groups, in which a high degree of affinity exits in the same group and apparent differences are present between different groups. A cluster analysis is employed to create groups and assist decision makings by pointing out common characteristics among groups.

Cluster analysis helps to reduce the distance among the data sets and enhance the similarity of the data sets in each cluster. Performing cluster analysis can enhance the reliability of the knowledge discovered in the next step (Xiao, Fan 2014). Cluster analysis has been successfully used to preprocess large datasets, identify outliers and discover underlying patterns (Olson, Delen 2008; Hastie *et al.* 2009; Maimon, Rokach 2010).

K-means is an algorithm commonly used in cluster analysis. A random selection of k seeds from the data is made in this algorithm according to the expected clusters (k) to be divided. These seeds will be the initial centers for the clusters, and once the k seeds are decided, the rest of the samples (p) will be assigned to the clusters in the nearest proximity. After that, the center of each cluster will be re-computed, the distance between each sample and the new cluster center be compared, and the clusters be regrouped. The whole process will be repeated again and again until the minimum SSE (sum of the squared errors) is reached. The calculation formula is shown as follows:

$$\text{SSE} = \sum_{i=1}^{k} \sum_{p \in ci} \left| p - mi \right|^2 , \quad (4)$$

where: k is the number of cluster; p is the sample in the space group, m_i the mean of the samples in the category of c_i, and SSE is the sum of the squared errors of all the samples.

First of all, in order to bring as close as possible the sample sizes in the inspection grades to create new grades, the K-means cluster analysis in SPSS was implemented on the 990 projects score and the defect frequencies (the number of times is 17,648). Ultimately, the sample sizes were produced from the four new grades: Class 1 = 458 projects, Class 2 = 135 projects, Class 3 = 303 projects and Class 4 = 94 projects.

2.3. ANOVA

If there are more than two tested populations, then the mean difference needs to be tested using an analysis tool that can analyze three samples simultaneously, which, in this case, is ANOVA (short for Analysis of Variance). The logic: the difference is tested using the quotient (F-value) calculated by dividing the variance between means (the between group variance) by the random variance (the within group variance).

That the F-value is larger means that the distribution of the mean scores of the between group variance is greater than those of the within group variance, i.e., if the difference of the means between the groups is greater, larger than the preset critical value, then the rejection of the null hypothesis (H_0) sustains and the opposite hypothesis is accepted.

The null hypothesis was used in the study to "hypothesize that that the variations of the means of two groups are not significant." If the hypothesis testing result by ANOVA appears significant, it means that there is a significant difference, indicating H_0 is rejected.

ANOVA can be used to test the impact of several independent variables on the dependent variable and also the interactions among the independent variables. Once the sources of the variances are determined when variances occur in a set of data, the answer to whether there exist any differences between the variances can be found. In this case, ANOVA is employed to see if a statistical hypothesis significance is reached. In this study, the four grades, Class 1, Class 2, Class 3 and Class 4, are the independent variables, and the dependent variable is defect.

In addition, ANOVA is a parametric method to compare clusters and must meet two assumptions, namely normal distribution and homogeneity of variance (Pallant 2013).

Gravetter and Wallnau (2007) stated that as long as the sample size of each cluster, i.e., the project numbers, exceeds 30, it does not significantly affect the statistical results even though the dataset does not pass the normality test. The sample size of each of the four new grades exceeds 30 in the cluster analysis of this study.

The inspection grades and defects imply the committee's inspection results on the construction quality; hence it is necessary for the study to move on to analyze which defects are influential over the inspection degrees by the running of ANOVA on SPSS Statistics to test the defects that verify the homogeneity of variance assumption. The analysis also aims to look for whether apparent significances ($p < 0.05$) occur or not between different grades and the defect types. If a defect is significant, then it fulfils one of the requirements for critical defect, association being the other requirement.

2.4. Fuzzy logic

Zadeh (1965) proposed the concept of fuzzy sets. Since the fuzzy set theory tolerates and adapts to inaccurate data in a way that is similar to human reasoning in the real world, a fuzzy set can precisely handle large-scale and complex systems. Consequently, this concept has been practically applied to various difficult problems related to control and decision-making.

A fuzzy set interfaces between natural (i.e., text) and machine (i.e., mathematical) languages. In other words, a fuzzy set takes an intermediate place between numerical and symbolic models (Vieira *et al.* 2015). Fuzzy sets are used to depict some fuzzy concepts (e.g., many vs. few; high vs. low; and good vs. poor). A fuzzy set composed of ordered pairs is defined as follows:

$$\text{Fuzzy set: } \tilde{A} = \left\{ \left(x,\ \mu_{\tilde{A}}(x) \right) \middle| \ x \in U \right\}, \quad (5)$$

where x is a certain measured value in U; $\mu_{\tilde{A}}(x)$ is called a membership function, which indicates the degree of membership of x in $\tilde{A}$; and x is the support of $\mu_{\tilde{A}}(x)$.

Fuzzy sets often use the membership functions with several similar measurement definitions to describe the possible values in a linguistic variable. For example, the fuzzy values of "defect frequency" can consist of very high, high, medium, low, and very low. Because these membership functions feature unsharp boundaries, the neighboring functions tend to be partially overlapping – a characteristic of fuzzy systems in which multiple fuzzy values collectively affect the system output.

This study first fuzzified the crisp inputs of the membership functions of the three variables, namely defect frequency, Eta, and score, and then the crisp outputs were calculated through fuzzy reasoning and defuzzification procedures, along with the IF-THEN preconditions. The main purpose of defuzzification was to compare the importance of critical defects and sequence each of the critical defect types. As a result, these sequences can then be used by the contractors and supervision units to prevent defects.

3. Analytical results

Xiao and Fan (2014) argued that whenever the Apriori algorithm is run for DM, two key parameters, the minimum support and minimum confidence, should be determined in advance. The former needs to be set relatively low to obtain the associations among infrequent events, whereas the latter should be set relatively high to ensure the reliability of the obtained association rules.

Han *et al.* (2002) pointed out that setting the minimum support threshold is quite subtle in rule mining. Meanwhile, setting appropriate confidence value is also a matter of trials. If the threshold is set too high, only a small number of rules will be generated; if it is set too low, too many (mostly redundant) rules will be generated (Mansingh *et al.* 2011).

There is a direct relationship between the threshold value setting of the support and confidence of the association rules and all the sample sizes (defect frequencies) and attribute items (defect types); hence there are different opinions about the ratios of the association analysis results and the threshold values, depending on how the researchers interpret the research purposes and the applications of the results. If the sample sizes or associated attribute items are too few and at the same time the threshold value is set too high, then no valuable information will be produced, leading to an insufficiency of meaningful interpretations. However, if the threshold value is set too low, then too many rules will be generated, meaning the information is not meaningful and not substantially instrumental in practical applications.

In other words, the number of rules and the usefulness of mining results vary with the threshold values for support and confidence, both of which are defined by users (Han, Kamber 2006). If the threshold values are set too high, some useful patterns will be pruned. In contrast, too low values will lead to the mining result full of useless patterns.

Accordingly, the minimum support threshold value in this study was set to greater than 10% and the minimum confidence greater than 80%; the setting was calculated and determined by analyzing and considering the threshold setting measures used in related literature (Coenen *et al.* 2004; Kouris *et al.* 2005; Olafsson *et al.* 2008; Mansingh *et al.* 2011) and by the analytical purpose requirements from these studies.

Both support and confidence are used to determine whether the rules are statistically significant, whereas lift measures the dependency and correlation between the antecedent and the consequent. When lift = 1, the antecedent and the consequent are independent from each other. Hence, the discovered knowledge exhibits little value. By contrast, when lift >1 (i.e., positive correlation), the antecedent absolutely affects the probability of the consequent (Tang *et al.* 2004).

The association rules with lift >1 were listed as items with causal meanings and special values for defect corrections or item managements. Ultimately, this study obtained 57 association rules (see Appendix).

The ANOVA tested whether significant differences ($p < 0.05$) existed between inspection grades and defects. Totally, 30 types of critical defect were found (Table 4) by using the above method to undertake the test analyses in the research, in which the defects were obtained from association rules.

The critical defects were gained from the statistical data of the defect frequencies and scores, which were obtained from the inspection data of 990 projects in the PCMIS (Table 4). The values of Eta regarding "critical defect" were produced by the use of descriptive statistics from IBM SPSS Statistics, in which defects and grades were established and analyses were done to see the degrees of significance between them. The calculation formula will be discussed and elaborated on later in section 3.2.

The influence and relative importance of the 30 critical defects can be obtained through reasoning process of fuzzy sets; this study used MATLAB for fuzzy reasoning. The fuzzy numbers of the linguistic variables were established by looking at the variance characteristics of the inspection data and the ranges based on the PCMIS. The input variables consist of defect frequency, effect size (Eta), and score; the output variable is the importance of each defect, as shown in Table 5.

The fuzzification of the input values of critical defects is performed by the use of the fuzzy reasoning process. During the fuzzification process, the membership function represents a resulted fuzzified number. Each input is a crisp value, which will be computed, with the already defined fuzzy set, using the membership function in order to produce the degree of membership of each variable. The four aforementioned variables are described as follows.

3.1. Defect frequency

The data retrieved from the construction inspection database of PCMIS feature 17,648 defect frequencies and 499 defect types. The statistical report reveals that the most common defects found in the construction inspections center on Quality Management System (Defect Code 4.00), and Construction Quality (Code 5.00), collectively accounting for 17,527 occurrences (99% of 17,648).

In this study, items with defect frequency ranging between 0 and 700 were retrieved from the inspection database, and the linguistic variables were configured according to defect frequency as follows: very high [75, 700], high [75, 525], medium [75, 350], low [75, 175], and very low [75, 0], as shown in Figure 2(a).

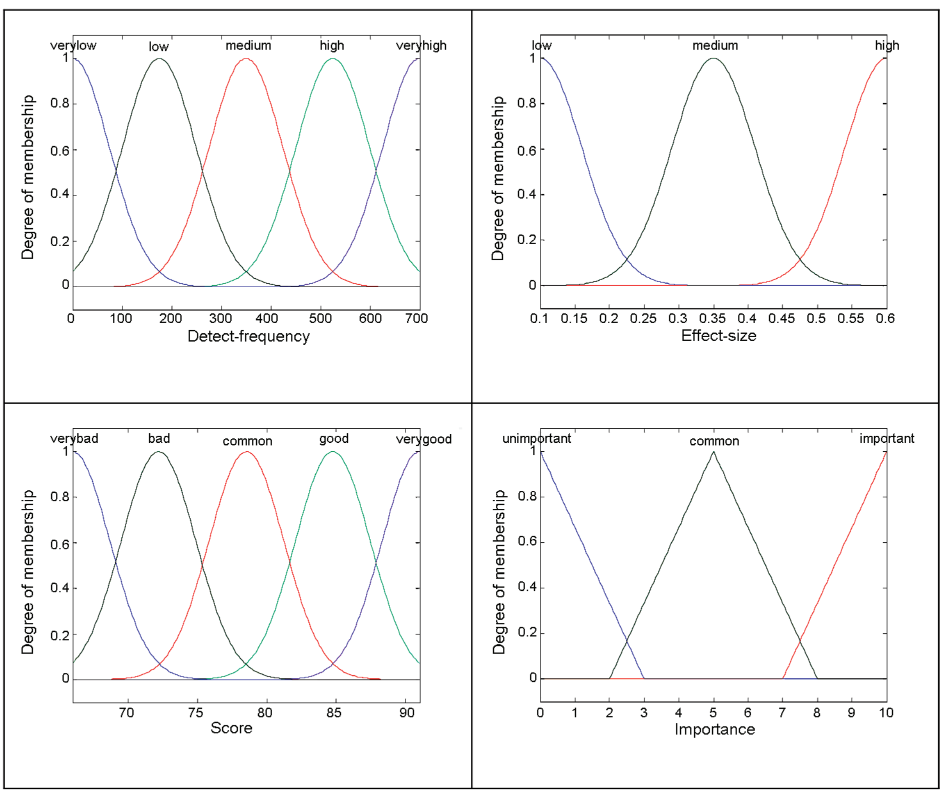

Figure 2. Linguistic variables

Table 4. Critical defect and inputs values

Item	Defect code	Critical defect	Inputs values		
			Defect (frequency)	Effect size (Eta)	Score (point)
1	4.01.04	Lack of, unimplemented, or incomplete quality supervision and inspection records	186	0.236	80.50
2	4.01.06	No approved record of supervision plans or inadequate reviewing	177	0.336	80.19
3	4.01.14	Failure to notify the supervision unit or contractor in written form to mitigate known construction defects within the deadline	112	0.143	80.06
4	4.01.99	Other defects from the organizing unit or project managing contractor	360	0.319	80.66
5	4.02.01.03	Lack of or unsatisfactory review deadlines for contractor's quality control and construction plans	138	0.121	80.99
6	4.02.01.05	Lack of or unsatisfactory standards for building materials, equipment, and quality management	183	0.248	80.15
7	4.02.01.06	Lack of or unsatisfactory inspection checkpoints for building materials, equipment, and construction	231	0.314	80.23
8	4.02.01.08	Lack of or unsatisfactory scope or frequency of quality inspections	119	0.344	80.64
9	4.02.03.04	Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation	293	0.567	80.30
10	4.02.03.05	Failure to notify the contractor to mitigate known defects; lack of or inadequate supervision on tasks such as jobsite safety, health, traffic control, and environmental protection	184	0.390	80.12
11	4.02.03.08	Failure to fill the supervision report in accordance with contractual obligations or inadequate recording	182	0.432	80.36
12	4.02.99	Other quality control errors from the supervisory unit	348	0.223	80.98
13	4.03.02.05	Failure to set the inspection time or frequency of building material, equipment, and construction	138	0.247	80.43
14	4.03.03	Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging	406	0.434	80.66
15	4.03.04	Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately	657	0.457	80.72
16	4.03.05	Failure to review the test report of building materials, failure to compile checklists for building materials or equipment tests, reviews or inspections, or failure to meet the project requirements	284	0.340	80.42
17	4.03.11.06	Failure to fill the inspection report or incomplete recording	102	0.246	80.25
18	4.03.99	Other quality control errors by the contractor	373	0.252	80.58
19	5.01.01	Substandard concrete pouring or ramming, resulting in cold joints, honeycombs, or pores	275	0.580	80.93
20	5.01.04	Debris on concrete surface (e.g., iron wires, iron pieces, and templates)	264	0.586	81.27
21	5.05.09	Failure to meet the garbage and waste cleaning requirements, either negatively impacting the environments or simply being against the law	157	0.474	79.82
22	5.07.01.99	Other common construction defects	208	0.328	80.54
23	5.08.99	Other construction that affect subsequent decorative works	173	0.178	80.46
24	5.09.08	Lack of construction signage or the content does not meet the requirements	121	0.249	80.42
25	5.09.99	Other managerial errors at jobsites	155	0.196	80.54
26	5.10.99	Other recording errors in building material and equipment reviews	457	0.386	80.65
27	5.14.01.01	Failure to install required fall protection facilities such fences, covers, safety nets, and seat belts on jobsite fringes and openings with height gaps of at least 2 m	167	0.505	80.32

End of Table 4

Item	Defect code	Critical defect	Inputs values		
			Defect (frequency)	Effect size (Eta)	Score (point)
28	5.14.04	Lack of or inaccurate safety inspection record by the contractor	229	0.162	80.46
29	5.14.06.03	The employer's failure to supply helmets or failure to provide instructions about the safe use of the protective equipment for workers entering the jobsite	110	0.337	80.05
30	5.14.99	Other violations against occupational safety and health regulations	336	0.313	81.00

Table 5. Fuzzy linguistic variables

	Linguistic variable	Fuzzy number
Inputs	Defect frequency (very high, high, medium, low, very low)	[75, 700] [75, 525] [75, 350] [75, 175] [75, 0]
	Effect size (Eta) (high, medium, low)	[0.06, 0.6] [0.06, 0.35] [0.06, 0.1]
	Score (very good, good, common, bad, very bad)	[2.7, 91][2.7, 84.8][2.7, 78.5][2.7, 72.2][2.7, 66]
Outputs	Importance (important, common, unimportant)	[7, 10, 10] [2, 5, 8] [0, 0, 3]

3.2. Effect size

Eta (η) measures the effect size in an ANOVA, and is similar to the R value in a multiple linear regression. Eta ranges between 0 and 1, and the ranges 0.10–0.25, 0.25–0.40, and >0.40 indicate small, medium, and large effect sizes, respectively (Cohen 1988).

Eta assesses the variance of mean values among clusters on the basis of standard deviation, and a large variance of mean values indicates a large effect size (Pallant 2013). It can represent the relative effects of the tested defect types. When two defect types are both tested as significant by applying ANOVA, their relative importance levels can be calculated by their effect sizes; a large effect size indicates the importance of a defect type. Formulaically, Eta^2, or η^2, is defined as follows:

$$\eta^2 = SS_{effect} / SS_{total}, \quad (6)$$

where: SS_{effect} – the sums of squares for whatever effect is of interest; SS_{total} – the total sums of squares for all effects, interactions, and errors in the ANOVA.

This study assigned the linguistic variables of Eta to three types: high, medium, and low. The effect sizes range between 0.1 and 0.6, and the fuzzy numbers of η are high [0.06, 0.6], medium [0.06, 0.35], and low [0.06, 0.1], as shown in Figure 2(b).

3.3. Score

The construction inspection scores were calculated from the average scores assessed by the committees. The projects scoring ≥90 were rated Grade S; those scoring ≥80 but <90 were rated Grade A; those scoring ≥70 but <80 were rated Grade B; and those scoring <70 were rated Grade C. A high score indicates that the construction project demonstrates a better quality on the control system, the construction itself, progress management, and planning and design. In other words, the scores reflected the extent to which the project was in compliance with the requirements of effective management performances.

The construction project inspection samples collected in this study are: Grade S, 6 projects; Grade A, 763; Grade B, 219; Grade C, 2. The highest score is 91, and the lowest, 66.

The linguistic variables of score were set up as follows: very good [2.7, 91], good [2.7, 84.8], common [2.7, 78.5], bad [2.7, 72.7], and very bad [2.7, 66]; the five categories are shown in Figure 2(c).

3.4. Importance

The primary objective of this study was to identify the relative importance of the critical defects. The output values were defined in a 1–10 range as follows: important [7, 10, 10], common [2, 5, 8], and unimportant [0, 0, 3]; these variables were presented in triangular membership functions, as shown in Figure 2(d). Because of their computational efficiency, triangular fuzzy sets have seen widespread use in research (Zimmermann 2001).

According to the membership degrees of the input and output variables, a series of fuzzy reasoning procedures were carried out in this study, e.g., the application of rules and preconditions for construction. The output values of fuzzy sets determine the effects of critical defects on inspection grades and the order of importance of these defects.

Fuzzy reasoning consists of two parts: the antecedent (IF) that assesses rules and applies the results to the next part, which is the consequent (THEN). The antecedent is

Table 6. IF-THEN preconditions

Rules	IF			THEN
	Defect frequency	Effect size (Eta)	Score	Importance
R1	very high	high	very bad	important
R2	very high	high	bad	important
R3	high	high	very bad	important
R4	high	high	bad	important
R5	medium	medium	common	common
R6	low	low	good	unimportant
R7	low	low	very good	unimportant
R8	very low	low	good	unimportant
R9	very low	low	very good	unimportant

described using the form of the fuzzy set, which is composed of one or multiple linguistic variables. An input value should be first fuzzified and then defuzzified to produce a crisp output value.

The IF-THEN rules could be fashioned from experts' opinions, by the digging of knowledge, or via the categorization of data characteristics, to create the fuzzy rule. The pre-conditions of establishing an IF-THEN in this study are the opinions from experts and based on the characteristics of the construction project inspection database consisting of the project names and numbers, inspection dates, defect items and frequencies, scores and grades, etc. As a result, nine IF-THEN rules (see Table 6) were established by the researcher after consulting some of the committee members. For example: IF a defect has a very high frequency in the inspection database, a high effect size and a very bad score, THEN it possesses an important importance value. The logic is shown as: R1: IF "Defect frequency = very high" AND "Effect size = high" AND "Score = very bad" THEN "Importance = important."

Furthermore, a fuzzy set analysis was conducted in this study on the defect frequencies, the effect sizes, and the scores of the 30 critical defects in the beginning step of the analytical procedures. Through the defuzzification process and by the application of fuzzy reasoning, the results are converted into numbers with corresponding values. In effect, the whole process is to convert fuzzy sets into crisp values, i.e., to find in the fuzzy sets crisp values that are most well suited to represent the IF-THEN rules. In so doing, the sequence of importance of the critical defects can be found and finalized.

Also, the fuzzy set analysis was performed in this study on the 30 critical defects obtained by the applications of association rules and ANOVA, and the relative importance levels of all critical defects were sorted by important value (IV) and divided into three categories, [Category I, defects of high importance (fuzzy outputs > 5); Category II, defects of medium importance (fuzzy outputs 4–5); Category III, defects of low importance (fuzzy outputs <4)], as shown in Table 7.

4. Discussion

Now each project is associated with two variables; the first variable is the sum of the important values (IVs) of the critical defects associated with the project (IV = 0 for the noncritical defect); the second variable is the project's newly assigned classes of the grade: 1~4 for Class 1~4 respectively. Then the correlation analysis between the aforementioned two variables is conducted for the 990 projects.

For instance, Project #1 is classified as Class 3 with five defect types, and two of them are rated critical with the IVs 8.3 and 5.0, respectively; the other three are not critical so their IVs are 0. The first variable in Project #1 is the sum of the IVs, which is 13.3 (8.3 + 5.0). The second variable is 3 (Class 3). By running the correlation analysis of the two variables using IBM SPSS Statistics on the 990 projects, a strong positive correlation coefficient 0.816 ($p < 0.001$) is derived. This result clearly indicates that critical defects strongly affect inspection grades.

Furthermore, from the derived association rules, it is found that occurrence of certain defects is accompanied by the occurrence of some other defects. This finding may help managers focus on a few critical defects and simultaneously prevent more other defects. More elaborations follow:

- Confidence in data mining is the probability of having defect B, given that defect A has occurred. For example, the rule with the highest confidence found in this research: If the following two defect types happen: (i) "Debris on concrete surface (e.g., iron wires, iron pieces, and templates)" (Defect Code 5.01.04) and (ii) "Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation" (Defect Code 4.02.03.04), then the occurrence probability of "Failure to implement quality control checklist, or failure to set up inspection standards/permissible errors, or failure to record the inspection correctly" (Defect Code 4.03.04) is the highest (Confidence = 93.94%).
- From the database of inspection records, it is found that, some defects often occur simultaneously; and that chance is defined as support of the association rule. For instance, a rule with three defects (4.03.03), (5.10.99) (4.03.04) happening at the same time has the highest "support" (= 17.37%). Project managers should pay more attention on the rule with high support. For the above instance, it may help managers focus on preventing a critical defect and simultaneously prevent the other two defects from happening.
- The lift of an association rule is the ratio of the confidence of the rule and the expected confidence of the rule. The lift can be interpreted as the importance of a rule. A higher value of lift means a more important rule. In this research, lift indicates the strength of association between defects in a rule. Defects in a rule of high lift value should be listed as a target of concern that needs more managerial attention.

Table 7. Important value of critical defects

Rank	Defect code	Category I: defects of high importance (fuzzy outputs >5)	Important value
1	4.03.04	Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately	8.3477
2	5.01.01	Substandard concrete pouring or ramming, resulting in cold joints, honeycombs, or pores	7.6089
3	4.02.03.04	Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation	7.5932
4	5.01.04	Debris on concrete surface (e.g., iron wires, iron pieces, and templates)	7.5194
5	4.03.03	Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging	5.0302
6	5.10.99	Other recording errors in building material and equipment reviews	5.0082
7	4.02.03.08	Failure to fill the supervision report in accordance with contractual obligations or inadequate recording	5.0004
8	5.14.01.01	Failure to install required fall protection facilities such fences, covers, safety nets, and seat belts on jobsite fringes and openings with height gaps of at least 2 m	5.0004
9	4.02.03.05	Failure to notify the contractor to mitigate known defects; lack of or inadequate supervision on tasks such as jobsite safety, health, traffic control, and environmental protection	5.0003
10	5.05.09	Failure to meet the garbage and waste cleaning requirements, either negatively impacting the environments or simply being against the law	5.0002
		Category II: defects of medium importance (fuzzy outputs 4–5)	
11	4.03.05	Failure to review the test report of building materials, failure to compile checklists for building materials or equipment tests, reviews or inspections, or failure to meet the project requirements	4.9992
12	4.01.99	Other defects from the organizing unit or project managing contractor	4.9962
13	5.14.99	Other violations against occupational safety and health regulations	4.9942
14	5.07.01.99	Other normal construction defects	4.9934
15	4.01.06	No approved record of supervision plans or inadequate reviewing	4.9909
16	4.02.01.06	Lack of or unsatisfactory inspection checkpoints for building materials, equipment, and construction	4.9900
17	4.02.01.08	Lack of or unsatisfactory scope or frequency of quality inspections	4.9549
18	5.14.06.03	The employer's failure to supply helmets or failure to provide instructions about the safe use of the protective equipment for workers entering the jobsite	4.8957
19	4.03.99	Other quality control errors by the contractor	4.8314
20	4.02.01.05	Lack of or unsatisfactory standards for building materials, equipment, and quality management	4.2794
21	4.02.99	Other quality control errors from the supervising unit	4.2386
22	4.01.04	Lack of, unimplemented, or incomplete quality supervision and inspection records	4.0138
		Category III: defects of low importance (fuzzy outputs <4)	
23	4.03.02.05	Failure to set the inspection time or frequency of building material, equipment, and construction	2.9076
24	5.09.08	Lack of construction signage or the content does not meet the requirements	2.4065
25	5.09.99	Other managerial errors at jobsites	2.0256
26	4.03.11.06	Failure to fill the inspection report or incomplete recording	1.8771
27	5.08.99	Other construction that affect subsequent decorative works	1.7105
28	5.14.04	Lack of or inaccurate safety inspection record by the contractor	1.4860
29	4.01.14	Failure to notify the supervision unit or contractor in written form to mitigate known construction defects within the deadline	1.4142
30	4.02.01.03	Lack of or unsatisfactory review deadlines for contractor's quality control and construction plans	1.2357

Due to the complexity of the construction process, the researcher is convinced that a single analysis method is not enough to explore the associations or cause-effect relationships between defects. It can only be done using the defect information collected in big data and the DM techniques to understand what correlations exist among the defects and mine useful knowledge buried under the defect data. The 57 association rules obtained from the study are a very valuable reference source.

Conclusions

Association rules and fuzzy logic are applications of machine learning which aim to explore patterns of human preference, behavior and mental model from big data.

This research explores the causal relations between defect types and inspection grades of 990 public construction projects by association rules and fuzzy logic.

The 30 critical defects obtained from this study are important items deserved more managerial attention during construction. The defect type (4.03.04) was the most critical defect which highlights the importance of self-management and active inspection on construction quality (IV = 8.35). In other words, malfunction of self-management mechanisms is very likely to cause poor construction quality.

The real value of datamining is to derive association rules which are hidden in a large number of databases. For instance, defect types (5.05.09) and (5.10.99) are both antecedents in the derived Rule #13 (see Appendix). However, that rule is beyond common understanding and this is not uncommon for the rules derived from data mining. However, these unreasonable rules may be useful and should be further explored in the future research.

Acknowledgements

I would like to express my sincere gratitude to Associate Professor Shih-Hsu Wang at the Department of Civil Engineering, R.O.C. Military Academy for his useful suggestions and immense knowledge contribution to this paper. My gratitude also goes to the Armaments Bureau for providing the needed data.

Disclosure statement

The authors declare no any competing financial, professional, or personal interests from other parties.

References

Agrawal, R.; Srikant, R. 1994. Fast algorithms for mining association rules, in *Proceedings of the 20th International Conference on Very Large Databases*, 12–15 September 1994, Santiago, Chile.

Aguinis, H.; Forcum, L. E.; Joo, H. 2013. Using market basket analysis in management research, *Journal of Management* 39(7): 1799–1824. https://doi.org/10.1177/0149206312466147

Ahzahar, N.; Karim, N. A.; Hassan, S. H.; Eman, J. 2011. A study of contribution factors to building failures and defects in construction industry, in *The 2nd International Building Control Conference*, 11–12 July 2011, Penang, Malaysia.

Aljassmi, H.; Han, S. 2013. Analysis of causes of construction defects using fault trees and risk importance measures, *Journal of Construction Engineering and Management* 139(7): 870–880. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000653

Aljassmi, H.; Han, S.; Davis, S. 2014. Project pathogens network: new approach to analyzing construction-defects-generation Mechanisms, *Journal of Construction Engineering and Management* 140(1): 04013028. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000774

Aljassmi, H.; Han, S.; Davis, S. 2016. Analysis of the complex mechanisms of defect generation in construction projects, *Journal of Construction Engineering and Management* 142(2): 04015063. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001042

Amadore, A.; Bosurgi, G.; Pellegrino, O. 2014. Classification of measures from deflection tests by means of fuzzy clustering techniques, *Construction and Building Materials* 53: 173–181. https://doi.org/10.1016/j.conbuildmat.2013.11.094

Amiri, M.; Ardeshir, A.; Zarandi, M. H. F.; Soltanaghaei, E. 2016. Pattern extraction for high-risk accidents in the construction industry: a data-mining approach, *International Journal of Injury Control and Safety Promotion* 23(3): 264–276. https://doi.org/10.1080/17457300.2015.1032979

Atkinson, A. R. 1999. The role of human error in construction defects, *Structural Survey* 17(4): 231–236. https://doi.org/10.1108/02630809910303006

Baralis, E.; Cagliero, L.; Cerquitelli, T.; Garza, P.; Marchetti, M. 2011. CAS-MINE: providing personalized services in context-aware applications by means of generalized rules, *Knowledge and Information Systems* 28(2): 283–310. https://doi.org/10.1007/s10115-010-0359-z

Berry, M. J. A.; Linoff, G. S. 1997. *Data mining techniques: for marketing, sales, and customer support*. New York: John Wiley & Sons.

Chae, M. J.; Abraham, D. M. 2001. Neuro-fuzzy approaches for sanitary sewer pipeline condition assessment, *Journal of Computing in Civil Engineering* 15(1): 4–14. https://doi.org/10.1061/(ASCE)0887-3801(2001)15:1(4)

Cheng, C. W.; Lin, C. C.; Leu, S. S. 2010. Use of association rules to explore cause–effect relationships in occupational accidents in the Taiwan construction industry, *Safety Science* 48(4): 436–444. https://doi.org/10.1016/j.ssci.2009.12.005

Cheng, H. D. 1996. Automated real-time pavement distress detection using fuzzy logic and neural networks, *SPIE Proceedings on Nondestructive Evaluation of Bridges and Highways*, 140–151. http://dx.doi.org/10.1117/12.259131

Cheng, Y. M.; Leu, S. S. 2011. Integrating data mining with KJ method to classify bridge construction defects, *Expert Systems with Applications* 38: 7143–7150. https://doi.org/10.1016/j.eswa.2010.12.047

Cheng, Y.; Yu, W. D.; Li, Q. 2015. GA-based multi-level association rule mining approach for defect analysis in the construction industry, *Automation in Construction* 51: 78–91. https://doi.org/10.1016/j.autcon.2014.12.016

Chew, M. Y. L. 2005. Defect analysis in wet areas of buildings, *Construction and Building Materials* 19(3): 165–173. https://doi.org/10.1016/j.conbuildmat.2004.07.005

Chou, J. S.; Cheng, M. Y.; Wu, Y. W. 2013. Improving classification accuracy of project dispute resolution using hybrid artificial intelligence and support vector machine models, *Expert Systems with Applications* 40(6): 2263–2274. https://doi.org/10.1016/j.eswa.2012.10.036

Chou, J. S.; Hsu, S. C.; Lin, C. W.; Chang, Y. C. 2016. Classifying influential for project information to discover rule sets for project disputes and possible resolutions, *International Journal of Project Management* 34(8): 1706–1716. https://doi.org/10.1016/j.ijproman.2016.10.001

Coenen, F.; Goulbourne, G.; Leng, P. 2004. Tree structures for mining association rules, *Data Mining and Knowledge Discovery* 8: 25–51. https://doi.org/10.1023/B:DAMI.0000005257.93780.3b

Cohen, E.; Datar, M.; Fujiwara, S.; Gionis, A.; Indyk, P.; Motwani, R.; Ullman, J. D.; Yang, C. 2001. Finding interesting associations without support pruning, *IEEE Transactions on Knowledge and Data Engineering* 13(1): 64–78. https://doi.org/10.1109/69.908981

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*. 2nd ed. New Jersey: Lawrence Earlbaum Associates.

Forcada, N.; Macarulla, M.; Gangolells, M.; Casals, M.; Fuertes, A.; Roca, X. 2013a. Post-handover housing defects: sources and origins, *Journal of Performance of Constructed Facilities* 27(6): 756–762. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000368

Forcada, N.; Macarulla, M.; Love, P. E. D. 2013b. Assessment of residential defects at post-handover, *Journal of Construction Engineering and Management* 139(4): 372–378. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000603

Georgiou, J.; Love, P. E. D.; Smith, J. 1999. A comparison of defects in houses constructed by owners and registered builders in the Australian State of Victoria, *Structural Survey* 17(3): 160–169. https://doi.org/10.1108/02630809910291343

Gravetter, F. J.; Wallnau, L. B. 2007. *Statistics for the behavioral sciences*. 7th ed. Belmont: Wadsworth.

Han, J. W.; Pei, J.; Yin, Y.; Mao, R. 2000. Mining frequent patterns without candidate generation, in *Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data*, 15–18 May 2000, Dallas, Texas. https://doi.org/10.1145/342009.335372

Han, J.; Kamber, M. 2006. *Data mining: concepts and techniques*. 2nd ed. Massachusetts: Morgan Kaufmann Publishers.

Han, J.; Wang, J.; Lu, Y. 2002. Mining top-k frequent closed patterns without minimum support, in *Proceedings of the 2002 IEEE International Conference on Data Mining*, 12–15 December 2002, Maebashi, Japan.

Hastie, T.; Tibshirani, R.; Friedman, J. 2009. *The elements of statistical learning: data mining, inference and prediction*. 2nd ed. Heidelberg: Springer. https://doi.org/10.1007/978-0-387-84858-7

Hong, T. P.; Lin, C. W.; Wu, Y. L. 2008. Incrementally fast updated frequent pattern trees, *Expert Systems with Applications* 34(4): 2424–2435. https://doi.org/10.1016/j.eswa.2007.04.009

Ilozor, B. D.; Okoroh, M. I.; Egbu, C. E.; Archicentre. 2004. Understanding residential house defects in Australia from the state of Victoria, *Building and Environment* 39(3): 327–337. https://doi.org/10.1016/j.buildenv.2003.07.002

Josephson, P. E.; Hammarlund, Y. 1999. The causes and costs of defects in construction: a study of seven building projects, *Automation in Construction* 8(6): 681–687. https://doi.org/10.1016/S0926-5805(98)00114-9

Karim, K.; Marosszeky, M.; Davis, S. 2006. Managing subcontractor supply chain for quality in construction, *Engineering, Construction and Architectural Management* 13(1): 27–42. https://doi.org/10.1108/09699980610646485

Koduru, H.; Xiao, F.; Amirkhanian, S.; Juang, C. 2010. Using fuzzy logic and expert system approaches in evaluating flexible pavement distress: case study, *Journal of Transportation Engineering* 136(2): 149–57. https://doi.org/10.1061/(ASCE)0733-947X(2010)136:2(149)

Kouris, I. N.; Makris, C. H.; Tsakalidis, A. K. 2005. Using information retrieval techniques for supporting data mining, *Data & Knowledge Engineering* 52: 353–383. https://doi.org/10.1016/j.datak.2004.07.004

La, P. T.; Le, B.; Vo, B. 2014. Incrementally building frequent closed itemset lattice, *Expert Systems with Applications* 41(6): 2703–2712. https://doi.org/10.1016/j.eswa.2013.11.002

Le, T. P.; Hong, T. P.; Vo, B.; Le, B. 2012. An efficient incremental mining approach based on IT-tree, in *2012 IEEE RIVF International Conference on Computing & Communication Technologies, Research, Innovation, and Vision for the Future*, 27 February – 01 March 2012, Ho Chi Minh City, Vietnam.

Lee, S.; Han, S.; Hyun, C. 2016. Analysis of causality between defect causes using association rule mining, *International Journal of Civil, Environmental, Structural, Construction and Architectural Engineering* 10(5): 654–657.

Li, H.; Li, X. Y.; Luo, X. C.; Siebert, J. 2017. Investigation of the causality patterns of non-helmet use behavior of construction workers, *Automation in Construction* 80: 95–103. https://doi.org/10.1016/j.autcon.2017.02.006

Liao, C. W.; Perng, Y. H. 2008. Data mining for occupational injuries in the Taiwan construction industry, *Safety Science* 46(7): 1091–1102. https://doi.org/10.1016/j.ssci.2007.04.007

Love, P. E. D. 2002. Auditing the indirect consequences of rework in construction: a case based approach, *Managerial Auditing Journal* 17(3): 138–146. https://doi.org/10.1108/02686900210419921

Love, P. E. D.; Edwards, D. J. 2004. Forensic project management: the underlying causes of rework in construction projects, *Civil Engineering and Environmental Systems* 21(3): 207–228. https://doi.org/10.1080/10286600412331295955

Love, P. E. D.; Irani, Z. 2003. A project management quality cost information system for the construction industry, *Information & Management* 40(7): 649–661. https://doi.org/10.1016/S0378-7206(02)00094-0

Macarulla, M.; Forcada, N.; Casals, M.; Gangolells, M.; Fuertes, A.; Roca, X. 2013. Standardizing housing defects: classification, validation, and benefits, *Journal of Construction Engineering and Management* 139(8): 968–976. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000669

Maimon, O.; Rokach, L. 2010. *Data mining and knowledge discovery handbook*. 2nd ed. Heidelberg: Springer. https://doi.org/10.1007/978-0-387-09823-4

Mansingh, G.; Osei-Bryson, K.; Reichgelt, H. 2011. Using ontologies to facilitate post-processing of association rules by domain experts, *Information Sciences* 181(3): 419–434. https://doi.org/10.1016/j.ins.2010.09.027

Mills, A.; Love, P. E. D.; Williams, P. 2009. Defects cost in residential construction, *Journal of Construction Engineering and Management* 135(1): 12–16. https://doi.org/10.1061/(ASCE)0733-9364(2009)135:1(12)

Olafsson, S.; Li, X.; Wu, S. 2008. Operations research and data mining, *European Journal of Operational Research* 187: 1429–1448. https://doi.org/10.1016/j.ejor.2006.09.023

Olson, D. L; Delen, D. 2008. *Advanced data mining techniques*. Heidelberg: Springer.

Pallant, J. 2013. *SPSS survival manual: a step by step guide to data analysis using SPSS*. 5th ed. New York: McGraw-Hill.

Shirkavand, I.; Lohne, J.; Lædre, O. 2016. Defects at handover in Norwegian construction projects, *Procedia Social and Behavioral Sciences* 226: 3–11.
https://doi.org/10.1016/j.sbspro.2016.06.155

Sinha, S. K.; Fieguth, P. W. 2006. Neuro-fuzzy network for the classification of buried pipe defects, *Automation in Construction* 15(1): 73–83.
https://doi.org/10.1016/j.autcon.2005.02.005

Sommerville, J. 2007. Defects and rework in new build: an analysis of the phenomenon and drivers, *Structural Survey* 25(5): 391–407. https://doi.org/10.1108/02630800710838437

SS-ISO Svensk Standard, SS 02010: 1987. Kvalitet-Terminologi, SIS-Standardiserings-kommissionen i Sverige [Quality Terminology, SIS Standardization Commission in Sweden]. Sweden Standard, 1987.

Tang, S. L.; Aoieong, R. T.; Ahmed, S. M. 2004. The use of process cost model (PCM) for measuring quality costs of construction projects: Model testing, *Construction Economics and Management* 22(3): 263–275.
https://doi.org/10.1080/0144619032000064091

Van, T. T.; Vo, B.; Le, B. 2014. IMSR_PreTree: an improved algorithm for mining sequential rules based on the prefix-tree, *Vietnam Journal of Computer Science* 1(2): 97–105.
https://doi.org/10.1007/s40595-013-0012-3

Vieira, S. M.; Silva, A.; Sousa, J. M. C.; Brito, J.; Gaspar, P. L. 2015. Modelling the service life of rendered facades using fuzzy systems, *Automation in Construction* 51: 1–7.
https://doi.org/10.1016/j.autcon.2014.12.011

Watt, D. S. 1999. *Building pathology: principles & practice*. Oxford: Blackwell Science.

Webster, N. 1828. *Merriam-Webster: Definition of defect* [online], [cited 12 December 2017]. Available from Internet:
https://www.merriam-webster.com/dictionary/defect

Xiao, F.; Fan, C. 2014. Data mining in building automation system for improving building operational performance, *Energy and Buildings* 75: 109–118.
https://doi.org/10.1016/j.enbuild.2014.02.005

Zadeh, L. A. 1965. Fuzzy sets, *Information and Control* 8(3): 338–535. https://doi.org/10.1016/S0019-9958(65)90241-X

Zaki, M. J. 2000. Scalable algorithms for association mining, *IEEE Transactions on Knowledge and Data Engineering* 12(3): 372–390. https://doi.org/10.1109/69.846291

Zaki, M. J.; Hsiao, C. J. 2005. Efficient algorithms for mining closed itemsets and their lattice structure, *IEEE Transactions on Knowledge and Data Engineering* 17(4): 462–478.
https://doi.org/10.1109/TKDE.2005.60

Zhang, C.; Zhang, S. 2002. *Association rule mining: models and algorithms*. Heidelberg: Springer.
https://doi.org/10.1007/3-540-46027-6

Zimmermann, H. J. 2001. *Fuzzy set theory and its application*. 4th ed. Dordrecht: Kluwer Academic Publishers.
https://doi.org/10.1007/978-94-010-0646-0

Appendix

Inspection defects association rules (excerpts)

Rule ID	Antecedent (A)	Consequent (B)	Confidence %	Support %	Lift
1	5.01.04 and 4.02.03.04 (Debris on concrete surface (e.g., iron wires, iron pieces, and templates)) and (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	93.939	10	1.416
2	4.03.08.05 (Quality documents, records management no proper control)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	92.105	14.141	1.388
3	4.01.06 and 4.03.03 (No approved record of supervision plans or inadequate reviewing) and (Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	91.304	10.606	1.376
4	4.02.03.04 and 4.01.99 (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation) and (Other defects from the organizing unit or project managing contractor)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	90.977	12.222	1.371
5	4.03.05 and 4.02.03.04 (Failure to review the test report of building materials, failure to compile checklists for building materials or equipment tests, reviews or inspections, or failure to meet the project requirements) and (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	90.714	12.828	1.367
6	4.02.03.08 (Failure to fill the supervision report in accordance with contractual obligations or inadequate recording)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	90.659	16.667	1.366
7	4.02.03.08 and 4.03.03 (Failure to fill the supervision report in accordance with contractual obligations or inadequate recording)and (Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	90.37	12.323	1.362
8	5.14.06.03 (The employer's failure to supply helmets or failure to provide instructions about the safe use of the protective equipment for workers entering the jobsite)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	90	10	1.356
9	4.02.03.04 and 4.03.03 (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation) and (Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	89.941	15.354	1.355

End of Appendix

Rule ID	Antecedent (A)	Consequent (B)	Confidence %	Support %	Lift
10	4.02.03.08 and 5.10.99 (Failure to fill the supervision report in accordance with contractual obligations or inadequate recording) and (Other recording errors in building material and equipment reviews)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	89.216	10	1.344
11	4.02.03.04 and 4.03.03 and 5.10.99 (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation) and (Other recording errors in building material and equipment reviews)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	89.216	10	1.344
12	4.02.03.04 and 5.14.99 (Failure to inspect construction progress, building material, or equipment; failure to fill or compile checklists; misjudgment, or failure of implementation) and (Other violations against occupational safety and health regulations)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	88.696	10.303	1.337
13	5.05.09 and 5.10.99 (Failure to meet the garbage and waste cleaning requirements, either negatively impacting the environments or simply being against the law) and (Other recording errors in building material and equipment reviews)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	88.679	10	1.336
14	5.14.04 and 4.03.03 (Lack of or inaccurate safety inspection record by the contractor) and (Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	88.034	10.404	1.327
15	4.02.01.05 and 4.03.03 (Lack of or unsatisfactory standards for building materials, equipment, and quality management) and (Failure to log the construction journal, failure to log in the predetermined format, or incomplete logging)	4.03.04 (Failure to implement quality control checklist, failure to quantify inspection standards or permissible errors, or failure to record the inspection accurately)	88	10	1.326