DOI: 10.6119/JMST-015-1228-1

This article has been peer reviewed and accepted for publication in JMST but has not yet been copyediting, typesetting, pagination and proofreading process. Please note that the publication version of this article may be different from this version. This article now can be cited as doi: 10.6119/JMST-015-1228-1.

MODEL FOR ASSESSING THE FUNCTIONALITY OF SOIL AND WATER CONSERVATION FACILITIES

Nai-Hsin Pan[1] and Kuei-yen Chen[2]

Key words: Fuzzy theory, maintenance, assessment, infrastructure

ABSTRACT

Most soil and water conservation facilities are located in remote areas, posing measurement difficulties for precision instruments. Therefore, visual inspection, which is advantageous because of its high speed, is the primary assessment method for such facilities. However, the degree of infrastructural damage subjectively assessed by various inspectors may vary. Therefore, to overcome the problem induced by inspectors' subjectivity in assessing facilities, this study adopted the concept of fuzzy set theory to establish a soil and water conservation facility assessment model that can define the membership functions of specific semantic ranges. This study applied semantics to infer current facility conditions, which were classified into various levels. The results can serve as a basis for managerial decisions regarding soil and water conservation facilities or for maintenance applications.

I. INTRODUCTION

With the abnormal worldwide weather patterns, excessive rainfall tends to strike particular areas, presenting considerable challenges to the structures of soil and water conservation facilities. The disaster engendered by Typhoon Morakot in 2009 forced the government to address the effects of soil and water conservation facilities on people's safety. From a life-cycle perspective, the construction cost constitutes a small proportion of the life-cycle cost of a structure; regular inspection and maintenance of a structure constitute 60% of the life-cycle cost of such a structure. In Taiwan, visual inspection is used extensively as a method of examining and maintaining public transportation routes such as bridges, tunnels, and harbors. However, the differences in the locations and functions of public structures necessitate defining various inspection criteria. In contrast to methods that are associated with difficulties in concurrently conducting detailed examinations, visual inspection is currently one of the most efficient and convenient approaches for inspecting numerous widely distributed structures. Therefore, visual inspection was applied for examining soil and water conservation structures. However, the results derived from the visual assessment of facilities indicated that inspectors adopted various criteria for determining the extent of damage and that human factors generated inconsistent damage scores.

To reduce inconsistencies in inspection results, the purpose of the current study was to resolve the current visual inspection problems. Nevertheless, the main reason for the differences in the assessment criteria used by various units is differentiating subjective semantics. One possible alternative to solving this problem is to apply fuzzy set theory for reducing semantic differences. In this study, a semantic scale developed through fuzzy set theory was employed to convert and reduce the scoring problems inherent in the visual inspection approach. According to damage extent and functional impact of the damaged structures, an assessment scale was developed, and this scale can be used by soil and water conservation departments. In addition, in this study, the scope of the membership function was defined, and fuzzy inference was performed to obtain a condition index (CI) score of the overall structure.

The scope of this study was limited to soil and water conservation facilities, including groundsill works, bank revetments, and sabo dams, that were installed underwater and have been operated for more than 5 years. Common types of damage to soil and water conservation facilities include displacement, cracks, and collapse; moreover, erosion is one of the types of river channel damage. Reinforced concrete was employed as the primary material for constructing the study subjects.

II. LITERATURE REVIEW

Water conservation structures may develop various defects during their life cycles. For example, certain defects are induced by factors such as current scour or debris flow, and other defects may be engendered by inappropriate design, construction, or maintenance. In Taiwan, the inspection and assessment of basic construction activities primarily involves visual inspection, but this approach is not currently a widespread practice among

---

Paper submitted 02/17/14; revised 08/11/15; accepted 12/28/15. Author for correspondence: Nai-Hsin Pan (e-mail: pannh@yuntech.edu.tw).
[1]Department of Construction Engineering, National Yunlin University of Science and Technology, Yunlin County, Taiwan, R.O.C.
[2] Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Yunlin County, Taiwan, R.O.C.

DOI: 10.6119/JMST-015-1228-1

water conservation organizations. Presently, inspections are primarily based on tests designed by the U.S. Army Corps of Engineers in 1995. These tests are used to evaluate corrosion, cracks, defective designs, and inappropriately constructed concrete bridges (U.S. Army Corps of Engineers, 1995). Bridge management in Taiwan relies on a visual inspection method that entails assessing degree, extent, relevancy, and urgency (DER&U) parameters. This method was developed by the Taiwan Area National Freeway Bureau (TANFB) and serves as a guideline for bridge management. Lin (1999) recorded DER&U values for bridges under the jurisdiction of the TANFB for 2 years. Lin used a facility functionality prediction model that was based on a Markov chain and the probability distribution of the current bridge state. Wang (2004) executed a general survey of bridges located in the Pingtung area of Taiwan by using DER&U to assess the current status of the bridges. Subsequently, the bridges were categorized as one of four types for designating the order of maintenance or repairs.

According to Fayek and Oduba (2005), human factors considerably influence an evaluation process when realistic constraints are considered in this process. Using a fuzzy logic algorithm can reduce the uncertainty or subjectivity of the results. Fayek and Oduba thus employed fuzzy logic and expert systems modeling to resolve problems posed by realistic constraints. Furthermore, Li et al. (2007) advanced fuzzy number theory on the basis of a fuzzy framework to resolve prequalification problems, including decision criteria analysis, weight evaluation, and decision model development, encountered by construction contractors. Finally, they conducted a case study to verify the feasibility of the fuzzy method. Poveda et al. (2009) also developed a fuzzy logic model for predicting and evaluating the work performance of construction foremen. The primary purpose of this model is to assess the effectiveness of foremen by monitoring their improvement over time and identifying areas in which they require training to improve their performance. Reshmidevi et al. (2009) performed suitability evaluations in arid agricultural watersheds to assess the potential for supplementary irrigation in surrounding areas. Because of uncertainty and vagueness, they used fuzzy sets as the research basis. Decision-making criteria were converted into fuzzy sets to assess land suitability on the basis of the environment as well as land potential and surface water potential. Liu and Wang (2009) explored third-party logistics (3PL) and discovered that supplier demands had become increasingly substantial. Therefore, to improve customer service and reduce costs, they proposed an integrated fuzzy method for assessing and selecting 3PL providers and applied fuzzy inference strategies to eliminate unacceptable providers. In addition., Wang and Elhag (2008) developed a method that can be used by the TANFB to establish a more systematic and efficient maintenance priority ranking system for evaluating bridge structures. Compared with current bridge risk assessment methods, which require the subjective opinions of numerous bridge experts, fuzzy inference has been validated to be highly effective and more useful than artificial neural networks and multiple regression analysis. Barreto et al. (2008) employed fuzzy logic modeling to estimate the amount of runoff in transition zones between geometric objects. The runoff amount in the watershed was estimated using fuzzy logic and Boolean methods to simulate natural phenomena. Saleh and Kim (2009) also proposed a fuzzy system for evaluating student grades. This system uses fuzzification, fuzzy inference, and defuzzification according to difficulty to resolve critical complex questions. They suggested that this proposed system is more reasonable and fair compared with other systems previously proposd because of its transparency, objectivity, and ease of application in automatically evaluating student grades.

Abdolreza (2014) proposed a risk assessment model according to the concepts of fuzzy set theory to valuate risk events during tunnel construction operations. To demonstrate the effectiveness of the proposed model, its results were compared with those of the conventional risk assessment method. The results revealed that the fuzzy inference system has high potential for accurately modeling such problems. Nieto-Morote and Ruz-Vila (2012) presented a systematic prequalification model on the basis of fuzzy set theory. This model is superior to other models because of its use of an algorithm to reconcile the inconsistencies in the fuzzy preference relationship when pairwise comparison assessments are employed as well as its use of linguistic assessment or exact assessment of contractor performance under the qualitative or quantitative criterion, respectively. Huang et al. (2010) asserted that a fuzzy comprehensive assessment should include assessment grade determination, membership function establishment, and composite operator selection. They established a set of fuzzy comprehensive assessment methods and applied them to long-span bridges. The fuzzy comprehensive assessment methods were applied to the Harbin Songhua River Cable Stayed Bridge, and the assessment result was reasonable and credible.

According to the aforementioned findings , Huang et al. (2010) demonstrated that bridge function assessments in Taiwan generally entailed employing DER&U as primary evaluation parameters, but human subjectivity caused uncertainty or bias in the results. In addition, fuzzy set algorithms have been used in various fields to reduce uncertainty or facilitate decision making. Therefore, fuzzy set algorithms were employed in the current study to reduce deviations in the assessment parameters.

1. Degree, Extent, Relevancy, and Urgency

This study reviewed the literature on the bridge visual inspection and assessment method. This method is known in Taiwan as the DER&U evaluation method, and it is utilized in bridge management systems to inspect the current status of bridges. This assessment method is a bridge management system developed by the TANFB. Since the implementation of the criteria for using this method, visual inspections have been employed extensively in Taiwan. The DER&U parameters are used to evaluate a structure's current status. However, previous studies have found that the criteria utilized for visual inspection may be inconsistent because of factors such as inspector subjectivity. The different opinions of inspectors resulted in as-

DOI: 10.6119/JMST-015-1228-1

sessment variations. The current study adopted relevant visual inspection parameters and incorporated parameters applicable to Taiwanese inspections regarding soil and water conservation facilities.

2. Fuzzy Set Theory

In 1965, Zadeh introduced fuzzy set theory to improve the either–or concept in conventional mathematics and combine the human brain characteristics, such as identification and judgment, with mathematics. Fuzzy set theory has since been applied to numerous fields including operations research, management science, artificial intelligence, automatic control, and statistics. Fuzzy set theory can be used for mathematically modeling uncertainties, thereby overcoming the disadvantages typical of specific mathematical models and increasing the persuasiveness of such models. The basic principle of fuzzy set theory is as follows: Accept the existence of fuzzy phenomena, and use a membership level to describe transitional fuzziness and subvert either–or binary logic. However, information collection typically involves rational assumptions because of difficulties in data collection and the possible bias of human decision making.

III. PROCEDURE FOR DEVELOPING THE VISUAL INSPECTION MODEL ACCORDING TO FUZZY SET THEORY

An analysis of on-site inspections regarding soil and water conservation facilities demonstrated that the expression levels under each parameter should be constrained to an appropriate number to ensure that inspectors can conveniently conduct visual inspections and fully articulate the conditions of the structures. Although numerous expression levels, such as those in a 10-point system, are beneficial for developing detailed assessments of structural deterioration, this frequently complicates judgments regarding differentiation and determination levels. In particular, inspectors may have differing opinions and thus adopt varying criteria in assigning damage levels. However, an excessively low number of levels, such as that in a 2-point system, may result in significant misjudgment of structural deterioration. In summary, the scores that inspectors assign during visual inspections may differ because of personal differences and semantic judgments. Therefore, assessment scales vary depending on inspectors and locations, and diverse criteria are adopted in the scoring system. In addition, no standard criteria have been adopted because the methods preferred by inspectors in compiling inspection records differ; for example, certain inspectors may use quantitative numbers, whereas others may utilize words for this purpose. Hence, the scoring system for assessing the extent and effects of damage is inconsistent.

In an actual case of erosion, semantics were used as defining criteria. In particular, the parameter for the damage extent was assessed from the perspective of area or depth, and the levels were low, medium, and high. The functional effects were measured according to the influence on the functions of the structures as well as the effects on structural stability and functionality. Moreover, the assessment was divided into three levels: minor, moderate, and substantial.

This study applied fuzzy semantic inference to resolve the primary problems resulting from visual inspections (i.e., the differences in inspectors' semantic judgments and quantification processes). Therefore, judgments regarding semantics and scores were first integrated before referential semantics and scores were determined. Applying fuzzy sets by integrating expert opinions is a common method; fuzzy preference relationships can be used to obtain the intersection of expert opinions. Hence, this study conducted interviews and adopted fuzzy set theory to redefine the membership score functions. In this study, fuzzy set theory was employed primarily because fuzzy theory can be used to describe indefinite logical problems and convert semantics into reasonable intervals. The following section explains the procedure of applying fuzzy set theory.

The Mamdani-style fuzzy inference is as follows.

(1) Fuzzification: Linking input values to corresponding fuzzy memberships
(2) Rule evaluation: Determining the correspondence degree of the rules
(3) Defuzzification: Converting the integrated results into well-defined outputs

This study applied trapezoidal fuzzy numbers, which are common in fuzzy theory.

Trapezoidal Membership Function

For example, a trapezoidal membership function can be determined using four values: a1, a2, a3, and a4, where a3 and a2 are the core of this set, and a1 and a4 are the left and right boundaries, respectively. The scope of the elements is limited between a2 and a3, as described in Equation (1).

The corresponding membership function is provided in Figure 1 (Equation 1).

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & , \quad x < a_1 \\ (x - a_1)/(a_2 - a_1) & , \quad a_1 \le x < a_2 \\ 1 & , \quad a_2 \le x < a_3 \\ (a_4 - x)/(a_4 - a_3) & , \quad a_3 \le x < a_4 \\ 0 & , \quad x \ge a_4 \end{cases} \tag{1}$$

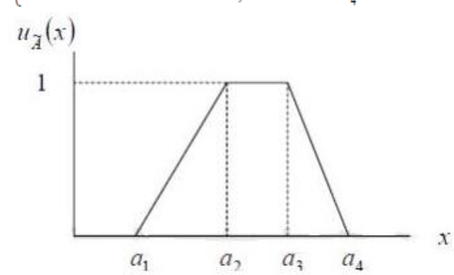

Fig1 Schematic of trapezoidal membership function

The defined interval can be used as the range of values for semantic conversion. However, because of the semantic differences resulting from individual inspectors, the scores may not reflect the explicitness of the semantics. Therefore, this study applied quantitative fuzzy semantics.

DOI: 10.6119/JMST-015-1228-1

1. Fuzzification

This study adopted the DER&U parameters, which are frequently used as the scoring method in visual inspections. The interview results demonstrated that although in practice, Parameters D and R were applicable to inspections regarding soil and water conservation facilities, Parameter E was inapplicable because it required tools for the measurement, and Parameter U should be considered at an overall level. The calculations of Parameter U are explained in a subsequent section by using quantitative formulaic calculations.

The proposed model defined the scope of the membership function. Parameter R is used as an example in the following paragraphs to elucidate the 10-point system. The left boundary can be set at 0, the right boundary at 10, and the median at 5. According to the calculations in Equation (1), the 10-point system can be segmented at 3 and 8 to create three sections.

The range of the value of the parameter that represents small structural damage can be set to [0, 4], in which 4, serving as the boundary, can be obtained according to the original definition of this assessment. Structures scoring between 0 and 4 points are considered to be minimally damaged. When the boundary is less than 1, the corresponding membership function is 1, and the corresponding values of the membership function for [2, 4] can be derived using the slash formula in Equation (2). The values of the parameter representing medium structural damage are [2, 4, 6, 8], [2, 4], and [6, 8], and the corresponding membership functions can also be obtained using the slash formula in Equation (3). The value of the parameter representing large structural damage is [6, 10]; when the boundary is greater than 10, the corresponding membership function is 1. The corresponding values of the membership function for [6, 8] can be obtained using the slash formula in Equation (4). The calculations for Parameter D are similar.

Calculations using Equation (1) are as follows:

$$\mu\text{D-Small(X)} = \begin{Bmatrix} 1, 0 \le x \le 2 \\ \frac{4-x}{3}, 2 \le x \le 4 \\ 0, 4 \le x \end{Bmatrix} \quad (2)$$

$$\mu\text{D-Medium (X)} = \begin{Bmatrix} 0, x \le 2 \\ \frac{4-x}{3}, 2\ x \le 4 \\ 1, 4 \le x \le 6 \\ \frac{8-x}{3}, 64x \le 8 \\ 0, 8 \le x \end{Bmatrix} \quad (3)$$

$$\mu\text{D-Lag (X)} = \begin{Bmatrix} 0, x \le 6 \\ \frac{8-x}{3}, 6 \le x \le 8 \\ 1, 10 \le x \end{Bmatrix} \quad (4)$$

The corresponding scores obtained after the semantic conversion are explained as follows: The fuzzy semantic scores for Parameter R were defined as small, medium, and large, and those for Parameter D were defined similarly (Figures 2 and 3, respectively).

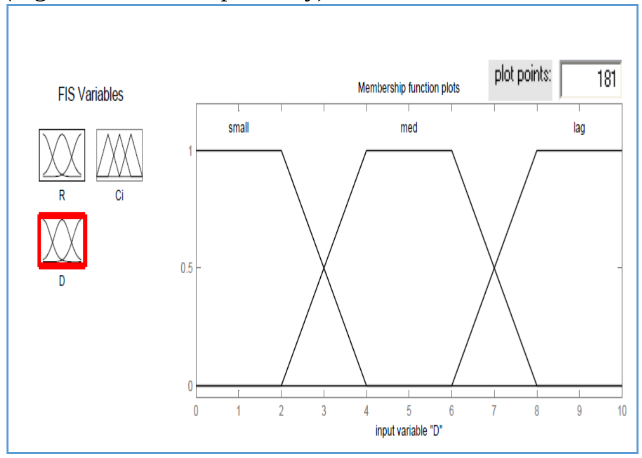

Fig2 parameter D defined by the membership function Parameters

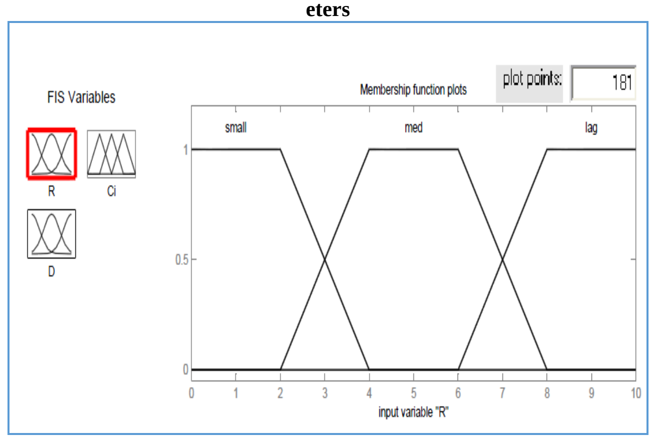

Fig3 parameter R defined by the membership function Parameters

2. Fuzzy Rule Inference

Damaged components were assessed during on-site inspections of soil and water conservation facilities. In this study, scoring systems applicable to assessing soil and water conservation facilities were identified, and these study assessment scores enable personnel to understand the current conditions of the facility. By using inference rules, people can comprehend the current conditions and delineate the overall CI of the facilities.

Fuzzification is a tool, and data can be entered into a program to be fuzzified. After the conversion of fuzzy membership functions, the data represent semantic descriptions. Figures 4 and 5 illustrate the inference regarding the first section of the membership functions of Parameters D and R, respectively.

This study converted and outputted two types of semantic variables into a single variable. The two variables were defined as X1 and X2, representing Parameters D and R, respectively. The corresponding semantics, {small, medium, large} and {small, medium, large}, were used as the output of the CI levels, and the CI output was {normal, bad, extremely damaged}, as illustrated in Figure 4. The five in-

DOI: 10.6119/JMST-015-1228-1

ference rules are presented in the following paragraphs. In the inference method, a sum set was employed to infer the area, after which the center of gravity method was utilized for defuzzification.

Inference rules

1. *If (R is small) and (D is small), then (ci is normal).*
2. *If (R is small) and (D is med), then (Ci is normal).*
3. *If (R is med) and (D is med), then (Ci is bad).*
4. *If (R is lag) and (D is med), then (Ci is bad).*
5. *If (R is lag) and (D is lag), then (Ci is extremely damaged).*

The semantic definition of the CI was divided into three levels, which were based on the fuzzy inference results derived from the membership functions of the on-site facility CI (Figure 4). The target range of the membership function was between 0 and 10 points. A CI value approaching 10 indicated severe damage. A triangular distribution was employed to define the normal, bad, and extremely damaged ranges. Specifically, normal was [0, 0, 0.5], bad was [0, 0.5, 1], and extremely damaged was [0.5, 1, 1]. In the inference results obtained using this inference method, a high score indicated severe damage, and 5 was the median (Table1).

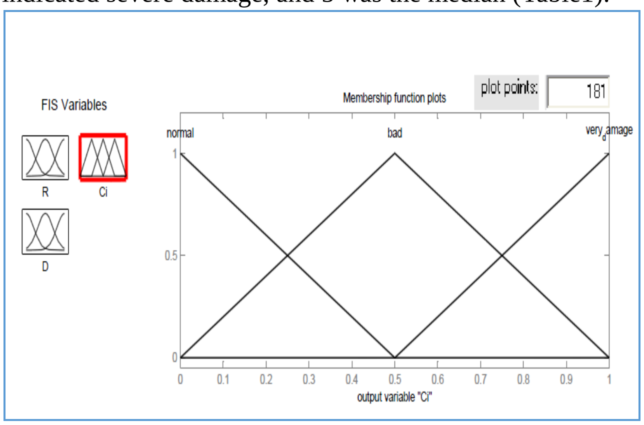

Fig 4 Inference output membership function Parameters

Table.1 Output fuzzy member function definition

Item	Symbol	Parameters
CI	Normal	[0, 0.5]
	Bad	[0, 0.5, 1]
	Vary damage	[0.5 ,1]

* Condition index: denotes the functional degree of a single facility structure, which is calculated from the parameters D and R.

3. Defuzzification

In this paper, Parameter D represents the damage extent, and Parameter R represents the level of impact. The systematic defuzzification results (Figure 5) demonstrated that defuzzification can accurately reflect the actual CI of a structure. This evaluation value can be used to achieve effective quantification, thereby reducing the errors resulting from human factors, which was the purpose of this study. The widely used center of gravity method, which was proposed by Yanger (1981) as a defuzzification method, was employed as the calculation equation in the current study. In addition, this study applied the widely used mean-of-maximum method: The membership function was divided at the premise α and the maximum membership, and 1 represents the number of memberships greater than or equal to the premise α or the defined membership, as shown in Figure 5 (Equation 5).

$$Y = \frac{(Aa*Ay)+(Ba*By)}{Aa+Ba} \qquad (5)$$

Y: Defuzzification explicit conversion value
Aa, Ba: A and B Area
Ay, By: A and B center of gravity

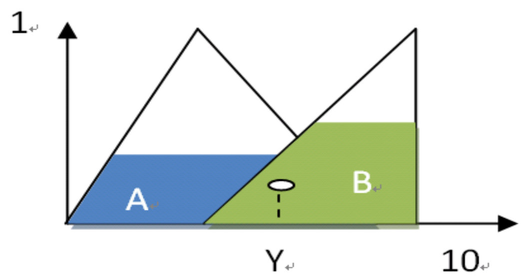

Fig 5 Gravity method schematically

According to the interview results, when the erosion depth exceeded 40 cm, the respondents considered Parameter D moderate (scoring 3 to 5 points) and Parameter R small (scoring 2 to 3 points). Subsequently, the corresponding positions were identified using fuzzy theory, and the expressions in the corresponding result intervals were defuzzified, yielding a minimum CI of 0.438. Therefore, the results were normal (Figure 6).

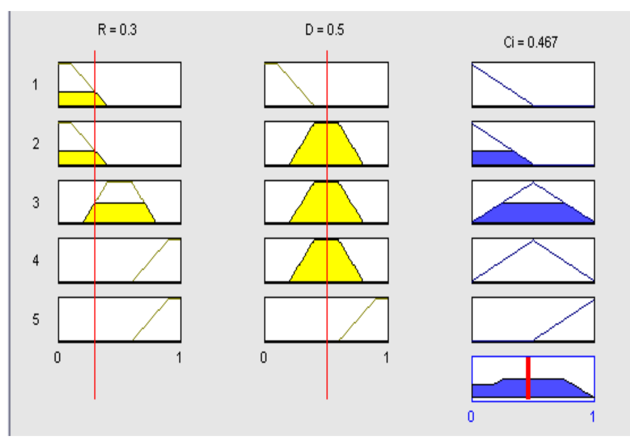

Fig 6 Defuzzification schematic diagram

4. CI Level

This study proposes CI to evaluate the soil and water conservation facilities' current status, which was determined through fuzzy inference. The extent Parameter D and impact Parameter R were divided into CI levels by conducting reference conversion. The CI values were classified into three levels that were converted from the CI values, which indi-

DOI: 10.6119/JMST-015-1228-1

cated the current state of the individual structure. Subsequently, all CI-level values were calculated using the arithmetic mean method. Finally, on the basis of the calculation results, three reference intervals were derived: Interval 1 ranged from 0 to 0.29 (Level A), Interval 2 ranged from 0.3 to 0.59 (Level B), and Interval 3 ranged from 0.6 to 1 (Level C). A high score indicated a low level, increasing the sufficiency of the functions. Therefore, Interval 3 (i.e., CI Level C) represented "low" functionality. These reference intervals were divided according to the scores. In the example, the CI was placed into Interval 2 (i.e., CI Level B).

5. Fuzzy Inference Verification

In this study, the fuzzy inference verification process involved inferring results from five historical data sets derived from case studies. The CI values obtained after the first ratings of the five cases were denoted as "CI-before" and were converted according to the functional classification scale defined in this study. Users were then asked to assign scores for these five historical cases. In the returned questionnaires, "D-max" and "R-max" represented the maximal values selected for Parameters D and R, respectively. The minimal values selected for these parameters were represented by "D-min" and "R-min," respectively. In addition, the fuzzy inference results were expressed using "CI-min" and "CI-max." Subsequently, the verified fuzzy inference CI values were converted into CI levels. Finally, these results were compared with the previous ratings to determine whether they were consistent with these ratings. The results were consistent (Table 2), indicating that the fuzzy inference results were within a reasonable range.

Table 2 Results of the verification obtained using fuzzy inference

	min				max				before
NO.	D	R	CI	CI-level	D	R	CI	CI-level	CI-level
1	2	1	0.18	A	3	2	0.21	A	A
2	8	7	0.81	C	9	8	0.86	C	C
3	4	3	0.47	B	7	5	0.5	B	B
4	5	4	0.5	B	8	6	0.5	B	B
5	8	7	0.81	C	10	8	0.84	C	C

*Authentication, a random sample of five cases verified as a representative description

IV. CASE STUDIES

In the two cases examined in this study, the maximum and minimum values of Parameters D and R were selected from the intervals yielded from actual inspections to conduct combination inference. Table 3 presents the inference results. Subsequently, the CI levels and urgency values were calculated in both cases to offer recommendations for future maintenance. The following sections briefly explain the results for the two cases.

1. Case A

The subjects of Case A include comprised two groundsill works, the images of which are depicted in Figures 7-1 and 7-2. Extensive erosion occurred in these groundsill works because of constant water scour.

On-site assessment results revealed that the scores that inspectors assigned for Parameter D regarding Groundsill Work 1 were between 6 and 7, whereas those for Parameter R were generally between 3 and 5 because the effects were frequently considered minor. Regarding Groundsill Work 2, unilateral erosion occurred because of flow offset. Because of the smaller area, the scores for Parameter D assigned by the inspectors during on-site inspections were between 2 and 3, and those for Parameter R were between 1 and 2 because the inspectors considered the effects to be minor.

Fig7-1. Groundsill work NO.1

Fig 7-2. Groundsill work NO.2

2. Case B

The subjects of Case B involved two sabo dams (Figures 8-1 and 8-2). A mudslide had struck the region and completely destroyed one dam and rendered the other dam temporarily and partially dysfunctional because of sediment deposition. The results of the on-site assessments revealed that Dam 1 was destroyed and that its functionality was lost. The inspectors unanimously assigned 10 points for Parameter D and assigned 9 to 10 points for Parameter R. Dam 2, which was affected by sediment deposition, was temporarily dysfunctional. The inspectors assigned 8 to 9 points for Parameter D and 7 to 8 points for Parameter R.

Fig 8-1. Sabo dam NO.1

Fig 8-2. Sabo dam NO.2

3. Inspection and Inference Results

To classify the CI levels of Case A, the mean scores assigned by the inspectors for Parameters D and R were used. The inference results (Table 3) obtained by applying fuzzy inference rules were examined to determine the CI of the structures. Subsequently, the CI values were integrated (CI levels), and the results showed the current CI levels of the structure. For Case A, the CI equation was integrated into (CI levels), and the results

DOI: 10.6119/JMST-015-1228-1

demonstrated that Groundsill Work 1 was at Level B (i.e., damaged), whereas Groundsill Work 2 was at Level A (i.e., normal).

In Case B, the values of Parameters D and R were entered into Matlab, and the fuzzy inference results (i.e., the CI values) represented the damage extent. Subsequently, the CI values were substituted into (CI levels), yielding a CI level of C, indicating severe structural damage and impaired functions.

Table 3 Case inspection results

Case	Structures serial	D	R	Ci	CI -level
A	Groundsill works 1	6	3	0.476	B
		7	5	0.5	B
	Groundsill works 2	2	1	0.178	A
		3	2	0.209	A
B	Sabo dam 1	10	9	0.837	C
		1	1	0.837	C
	Sabo dam 2	8	7	0.779	C
		9	8	0.822	C

4. Discussion and Analysis

The inspection reports drafted using the proposed method comprised individual assessments regarding the damage extent (Parameter D) and effects (Parameter R) on the damaged structures. This study applied fuzzy sets to integrate relevant semantics and scoring criteria and divided the structural inspection results into various CI levels to reduce the substantial differences in scores engendered by the inspectors' subjectivity.

The water conservation inspection results were rated as Levels A, B, C, or D. If the inspection results indicated Levels C or D, then a second inspection was required. Furthermore, before the fuzzy inference model was adopted, inspecting and rating a structure required approximately 20–30 min, rendering the process considerably time consuming. The primary purpose of using fuzzy inference (instead of a formula to facilitate level designations during inspection and to reduce inspection times) in this study was to eliminate the differences in human judgment, instead of employing. This study adopted a feedback questionnaire, which was completed by seven water conservation experts who had more than 10 years of professional experience on average. In the feedback questionnaire, the letters A, B, C, D, E, and F corresponded to satisfaction scores of 5, 4, 3, 2, 1, and 0, respectively. The mean and standard deviation values of the satisfaction score were then calculated (Table 4), and the results indicated that inspection time reduction was the item that improved most significantly, followed by the consistency of results and urgency parameter classification. All the mean values exceeded 4, signifying that the inspection process improved markedly.

Table 4 The satisfaction score of improved parameters based on the questionnaire results

Item	Mean	SD
Inspection times	5	0
Consistency of results	4.86	0.35
CI-Level	5	0

Integrating visual inspections with fuzzy inference provides the following advantages:

(1) Simplifying inspection procedures

The visual inspection assessments were limited to the damaged parts of structures, and undamaged components remained unexamined. Therefore, the inspection procedures were simplified, and the priorities in repairing damaged soil and water conservation facilities could be identified using the CI levels.

(2) Modifying the damage inspection scoring system

The proposed method can be used to assess the extent of damage and the effects of the damage on the overall structural safety of soil and water conservation facilities. Fuzzy-theory-based tools were employed in this study to reduce the differences in the subjective assessments. After the fuzzy inference and defuzzification processes, the CI values were converted into the current CI levels of a structure, thereby enhancing the consistency of the inspection results.

(3) Understanding regional urgency by using comprehensive condition values

After the inference and fuzzification processes, the individual CI scores of the facilities could be understood clearly, and the means of the overall CI levels indicated the overall urgency.

The results of this study can be used to effectively reduce the influence of inspector subjectivity, calculate the functionality of facilities, and identify the overall urgency values of particular regions for facilitating maintenance repairs.

V. CONCLUSIONS AND RECOMMENDATIONS

The proposed method enables inspecting the current status of soil and water conservation facilities, and the analysis results reveal that the proposed method can reduce inspection time, thereby increasing the efficiency of routine inspections of soil and water conservation units. Additionally, the fuzzy inference algorithm can be employed to effectively reduce inconsistencies in assessment criteria and assessment subjectivity in case studies.

The CIs derived from the proposed method through the fuzzy inference approach can be used to further evaluate the structural CI levels.

VI. ACKNOWLEDGMENTS

We thank the Soil and Water Conservation Board Slopeland Conservation and Utilization group for providing the research funding and obtaining relevant results.

REFERENCES

Barreto-Neto,A. and Filho, C. R. d. S., “Application of fuzzy logic to the evaluation of runoff in a tropical watershed”, Environmental Modelling & Software, Vol.23, No.2, pp. 244–253(2008).

Fayek, R. and Oduba, A., “Predicting Industrial Construction Labor Productivity Using Fuzzy Expert Systems,” Journal of Construction Engineering & Management, Vol.131, No.8, pp. 938-941 (2005).

Huang, Q., Tang, H., and Ren, Y., “Study of Assessment Theory of Long-span Bridges Based on Fuzzy Theory.” Journal of Highway and Transportation Research and Development , Vol.27, No.1, pp: 62-66. (2010). http://worldcat.org/issn/10020268

Lin,H.Y., Channel Morphological Evolution in Mud Rock Area of River Erhjen Upstream, PhD thesis, Department of Geography, National Taiwan University,Taipai, Taiwan,1999.

DOI: 10.6119/JMST-015-1228-1

Li, Y., Nie, X., Chen, S., “Fuzzy Approach to Prequalifying Construction Contractors, “Journal of Construction Engineering & Management, Vol.133, No.1, pp. 40-49 (2007).

Liu, H.T., Wang, W.K., “An integrated fuzzy approach for provider evaluation and selection in third-party logistics,” Expert Systems with Applications, Vol.36, No.3, pp. 4387-4398(2009).

Nieto-Morote, A. and Ruz-Vila, F., “A fuzzy multi-criteria decision-making model for construction contractor prequalification.” Automation in Construction, Vol.25, pp: 8-19. (2012). DOI: 10.1016/j.autcon.2012.04.004

Poveda, A. and Fayek, A. R., “Predicting and Evaluating Construction Trades Foremen Performance: Fuzzy Logic Approach”, Journal of Construction Engineering & Management, Vol.135, No.9, pp. 920-929(2009).

Reshmidevi,T.V., Eldho, T.I. and Jana, R., “A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds,” Agricultural Systems, Vol.101, No.(1-2) pp.101-109 (2009).

Saleh, andS.i. Kim, “A fuzzy system for evaluating students’ learning achievement,” Expert Systems with Applications, Vol.36, No.3, pp. 6236-6243 (2009).

Wang,W. Z., Preliminary Structural Investigations and Suggestions of Maintenance for Major Bridges in Pingtung, Master's thesis, Department of Civil Engineering, National Pingtung University of Science and Technology, Pingtung, Taiwan 2004.

Wang, Y. M. And Elhag, T.M.S., “An adaptive neuro-fuzzy inference system for bridge risk assessment,” Expert Systems with Applications, Vol.34, No.4, pp. 3099–3106(2008).

US Army Corps of Engineers, Engineering and Design Evaluation and Repair of Concrete structures, Washington, DC. USA. (1995).

Yazdani-Chamzini, A., “Proposing a new methodology based on fuzzy logic for tunnelling risk assessment.” Journal of Civil Engineering and Management, Vol.20, NO.1, pp: 82-94. (2014)