

A Knowledge-based Fuzzy Multi-criteria Evaluation Model of Construction Robotic Systems

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Abstract

In recent years, construction projects have been forced to cope with lack of skilled labor and increasing hazard circumstance of human operations. A construction robotic system has been frequently accomplished as one alternative for overcoming these difficulties in increasing construction quality, enhancing productivity, and improving safety. However, while the complexity of such a system increases, there are few ways to carry out an assessment of the system. This paper introduces a knowledge-based multi-criteria decision-making process to assist decision makers in systematically evaluating an automated system for a given project and quantifying its system performance index. The model employs linguistic terms and fuzzy numbers in attempts to deal with the vagueness inherent in experts' or decision makers' subjective opinions, considering the contribution resulted from their knowledge on a decision problem. As an illustrative case, the system, called Robotic-based Construction Automation, for constructing steel erection of high-rise buildings was applied into this model. The results show the model's capacities and imply the application to other extended types of construction robotic systems.

Keywords : A Construction Robotic System, Fuzzy Numbers, Knowledge-based Multi-criteria Decision-making, System Performance Index

1. INTRODUCTION

During a last decade, there are many attempts to apply diverse robots into construction projects because they are more labor-intensive than those in other industrial applications. Also, the recent aging of the workforce and lack of skilled labors may accelerate increasingly robotic systems in the construction industry. Construction automation has been commonly characterized with the definition that it is "the work using construction techniques including equipment to operate and control construction production in order to reduce labor, reduce duration, increase productivity, and improve the working environment of labor during construction process" (Hsiao, 1994). Recently, a construction robotic system is widely being employed as an effective alternative for insufficient supply of experienced labors, and the bigger and more multifunctional building projects have gradually been deploying such a system. Especially partial robots have been developed and are being successfully used for concrete surface treatments, road-lane paintings (Woo et al., 2008), exterior wall-paintings (Kim et al., 2007), and so on. There have also been other technologies, including the so-called automated building construction systems, such as SMART (Yamazaki and Junichiro, 1998), ABCS (Ikeda and Harada, 2006), BIG CANOPY (Wakisaka et al., 2000), and the Sky Factory system (Tanijiri et al.1997). Furthermore, Lee et al. (2006) developed a machine vision-assisted teleoperated pavement crack sealer and evaluated productivity. Ham et al. (2006) developed road-stripe-removing equipment to save on labor and prevent traffic accidents. This equipment was evaluated on the degree of productivity improvement, quality, and safety. Woo et al. (2008) developed a robotic system for road-lane painting and assessed the performance and capacity of the robot in terms of quality. These previous works have independently focused on measuring

the productivity of the developed robot, the quality of robot's work regarding the required specifications, or environmental safety. However, these previous studies are rarely focused on evaluating the overall performance of a new system because of lack of systematic assessment tools with an indicator.

As the complexity of a system increases, few numerical data exist and only ambiguous or imprecise information may be available, fuzzy multi-criteria decision-making processes provide a way to understand system behaviors and are useful for quantifying uncertainties due to the complexity of contemporary construction robotic systems (Ross, 1995). Experts or decision makers may be unsuccessful in carrying out quantitative assessments, whereas they are comparatively efficient in qualitative evaluations. Further, they are more prone to interference from biasing tendencies if they are forced to provide numerical estimates since the elicitation of numerical estimates forces an individual to operate in a mode which requires more mental effort than that required for less precise verbal statements (Karwowski and Mital, 1986). The applications of fuzzy theory-based approaches have been useful for making a decision in attempts to deal with the vagueness inherent in subjective determinations of preferences (Yager, 1982). This paper introduces a knowledge-based fuzzy multi-criteria evaluation model to assist decision makers in assessing an automated system for a given project, different from an existing computational process.

2. OBJECTIVES AND SCOPE

In this study, the primary goals are to construct a model for evaluating a new or alternative construction robotic system and to improve conventional multi-criteria decision-making approaches, based upon experienced experts'

subjective knowledge. The considerable criteria in evaluating the overall performance of such a system are focused on aspects of construction quality, productivity, and safety enhancement. Here, the productivity assessment is limited on the required labors and time, task-loadings, and constructability, except the increase and decrease of cost. As seen in Figure 1, the study, using the proposed model, explores the ways of handling the ambiguity inherent in subjective opinions and quantifying qualitative information. Also, this study proposes a mathematical function to allocate the contribution of human's knowledge on the decision problem in robot-based automated steel erection and fabrication process, in which a bolting robot is developed as an alternative of the aging and skilled labors. The proposed model is extended to different construction robotic systems in few available data and is intended for the implementations by decision makers in establishing strategic management plans.

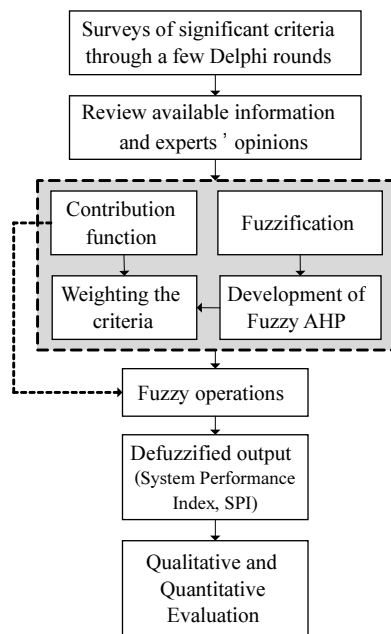


Figure 1. Operation process of the proposed model

3. ASSESSMENT MODEL

As one of popular multi-criteria hierarchical approaches, fuzzy analytic hierarchy process (AHP) has been helpful for evaluating the system performance with the ambiguous subjectivities. Many significant criteria are considered and identified by the experts using a systematic approach like Delphi technique, which has been utilized in pursuing consensus among experts on an uncertain issue (Chan et al., 2001). This technique can efficiently accomplish tasks where there is a lack of statistical support for the conclusion drawn. In general, performance evaluation of a new system may depend greatly on the experts' opinion, intuition, and knowledge. However, there is a difficulty to reflect the contribution of their knowledge corresponding to experience on a decision problem.

3.1. Identifying criteria and constructing hierarchical structures

The lists of significant criteria compiled from open discussions are first clarified in the expert panel. This panel that served as the knowledge source for a system comprises multi experts who participated mainly in its development and applications. Fundamentally, the analytic hierarchy process developed by Saaty (1980) has been utilized for structuring hierarchically multi-criteria and generating rationally numerical weights of criteria from subjective judgment in pair-wise comparison matrices. From the questionnaire surveys, experts' opinions regarding the relative importance of each pair criteria can be collected with the scaled values (Mahdi and Alreshaid). However, this conventional AHP is incapable of handling the inherent ambiguity associated with the mapping of one's perception to an exact number (Pan, 2008). Also, in constructing a pair-wise comparison matrix and weighting the criteria, multiple experts are assumed that they have an equal probability of being correct regardless expertise and experienced knowledge (Aczel and Saaty, 1983). On the other hand, fuzzy approach has been widely used to handle such a subjective and qualitative data to reach a reliable decision (Wardhana and Hadipriono, 2003; Zeng et al., 2007). This paper proposes an advanced fuzzy AHP with a mathematical function that reflects the contribution of the subjectivities into a decision variable and that differentiates the experts' expertise. Since identifying the criteria, this classifies them into a few hierarchical levels on the basis of functional similarities. Their relative importance is presented with linguistic terms or fuzzy numbers instead of 9 scaled values unlike conventional AHP.

3.2. Aggregation of the subjectivities

Once hierarchical levels are structured, the weights of criteria are estimated from a fuzzy pair-wise comparison matrix (\tilde{A}). Based on the modification of Chen's definition (2000), five linguistic terms, "very unimportant (VU)", "less important (LI)", "equally important (EI)", "more important (MI)" and "very important (VI)" ranging 0–10 are used to develop the entries in such a matrix. Among these five linguistic variables, fuzzy numbers representing the VU and VI contain half trapezoidal membership functions, and others are characterized by symmetric triangular membership functions.

$$\tilde{A} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}, \text{ where } r_{ii} = 1 \quad r_{ij} = 1/r_{ji}$$

In this matrix, Buckley (1985) has proposed that the element of the negative judgment is treated as an inverse and reversed order of the fuzzy number of the corresponding positive judgment. Hence it requires careful checks to

avoid errors arising from such tedious manipulations while constructing a reciprocal matrix.

The questionnaire surveys are accomplished since experts or practitioners are fully aware of enough information regarding a given system. They have particularly sufficient experience in fabricating steel erection. In estimating the entries (r_{ij}), if there are k experts, then k numbers $r^1_{ij}, r^2_{ij}, \dots, r^k_{ij}$ are aggregated. However, there is a question how their opinions could be contributed on weighting the criteria. We attempt to investigate how they can be appropriately contributed on assessing the criteria's relative importance. In this study, three types of S-shaped growth curves, the Gompertz, Logistic, and Reverse-Gompertz, are employed to determine the fitted contribution curve through regression analysis. The Gompertz curve models a steep initial increase, and its increment decreases over the experience period. Conversely, the Reverse-Gompertz function shows the opposite behaviour. However, the Logistic curve describes the gradual increase and decrease in learning rate when expertise is increased. These applicable curves are represented as follows:

- Gompertz curve: $y(t)=\exp(-a \times \exp(-b \times t))$
- Logistic curve: $y(t)=1/(1+a \times \exp(-b \times t))$
- Reverse-Gompertz curve: $y(t)=1-\exp(-a \times \exp(-b \times t))$

In the above curves, 'a' is a shift parameter. It is a constant of integration that shifts the curve along the time axis. 'b' controls the increasing rate of the expertise. For computing the values of these parameters, regression analysis is conducted with the data collected by an expert group. For instance, the Gompertz curve can be linearized by taking some algebraic manipulation and logarithms, where $\ln(\ln(y(t))), \ln(-a)$, and $-b$ are replaced with $Y(t), \beta_0$, and β_1 , respectively. These values are presented in Table 1 with R-square, and the fitted curve is also compared to the result from Genetic Algorithms (GAs). The GAs have been widely known as one of powerful ways to search for optimal values (Berry and Linoff, 1997). Figure 2 shows their comparison to the average of the surveyed data for steel erection works, which are derived from the experts and practitioners with experience from 1 to 30 years. The fitted curve on this average is described as follows:

$$\hat{y}(t) = \exp(-1.702 \times \exp(-0.24 \times t)) \dots \dots \dots \text{Eq. (1)}$$

$\hat{y}(t)$ presents the contribution of an expert's opinion, ranging from 0 to 1. This functional curve is efficient to provide a concrete measure of the rate at which an expert is learning a task (Fedorowicz et al., 1992; Lloyd, 1979). The proposed model employs the $\hat{y}(t)$ to differentiate the contribution of the experts' subjectivities according to experience and to aggregate all entries in fuzzy pair-wise comparison matrices as follow:

$$\hat{r}_{ij} = r^1_{ij} \times e_1 + r^2_{ij} \times e_2 + \dots + r^k_{ij} \times e_k, \dots \dots \dots \text{Eq. (2)}$$

$$e_i = \frac{\hat{y}_i(t)}{\sum_{i=1}^k \hat{y}_i(t)}, \sum_{i=1}^k e_i = 1$$

e_i is the contribution degree of i^{th} expert's opinion with experience of t years, and is calculated by the fitted function ($\hat{y}(t)$). In this way, the entry, \hat{r}_{ij} , is aggregated into a trapezoidal fuzzy number ($\hat{a}_{ij}, \hat{b}_{ij}, \hat{c}_{ij}, \hat{d}_{ij}$) because the relative importance from k experts is represented with fuzzy numbers. Then, these fuzzy numbers are converted into matching crisp entries (c_{ij}) within the range of [0, 10] as follows (Saaty, 1990):

$$c_{ij} = \frac{\hat{a}_{ij} + 2(\hat{b}_{ij} + \hat{c}_{ij}) + \hat{d}_{ij}}{6}, c_{ii} = 1 \quad c_{ij} = 1/c_{ji} \dots \dots \dots \text{Eq. (3)}$$

Based on crisp entries, the weights of criteria are computed and utilized for providing a quantitative system performance index (SPI).

Table 1. Results of regression analysis

	Fitted linear equation: $Y(t) = \beta_0 + \beta_1 \times t$				
	β_0	β_1	"a" value	"b" value	R-square
Logistic	1.004	-0.265	2.73	0.265	0.912
Gompertz	0.532	-0.240	1.70	0.240	0.947
Reverse-Gompertz	-0.758	0.113	0.47	0.113	0.861

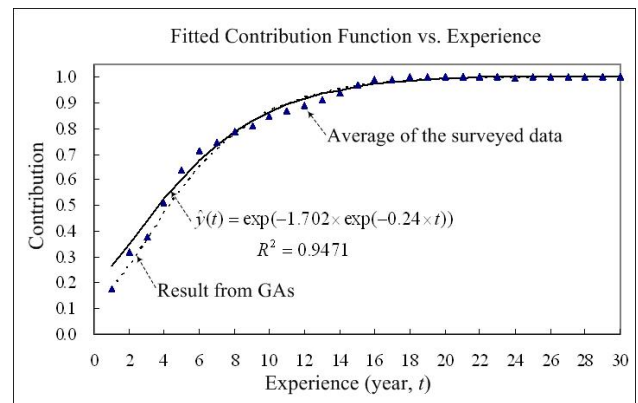


Figure 2. The fitted contribution curve for steel erection work

3.3. Weightings and computing the SPI

To weight the criteria, the aggregated entries, which are converted into trapezoidal fuzzy numbers, are operated by fuzzy multiplication and addition principles. Supposing that there are n main criteria (i.e., $A, B, C \dots$) at 1st hierarchical level, the weights can be calculated as follows:

$$w_{\text{criterion } i \text{ at level } 1} = \frac{1}{n} \left(\sum_{j=1}^n \frac{c_{ij}}{\sum_{k=1}^n c_{kj}} \right) \quad i, j = 1, 2, \dots, n \dots \dots \dots \text{Eq. (4)}$$

In this manner, the equation (4) can be applied into sub-hierarchical levels. For instance, supposing that three sub-criteria (“A1”, “A2”, and “A3”) are involved in the section “A”, their weights are also computed like the below.

$$w_{relative\ weight\ of\ A1} = \frac{1}{3} \left(\frac{\sum_{j=1}^3 c_{ij}}{\sum_{k=1}^3 c_{kj}} \right)$$

The final weight of “A1” can be calculated by $w_{final\ weight\ of\ A1} = w_{relative\ weight\ of\ A1} \times w_A$. All final weights of sub-criteria at the bottom level are used for determining the membership function (MF) of the overall performance. In the application of an illustrative case, using membership functions for standard performance values proposed by Hadipriono (1987), the expert group assesses each criterion of a construction robotic system. This MF is quantitatively computed into a defuzzified value by the center of area (COA) method, which is known as one of the most common defuzzification methods. In other words, the SPI is calculated on the basis of a contribution function handling experts’ subjective knowledge.

$$SPI : y = \frac{\int y_i \times \mu_{SPI}(y_i) dy}{\int \mu_{SPI}(y_i) dy} \dots\dots\dots Eq. (5)$$

,where y indicates the numerical index for the system performance. The $\mu_{SPI}(y_i)$ is its membership function, which is represented by a triangular fuzzy number, $Tri(a_f, b_f, c_f)$, for consistent arithmetic operations with standard performance values.

$$\mu_{SPI}(y : a_f, b_f, c_f) = \begin{cases} 0, & y < a_f \\ \frac{y - a_f}{b_f - a_f}, & a_f \leq y \leq b_f \\ \frac{c_f - y}{c_f - b_f}, & b_f \leq y \leq c_f \\ 0, & y > c_f \end{cases}$$

Here, a_f , b_f , and c_f are derived from multiplication and addition principles of fuzzy numbers of each criterion assessed by multiple evaluators at the bottom level.

$$Tri(a_f, b_f, c_f) = Tri\left(\sum_{i=1}^m a_{Li} \times w_{Li}, \sum_{i=1}^m b_{Li} \times w_{Li}, \sum_{i=1}^m c_{Li} \times w_{Li}\right)$$

,where m is the number of criteria at 1st hierarchical level, and w_{Li} is the weights of each criterion. In the same way, fuzzy number of “L1” criterion, which is presented with $Tri(a_{L1}, b_{L1}, c_{L1})$, is estimated as follows:

$$Tri(a_{L1}, b_{L1}, c_{L1}) = Tri\left(\sum_{i=1}^l a_{L1i} \times w_{L1i}, \sum_{i=1}^l b_{L1i} \times w_{L1i}, \sum_{i=1}^l c_{L1i} \times w_{L1i}\right)$$

Also, t indicates the number of criteria involved by “L1” section at the next level. In this expression, a_{L1i} is instantly described by the summation of the products of the contribution degree and the surveyed fuzzy number like the following.

$$a_{L1i} = a^1_{L1i} \times e_1 + a^2_{L1i} \times e_2 + \dots + a^n_{L1i} \times e_n$$

a^1_{L1i} , a^2_{L1i} , ..., and a^n_{L1i} are determined of n evaluators. For implementing the model’s capacity, information regarding the variation of the SPI helps to verify a contribution function allocating the experts’ subjective opinions. Also, knowing this variation assists in demonstrating that the computed SPI is convincible. A numerical simulation is used to randomize such a contribution with a random number generator to create real numbers between 0 and 1.

4. AN ILLUSTRATIVE CASE

4.1. Overview of a robot-based construction automation system

Many construction automation systems have often provided insufficiently economical benefits in spite of the wide applications into the construction industry because they have focused on the system’s development, but not its practical use. A robot-based construction automation (RCA) system is developed in Korea and its application is in progress to constructing a 7-stories building as a pilot project. The RCA system consists of three main technologies: (1) intelligent tower crane (ITC) based on radio frequency identification (RFID) devices and global position system (GPS), (2) bolting robot for steel erection and supporting mechanics, and (3) 4D-based monitoring system for robot control, which presents visually construction progresses.

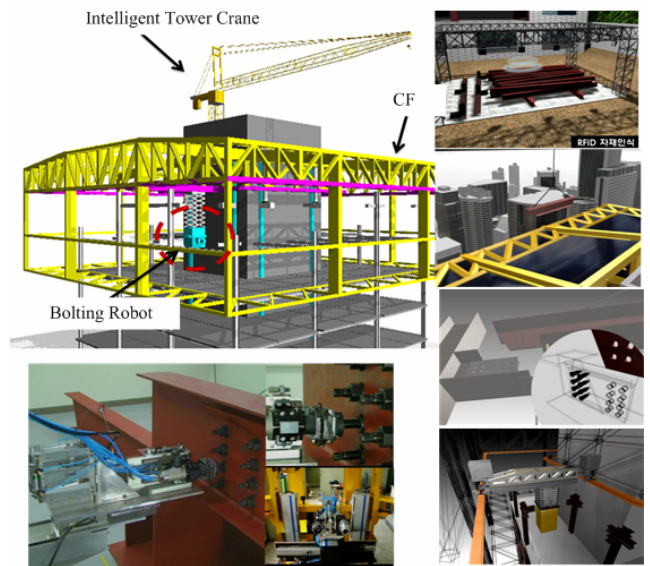


Figure 3. The configurations of the RCA system

As shown in Figure 3, the ITC identifies and moves materials from storage yards to the planned place using the

RFID-based sensor and the GPS. Then, the bolting robot developed by the RCA research group is moved on guard-rails. The rails are supported by the construction factory (CF) (Kim et al., 2009). The CF is fixed to the core and moved vertically using a hydraulic device. In the RCA system, radio-frequency identification (RFID) technology is applied for a tower crane to identify and to move steel structures toward a targeted location without the labors. In detail, recognizable tags, which are attached to steel structures, force their locations to transmit into a main control center via 4D-based monitoring for robot control (4DMRC) system, and all recognized information is re-sent to the tower crane for its intelligent operation (Do et al., 2009). Steel structures are moved from storage yards to the places traced from global positioning system (GPS) with three phases; lifting, horizontal movement, and un-loading. The 4DMRC system checks progress in real-time and monitors information obtained via the RFID and GPS. On the basis of this information, construction managers on site can investigate proactively possible problems and interferences between automated activities or tasks.

As another core technology, the bolting robot introduced in the RCA system is utilized for reducing the potential of the workers' falling accidents in fabricating steel structures at high elevation. The robot's operation is supported by automatic movement guardrail and construction factory (CF) because it is difficult to maintain autonomously the stability. The moving-route is determined by information transmitted from the 4DMRC system. The assembly design for automation (DFA) of steel columns and girders, which is developed by the research group, is employed for aligning the bolts and nuts. Also, the bolting robot is vertically moved with the CF, which protects interferences from external activities and circumstances and improves labors' mental stability.

4.2. Comparison of conventional process and the RCA system

The RCA system can be compared with conventional construction process in five technical aspects as seen in Table 2. Firstly, the lifting task in conventional process is operated by the workers who confirm the needed materials and send a signal to crane operators. However, in the RCA system, steel structures are traced and lifted from storage yards through the 4DMRC system. Information transmitted by an automatic identification device, which is attached to the ITC, is sent to this system in order that the ITC can be automatically operated. Secondly, while erection and fabrication are also positioned and conducted by the workers in conventional process, the ITC and bolting robot substitute these tasks in the application of design for automation (DFA). In particular, the DFA is intended for simplifying connection of a column to a girder and reducing the possibility of the workers' falling accidents. Thirdly, a developed bolting robot is utilized to assemble steel structures, such as columns and girders, with end-effectors selecting and feeding the bolts and nuts.

4.3. The output explanation

Table 2 shows the criteria to assess the overall performance in aspects of construction quality, productivity, and safety. Using the equations (1), (2), (3), and (4), the weights of each criterion are computed on the basis the surveyed results from the expert group consisting of 13 practitioners with different experience. For instance, $\tilde{A}_{quality, productivity, \text{ and } safety}$ is a fuzzy pair-wise comparison matrix for main criteria at 1st hierarchical level, and the entries are represented by crisp values, which are derived from fuzzy numbers aggregated by a contribution function ($\hat{y}(t)$).

$$\tilde{A}_{quality, productivity, \text{ \& } safety} = \begin{bmatrix} 1 & 1.01 & 0.13 \\ 0.99 & 1 & 6.37 \\ 7.69 & 0.157 & 1 \end{bmatrix}$$

$$W_{Main\ criteria} = \{W_{quality}, W_{productivity}, W_{safety}\} \\ = \{0.201, 0.471, 0.328\}$$

Table 2. Comparison of technical operations in steel fabrication

Operations	Conventional process	RCA system
Lifting	Materials' trace, delivery, supervision, and control by labors and crane operators	Materials' trace, delivery, supervision, and control by the RFID wireless recognition and intelligent tower crane
Erecting	Positioned by labors	Positioned by the ITC and 4DMRC system, based upon design for automation (DFA)
Bolting	By skilled labors with equipment to maintain the vertical stability	By a bolting robot developed in the RCA system
Plumbing	Done by labors	Done by labors
Welding	Done by labors	Done by labors

Hence, the final weights of nine sub-criteria under three major categories (quality, productivity, and safety) are computed from their relative weights. The four highest weights are "reduction of the needed labors and time", "increase of labors' psychological stability", "decrease of intensive task-loadings of tower cranes", and "increase of bolting successes". Their summation makes up 72.2% of the whole weight.

In order to compute the SPI, an evaluation group consisting of 2 practitioners, 5 engineers, and 3 steel fabrication managers is surveyed. Based on Hadipriono's model (1987), eleven linguistic terms regarding performance evaluation 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. The evaluation group determines linguistic values for nine sub-criteria, which are converted into fuzzy numbers. Figure 4 shows the membership functions for standard performance values of each linguistic term.

Table 3. Criteria’s hierarchical structures and weightings for assessing the RCA system

Goal	1 st hierarchy	2 nd hierarchy	Relative weight	Final weight	Simulation	
					Mean	Std.
Quality (L1)		L11: Increase of bolting successes	0.677	0.136	0.133	0.041
		L12: Enhanced simplicity of complicated tasks	0.254	0.051	0.049	0.012
		L13: High-qualified assemblies	0.070	0.014	0.014	0.007
		L21: Reduction of the needed labors and time	0.484	0.228	0.231	0.097
SPI	Productivity (L2)	L22: Decrease of intensive task-loadings of tower crane	0.329	0.155	0.149	0.031
		L23: Enhanced constructability	0.187	0.088	0.091	0.023
		L31: Increase of labors’ psychological stability	0.632	0.203	0.207	0.108
Safety (L3)		L32: Decrease of hazard circumstances	0.290	0.093	0.097	0.031
		L33: Precaution of unexpected accidents	0.098	0.032	0.029	0.012

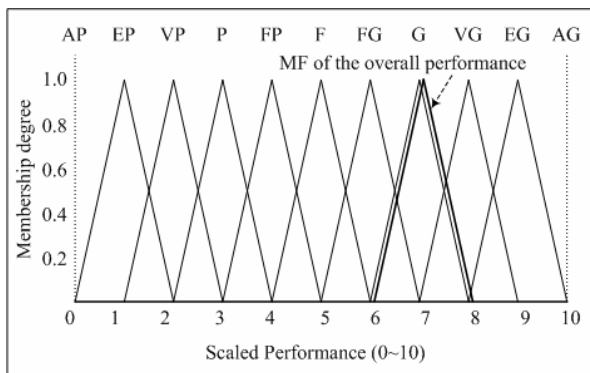


Figure 4. Example of standard performance values (Hadipriono, 1987) and membership function of the system’s overall performance

Using the equation (5), the final membership function of the SPI is converted into a defuzzified value. The mean and standard deviation of the results from numerical simulation, which is utilized for randomizing the contribution, help to verify the allocation of experts’ knowledge using the fitted curve. Figure 5 shows the results from 1,000 si-

mulation cycles under the randomized contributions. The mean and standard deviation are 7.19 and 0.345, respectively. The defuzzified SPI agrees closely with the mean, and is also in the boundaries of “mean – std.” (6.84) and “mean + std.” (7.53). Consequently, the overall performance of the RCA system lies between good and very good, but closer to good.

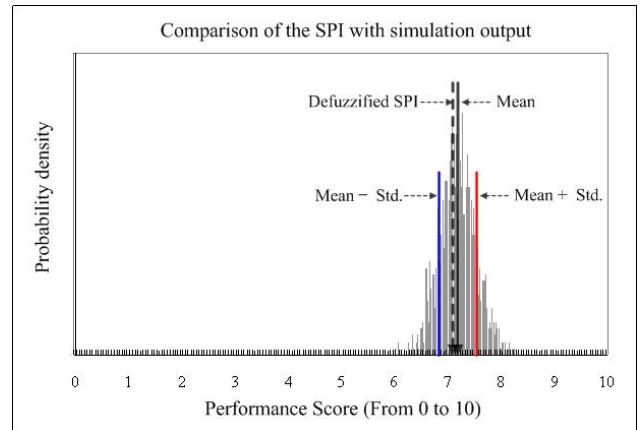


Figure 5. Comparison of the defuzzified SPI and simulation output

5. CONCLUSIONS

In the past, there are many attempts to carrying out an assessment of various robot-based systems or technologies, based on the quantitative and qualitative manner. In the industrial applications, many performance evaluation techniques are comparatively mature tools and applied to demonstrating the system’s capabilities. However, in the construction industry, they may not give satisfactory results due to the incomplete data and insufficient information from a new system. It is vital to develop one systematic approach to assess the system performance in an acceptable way. This study focused on the development of a knowledge-based fuzzy multi-criteria decision-making process, which evaluates the overall performance of a construction robotic system. As an illustrative case, the RCA system was applied into this model, and the result was rationally agreed with simulation output. This system was developed to improve construction quality, productivity, and safety performance in the steel erection work of high-rise buildings. In particular, the RCA system is expected to reduce steel erection time, to increase psychological stability of workers, to decrease of intensive task-loadings of tower cranes, and to increase bolting successes in fabricating the steel structures. A few advantages of the model developed in this study are summarized as follows:

- Provide ability to allocate the contribution of experts’ knowledge on the decision problem of a characterized work and to deal with the vagueness inherent in subjective judgments, unlike conventional multi-criteria evaluation model;

- Enable a contribution function derived from regression analysis to be extended to other types of construction robotic systems with the various technologies; and
- Indices for illustrating the system's performance are computed in a quantitative way, which assists decision makers in establishing strategic operation plans.

To illustrate a mathematical contribution function, numerical simulation has been conducted and the results showed that the model introduced in this study might be utilized as quantitative indicators for assessing a new robot-based system or technology. Nevertheless, this research has a difficulty to assess a virtual system that is not experienced, such that the performance evaluation of such a system is dependent on the experts' subjective intuition and knowledge. In the further, the efficiency of the presented model would also be reviewed since a pilot project is completed, on aspect of cost reduction derived from the RCA system. Even if the model implies useful capacities, it is suggested that an ultimate decision is performed simultaneously with professional judgment of experts or decision makers due to inherent characteristics of the complicated robot-based systems. Furthermore, vital areas of future research are to derive the beneficial achievements in a quantitative way and to assess them over the costs for practical applications.

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