FUZZY-BASED APPROACH FOR EVALUATING THE PERFORMANCE OF A NEW TECHNOLOGY IN CONSTRUCTION SITES

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ABSTRACT: Although there have been many efforts to reduce accidents on construction sites, such accidents continue to occur. New technologies have recently been developed to improve safety and their performance needs to be evaluated to determine their suitability prior to the application. The assessment for safety performance mainly is conducted depending on qualitative and subjective judgment of supervisors. However, there are rarely proper approaches to assess such qualitative measures. Therefore, we propose a fuzzy-based approach to assessing the performance of a new technology. The assessment of a new technology, called a mobile detector (MD), was carried out as a case study. The output is compared with those by a numerical simulation. As a result, the fuzzy-based performance assessment is shown to be appropriate for this evaluation.

Keywords: advanced technology; fall accidents; fuzzy-based approach; safety performance

1. INTRODUCTION

Tasks in the construction industry are more labor-intensive and hazardous than those in other manufacturing industries. Thus, fatal accidents causing deaths or serious injuries of workers occur more frequently on construction sites. To prevent such accidents, equipment such as safety fences and guardrails have been installed in dangerous places. Moreover, various safety management techniques have been employed, such as safety programs and training, and safety information systems based on historical cases of construction accidents [1].

Recently, new technologies and systems have been introduced to enhance safety based on state-of-the-art technologies such as sensing technologies [2]. Their performance should be initially assessed to ensure efficiency and applicability. The performance of newly developed systems is generally measured quantitatively by comparison between before and after installation or under the same conditions with a conventional system. However, new systems for safety management are difficult to assess quantitatively because other safety issues are directly concerned in the occurrence of accidents. Therefore, their assessment relies on qualitative and subjective judgment of supervisors, engineers, inspectors, or other individuals responsible for the safety of the construction facilities during their operation. However, qualitative measures are frequently expressed linguistically, and standards are often misinterpreted [3]; in turn, conditions are misrepresented because there are rarely proper approaches to assess such qualitative measures. This study introduces a fuzzy-based approach to assess the safety performance of a new technology. We applied the method to assess a new technology, called a mobile detector (MD) [2], to illustrate the method's usefulness. Safety performance effects were first established from previous studies and interviews with safety managers. A questionnaire survey was then implemented so experts could investigate performance effects, and the values expressed linguistically were transformed into quantitative values by fuzzy operations. Finally, the results from the proposed model were verified through comparison with a numerical simulation.

2. BACKGROUNDS

2.1 Safety in Construction Sites

Every construction project has different conditions because of the different management organizations and workforce on the construction site. In addition, the tasks in construction processes are more dangerous than those in other industries. For these reasons, construction accidents, often fatal, occur more frequently than the proportion of the construction industry to all industry. The statistical data for the Korean construction industry demonstrate the seriousness of construction accidents. The number killed or injured accounts for about thirty percent of that in all industry, while the number of employees in the construction industry is less than nine percent of that in all industry [4]. This phenomenon results in heavy economic losses, and consequently interferes with development in the construction industry.

The construction industry requires effective prevention and safety management in view of the frequency and seriousness of accidents. The systems for precautions and safety enhancement have been improved based on the relevant theories. Heinrich [5] first proposed causal management theory, called the domino theory. The theory helps to prevent accidents by eliminating the causes of accidents. Figure 1 shows the PDCA cycle popularized by Deming for continuous management activity. The theory has caused changes in overall management systems. The activities for safety management are fundamentally based on the PDCA theory.

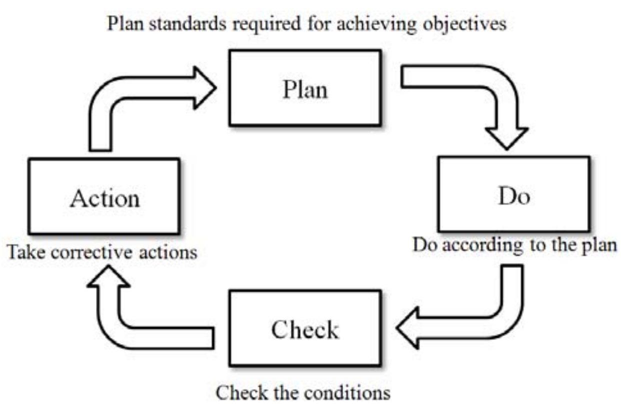

Figure 1. The PDCA cycle [6]

However, the activities conducted at the "check" stage are discrete activities, i.e., activities using checklists or education and training at a fixed time on a daily basis. Thus, they have limitations for continuous management. To carry out the activities constantly at the "check" stage, recent studies have attempted to improve management processes using wireless sensor network (WSN) technology [7–11]. The development of a new system or technology using WSN technology will facilitate more direct and active safety management.

2.2 Qualitative and Quantitative Measurement

One of the critical challenges in assessing the performance of a new technology is how to deal with quantitative and qualitative data. The effective way to cope with such a challenge is to make an effort to measure the variables. One way to determine the amount of their uncertainty is to start with the individual components in the quantitative and qualitative measurement and to assess their performance as accurately as possible. In measuring the uncertainty of quantitative data, there are two common ways to determine it: deterministic approaches, such as single-point estimates; and ranged estimates, like the Monte Carlo technique. The uncertainty in qualitative information can be estimated using the concept of fuzzy sets as an alternative approach for measuring its magnitude [12]. Fuzzy set theory was introduced in 1965 by Zadeh as a mathematical theory of vagueness. This theory helps to transfer a linguistic model of experts' subjective judgment to an algorithm that emphasizes the experts' ability to extract information from masses of inexact or fuzzy information. Furthermore, the implementation of this theory in explaining linguistic judgments seems to have considerable impact on the reduction of difficulties in explaining qualitative data.

3. FUZZY-BASED ASSESSMENT MODEL

3.1 Fuzzy Set Theory

This theory was developed for solving problems in which descriptions of observations are imprecise, vague, and uncertain. The term "fuzzy" refers to a situation in which there are ill-defined boundaries on the set of observations to which the descriptions apply. The theory was developed specifically to deal with uncertainties that are not statistical in nature [13]. From questionnaire surveys, respondents' judgments can be linguistic terms or fuzzy values. Fuzzy operations allow for the arithmetic combination of fuzzy numbers [14]. Arithmetic operations, such as addition, subtraction, multiplication, and division, can be performed on fuzzy numbers converted from linguistic terms.

In this study, each expected performance of one new technology for safety improvement was evaluated by 52 practitioners and engineers using linguistic terms as shown in Figure 2. Based on Hadipriono's model (1988), eleven linguistic values of the technology are represented as "absolutely poor (AP)", "extremely poor (EP)", "very poor (VP)", "poor (P)", "fairly poor (FP)", "fair (F)", "fairly good (FG)", "good (G)", "very good (VG)", "extremely good (EG)", and "absolutely good (AG)" ranging from 0 to 1. These linguistic values are converted into fuzzy numbers for fuzzy operations. Figure 2 shows the membership functions for standard performance values of each linguistic term.

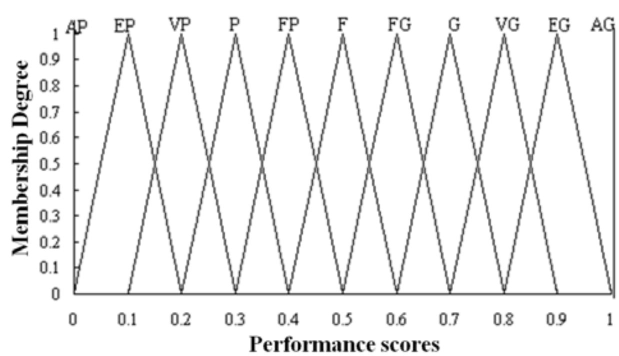

Figure 2. Standard performance values [3]

3.2 Assessment of Safety Performance

In this study, safety improvements were divided into three categories with fourteen expected performance elements, as presented in Table 1: "improvement effects", "assistant effects for deficient precautions", and "elimination of hazard causes". Detailed safety performance was derived from previous research [15] and interviews with safety managers. The surveys measured the effectiveness of the technology in removing accident causes and evaluated safety improvement through the MD's ability to prevent fall accidents. The respondents were assumed to possess sufficient information regarding the application of the system.

Table 1. Expected safety performance of the MD

Categories of effect	Expected performances	
Improvement effects	P1	Precaution
	P2	Respond after fall accidents
	P3	Influence on external reliability
Assistant effects for deficient precautions	P4	Support insufficient training or education
	P5	Effective control and management
	P6	Implementation of inappropriate plan
Elimination of hazard causes	P7	Elimination of hazards by lack of proper training
	P8	Reduction of hazards by deficient enforcement of safety
	P9	Eliminating hazards from unprovided safety equipment
	P10	Protecting from unsafe construction methods or sequencing
	P11	Reduction of unsafe site conditions
	P12	Elimination of accidents by not using provided safety equipment
	P13	Improvement of workers' attitude toward safety
	P14	Protection of accidents by isolated, sudden deviation from prescribed behaviors

3.3 Fuzzy Operations

3.3.1 Fuzzy Aggregated Values

Practitioners' and engineers' subjective judgments were used to compute the quantitative impacts on safety performance of the MD system; however, their knowledge and experience may differ, and we therefore prepared a questionnaire to evaluate how their expertise could contribute to assessing the system's performance. We assumed that their experience would influence their assessment. We used a common type of learning pattern of increasing expertise from experience, the "S-shaped learning curve", shown in Figure 3. The learning effect from experience is functional. For instance, as this is an influential force in repetitive tasks, expertise and knowledge about a task increases over time. The patterns are expressed by a mathematical equation to describe the relationship between the experience period and expertise. The relation also provides a concrete measure of the rate at which an expert learns a task [16]. The reliability of subjectivities can be improved by increased skill and proficiency in the tasks. Typically, the learning effect for the repetitive tasks depicts a rapid increase after an initial period, then the rate of increase declines over time. We applied this learning curve in aggregating fuzzy numbers, which were converted from linguistic values for each performance effect.

For consistent fuzzy operations, all linguistic terms are converted into triangular fuzzy numbers. Fuzzy operations allow for arithmetic operations, such as addition, subtraction, multiplication, and division on fuzzy numbers [14]. A linguistic term (r_i) describing the *i*th performance effect can be estimated by a triangular fuzzy number, (a_i, b_i, c_i), and aggregated with the contributions $(e_1, e_2, \cdots e_n)$ of n respondents' expertise and subjectivities; the range is between 0 and 1. The aggregated fuzzy value, $\hat{r}_i$, can be calculated by the fuzzy multiplication and addition operators as follows.

$$\hat{r}_i = (r_i^1 \times e_1) + (r_i^2 \times e_2) + \cdots (r_j^n \times e_n) , \tag{1}$$

where $e_1, e_2, \cdots e_n$ indicate the subjective contributions of respondents, which are based upon the learning effect from their experience presented in Figure 3.

3.3.2 Computation of Rating Index

We computed the rating index (RI) of each performance effect for assessing an increase of overall safety performance by the MD system. This procedure was applied by converting the linguistic values obtained from several experts into a standard performance model, and the performance effects (PEs) were computed using the formula proposed by Hadipriono (1988)[3].

$$PE = \frac{\sum_{i=1}^{n} RI_i \times C_i}{\sum_{i=1}^{n} C_i} \tag{2}$$

The outputs of the PEs are fuzzy numbers, and are defuzzified by the Center of Area (COA). The COA, which is also known as the center of gravity method, is the most common method for defuzzification. It determines the center of gravity of the area under the membership function.

$$TPI = \frac{\sum_{i=1}^{n} x_i \times f(x_i)}{\sum_{i=1}^{n} f(x_i)}, \quad i = 1,2,\cdots,n \tag{3}$$

where Total Performance Index(*TPI*), x_i, and $f(x_i)$ indicate the crisp defuzzified output, output variable, and aggregated membership function, respectively. The output explanation is necessary in some situations for securing a reliable decision.

3.4 An Illustrative Example

Fatal accidents in construction sites occur frequently compared with other industries, and fall accidents particularly account for about 49.3% of all fatal accidents in Korea [17]. Recently, Lee [4] proposed a new technology, named a mobile detector (MD), to prevent fall accidents. To demonstrate the effectiveness of the proposed approach, we assessed the safety performance of the MD. The questionnaire survey was completed by 58 experts working in the construction domain. The number of experience and proportion of occupational areas are shown in Table 2 and Table 3. Each respondent expressed the effects of the MD using the fourteen performance variables in Table 1 in linguistic terms. After six questionnaires were rejected as insincere responses, the results from 52 questionnaires were analyzed using the fuzzy-based approach. Table 4 presents the results of the questionnaire survey.

Table 2. The number of Respondents

Experience(years)	frequency
1~3	10
4~6	11
7~9	8
10~12	7
13~15	6
16~18	5
19~21	1
22~24	0
25~27	3
28~30	1

Table 3. Proportion of occupational area

Occupational area	Proportion (%)
Construction (site)	77
Construction (head office)	15
The academic world	4
The others	4

Table 4. Results of questionnaire survey

Respondents	Experience (years)	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
1	5	G	F	VG	FP	G	G	FG	G	FG	VG	G	G	VG	VG
2	10	P	P	P	FP	P	P	F	F	P	P	P	P	F	P
3	2	FG	FG	P	P	F	P	P	FG	P	FP	F	P	F	FG
4	4	G	F	F	P	F	F	P	F	G	G	G	F	VG	P
5	14	G	FG	G	G	G	G	G	G	FG	G	G	FG	G	G
6	10	FP	F	P	FG	FG	FG	F	F	FG	FP	F	FP	FG	FP
7	14	F	F	F	FG	G	FG	FG	G	F	F	FG	FP	P	FG
8	8	G	G	F	F	F	G	F	G	F	F	G	G	F	G
9	17	FG	FG	FG	F	FG	FG	FG	FG	F	F	F	F	P	P
10	4	FG	FP	FG	G	VG	F	FG	F	G	F	G	G	G	VG
11	3	FG	F	FG	G	G	F	G	FG	F	F	G	P	G	G
12	9	G	G	G	G	G	G	G	VG	FG	FG	G	FG	FG	G
13	15	VG	G	G	VG	VG	G	VG	VG	G	G	VG	G	VG	VG
14	17	G	P	F	G	G	G	G	VG	G	F	FG	FP	FP	G
15	6	G	FG	G	F	G	G	G	VG	F	F	G	F	FG	G
16	13	G	VG	G	G	G	FG	FG	FG	G	F	VG	G	G	G
17	14	VG	G	G	G	VG	G	F	VG	G	F	VG	G	G	VG
18	10	G	G	G	G	VG	G	G	G	G	G	G	G	VG	VG
19	8	G	G	FG	FG	G	G	FG	G	G	FG	G	FG	G	G
20	12	G	G	VG	G	VG	G	G	VG	VG	G	VG	VG	G	VG
21	30	FG	FG	FG	FG	FG	G	FG	FG	FG	FG	G	G	FG	G
22	10	FG	G	G	FG	G	G	FG	FG	FG	G	FG	G	G	VG
23	18	G	G	G	G	VG	G	G	G	VG	VG	G	VG	VG	VG
24	25	G	FG	FG	FG	G	FG	FG	FG	G	G	G	G	G	G
25	5	F	FG	FG	G	FG	G	G	FG	FG	FG	G	FG	FG	G
26	25	FG	FG	F	G	G	G	G	VG	P	P	FP	F	P	P
27	25	G	FG	G	G	G	FG	G	G	G	G	G	G	G	G
28	17	FG	G	G	FG	G	G	FG	G	G	F	G	G	G	VG
29	6	FG	G	FG	G	G	G	FG	VG	FG	G	VG	G	VG	G
30	20	G	G	G	FG	G	G	FG	G	FG	F	G	FG	FG	G
31	7	VG	G	G	G	FG	FP	FG	FG	FG	G	G	G	F	FG
32	2	VG	VG	G	F	VG	G	F	G	VP	VG	G	F	F	F
33	5	G	G	G	FP	G	FG	F	FG	G	G	G	G	F	G
34	8	F	FG	FG	FG	G	G	G	FG	FG	G	G	G	G	G
35	4	P	P	P	P	FG	P	P	VP	P	F	FG	P	F	G
36	3	F	F	FG	F	VG	FG	F	FG	P	F	F	P	F	F
37	1	G	G	G	FG	G	G	P	FP	FP	FG	G	FG	G	G
38	3	FG	P	FG	FG	FG	FP	FG	FG	FG	F	FG	FG	FP	FP
39	10	VG	FG	FG	FG	VG	VG	VG	VG	F	VG	VG	F	VG	F
40	9	FG	P	F	F	FG	FP	P	FP	P	F	FG	P	FG	FG
41	5	FG	P	F	P	F	P	G	P	G	F	F	G	FG	G
42	3	FG	FG	FP	F	G	FP	P	P	FG	FG	FG	G	G	G
43	3	FG	P	FG	G	G	F	P	G	FG	FP	G	G	F	VP
44	1	VG	F	F	VP	VG	VG	VP	VG	VG	VG	VG	F	F	F
45	4	VG	G	G	G	G	G	G	FG	VG	FG	G	P	F	FG
46	3	G	G	FG	G	FG	G	G	FG	G	FG	G	G	G	G
47	18	F	F	F	F	F	F	FG	FG	P	FP	F	F	F	FG
48	9	G	G	FG	FG	G	FG	FG	FP	FG	FP	G	FG	P	P
49	15	VG	G	G	G	G	G	FG	G	FG	FG	G	G	VG	VG
50	12	F	F	F	FP	F	FP	FP	FP	FP	FG	FP	F	G	G
51	8	F	G	G	G	G	G	F	F	G	F	F	G	F	G
52	4	FG	F	FG	F	FG	P	FG	FG	P	VP	G	VP	G	FG

The linguistic values were converted to fuzzy numbers using the standard performance values presented in Figure 2. As described in Section 3.3.1, the subjective contributions of experts should be considered prior to fuzzy operations because their expertise from experience could influence the reliability of the estimation. Based on this assumption, this study employed a typical learning curve presenting the relationship between experience and expertise to aggregate the fuzzy numbers, as seen in Figure 3. To evaluate the safety performance of the MD, the rating index (RI) of each performance effect was first computed based on Eq. (2). From these results, these fuzzy indices were defuzzified using Eq. (3) to assess the performance level as a crisp value. Table 5 shows the levels of each expected performance.

As shown in Table 5, the RI of P10 at 0.860 is the highest of the values. This indicates that the performance level of P10 is between very good and extremely good, and this can be interpreted as very good. On the other hand, P5 has the lowest RI value of 0.649. This score is between fairly good and good; however, it can also be assessed that the performance of P5 is fairly good.

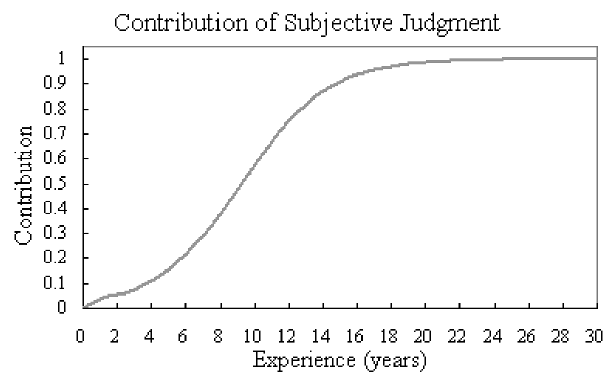

Figure 3. Contribution of evaluators' subjectivities

Table 5. Rating indices of performance level

Categories of effect	Performances	a	b	c	Rating Index
Improvement effects	P1	0.54	0.64	0.74	0.711
	P2	0.50	0.60	0.70	0.792
	P3	0.51	0.61	0.71	0.775
	Average	0.517	0.617	0.717	**0.767**
Assistant effects for deficient precautions	P4	0.52	0.62	0.72	0.764
	P5	0.58	0.68	0.78	0.649
	P6	0.53	0.63	0.73	0.737
	Average	0.543	0.643	0.743	**0.714**
Elimination of hazard causes	P7	0.51	0.61	0.71	0.774
	P8	0.56	0.66	0.76	0.689
	P9	0.49	0.59	0.69	0.822
	P10	0.47	0.57	0.67	0.860
	P11	0.55	0.65	0.75	0.703
	P12	0.50	0.60	0.70	0.799
	P13	0.51	0.61	0.71	0.780
	P14	0.55	0.65	0.75	0.700
	Average	0.517	0.617	0.717	**0.766**

Based on the results in Table 5, the performance index of the MD with regard to all performance effects can be assessed. To aggregate the rating indices from P1 to P14, a uniform weight (0.0714) was assigned to each performance, and the total performance index(TPI) was computed as 0.761. It is assumed that every performance variable has the same weight because there is no information about the relative contributions. To verify whether the result from the approach is appropriate, we performed a numerical simulation. To simulate the contribution of each performance effect in the entire index, a random number generator was used to create real numbers between 0 and 1. Figure 4 shows the probability distribution of the overall performance index of the MD over 3000 simulations. The mean of the simulation outputs is about 0.763, and this agrees closely with the defuzzified TPI with a weighting of 0.0714 for each performance variable. This value is also in the boundaries of (mean–Std) and (mean+Std). Consequently, the fuzzy-based model proposed in this study is considered appropriate for assessing the overall safety performance effect of the MD.

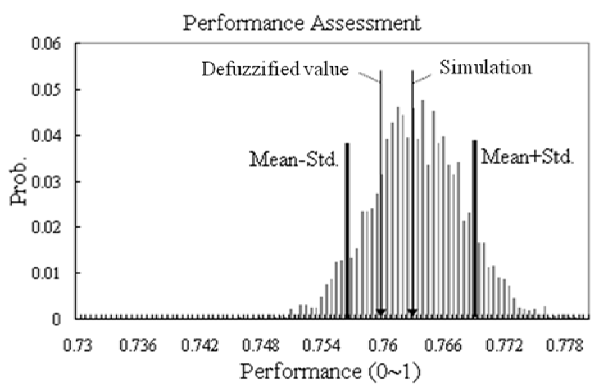

Figure 4. Comparison with simulation output

4. SUMMARY AND CONCLUSIONS

In this study, a fuzzy-based approach is proposed for evaluating the performance of a new technology that is developed for preventing accidents on construction sites. To demonstrate the proposed model, a case study was implemented for the mobile detector (MD), a new safety technology to protect against fall accidents on construction sites.

The results showed that the TPI of the MD would be 0.761, and that the performance in avoiding “unsafe construction methods or sequencing” would be the highest of the expected performance values; its linguistic term would be between “very good” and “extremely good” in Figure 2. Moreover, the output of 3000 simulations using randomly generated contributions of subjective judgments was compared with the quantified value of overall performance to illustrate the model’s capabilities. The comparison shows that this TRI is close to the expected value of the outputs by the simulation. This indicates that safety performance evaluation on the basis of the proposed model is appropriate and practical for assessing a new technology. We expect that the approach introduced in this study could be applied not only to assessing safety performance but also to evaluating other qualitative values in the construction industry.

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