



## EVALUATING MOTIVATION OF CONSTRUCTION WORKERS: A COMPARISON OF FUZZY RULE-BASED MODEL WITH THE TRADITIONAL EXPECTANCY THEORY

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**Abstract.** Measuring workers' performance and the level of motivation is of paramount importance as the productivity of workers at a workplace primarily depends upon their level of motivation. However, measuring the level of workers' motivation at workplace is not always straightforward because the workers' motivation is a function of various personal and external factors. This paper proposes a fuzzy rule-based model for evaluating the motivation level of construction workers using their working patterns. The motivation level evaluated using the fuzzy rule-based model was compared with motivational levels determined by the traditional Vroom's expectancy theory or Expectancy-Instrumentality-Valence (EIV) method. EIV method used questionnaire surveys and interviews to determine workers' motivation. The results of fuzzy rule-based models aligned closely with the EIV model, especially for the middle range of motivation levels. Compared to traditional EIV model, the fuzzy rule-based system is simple to implement and found to be very pragmatic in construction field settings.

**Keywords:** worker motivation, construction productivity, expectancy theory, fuzzy set theory, fuzzy rule-based model.

### Introduction

The construction industry is an important industrial sector that plays a vital role in the national economy including Canada and the rest of North America due to the usage of its end products such as roads, buildings, dams etc. However, decline of construction productivity in North America has been reported by many researchers over the past decades (Choy, Ruwanpura 2006; Hewage, Ruwanpura 2006, 2009; Song, AbouRizk 2008). There are many factors which contribute to the decline in construction productivity including low worker motivation, inadequate communication, unclear instructions, worker fatigue, poor materials and tools management standards, poor relations between workers and management, poorly organized projects, unfair work assignments, incomplete design/engineering work, lack of cooperation among different crafts, poor supervision, rework, no worker participation in the decision-making process, restrictive and burdensome procedures, and so on (Hewage 2007).

A major portion of construction budget, about 25–40% of the project capital cost, is allocated to labour expenses (Nasirzadeh, Nojedehe 2012; Ng *et al.* 2004). Many recent researches emphasize on the fact that labour force plays a crucial role in the construction process, thus there is a need to maximize the productivity of labour re-

sources (Jergeas, Ruwanpura 2009; Nasirzadeh, Nojedehe 2012; Ng *et al.* 2004). Therefore, it is very important to find solutions for declining construction productivity in terms of labour issues that may save billions of dollars and make construction an attractive business.

Productivity has many definitions based on selected performance factors such as production rate, unit person hour rate, etc. In the context of construction, however, project managers and construction professionals recognize productivity as an in-place value divided by inputs, such as work hours (Hanna *et al.* 2005; Nasirzadeh, Nojedehe 2012). High productivity refers to the intensive and/or efficient use of scarce resources converting inputs into outputs, which ultimately lead to more profit (Arditi 1985; Dai *et al.* 2009). Some argue that the productivity can be achieved/increased by working harder, faster, or longer. However, in the real world, productivity cannot be achieved by only speed and hard work without adopting the best management and work practices (Banik 1999). Even with the advent of more sophisticated technology, the construction industry continues to be predominantly labour-intensive, suggesting for the need to give proper emphasis to such matters like communications, participation, and motivation (Hwang, Liu 2010; Mansfield, Odeh 1991).

## 1. Background

### 1.1. Motivation as a tool for improving productivity

Motivation has a wide variety of definitions. According to Jenkins *et al.* (1982), motivation is intangible: a hypothetical construct that is used to explain human behaviour. Motivation can be either intrinsic or extrinsic. Intrinsic motivation is generated by a factor that comes from within the subject (self-actualisation, satisfaction, more individual control). Extrinsic motivation is generated by a factor that comes from the exterior (e.g. pay increase, promotion, quality awards, etc.).

Recently, Westover *et al.* (2010) conducted a research to explore 17 key work domains that impact workers' productivity and motivation. Both recent and earlier researches in the construction industry have revealed that productivity and motivation are interdependent (Rose, Manley 2011; Warren 1989).

The imperative need of discovering, comprehending, and implementing employee motivation has been a principal concern for organizations, managers, and even first line supervisors because employee motivation has been and will be the deciding factor in work performance which lead to the success or failure of an organization (Dongho 2006). Consequently, considerable research has been reported on the relationship between motivation and productivity in the construction industry over the last 40 years (Edwards *et al.* 2007; Hewage 2007; Love *et al.* 2005; Olomolaiye, Price 1998; Zhou 2004).

In an earlier research Maloney and McFillen (1987) conducted a comprehensive research study on construction labourers' motivational patterns, which focused on the importance attached to various job-related factors and their satisfaction over each factor. Further, they said that the motivation has a direct impact on the work performance, and it can be positively influenced or managed by external factors, such as incentives and rewards.

Zhou (2004) conducted a research on motivating construction management professionals and indicated that motivation, when it is combined with work experience and education, is an important factor in improving performance and thus productivity. Hewage (2007) studied fifty one factors affecting productivity and prioritized those factors into nine categories. In that research motivation ranked the second important factor affecting the workers' productivity. Accordingly, motivators should be of a great concern to managers in construction organizations, as the proper implementation of motivational programmes can encourage employees to act in the desired way to accomplish the organization's goals at the same time as they meet their own personal objectives or motives (Mansfield, Odeh 1991).

Theories of motivation are not discussed in detail in this paper, as such information already available in literature. Hewage (2007) provided one such review, which clearly outlined the origins of motivation theories that applied to study construction workers. Hewage (2007) explained several theories available to present the con-

cept of motivation. The list includes Maslow's Hierarchy of Needs Theory (Huitt 2004; Maslow 1943), Herzberg Motivational Theory (Herzberg *et al.* 1959), McGregor's theories X and Y (McGregor 1960), Adams' Equity Theory (Adams 1963), Vroom's expectancy theory (Vroom 1964), Brehm's Reactance theory (Brehm 1966), Locke's Goal theory (Locke 1968), Reinforcement Theory (Skinner 1969), Alderfer's ERG Theory (Alderfer 1969), and Ouchi's theory of Z (Ouchi 1981). Detailed definitions, background information, and other related issues of these theories can be also found in Jang *et al.* (1997), Latham and Pinder (2005).

This research mainly aims to demonstrate the application of the expectancy theory of Vroom (1964) to quantify motivation in the construction industry. Several new researches used and improved the expectancy theory in different management extents. Chiang and Jang (2008) applied a modified expectancy theory with five components to investigate employee motivation in the hotel setting and confirmed the validity of expectancy theory. Gorges and Kandler (2012) examined the applicability of expectancy-value theory to adults' learning motivation. Kominis and Emmanuel (2007) investigated the relationship between managerial perceptions of elements of the performance measurement, evaluation and reward system, and motivation. They developed an extended version of the traditional expectancy–valence model to conceptualise the process of motivation at the middle management level.

There is a strong history of researchers who explored motivational expectancy theories in a wide variety of formats, including case studies. Yet, too few have focused their work specifically on *construction workers*. Among formerly researches Maloney and McFillen (1986, 1987) conducted a research to study operational construction employee motivation amongst union members in America. They determined that the expectancy theory is a workable conceptual base for understanding the motivation of construction workers (Maloney, McFillen 1986). They conclude that application of expectancy theory principles to construction work pinpoints significant areas for action if construction workers are motivated towards higher productivity (Maloney, McFillen 1986).

In more recent works Lam and Tang (2003) review key motivation concepts, and describes how to apply the theory into practice in construction projects. The authors offered a viewpoint with both short-term and long-term motivation schemes. Price *et al.* (2004) presented empowerment as the key tool to motivate the workforce. The researchers suggested that culture, training, and knowledge management lead to workers empowerment through incentive, thus motivate the workforce, and ultimately improve construction performance.

Hewage and Ruwanpura (2006), Hewage (2007) applied Vroom's expectancy theory as the bases to quantify construction worker motivation. They investigated work-

er motivation and productivity, which are under human issues. They overcame the challenge of quantification of motivation by using Vroom's motivational expectancy theory with other "construction" applicable theories such as equity theory, Herzberg's hygiene theory, and reinforcement theory. The background information on expectancy theory is provided below.

The expectancy theory of motivation (also called the Expectancy-Instrumentality-Valence (EIV) model) is a theory explaining the process of individuals' decisions on various behavioural alternatives. To relate performance to motivation in a mathematical form, Vroom (1964) defined the performance (P) as a function of the product of motivational force (M) and workers' ability (A), i.e.,  $P = f(M.A)$ . Expectancy theory suggests that motivation depends on individuals' expectations on their ability to perform tasks and receive desired rewards. Expectancy theory can be expressed using following equation:

$$\text{Motivation} = f \sum (E \rightarrow P) \times (P \rightarrow O) \times V, \quad (1)$$

where:  $E \rightarrow P$  – Effort to performance expectancy (Expectancy);  $P \rightarrow O$  – Performance to outcome expectancy (Instrumentality); and  $V$  – Valence.

Effort to Performance expectancy ( $E \rightarrow P$ ) is the belief that effort leads to a desired performance level. In other words, workers tend to perform more if they believe in and feel confident about their efforts. Performance to Outcome expectancy ( $P \rightarrow O$ ) is the belief that performance will be followed by the desired outcome. Valence is the preference or appreciation of the outcomes or end results.

Vroom's expectancy theory has been selected for this study because (i) this theory is based on the relationship between the individual's effort, individual's performance, and the desirability of outcomes associated with high performance, (ii) this theory provides a general framework for assessing, interpreting, and evaluating employee behaviour in learning, decision-making, attitude formation, and motivation, (iii) this theory has been rigorously tested and has received strong support (Fudge, Schlacter 1999), and (iv) this theory would seem most applicable to the construction work in which motivation level of employees depends on either they want the reward on offer for doing a good job or if they believe more effort will lead to that reward (Hewage, Ruwanpura 2006).

## 1.2. Fuzzy rule-based model (FRBM) for evaluating motivational force

Subjective (asking workers about their perceptions of motivation and what influences it) or objective measures (directly observing factors such as timeliness, or checking attendance records) have been widely used to measure the performance and the level of employees' motivation (Bennett et al. 2001). Questionnaire and interview sur-

vey techniques are also frequently used in the construction management field (Lyons, Skitmore 2004; Mangione 1995). However, the questionnaire and interview survey techniques have limitations. The major limitation of the survey method is that it relies on a self-reporting method of data collection. Intentional deception, poor memory, or misunderstanding of the questions, all can contribute to inaccuracies in the data (Trochim, Donnelly 2007). Questionnaires usually have low response rates, require longer time periods, and are more affected by self-selection, lack of interviewer involvement, and lack of open-ended questions. Similarly, interviews are labour-intensive, time-consuming and expensive, and it requires trained interviewers. Collecting data through survey methods is also an imposition if it does not benefit the individual surveyed. Likert scales are widely used in these survey questions to elicit preferences or evaluations (Gob et al. 2007; Tsaur et al. 2000). However, due to intangible and subjective information often appearing in the evaluation process, crisp values in traditional Likert scale are inadequate to present the evaluation ratings of interviewees (Hu et al. 2010; Lalla et al. 2004). Some of the problems associated with the Likert scale method include: (1) social desirability bias, i.e. tendency to provide responses that the respondent believes are those which make him or her "look good"; (2) acquiescence bias, i.e. the tendency to agree rather than disagree with any statement; (3) central tendency bias, i.e. the tendency to respond towards the center of the response scale (Lalla et al. 2004).

Fuzzy logic model, also known as fuzzy inference system or fuzzy rule-based model, is a logical-mathematical procedure based on fuzzy set theory (Zadeh 1965) that is considered suitable for dealing with many real world problems, characterized by complexities, uncertainties, and a lack of knowledge of the governing physical laws (Kumar et al. 2007). Fuzzy logic extends the general form of Boolean logic, true and false to handle the concept of vagueness and uncertainty. This approach takes a value between 1 (full belongingness) and 0 (no belongingness), rather than a crisp value. The degree of belongingness is called the membership function (Erinawati, Fenton 2004). This characteristic allows capturing the uncertainty inherent to real data.

A typical fuzzy logic system consists of three major components: fuzzification, fuzzy inference, and defuzzification. Fuzzification comprises the process of transforming crisp values into grades of membership for linguistic terms of fuzzy sets. The membership function is used to associate a grade to each linguistic term (Kramer et al. 2009). The shape of membership functions of fuzzy sets can be triangular, trapezoidal, bell-shaped, sigmoidal, or another appropriate form, depending on the nature of the system being studied (Sadiq et al. 2004). Among them, triangular and trapezoidal shaped membership functions are predominant in current applications of fuzzy set theory, due to their simplicity in both design and implementation based on little information (Rihani et al. 2009).

The second step, fuzzy inference is a process of formulating a mapping from inputs to output using fuzzy logic. A fuzzy inference system is composed of fuzzy if-then rules relating different fuzzy sets (linguistic constants), which are stored in a knowledge-base, and an inference engine that performs approximate reasoning (Ross 2004). Finally, in defuzzification, the linguistic results obtained from the fuzzy inference are translated into a real crisp value (Ross 1995). This phase is responsible for transforming the fuzzy results from the fuzzy system into crisp values (Kusan *et al.* 2010). There are several defuzzification methods, such as the max-membership, center of gravity, weighted average, mean-of-maxima membership, center of sums, center of the largest area, and first or last of maxima methods (Ross 1995). Among all these methods, center of area method is used in most of the applications.

Fuzzy logic has been successfully applied in virtually all areas of engineering and computer sciences, as well as in areas of decision making, optimization, management, and operations research (Klir, Yuan 1995). Some advantages of fuzzy logic and fuzzy inference system recently stressed in different research areas (e.g., Hajkiewicz, Collins 2007; Islam *et al.* 2013; Jaramillo, González 2009; Lermontov, Yokoyama 2009). These advantages include, but not limited to: (1) developing a clear mathematical model; (2) describing nonlinear relationships using simple rules; (3) formalizing the reasoning process of human language using fuzzy logic; and (4) incorporating expert opinions with real data (Chang *et al.* 2001; Islam *et al.* 2013).

According to Fayek and Flores (2010), fuzzy logic has been used in construction industry for risk assessment (Tah, Carr 2000; Nasirzadeh *et al.* 2008), range estimating (Shaheen *et al.* 2007), predicting and diagnosing construction performance (Dissanayake, Fayek 2008), assessing working conditions (de Vries, Steins 2008), contractor selection (Bendaña *et al.* 2008), and determining cost estimating relationships (Mason, Kahn 1997). However, there are limited studies on the use of fuzzy logic to predict and evaluate the performance and motivational levels of workers in construction industry.

This paper aims to indicate the application of fuzzy rule-based model, with observed working patterns of workers, as a tool to evaluate the motivation levels of workers in the construction industry. In addition, this research also involves the following sub-objectives: (i) evaluation of motivation of the construction workers using the expectancy theory based on the survey research method (questionnaire survey) and (ii) application of fuzzy-Likert scale to quantify and analyse questionnaire survey data collected by traditional Likert method to improve the evaluation of workers' motivation using expectancy theory.

## 2. Research methodology

This section provides a brief overview of the methodological consideration and approach of the study. It describes

the data collection methods and outlines the expectancy theory and fuzzy inference methods of evaluating motivation and productivity of construction workers.

### 2.1. Evaluation of worker motivation using expectancy theory (EIV model)

#### 2.1.1. Questionnaire survey

A questionnaire survey was used to collect data for evaluating motivation of construction workers using the EIV model. The questionnaire surveys were anonymous. The researcher assigned a number to each worker and asked the project coordinator to pick a number. Neither the worker nor the coordinator were aware of the assigned numbers to individual workers. Workers (research subjects) were selected for interviews and questionnaire surveys on a random and voluntary basis. An “anonymous” questionnaire was given to the selected participant after a short interview.

Observation of a given worker were conducted on the same day after the project coordinator picked a number (worker). Worker was not aware of individual “observation”. However, all the workers were informed (in general) of potential “observations”, in the given research period, in a particular construction project. Observations were used to verify the views expressed in the interview against the observed working patterns. The format settled for observation was a 30 minute observation in the morning, followed by the interview conducted after the morning coffee break (usually at 9:45 am), and then 30 minutes of observation of the same worker in an afternoon of a different day. As mentioned above, the research subjects were not aware of individual observation focuses of a given time. In addition, the observation was conducted from a distant location to minimize the disturbances to construction workers.

A total of 101 workers from four projects were interviewed, observed, and then invited for participating in the survey (information regarding sample size validity has been provided in Appendix). The authors had several discussions with social science research methods experts (professors) and psychology doctoral students to verify the face validity of the intended research tools (interview and observation). Face validity was based on the rational judgment of the researchers and experts (whether or not an object is truthful about what is saying and/or behaving) to indicate the appropriateness of a measurement instrument to measure a given phenomenon. The researchers were well satisfied with the methods employed during the direct observation and interview conducted to measure the intended phenomena. All participants of the survey were allowed to take questionnaire home for completion and return later. Answering to the questionnaire survey was optional and on a voluntary basis in order to assure the truthfulness of the survey responses.

Out of 101 interviewed and observed workers, 39 workers returned the responses, representing 39% response rate. Of the 39 returned responses, one was not

usable due to substantial missing information. Thus, remaining 38 responses were used for the analysis. The construction workers who participated in the survey included carpenters, carpentry foremen, and carpentry helpers working in various construction activities including formwork, false work (the supporting structure for formwork such as jacks and props), and columns. The background information of participants in the questionnaire survey is summarized in Table 1. Detailed information on the type and nature of survey questions and the background information of participants in the questionnaire survey were presented in Hewage (2007).

The questions of the survey were divided into three sections: two questions designed to measure the worker's beliefs about the possibility of certain outcomes when working in the construction; 23 questions related to instrumentality designed to measure the possibility of getting certain rewards attainable while working in the construction site; and 23 questions related to valence designed to measure the importance of each outcome that might result from working in construction site. These questions were answered on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree as shown in Table 2.

Table 1. Profile of respondents

Profile	Total number = 38	
	N	%
Gender		
Male	38	100
Education		
Primary School/Intern	2	5.3
High school degree	12	31.6
Completed some college	4	10.5
Technical College or university	13	34.2
No response	7	18.4
Department		
Carpenters	18	47.4
Foremen/Surveyors	11	28.9
Labours	3	7.9
No response	6	15.8
Year of experience		
10 years and below	13	34.2
11–20 years	12	31.6
20 years and above	6	15.8
No response	7	18.4

### 2.1.2. EIV model and data analysis

The motivation ( $M$ ) of the construction workers using expectancy theory is evaluated by using Eqn (2):

$$M = \sum E \times I \times V, \quad (2)$$

where:  $M$  – Motivation,  $E$  – Expectancy,  $I$  – Instrumentality and  $V$  – Valence.

Because of the limitations of traditional Likert scale (crisp value) discussed in the introduction section of this paper, both traditional Likert scale and fuzzy-Likert scale were used for the questionnaire data in the EIV model. First, each crisp Likert scale was normalized within the range of 1/7 to 1 as shown in Table 2. Then the fuzzy-Likert scales were obtained by transforming every element of the discrete normalized Likert scale to a Fuzzy set using Eqn (3). Triangular fuzzy membership was used for simplicity although the selected shape should be justified by available information (Guyonnet *et al.* 1999):

$$\mu(L_N, x) = \begin{cases} 1 - 7|L_n - x|, & \text{if } |L - x| \leq \frac{1}{7}, \\ 0, & \text{otherwise} \end{cases}, \quad (3)$$

where:  $\mu(LN, x)$  – the membership function of the fuzzy-Likert scale, and  $LN$  – normalized crisp Likert scale.

Table 2. Description of Likert scale and assumption of fuzzy numbers

Linguistic Variables	Likert scale	TFN representation	Normalized TFN values
Strongly disagree / Very low	1	[0,0,1]	[0,0,1/7]
Disagree / Low	2	[1,2,3]	[1/7,2/7,3/7]
Somewhat disagree / somewhat low	3	[2,3,4]	[2/7,3/7,4/7]
Neutral / Average	4	[3,4,5]	[3/7,4/7,5/7]
Somewhat agree / Somewhat high	5	[4,5,6]	[4/7,5/7,6/7]
Agree / High	6	[5,6,7]	[5/7,6/7,1]
Strongly agree / Very high	7	[6,7,7]	[6/7,1,1]

## 2.2. Modelling worker motivation using FRBM

The proposed fuzzy rule-based model used observation data (working time distribution) to evaluate the motivation level of workers in construction industry. In this study, all 38 workers who returned the questionnaires were continuously observed twice: 30 minutes in the morning shift and 30 minutes in the afternoon shift, to measure working time (tool time) and other time spent on different activities. During the observation data collection, the time spent for construction activities by each worker was divided into two main categories: working (tool time) and non-working time. The non-working time is further divided into seven sub-categories: materials searching time, tools searching time, socializing time, moving time, instructions time, idle, and time for others.

### 2.2.1. Variable selection

If all these eight time categories were described by three linguistic descriptors/constants (i.e., three membership functions), then  $3^8 = 6561$  rules would be required to develop a FRBM. According to Gallo *et al.* (1999) and Dubois and Prade (1980), the development of fuzzy inference system characterised by a large number of input

variables (more than five or six), appears very difficult especially in knowledge engineering in order to specify the real input variables, the relative relations, such as the consequent complexity of the knowledge base. Bendaña *et al.* (2008) applied fuzzy-logic-based systems for evaluating different qualitative and quantitative criteria for selecting contractors. They established specific ways to facilitate working with higher numbers of input variables.

In construction environment, the amount of working time has a direct impact on the Output (Choy, Ruwanpura 2006). Choy and Ruwanpura (2006) indicated that the relationship between working time and output can be expressed as the efficiency, which is the amount of work done per unit of the working time, not the total time. Accordingly, in the current study, workers' time spent on construction activities were divided into two main categories: working and non-working time. Non-working time consists of activities such as looking for materials and tools, idling, socializing, and moving. Table 3 shows all the observed time categories.

Table 3. Working patterns of construction workers and observational categories

Category	Definition
Work (tool) time	Direct effective working time.
Looking for materials	Time spent on searching, waiting, or moving materials from another place away from individual's working area.
Looking for tools	Time spent on searching, waiting or moving tools from another place away from individual's working area.
Socializing	Socializing or chatting time on top of the assigned breaks.
Moving	Moving around the site without performing anything related to the given work.
Instructions	The time spent for receiving or giving instructions.
Idle	Time spent in construction site without performing anything related to the assigned job.
Other	Moving away from the working/observational area, staying near heaters, or something not mentioned in above categories.

Based on the observation results, the average effective working time (tool time) of observed workers was 47.7%, as shown in Figure 1. This does not mean the workers were engaged in non-work related activities for the remaining 52.3% of the non-tool time. Non-tool time consists of some supporting activities such as material handling and instructions. The largest portion of non-tool time in Figure 1 is "looking for materials" (definition in Table 3). When workers were looking for materials, it led to other interruptions such as stopping at several other places, chatting, and smoking. On many occasions, it was observed that workers and foremen did not plan for material requirements based on work progress or the work targets of the day. As a result, workers had

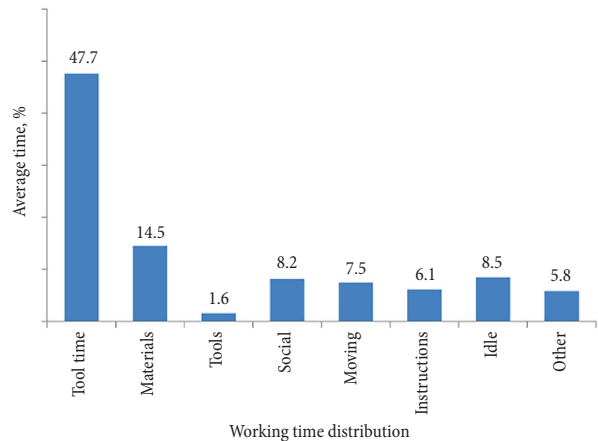


Fig. 1. Working time distribution of the 38 construction workers

to deal with the immediate demands of issues related to materials. "Idling" was the second largest portion of non-working time. Construction workers spent about 8.2% of their "total working time" for socializing. Based on the observation results, some workers tend to use working time as a socializing time. However, observers couldn't identify any direct relationship between social time and motivation level of individual workers.

In this research, four out of eight variables with observable effects on lowering/increasing the workers' motivation were selected. A detailed analysis of working efficiencies and the working patterns of construction workers was presented by Hewgae (2007). In addition, Choy and Ruwanpura (2006) discussed the impacts of non-tool time on other time categories in detail. The four selected worker time distributions are tool time, time for looking tools, time for looking materials, and idle time. The working (tool) time is the direct effective working time. It is directly related to worker's efficiency (performance) and automatically considered as input variable. The effective working (tool time) time of all 38 construction workers included in this study is the largest portion of the time distribution, as shown in Figure 1. Similarly, the time for searching materials that refers to the time spent on searching, waiting, or moving materials from another place away from individual's working area was the largest portion of non-tool time. Searching for tools is the time spent on searching, waiting, or moving tools from another place away from individual's working area. The time for searching materials and the time for searching tools were combined together and considered as a single input (variable) in the proposed FRBM. Hence, three input variables used in fuzzy rule-based models are working (tool) time, materials and tools searching time, and an idle time.

Other time variables with imprecise observable effects on motivation, i.e. social time, moving time, and instruction times, were eliminated. This means that the observers couldn't identify any distinct relationship between these time variables and workers' motivation.

It is necessary to mention that none of the existing engineering literature reported a behavioral study on construction workers to identify direct or indirect correlation between these eliminated time variables and motivation of construction workers.

### 2.2.2. FRBM setup

The Mamdani-type fuzzy inference system was used to define the relationships between the inputs and outputs using the fuzzy logic toolbox in MATLAB (Mamdani, Assilian 1975; Pedrycz 1996). The input and output membership functions for this study were constructed based on the time distribution data collected in the field. Mixed membership functions with three linguistic constants were chosen to describe each input variable, namely: low (trapezoidal membership function (TzMF)), medium (triangular membership function (TMF)), and high (trapezoidal membership function (TzMF)). Five membership functions, namely very low (TzMF), low (TMF), medium (TMF), high (TMF), and very high (TzMF) were used to define the output (motivation). The membership functions used for the input and output variables are illustrated in Figures 2 (a)–(d).

The fuzzy operator “minimum” was applied as the “AND” function to combine the variables. Table 4 shows the verbal representation of all 27 ( $= 3^3$ ) rules

developed to define the relationships between the inputs/antecedents (worker distribution time) and the output/consequent membership functions (motivation).

The rules were inferred from interviews with experts and construction project management professionals including 4 senior academic and project management professors, 4 senior construction managers with 10 years or more construction management work experience, and 5 graduate students with 5 years or more field experience in construction projects. All the experts had a bachelor or master degree in civil engineering and experience of working with carpentry labours. The experts were presented with the antecedents of all 27 rules and they were asked to specify the consequent of each rule, by choosing one output to each rule among five possible outputs: very low, low, medium, high or very high.

The rules were considered independent and no weightings were applied, which means no rule was emphasized as more important in respect to estimating the output. Implication was performed with the minimum function, and aggregation was performed with the maximum function. The centroid method was applied as a means of defuzzification of the output membership functions to determine a crisp set.

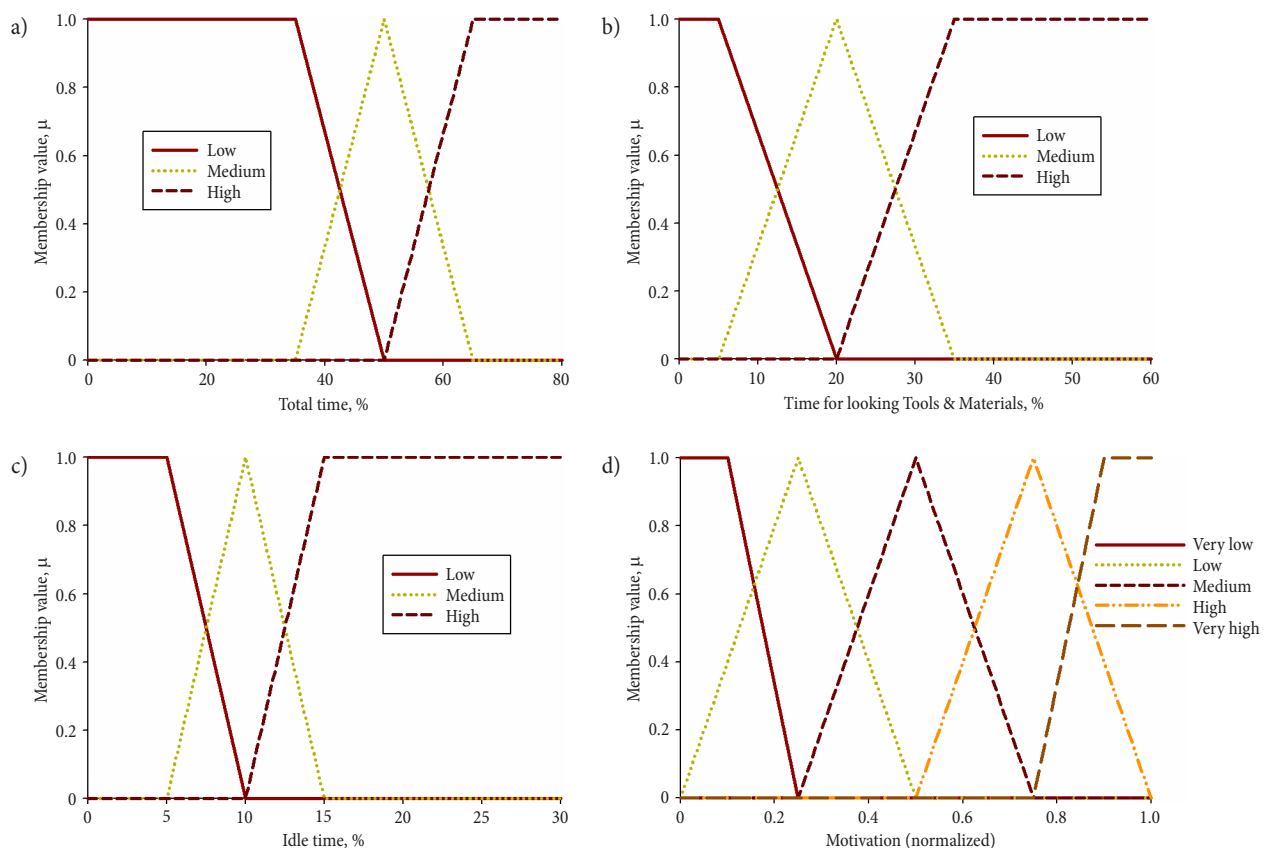


Fig. 2. Membership functions of input and output variables: (a) working (tool) time, (b) materials and tools searching time, (c) idle time, and (d) motivation

Table 4. A rule set for predicting construction workers' motivation

Rule #	if	working (tool) time	and	materials and tools searching time	and	idle time	then	motivation (outcome)
1	if	L	and	L	and	L	then	M
2	if	L	and	L	and	M	then	L
3	if	L	and	L	and	H	then	VL
4	if	L	and	M	and	L	then	L
5	if	L	and	M	and	M	then	L
6	if	L	and	M	and	H	then	VL
7	if	L	and	H	and	L	then	M
8	if	L	and	H	and	M	then	L
9	if	L	and	H	and	H	then	L
10	if	M	and	L	and	L	then	M
11	if	M	and	L	and	M	then	M
12	if	M	and	L	and	H	then	L
13	if	M	and	M	and	L	then	M
14	if	M	and	M	and	M	then	M
15	if	M	and	M	and	H	then	L
16	if	M	and	H	and	L	then	M
17	if	M	and	H	and	M	then	M
18	if	M	and	H	and	H	then	L
19	if	H	and	L	and	L	then	VH
20	if	H	and	L	and	M	then	H
21	if	H	and	L	and	H	then	M
22	if	H	and	M	and	L	then	H
23	if	H	and	M	and	M	then	H
24	if	H	and	M	and	H	then	M
25	if	H	and	H	and	L	then	VH
26	if	H	and	H	and	M	then	H
27	if	H	and	H	and	H	then	H

### 3. Results and discussion

Figure 3 shows the relationship between the motivation levels of 38 construction workers evaluated using the FRBM and the EIV model. The matching between the motivation values predicted by FRBM and the motivation values obtained from EIV are shown with the line of equity ( $y = x$ ). The figure clearly shows that the data from both methods are very close to the line for “medium” motivation ranges, indicating that both FRBM and EIV methods are in agreement to predict the motivation level of construction workers at and near the medium ranges. However, the two models failed to match for few construction workers with “extreme” motivation ranges, i.e. those with very low and very high motivation levels. For lower motivational ranges, the motivational values predicted by FRBM are generally higher than the motivational values obtained from EIV method. Contrarily, the motivational values predicted by FRBM are consist-

ently lower than the motivational values obtained from EIV method for high motivational levels. This discrepancy at extreme ranges is most likely due to the phenomenon called the “extreme response bias” from Likert scale which subsequently affected the motivation values calculated using the EIV method. Extreme response bias refers to the tendency of making disproportionate use of the extreme ends of a Likert type response scale (e.g. strongly agree or strongly disagree).

Figure 4 shows the relationship between the motivation levels of 38 construction workers evaluated using the FRBM and the EIV model calculated using crisp or fuzzy-Likert scales. As it can be seen in Figure 4, the use of fuzzy-Likert scale for the EIV model slightly improves the extreme response bias. The use of truncated triangular fuzzy membership for extreme Likert scales (for 1 and 7) coupled with the ability of fuzzy system to capture the uncertainty of the workers' response helped to reduce the extreme response bias shown at extreme ranges of motivation values estimated using the EIV method.

The expectancy theory (EIV model) can be useful to construction managers to find out which rewards are seen as valuable by the employees, to create instrumentality that the accomplishments of certain tasks will generate the rewards valued by the employees, and to ensure that the employees have the necessary capabilities to accomplish the given task. However, the expectancy theory

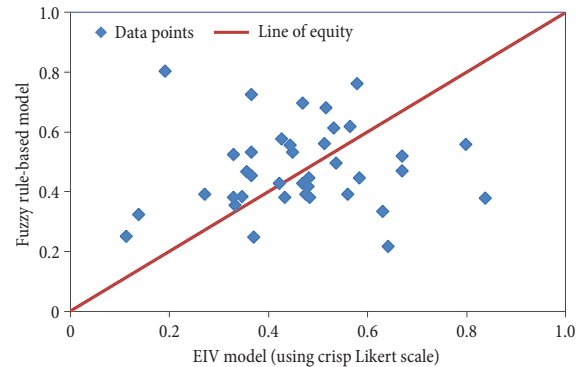


Fig. 3. Scatter plot of workers' motivation calculated using EIV method and fuzzy rule-based model

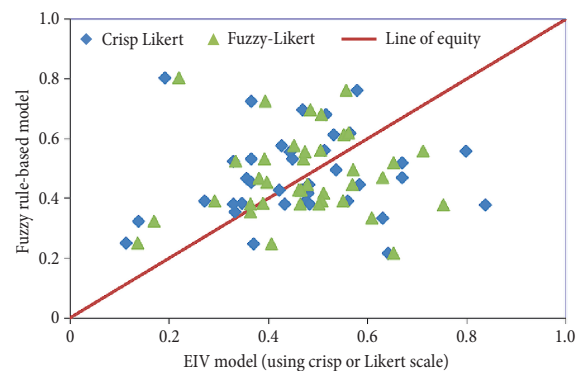


Fig. 4. Scatter plot of workers' motivation calculated using fuzzy rule-based model and Likert EIV or fuzzy-Likert EIV methods



requires traditional methods of data collection system through questionnaire and interview survey techniques that are generally considered as labour-intensive, time-consuming, and expensive.

The fuzzy rule-based model developed using easily measurable and observable worker time distribution data seems very practical and well suited to evaluate the overall motivational status of construction workers. The FRBM results matched well in the middle motivational ranges and gave more plausible results at the extreme motivation ranges compared to the traditional EIV estimates. The fuzzy rule-based system is also quite easy to develop and to understand compared to the traditional EIV model. It may be possible to further improve the FRBM performance by incorporating more input variables (work time distributions) in the expert system, changing shape or increasing the number of membership functions of input variables, introducing different weighting factors to the fuzzy expert rules, or modifying the relative contribution of the input variables to the overall motivation of the construction workers. Further research should also explore the effect of increasing data set (number of workers) and number of projects so that the FRBM model can be adopted for other construction disciplines and sectors.

## Conclusions

A fuzzy rule-based model is proposed to determine the motivation levels of construction workers. The model was constructed on the basis of expert knowledge and observed worker time distribution data, i.e. working (tool) time (%), searching for tools and materials time (%), and idle time (%). The motivational level of workers obtained by the fuzzy expert system is compared with the motivational levels calculated using the traditional expectancy theory (EIV) method. The results of fuzzy rule-based models were in good agreement with EIV model for the middle range motivation values. The fuzzy rule-based system is quite easy to develop and easy to understand compared to the traditional EIV model commonly used in performance evaluation.

Indeed the proposed fuzzy rule-based model used for carpentry construction workers can be easily transferred to analyze the motivational aspects of other workers involved in construction industries. However, in order to apply the same motivational evaluation analysis for workers of other industries with a very different work environment (e.g., Hotel or tourism industry), further research will require identifying relevant motivational variables such as worker time variables.

There are indeed some limitations for different uncertainty modeling tools including fuzzy inference system. The main reason for selecting fuzzy inference system in this study is the measurement efficiency and simplicity based on fuzzy logic, comparing to analytical propagation methods that require complex mathematical expressions. In addition, fuzzy inference system can be

implemented with limited data to handle different epistemic uncertainties (e.g. uncertainty due to subjective and objective measures, expert opinions, natural languages), in terms of degree of membership. This research designed to indicate and simplify the application of fuzzy rule-based model as a complement tool for EIV model and motivational analysis in construction industry. Additional research, development, and testing can be done to make it more comprehensive in addressing a wider range of factors and to make it more generalizable in nature.

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## Appendix

Sample validity and reliability of research tools are key pre-requisites in social science research methods. All the data analysis and conclusions are dependent on the degree of satisfaction of these concepts. It is possible to determine the degree of accuracy of the conclusions formulated with the data from the questionnaire surveys and interviews. In this study central limit theorem was used for sample size validity.

The central limit theorem in statistics indicates that “obtaining large samples (generally sample size >30) from any population, the sample mean will follow an approximate normal distribution” (Kvanli et al. 2000). Welkowitz et al. (2006) presented Eqn (A-1) for sample size calculations in social sciences:

$$n = [z_{\alpha/2} \sigma/d]^2 \quad (\text{A-1})$$

when the  $n > 30$ ,

where:  $n$  – Sample size;  $d$  – Desired error margin;

$1 - \alpha$  – Probability associated with the error margin;  $\sigma$  – Standard deviation of results.

In the current study, an initial pilot study<sup>1</sup> of 3 months with carpentry workers revealed that the standard deviation of working time is 15.4%. Initially the observations were planned for an error margin of 3% with 90% certainty. This was based on the level of accuracy experienced (variance experienced) during the pilot study observations where three researchers observed the same subject.

Then:

$$d = 3\%;$$

$1 - \alpha = 90\%$  certainty with the error estimation; then  $\alpha = 0.05 = 15.4\%$ ;

Based on the Eqn (A-1), the calculations are as follows;

$$n = [z_{0.05} \times 0.154 / 0.03]^2, \text{ where } z_{0.05} = 1.645.$$

Therefore  $n = 72$ .

Based on the above analysis, at least 72 observations were needed to draw conclusions with 90% certainty. Therefore, it was planned to observe 101 workers (more than 72) in actual construction settings, with an a.m. observation, an interview, the presentation of the

questionnaire, a p.m. observation and then collect the completed questionnaire at a later date. Answering to the questionnaire survey was optional in order to assure the truthfulness of the survey responses.

Workers returned 39 questionnaires (out of 101) where all the questions were rated on a 1–7 Likert scale (48 questions). The average standard deviation of all the ratings was 1.28 out of 7. Using above equation:

$$39 = [z_{0.05} \times 1.28 / d]^2, \text{ where } z_{0.05} = 1.645.$$

Therefore  $d = 0.337$  out of 7.

The 39 returned questionnaire surveys are statistically valid and the conclusions drawn are valid with  $\pm 0.337$  variation with 90% certainty.

In addition, 101 workers were interviewed and some of the interview questions were also rated on a 1–7 Likert scale. Open-ended questions were another component of the interviews. The standard deviation for the responses to the questions with a Likert scale was 1.39. Using above equation:

$$101 = [z_{0.05} \times 1.39 / d]^2, \text{ where } z_{0.05} = 1.645,$$

Therefore  $d = 0.228$ .

The responses to the Likert scale interview questions are valid to draw conclusions with  $\pm 0.228$  variation with 90% certainty.

<sup>1</sup> In this research, initially, a pilot survey was conducted. Two research assistants and one of the authors made the observations. During the pilot study, direct and work sampling methods of observations were tested. The three observers analysed and discussed the variations in the collected data.

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