Canadian Journal of Civil Engineering
 Revue canadienne de génie civil

CONSTRUCTION PRODUCTIVITY FUZZY KNOWLEDGE BASE MANAGEMENT SYSTEM

Journal:	<i>Canadian Journal of Civil Engineering</i>
Manuscript ID	cjce-2017-0540.R1
Manuscript Type:	Article
Date Submitted by the Author:	13-Dec-2017
Complete List of Authors:	Elwakil, Emad; Purdue University, School of Construction Management Zayed, Tarek; Concordia University Department of Building Civil and Environmental Engineering
Is the invited manuscript for consideration in a Special Issue? :	N/A
Keyword:	model, knowledge base, construction < type of paper to review

SCHOLARONE™
 Manuscripts

CONSTRUCTION PRODUCTIVITY FUZZY KNOWLEDGE BASE MANAGEMENT SYSTEM

Authors:

Emad Elwakil, Assistant Professor, School of Construction Management, Purdue University, West Lafayette, IN, 47907, USA.

Tarek Zayed, Professor, Department of Building, Civil & Environmental Engineering, Concordia University, Montreal, Canada H3G 1M8.

Corresponding Author:

Emad Elwakil PhD, PE, CCP, PMP
Purdue University
School of Construction Management
401 N. Grant St.
West Lafayette, IN, 47907
Phone: 1(765)494-6452
Email: eelwakil@purdue.edu

Draft

Construction Productivity Fuzzy Knowledge Base Management System

Abstract: Construction companies need a Knowledge Management system in order to collate, share and ultimately apply this knowledge in various projects. One of the most important elements that determine the time estimates of any construction project is Productivity. Such projects have a predilection towards uncertainty and therefore require new generation of prediction models that utilizes available historical data. The research presented in this paper develops, using Fuzzy approach, a knowledge base to analyze, extract and infer any underlying patterns of the data sets to predict the duration and productivity of a construction process. A six-step protocol has been followed to create this model: (1) determine which factors affect productivity; (2) select those factors which are critical; (3) build the Fuzzy sets; (4) generate the Fuzzy rules and models; (5) develop the Fuzzy knowledge base; and (6) validate the efficacy and function of these models in predicting the productivity construction process. The Fuzzy knowledge base was validated and verified using a case study and the results were satisfactory with 92.00 % mean validity. In conclusion, the developed models/system demonstrated the ability of a knowledge base management to predict the patterns and productivity of different construction operations.

1. INTRODUCTION

Productivity, defined as “*the ratio of output of required quality to the inputs*” (Al-Zwainy et. al. 2013), is a vital factor regarding the management of construction projects and predicting the time estimates of specific processes. Various statistical methods, such as probability functions, regression analysis, stochastic techniques, and mathematical curves, have been used to simulate and predict construction processes to optimize management (Bee Hua 2008). However, a limitation of using such statistical analyses is that the raw data can be confounding and ultimately lead to unreliable data mining and modeling (Han and Kamber 2006). Most research unfortunately has focused only on modeling while neglecting proper data preparation. It is imperative that any problems with the raw data are identified before starting the modeling process. The most common problems with raw data are missing data and outliers, which need to be identified and then removed. This process of obtaining useful and hidden information from

extensive data sets is known as data mining. Since this is not possible with the standard statistical methods, an inter-disciplinary domain called Knowledge Discovery in Database (KDD) was created for identifying patterns in data and mining the useful parts (Fayyad et. al 1996). The KDD uses concepts from basic mathematics, statistics, machine learning, database query, and visualization (Anand et al. 1998). However, most modern KDD tools focus largely on building models rather than data mining (Cox and Wills 1997). Although 60% of the time goes into data preparation, only 10% of the overall effort is utilized in the actual mining step (Cabena et al. 1998). KDD ideally comprises of data understanding and data preparation, data mining, pattern detection and finally application (Chapman et al. 1999). KDD has also been applied to the construction industry since the rapid increase in computerized historical databases (Buchheit et al. 2000; Soibelman and Kim 2002). In addition, a data warehouse application to gather data insights and support decision making was developed by Chau et al. (2002) to aid the construction industry.

2. RESEARCH OBJECTIVES

The main objective of this study is to check the ability of a knowledge base management system to predict the patterns and productivity of different construction operations. This objective is to be achieved via successive steps as outlined below:

- Design a model to utilize and extract the underlying patterns from the raw project data.
- Integrate this extracted and usable data from past/historical sources with the knowledge base design to predict construction productivity.
- Verify and validate the knowledge base using a case study.

3. BACKGROUND

The idea of knowledge management (KM) was first articulated by Horton (1979) in a research monograph. The 1980s was marked by a greater awareness of KM with analysts such as Rogers, and Edvinsson who began appreciating this concept (Edvinsson 1987; Rogers 1987). KM was finally recognized as a branch of science in 1991 (Nonaka 1991) and began garnering more attention from the 1990s onwards (Nonaka and Takeuchi 1995). Since the dawn of new millennium, various large organizations and companies have been relying on knowledge as a

vital asset, needed in order to maintain their competitive edge in the market (Bruton et al. 2007; McRea and Langdon 2003; Senaratne and Sexton 2009; Yu and Yang 2016). However, the research available on KM in the civil infrastructure and construction industry is unplanned and fragmented, in part due to the rapid changes this field has seen in the past years and decades. It is imperative therefore to collect and analyse historical data, identify any unique patterns and use this information to predict future trends (Deng 2007; Yu and Yang 2016).

Since research into the construction management is based on the fuzzy set theory, fuzzy logic, and hybrid fuzzy techniques, many studies attempted to combine those techniques with artificial neural networks to create an optimized hybrid model to study the effect of various factors on productivity (Bee Hua 2008). As examples, the National Electrical Contractors Association (NECA) studied the effect of seasonal factors such as humidity and temperature on labor productivity (Sonmez & Rowings 1998) while another study correlated multiple factors with specific construction tasks with the help of regression analysis and neural network modeling (Sonmez & Rowings 1998). In addition, a number of mathematical models such as the straight-line power model, cubic power model exponential model and piecewise model have been used to create learning curves that predict future trends (Thomas et. al. 1986). In this study, the learning curve showed that an increase in product output by a factor of two is correlated with a decrease in man-hours and other costs by a fixed percentage of the previous costs. The most reliable and therefore the most commonly used mathematical curve model in construction productivity is the straight-line power model (Everett and Farghal 1994). Some recent studies have applied the learning curves to virtual construction processes (Hildreth 2012) while others have used algorithms to evaluate these mathematical curves and their ability to predict future performance (Malyusz and Pem 2014).

The main factors affecting productivity are the labor, weather, materials, time and changing requirements (Park 2006). In addition to identifying these initial factors, it is also important to review data from previous projects and use that as the foundation for building up the prediction model. For example, the WEATHER system was developed to evaluate the impact of weather conditions on construction productivity and to study past weather patterns for better scheduling (Moselhi 1997). In addition to building this model, Moselhi et al. (1991) studied as many as 57 different projects to find any correlation between order change and productivity and found a direct link between changing labor requirements and lowered productivity. Models based on

historical data help better forecast trends and predict overall productivity with greater accuracy (Mirahadi & Zayed 2016). Other notable examples include the study of Lv and El-Gohary (2016) which used text analytics to main stakeholders' opinions for highway construction projects and a Fuzzy Knowledge Approach developed by Elwakil and Zayed (2014) as a means to extract data for accurate prediction of task duration. Despite the prevalence of KM systems in data mining and pattern finding, the use of historical data is still lacking. Therefore, the models build with the current data systems do not represent the knowledge in its entirety that would be essential for predicting construction productivity (Soibelman and Kim 2002; Soibelman et al. 2004; Reffat et al. 2006; and Mougél et al. 2010; Guns 2016; and Silva and Antunes 2016).

RESEARCH METHODOLOGY

The research methodology consists of five phases – a) an exhaustive literature review on the current trends in data mining pertaining to the construction industry as well as building a Fuzzy knowledge base; b) development and implementation of steps that include Variable Selection, Fuzzy Sets, Fuzzy Rule Induction, and Fuzzy Knowledge Base; c) data collection and verification of the developed system; d) validation of the said system using a case study; and e) conclusions and future directions. Each of the aforementioned steps are explained in detail below.

4. PRODUCTIVITY DATA MANAGEMENT SYSTEM DEVELOPMENT

The following functional steps make up the system – variable selection, Fuzzy sets formation, Fuzzy rules' induction and Fuzzy knowledge base construction. The knowledge base is finalized only after it passes a validation process with an acceptable percentage.

4.1 Variables selection

All the variables that can potentially affect the output and productivity are selected. Fuzzy average method is commonly used and begins with producing the fuzzy curve and then ranking those variables (Lin et al.1996). The Fuzzy modeling has been used to avoid the effect of correlation using Membership Functions instead of Crisp sets as the correlation between

variables or attributes, the correlation coefficients defined on ordinary crisp sets (Chiang & Lin 1999; Ye 2014; Tyagi 2015).

a. Producing the fuzzy curve

The following steps are used to produce a Fuzzy curve:

- 1- Plot the M data points (X_i, Y_j) , $k = 1, 2, \dots, M$, in each x_i -y space, $i = 1, 2, N$ For each input variable x_i .
- 2- Create fuzzy membership function for each data point (X_i, Y_j) in each x_i -y space using Equation 1 to calculate the membership function for each input and output variables (X_i, Y_j) (Lin and Cunningham 1995).

$$\mu_{i,k}(x_i) = \exp\left(-\frac{(x_i - x_{i,k})^2}{b}\right) \quad (\text{Equation 1})$$

Where:

K: 1, 2, 3, ..., M

b: The width of the influence interval is 20% of variable range

- 3- Create a fuzzy curve c_i point for each data point by ‘de-fuzzifying’ the fuzzy membership functions to produce a fuzzy curve, using Equation 2.

$$c_i(x_i) = \frac{\sum_{k=1}^M y_{k,i} \mu_{i,k}(x_i)}{\sum_{k=1}^M \mu_{i,k}(x_i)} \quad (\text{Equation 2})$$

b. Ranking the variables

The variables are ranked using the Mean Square Error (MSE). The MSE is calculated for each Fuzzy curve and the input variables are ranked in the ascending order of their MSEs using Equation 3. The relationship between the input and output is only significant when the MSE value is small. A large MSE value indicates a complete lack of correlation between the input and

output and the Fuzzy curve ends up being flat. In other words, the input variable with smallest MSE is the most significant and that with highest MSE value is the least important.

$$MSE_{ci} = \frac{1}{M} \sum_{k=1}^M (ci(x_i, k) - y_k)^2 \quad (\text{Equation 3})$$

4.2 Forming the Fuzzy sets - 'Fuzzification'

The tangible or 'crisp' quantitative variables are converted into Fuzzy sets during this step. This begins with identifying some of the underlying uncertainties in these values and then converting them to fuzzy values. Each crisp quantity is assigned a membership value with the help of a neural network which uses historical data to build up the membership functions. The neural network in turn is modeled using data sets of selected variables, which then uses these same values to self-train. The training is suitably programmed to simulate the relationship between the coordinate locations and membership values and continued till the network can simulate all the input and output values. This is followed by validating the network using test data and when finally ready, is used to determine the membership value of any input data set in any location.

The network is build up using data in the form of clusters: say C_i represents the cluster numbers, R_{ij} the membership function values (output), X_{ij} the data points of the variables (input) and random values are assigned to all the weights connecting the paths between the elements in the layers of the network W_{nn}^n , the outputs can be calculated using Equation 4 below (Takagi and Hayashi, 1991). To test the network, an input value of x is passed through it and the network computes an output value ($f(x)$ output) which is compared to the actual value ($f(x)$ actual = y). The error measure E is computed from these two output values using Equation 5. This error is linked with the last layer of the neural network and is distributed to the elements in the hidden layers via the back propagation technique using Equation 6 (Takagi and Hayashi 1991). When

the errors associated with each element in the network are known, the weight of each of these elements is calculated using Equation 7 (Takagi and Hayashi 1991). In this way, the neural network is able to approximate the actual output closely. The X_{ij} is again passed through the network, this time with the updated weights and the errors are calculated again. This entire procedure is repeated until the error value of the final output is within certain limits or remains constant. Finally, a validation data set is used to feed through the network to simulate the relationship.

$$O = \frac{1}{1 + \exp[-(\sum x_i w_i - t)]} \quad (\text{Equation 4})$$

Where:

O : output of the threshold element computed using the sigmoidal function

x_i : inputs to the threshold element ($i = 1, 2, \dots, n$)

w_i : weights attached to the inputs

t : threshold for the element

$$E = f(x)_{\text{actual}} - f(x)_{\text{output}} \quad (\text{Equation 5})$$

$$E_n = O_n(1 - O_n) \sum_j w_{nj} E_j \quad (\text{Equation 6})$$

$$w_{jk}^i(\text{new}) = w_{jk}^i(\text{old}) + \alpha E_k^{i+1} x_{jk} \quad (\text{Equation 7})$$

Where: w_{ijk} : represents the weight associated with the path connecting the j^{th} element of the i^{th} layer to the k^{th} element of the $(i + 1)^{\text{th}}$ layer

α : learning constant

E_k^{i+1} : error associated with the k^{th} element of the $(i + 1)^{\text{th}}$ layer; and

x_{jk} : input from the j^{th} element in the i^{th} layer to the k^{th} element in the $(i + 1)^{\text{th}}$ layer (O_{ij}).

4.3 Fuzzy rules induction

This step is used to determine the functional relationship between each of the independent variables' membership values and the dependent variables (e.g task duration) in order to generate actual models. The aim of Fuzzy Rule induction is to create a knowledge base of fuzzy 'if-then' rules which describe this functional relationship as well as trends in a large collection of data sets. This step is a supervised knowledge discovery approach since it is concerned with at-least one dependent or outcome variable and a wider set of independent variables. The concept of a rule-based model is to understand what a particular data means and how it can be extracted and applied. There are two steps in the rule induction process:

a. Generation of Candidate Fuzzy Rules

The fuzzy sets discussed in the previous sections are used as the input variables and the relationship between the dependent and independent variables is determined as follows:

i. *Isolation of the fuzzy sets into individual data points*

The fuzzy sets that are isolated to data points with the highest membership degree – possible when two data sets occur in the same fuzzy set – are selected.

ii. *Conversion of all fuzzy relations to rules*

The fuzzy relations are converted into the if-then rules with the help of certain standardized rules, without any relation to the data set. Each rule is then separated in a final rule selection process.

b. Selection of the Final Rule Set

The final rules are selected from a vast pool of data pairs and to avoid any conflicts, the degree of effectiveness (E) for each rule is computed and the most effective rules amongst them are

selected. The effectiveness of each rule is the product of its component of fuzzy set membership degree, as shown in Equation 8 (Cox 2005).

$$E(r_i) = \mu_x(v_1) \times \mu_y(v_2) \times \mu_z(v_3) \quad (\text{Equation 8})$$

4.4 Fuzzy knowledge base (FKB)

The combination of all previous steps – variables, fuzzy sets and fuzzy rules – results in the fuzzy knowledge base. The FKB, although not a complete representation of a system, can represent a model and a collection of FKBs may approximate a complex system. The FKBs store the variables, concept hierarchies to organize attributes and the rules required to solve a set of outcomes associated with the system. The FKB needs to be validated before it is finalized.

4.5 Validation

A mathematical validation process will be used to determine how effectively the FKB can predict. The average invalidity percent (AIP) and the Average Validity Percent (AVP) will be calculated using Equation 9 and 10 respectively. AIP value closer to 0.0 indicates soundness of the model while a value closer to 100 indicates failure (Zayed and Halpin 2005). The Root Mean Square Error (RMSE) is calculated using Equation 11. As with AIP value, RMSE values closer to 0 indicates that the model is sound and closer to 100 indicates failure. The Mean Absolute Error (MAE) is calculated using Equation 12 and its value ranges from 0 to infinity. However, the MAE should be close to zero for sound results (Dikmen et al. 2005).

$$AIP = \left(\sum_{i=1}^n \left| 1 - \left(\frac{E_i}{C_i} \right) \right| \right) * 100/n \quad (\text{Equation 9})$$

$$AVP = 100 - AIP \quad (\text{Equation 10})$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (C_i - E_i)^2}{n}} \quad (\text{Equation 11})$$

$$MAE = \frac{\sum_{i=1}^n |C_i - E_i|}{n} \quad (\text{Equation 12})$$

Where:

AIP: Average Invalidity Percent

AVP: Average Validity Percent

RMSE: Root Mean Squared Error
 E_i : Estimated Value

MAE: Mean Absolute Error
 C_i : Actual Value

5. ANALYSIS AND IMPLEMENTATION TO A CASE STUDY

The field observations and data collection were carried out for a period of eighteen months on an under-construction building: The Engineering, Computer Science and Visual Arts Complex of Concordia University. It is a 17-storey integrated educational facility with a surface area of 86,000 square meters. For this paper, the process of concrete pouring was considered.

5.1 Data collection process

Data acquisition from historical records is a cost-effective approach as shown by Khan (2005) and Wang (2005) while studying labor productivity. The data for this study was collected from publicly available data records such as Infrastructure Canada and weather networks on the internet. As shown in Figure 1, there were four groups of variables: a) weather - temperature, b) crew – labor size, c) project type – methods and d) operational – drivers and transportation. Both qualitative and quantitative variables, as shown in Table 1, from each group have been studied for their effect on productivity. The time of concrete pouring operations, which included pouring, hauling, loading and return times was recorded at the jobsites. These processes are outlined in Figure 2.

Insert Figure 1

i. Concrete Pouring Process

The concrete pouring process is the first process in the concrete pouring operation and dependent on eight variables - precipitation and method which are qualitative variables, and temperature,

humidity, wind speed, gang size, labor percentage and floor level, which are the quantitative variables as shown in Table 2. A total of 95 data points was collected and used in the modeling and validation processes.

Insert Table 1

ii. Hauling process

Hauling depends on six variables - precipitation, driver skills, truck status, and road conditions (qualitative), and temperature and wind speed (quantitative) as shown in Table 3. One hundred and ten data points were collected for the modeling and validation processes.

Insert Figure 2

Insert Table 2

Insert Table 3

iii. Loading process

Loading also depends on six variables – only one qualitative i.e. precipitation and five quantitative including temperature, humidity, wind speed, gang size and labor percentage as shown in Table 4. One hundred data points were collected for this process.

Insert Table 4

iv. Return process

The final process in the loading operation is returning which is influenced by six variables - precipitation, driver skills, truck status, and road condition (qualitative) and temperature and wind speed (quantitative) as shown in Table 5. One hundred and ten data points were collected for the modeling and validation processes. As shown in Figure 3, several data points were randomly removed from the data sets to check the validity of the proposed system.

Insert Table 5

As indicated in Figure 4, the statistical parameters and probability density functions were calculated for all variables that affect the processes. The probability Density functions have been generated using Minitab software to specify the probability of the random variable falling within a particular range of values, as opposed to taking on any one value. This probability is given by the integral of this variable's PDF over that range (Minitab 2000). Figure 3 shows for each variable the number of points in each data set and number of missing data. In addition to being presented in graphs, some common parameters often can be used to describe sets of numbers.

Insert Figure 3

Insert Figure 4

5.2 Selection of variables

The variables affecting the output i.e. work task duration were selected using the fuzzy average method and to validate this method, it was compared to the outputs of Artificial Neural Network (ANN) and Regression methods.

a. Building fuzzy curve

A fuzzy curve was built by plotting the data points (X_i, Y_j) in the $(x_i - y_i)$ space for all variables and fuzzy membership functions were then created for each data point (X_i, Y_j) and for each input and output variable as shown in Equation 1. A fuzzy curve c_i point was created for each set of data points by ‘defuzzifying’ the fuzzy membership functions using Equation 2. As an example, fuzzy curve for “Gang Size” is shown in Figure 5. A flat fuzzy curve indicates a completely random relationship between the input and output variables whereas a positive or negative shaped curve shows a strong relation.

b. Ranking

The variables are ranked using the Mean Square error (MSE) as shown in Equation 3. As already described, larger MSE values indicate a poor representation of the input-output relation by the fuzzy curve resulting in a flat curve while smaller values mean that the relationship is significant. The mean square error MSE was calculated for each fuzzy curve as shown in Table 6. All the variables were ranked according to the ascending order of the MSE as shown in Table 7. In order to validate the fuzzy average method, ANN and Regression methods were used to compare the ranking of the selected variables described below.

Insert Figure 5

Insert Table 6

Insert Table 7

1- Variables Selection Using the ANN Method

Input variables need to be ranked in order to determine the relative importance of each variable on the duration of the process. The contributing percentages of each of the variables are then derived with the help of a trained neural network. The higher the number, greater the contribution of that variable to making an accurate prediction. Table 8 shows the contribution percentage (relative significance) of eight variables. By comparing the results of fuzzy average method and ANN methods, it was clear that four out of the eight variables have similar rankings while the other variables have different rankings. In addition, the last-ranked variable – the method variable - was the same as per both approaches. However, the R^2 for ANN model (88.8 %) was lower than that of the fuzzy average method model indicating that the latter is more robust in ranking variables.

Insert Table 8

2- Variables Selection using Regression Method

The Regression method simply shows the best subset of variables instead of their contributing percentages. Table 9 lists the status of the contribution of the eight variables. A comparison of the fuzzy average method with regression revealed that six of the eight variables were included in the regression model. The remaining two were not included since they had less contribution to

the fuzzy average method model. The R^2 for the regression model (88%) was lower than the fuzzy average method indicating the greater efficacy of the latter.

Insert Table 9

From the two comparisons, we can conclude that the fuzzy average method works better when the relationship between the variables is unclear. As a result, the fuzzy approach improved the modeling of qualitative variables and the relation between the qualitative variables and process durations.

5.3 Fuzzy sets conversion

This step converts the crisp quantities into fuzzy sets by identifying some of the uncertainties present in the crisp values. As mentioned in the previous sections, the conversion to fuzzy values is represented by the membership functions which are assigned for each given quantity – a process called ‘fuzzification’. Membership values were assigned using the neural network technique to model the relation between the fuzzy membership functions and process duration and predict the duration.

5.4 Fuzzy rule induction

The goal of this step is to model the functional relationship between independent variables’ membership values and dependent variables (Task Duration) as a set of fuzzy if-then rules as shown in Table 10. First, the actual models of the underlying processes are generated and then

induction rule is used to create a knowledge base of fuzzy if-then rules which model one or more trends in a large collection of data sets.

Generation of the candidate fuzzy rules

The inputs of this process are fuzzy sets, model variables and system definitions, which have been already discussed. The fuzzy relations are produced from both dependent and independent variables and the converted to “If-Then” rules, as shown in Table 11.

a. Selection of a final rule set

The final rules were selected from all of the candidate rules presented in Table 11, which are essentially repetitive rules representing the same duration. The effectiveness of each rule was calculated using Equation 8 and the highest effectiveness-degree rules were selected, as shown in Table 12. For instance, Rule 36 was replaced by Rule 24 due to the degree of effectiveness. The selection of the final rules should decrease the number of rules without affecting the performance of the rules system.

Insert Table 10

5.5 Fuzzy knowledge base

A fuzzy knowledge base includes all the previous steps, i.e. the selected variables, fuzzy sets, and fuzzy rules. As shown in Table 13, the FKB is a representation of a separate model of each process, meaning that the concrete pouring process and the loading process each will have a different FKB. A collection of FKBs cooperates to form a solution to a concrete pouring operation.

5.6 Fuzzy knowledge base validation

To test the prediction efficacy of this system, a validation data set was embedded into the developed FKB and its results were compared with the actual data. The first test was to compare the actual and the predicted plots and the results were satisfactory; briefly, the predicted values were within acceptable limits and scattered around the actual values, as shown in Figure 6. The second test was a mathematical and descriptive validation using the Equations 9 to 12. The average invalidity percent (AIP), which denotes the prediction error, was calculated using Equation 9. A sound model has an AIP value closer to 0 while an unsound one has values closer to 1. Equation 11 was used to calculate the root mean square error (RMSE), which, at values closer to 0 indicated sound model and vice versa. Finally, Equation 12 was used to calculate the mean absolute error (MAE) which lies between 0 and infinity, but should be close to 0 for an optimum model. The results of these equations are summarized in Table 14.

Insert Table 11

The AIP was 92%, RMSE was 2 and the MAE was 5. Therefore, the fuzzy knowledge base developed in this study is acceptable, robust, and can be applied for further steps. The aim of setting more than one validation point in this system was to improve the simulation process and aid the decision maker in improving the entire modeling process. For instance, if the validation is not acceptable after the data mining phase, the decision maker has to improve the data sets by simply increasing the number of data points or by collecting other data sets with different data quality rules. Since this validation process was satisfactory completed, the Knowledge Discovery Stage (KDS) can present the data to the Simulation Stage (SS). There KDS prepared data differs from that of the other available simulation systems: (1) the data is clean and complete without

any fuzziness; (2) to have access to all data patterns, the outliers are separated in special clusters for the simulation process; (3) the qualitative and quantitative variables are considered while predicting the processes' durations; (4) historical data plays an important role in predicting the duration, rather than vague probabilities and expert opinions; (5) the input data can be controlled through a validation procedure to improve the modeling and simulation procedure; and (6) the procedure to predict durations is easier and more accurate.

Insert Table 12

Insert Table 13

Insert Table 14

Insert Figure 6

6. CONCLUSIONS

The research presented in this paper uses data mining, and construction knowledge base to extract hidden patterns from data sets to improve productivity in the construction industry. The efficacy of data mining depends on collecting historical data and identifying the variables which affect the construction processes. Our results show that various qualitative and quantitative variables have significant effect on task duration and productivity. We were able to show that the fuzzy approach is effective in modeling the hidden patterns of construction data sets and validated this system with 92.00 % average validity percent. The knowledge base management systems (KBMS) can predict the duration of different construction processes and can therefore benefit both researchers and practitioners. The main component of (KBMS) is the Knowledge Discovery Stage (KDS) where the Patterns are extracted, which implicitly represent knowledge that is stored or captured

in large databases. This stage models the effect of qualitative and quantitative variables on the construction process. The KDS includes data cleaning, integration, selection, transformation, and mining as well as pattern evaluation and knowledge presentation. This research presents the following contributions to the state of the art in construction knowledge base management systems: 1) Develops a strategy and methodology to manage the uncertainties in a project productivity; and 2) Integrates the enormous amount of historical data and design into a fuzzy knowledge base that can be used to predict process' productivity instead of approximated probability distribution.

There are however several limitations and delimitations of this system which need to be addressed in future studies: a) the relation between variables affecting the project e.g. management and organization of the project; and their overall effect on the construction operations should also be studied; b) it is important to address the relation between the number of variables and the number of data points in order to enhance predictive potential. This is because if data size is increased, there might be a chance of improving the prediction of the process duration. In case of limited data sets, it will be helpful to use indices and graphs with a reliable threshold of the number of variables and data sets; and c) Study more variables which might affect productivity. For example, for the Concrete Pouring Process, like concrete placement method including: concrete pump, direct chute, conveying, crane and bucket, etc. Some of these methods would be more suitable for a horizontal (e.g. SOG) than to a vertical (e.g. wall) placement. Similarly, whether the condition (status) of the equipment used in the direct placement has an effect on the productivity or not. Some equipment might be inefficient due to lack of maintenance for the concrete pump, old or inefficient compressor, etc.

7. REFERENCES

- Al-Zwainy, F. M. S., Abdulmajeed, M. H., & Aljumaily, H. S. M. 2013. Using Multivariable Linear Regression Technique for Modeling Productivity Construction in Iraq. *Open Journal of Civil Engineering*, 03(03), 127–135. doi:10.4236/ojce.2013.33015
- Anand, S. S., Patterson, D., Hughes, J. G., Bell, D.A. 1998. Discovering case knowledge using data mining. *Proceedings of the Second Pacific-Asia Conference in Knowledge Discovery and Data Mining (PAKDD)*, Melbourne, Australia, 1998; pp.25-35
- Arditi, D., & Mochtar, K. 2000. Trends in productivity improvement in the US construction industry. *Construction Management and Economics*, 18(1), 15–27. doi:10.1080/014461900370915
- Bee Hua, G. 2008. The state of applications of quantitative analysis techniques to construction economics and management (1983 to 2006). *Construction Management and Economics*, 26(5), 485–497. doi:10.1080/01446190801998716
- Bruton, G., Dess, G., & Janney, J. 2007. Knowledge management in technology-focused firms in emerging economies: caveats on capabilities, networks, and real options. *Asia Pacific Journal of Management*, 24(2), 115–130.
- Buchheit, R.B., Garrett, J.H., Lee, S.R. and Brahme, R., 2000. A knowledge discovery framework for civil infrastructure: a case study of the intelligent workplace. *Engineering with Computers*, 16(3-4), pp.264-274.
- Cabena, P., Hadjinian, P., Stadler, R., Verhees, J., & Zanasi, A. 1998. *Discovering data mining from concept to implementation* 1998; NJ: Prentice Hall.
- Chapman, P., Clinton, J., Khabaza, T., Reinartz, T., & Wirth, R. (1999). The CRISP-DM process model. *The CRIP-DM Consortium*, 310.
- Chan, A. P., Chan, D. W., & Yeung, J. F. 2009. Overview of the application of “fuzzy techniques” in construction management research. *Journal of Construction Engineering and Management*, 135(11), 1241–1252. Retrieved from [http://ascelibrary.org/doi/abs/10.1061/\(ASCE\)CO.1943-7862.0000099](http://ascelibrary.org/doi/abs/10.1061/(ASCE)CO.1943-7862.0000099)
- Chau, K.W., Cao, Y., Anson, M. and Zhang, J., 2002. Application of Data Warehouse and Decision Support System in Construction Management. *Automation in Construction*, 12(2), pp.213-224.
- Chiang, D. A., & Lin, N. P. 1999. Correlation of fuzzy sets. *Fuzzy sets and systems*, 102(2), 221-226.
- Choy, E., & Ruwanpura, J. Y. 2006. Predicting construction productivity using situation-based simulation models. *Canadian Journal of Civil Engineering*, 33(12), 1585-1600.
- Cox, E. 2005. *Fuzzy modeling and genetic algorithms for data mining and exploration* Morgan Kaufmann Publishers, Elsevier.

- Cox, E., Wills, B. 1997. Visual Data Mining: Recognizing Telephone Calling Fraud. *Data Mining and Knowledge Discovery*, Vol. 1, 1997; pp. 225-231.
- Dikmen, I., Birgonul, M. T., & Kiziltas, S. 2005. Prediction of organizational effectiveness in construction companies. *Journal of Construction Engineering and Management*, 131, 252.
- Deng, G. 2007. Simulation-based optimization. Ph.D. thesis, University of Wisconsin–Madison.
- Deogun, J. Spaulding, W. Shuart, B., Li, D. 2004. Towards Missing Data Imputation: A study of fuzzy K-means Clustering Method, In *Rough Sets and Current Trends in Computing. Lecture Notes in Computer Science 3066*, Springer-Verlag, 2004, pp.573-579.
- Edvinsson, L. 1987. The new business focus. *Service Industries Journal*, 7(7), 195–206.
- Elwakil, E., & Zayed, T. 2014. Construction knowledge discovery system using fuzzy approach. *Canadian Journal of Civil Engineering*, 42(1), 22-32.
- Everett, J.G. and Farghal, S., 1994. Learning curve predictors for construction field operations. *Journal of construction engineering and management*, 120(3), pp.603-616.
- FAHW.2014. Federal Highway administration Policy. Retrieved from : https://safety.fhwa.dot.gov/tools/data_tools/mirereport/29.cfm.
- Fayyad, U, Piatetsky-Shapiro, G. Smyth, P.1996. From data mining to knowledge discovery: an overview, *Advances in knowledge discovery and data mining. American Association for Artificial Intelligence*, Menlo Park, CA, 1996.
- Guns, T. 2016. Towards generic and efficient constraint-based mining, a constraint programming approach. In *Proceedings of the 16ieme Journees Francophones Extraction et Gestion des Connaissances (EGC)* (pp. 13-20).
- Han, J., Pei, J., & Kamber, M. 2011. *Data mining: concepts and techniques*. Elsevier. San Francisco, CA.
- Hildreth, J. 2012. Using Construction Equipment Simulators to Teach Learning Curve Theory Paper presented at 2012 ASEE Annual Conference & Exposition, San Antonio, Texas. <https://peer.asee.org/22179>
- Horton, F. W. 1979. *Information resources management: concept and cases*. Ohio: Association for Systems Management Press.
- Khan, Z. U. 2005. Modeling and parameter ranking of construction labor productivity. Master's thesis, Concordia University.
- Kivrak S, Arslan G, Dikmen I, Birgonul, MT. 2008. Capturing knowledge in construction projects: knowledge platform for contractors. 2008, *Journal of engineering Management*, volume 24;pp 87–95.
- Lin, Y., Cunningham, G. A., & Coggeshall, S. V. 1996. Input variable identification—fuzzy curves and fuzzy surfaces. *Fuzzy sets and systems*, 82(1), 65-71.

- Lv, X. and El-Gohary, N., 2016. Text Analytics for Supporting Stakeholder Opinion Mining for Large-scale Highway Projects. *Procedia Engineering*, 145, pp.518-524.
- Malyusz, L., & Pem, A. 2014. Predicting Future Performance by Learning Curves. *Procedia-Social and Behavioral Sciences*, 119, 368-376.
- McRea, A., & Langdon, D. 2003. Knowledge management in construction. *Structural Engineering*, 81(13), 14.
- Minitab, I. N. C. 2000. MINITAB statistical software. Minitab Release, 13.
- Mougel, P. N., Plantevit, M., Rigotti, C., Gandrillon, O., & Boulicaut, J. F. 2010. Constraint-based mining of sets of cliques sharing vertex properties. *ACNE*, 10, 48-62.
- Moselhi, O., Gong, D., El-Rayes, K., 1997. Estimating weather impact on the duration of construction activities, *Can. J. Civ. Eng.* 24 (3) (1997) 359–366.
- Moselhi, O., Leonard, C., Fazio, P. 1991. Impact of change orders on construction productivity, *Can. J. Civ. Eng.* 18 (3) (1991) 484–492.
- Nonaka, I. 1991. The knowledge creating company. *Harvard Business Review*, 69(6), 96–104.
- Nonaka, I., & Takeuchi, H. 1995. *The knowledge creating company*. Oxford: Oxford University Press.
- Park, H. 2006. Conceptual framework of construction productivity estimation, *KSCE J. Civ. Eng.* 10 (5) (2006) 311–317.
- Mirahadi, F., & Zayed, T. 2016. Simulation-based construction productivity forecast using neural-network-driven fuzzy reasoning. *Automation in Construction*, 65, 102-115.
- Reffat, R. M., Gero, J. S., & Peng, W. 2006. Improving the management of building life cycle: A data mining approach. *Innovation International Conference*, 25 – 27 October 2004, Surfers Paradise, Australia.
- Rogers, D. M. A. 1987. Opening remarks—roundtable on critical issues: management of knowledge assets into the 21st century. *Journal of Technology Transfer*, 11(2), 75–79.
- Senaratne, S., & Sexton, M. 2009. Role of knowledge in managing construction project change. *Engineering Construction and Architectural Management*, 16(2), 186–200.
- Silva, A., & Antunes, C. 2016. Constrained pattern mining in the new era. *Knowledge and Information Systems*, 47(3), 489-516.
- Soibelman, L. and Hyunjo, K. 2002. Data Preparation Process for Construction Knowledge Generation through Knowledge Discovery in Databases. *Journal of Computing in Civil Engineering*, American Society of Civil Engineers (ASCE), January 2002, Volume 16, Number 1 pp 39-48.

- Soibelman L, Liu L, and Wu, J. 2004. Data Fusion and Modeling for Construction Management Knowledge Discovery 10th International Conference on Computing in Civil and Building Engineering, June, 2004, Weimar, Germany.
- Sonmez, R., & Rowings, J. E. 1998. Construction labor productivity modeling with neural networks. *Journal of Construction Engineering and Management*, 124(6), 498–504. Retrieved from [http://ascelibrary.org/doi/abs/10.1061/\(ASCE\)0733-9364\(1998\)124:6\(498\)](http://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9364(1998)124:6(498))
- Takagi, H., & Hayashi, I. 1991. NN-driven fuzzy reasoning. *International Journal of Approximate Reasoning*, 5(3), 191-212.
- Thomas, H. R., C. T. Mathews, and J. G. Ward, 1986. Learning Curve Models of Construction Productivity. *Journal of Construction Engineering and Management*, ASCE, 112(2), 245-258.
- Tyagi, S. K. 2015. Correlation coefficient of dual hesitant fuzzy sets and its applications. *Applied mathematical modelling*, 39(22), 7082-7092.
- Wang, F., 2005. On-Site labor productivity estimation using neural networks. Master's thesis, Concordia University, Montreal, Canada
- Ye, J., 2014. Correlation coefficient of dual hesitant fuzzy sets and its application to multiple attribute decision making. *Applied Mathematical Modelling*, 38(2), 659-666.
- Yu, D., & Yang, J. 2016. Knowledge Management Research in the Construction Industry: a Review. *Journal of the Knowledge Economy*, 1-22.
- Zayed, T. M., & Halpin, D. W. 2005. Pile construction productivity assessment. *Journal of Construction Engineering and Management conference*, 131, 705-714.

Table 1 Variables description

No.	variables	Description
1	Temperature (°C)	Average of eight working hours of the day
2	Humidity(%)	Average of eight working hours of the day
3	Precipitation	Incorporated in terms of four numerical values as follows: No precipitation = 0, Light rain = 1, Rain = 2, and Snow = 3
4	Wind Speed (km/h)	Average of eight working hours of the day
5	Floor Height	The floor number
6	Work Type	Two types of activities will be considered as follows: Slabs = 1 and walls = 2
7	Gang Size (workers)	Number of workers (skilled + labor) in the gang
8	Labor Percent (%)	The percentage of the labor (non skilled workers) in the gang
9	Driver Skills	1 = Excellent , 2 = Very Good , 3 = Good and 4 = Bad (depending on the number of years of experience)
10	Truck Status	1 = Excellent , 2 = Very Good , 3 = Good and 4 = Bad (depending on the annual safety check for insurance)
11	Road Conditions	1 = Excellent” <i>Only new (or nearly new) superior pavements are likely to be smooth enough and distress free</i> ”, 2 = Very Good” <i>Pavements in this category, although not quite as smooth as those described above, give a first class ride and exhibit few, if any, visible signs of surface deterioration</i> ”, 3 = Good” <i>The riding qualities of pavements in this category are noticeably inferior to those of new pavements, and may be barely tolerable for high-speed traffic</i> ” and 4 = Bad” <i>Pavements in this category have deteriorated to such an extent that they affect the speed of free-flow traffic</i> ” (depending on Serviceability Rating of FHWA, 2014).

Table 2 Variables affecting the concrete pouring process (Sample Cases)

Temperature °C	Humidity %	Precipitation	Wind speed (K/h)	Gang size (workers)	Labor Percentage %	Floor level	Method	Time (min)
-8.5	46	0	6.6	7	57	2	1	63.00
-15	50	0	12	5	60	2	1	53.70
7	90	1	-	5	60	9	1	53.40
-14.5	42	0	7.5	11	63	4	1	59.10
23	82	0	11	8	-	12	2	75.90
3	97	0	8	11	63	5	1	62.70

Table 3 Variables affecting the hauling process (Sample Cases)

Temperature °C	Precipitation	Wind speed (K/h)	Driver Skills	Truck Status	Road Conditions	Time (min)
6.5	0	11.3	1	2	2	23.75
5.5	0	12	3	3	4	27.50
-5	0	15.8	3	2	4	28.75
7	1	5.4	3	4	4	30.62
6	1	11.9	3	3	3	29.37
15.5	0	18.3	2	4	3	26.25

Table 4 Variables affecting the loading process (Sample Cases)

Temperature °C	Humidity %	Precipitation	Wind speed (K/h)	Gang size(workers)	Labor Percentage %	Time (min)
23	82	0	11	4	45	30.36
24	82	0	8	5	39	30.96
16	73	1	14	4	36	25.44
15	64	1	19	6	40	21.84
16	60	0	6	5	36	30.36
18	58	0	6	6	40	31.32

Table 5 Variables affecting the return process (Sample Cases)

Temperature °C	Precipitation	Wind speed (K/h)	Driver Skills	Truck Status	Road Conditions	Time (min)
16	1	14	3	4	4	24.25
13	0	13	2	4	3	23.00
21	0	8	1	2	2	18.50
20	0	23	1	2	2	17.45
16	0	8	1	2	2	16.50
17	0	6	1	3	2	19.00

Table 6 Fuzzy curve and mean square error calculations for gang size

X5	X5 Normalized	Y	Y Normalized	Mi,k(Xi)	C5	(Ci(xi,k)-yk)^2
7	0.33	63.00	0.46	3.68	1.70	10.36
11	1.00	62.70	0.46	3.10	1.41	7.00
5	0.00	69.90	0.61	4.03	2.45	11.69
11	1.00	51.60	0.22	3.10	0.69	8.30
11	1.00	48.90	0.16	3.10	0.51	8.63
11	1.00	41.10	0.00	3.10	0.00	9.62
7	0.33	51.60	0.22	3.68	0.82	11.96
5	0.00	58.80	0.37	4.03	1.50	13.35
11	1.00	66.90	0.54	3.10	1.69	6.54
8	0.50	67.80	0.56	3.52	1.98	8.76
9	0.67	54.00	0.27	3.37	0.92	9.62
5	0.00	53.40	0.26	4.03	1.04	14.19
9	0.67	46.20	0.11	3.37	0.36	10.67
9	0.67	77.70	0.77	3.37	2.60	6.77
5	0.00	75.60	0.73	4.03	2.93	10.88
8	0.50	75.90	0.73	3.52	2.59	7.77
9	0.67	77.40	0.77	3.37	2.58	6.80
8	0.50	63.60	0.47	3.52	1.67	9.29
11	1.00	54.60	0.28	3.10	0.88	7.94
10	0.83	75.90	0.73	3.23	2.37	6.25
11	1.00	78.30	0.78	3.10	2.43	5.37
11	1.00	85.50	0.94	3.10	2.91	4.69
9	0.67	79.80	0.82	3.37	2.75	6.54
6	0.17	54.90	0.29	3.85	1.12	12.65
8	0.50	76.50	0.75	3.52	2.63	7.70
9	0.67	88.50	1.00	3.37	3.37	5.63
9	0.67	80.40	0.83	3.37	2.80	6.47
10	0.83	49.20	0.17	3.23	0.55	9.38
8	0.50	54.60	0.28	3.52	1.00	10.48
11	1.00	57.30	0.34	3.10	1.06	7.62
11	1.00	75.60	0.73	3.10	2.26	5.64
10	0.83	58.20	0.36	3.23	1.17	8.25
11	1.00	74.40	0.70	3.10	2.18	5.76
10	0.83	42.60	0.03	3.23	0.10	10.25
11	1.00	44.40	0.07	3.10	0.22	9.19

9	0.67	49.20	0.17	3.37	0.58	10.26
MSE5				8.92		

Table 7 Variables ranking using fuzzy average method

Rank	MSEi	Variables
3	8.98	Temperature
5	9.86	Humidity
7	11.49	Precipitation
6	10.72	Wind speed
2	8.97	Floor level
8	11.77	Method
1	8.92	Gang Size
4	9.67	Labor Percentage

Table 8 Variables ranking using ANN

Rank	Contribution	Variables
1	0.3191	Temperature
4	0.1004	Humidity
2	0.1213	Precipitation
6	0.0946	Wind speed
3	0.1200	Floor level
8	0.0686	Method
5	0.1001	Gang Size
7	0.0754	Labor Percentage

Table 9 Variables ranking using regression method

Contribution	Variables
YES	Temperature
YES	Humidity
No	Precipitation
YES	Wind speed
YES	Floor level
YES	Method
YES	Gang Size
NO	Labor Percentage

Table 10 Fuzzy cluster membership values and task durations (Sample Cases)

C1	C2	C3	Task Duration(min)
0.5488	0.2387	0.2125	63.0
0.6255	0.2049	0.1696	53.7
0.5461	0.2571	0.1968	59.1
0.7503	0.1273	0.1224	62.7
0.7221	0.1411	0.1368	69.9
0.6182	0.2067	0.1751	51.6
0.4964	0.3138	0.1898	48.9
0.6287	0.2007	0.1706	41.1
0.5443	0.2758	0.1799	51.6
0.5713	0.2433	0.1854	58.8
0.4422	0.3323	0.2255	62.1
0.4686	0.3416	0.1898	66.9
0.4438	0.314	0.2422	67.8
0.4764	0.3072	0.2164	54.0
0.6563	0.1799	0.1638	53.4

Table 11 A sample of candidate rules

Rule 1	If C1 is	0.5488	and C2 is	0.2387	and C3 is	0.2125	Then Time is	63.0
Rule 2	If C1 is	0.6255	and C2 is	0.2049	and C3 is	0.1696	Then Time is	53.7
Rule 3	If C1 is	0.5461	and C2 is	0.2571	and C3 is	0.1968	Then Time is	59.1
Rule 4	If C1 is	0.7504	and C2 is	0.1273	and C3 is	0.1224	Then Time is	62.7
Rule 5	If C1 is	0.7221	and C2 is	0.1411	and C3 is	0.1368	Then Time is	69.9
Rule 6	If C1 is	0.6182	and C2 is	0.2067	and C3 is	0.1751	Then Time is	51.6
Rule 7	If C1 is	0.4964	and C2 is	0.3138	and C3 is	0.1898	Then Time is	48.9
Rule 8	If C1 is	0.6287	and C2 is	0.2007	and C3 is	0.1706	Then Time is	41.1
Rule 9	If C1 is	0.5443	and C2 is	0.2758	and C3 is	0.1799	Then Time is	51.6
Rule 10	If C1 is	0.5713	and C2 is	0.2433	and C3 is	0.1854	Then Time is	58.8
Rule 11	If C1 is	0.4422	and C2 is	0.3323	and C3 is	0.2255	Then Time is	62.1
Rule 12	If C1 is	0.4686	and C2 is	0.3416	and C3 is	0.1898	Then Time is	66.9
Rule 13	If C1 is	0.4438	and C2 is	0.3140	and C3 is	0.2422	Then Time is	67.8
Rule 14	If C1 is	0.4764	and C2 is	0.3072	and C3 is	0.2164	Then Time is	54
Rule 15	If C1 is	0.6563	and C2 is	0.1799	and C3 is	0.1638	Then Time is	53.4
Rule 16	If C1 is	0.4630	and C2 is	0.3096	and C3 is	0.2274	Then Time is	46.2
Rule 17	If C1 is	0.4829	and C2 is	0.3323	and C3 is	0.1848	Then Time is	77.7
Rule 18	If C1 is	0.5289	and C2 is	0.2885	and C3 is	0.1825	Then Time is	75.6
Rule 19	If C1 is	0.6187	and C2 is	0.1751	and C3 is	0.2062	Then Time is	60.3
Rule 20	If C1 is	0.3454	and C2 is	0.2165	and C3 is	0.4381	Then Time is	76.2
Rule 21	If C1 is	0.4806	and C2 is	0.2342	and C3 is	0.2853	Then Time is	75.9
Rule 22	If C1 is	0.5063	and C2 is	0.2639	and C3 is	0.2297	Then Time is	77.4
Rule 23	If C1 is	0.5351	and C2 is	0.2522	and C3 is	0.2127	Then Time is	63.6
Rule 24	If C1 is	0.5727	and C2 is	0.2482	and C3 is	0.1791	Then Time is	54.6
Rule 25	If C1 is	0.4277	and C2 is	0.2974	and C3 is	0.2748	Then Time is	75.9
Rule 26	If C1 is	0.4184	and C2 is	0.3372	and C3 is	0.2443	Then Time is	78.3

Table 12 A sample of the rules' effectiveness degrees

Rules	Degree of effectiveness	Rules	Degree of effectiveness
Rule 1	0.012	Rule 19	0.006
Rule 2	0.007	Rule 20	0.021
Rule 3	0.013	Rule 21	0.016
Rule 4	0.002	Rule 22	0.016
Rule 5	0.003	Rule 23	0.014
Rule 6	0.007	Rule 24	0.011
Rule 7	0.019	Rule 25	0.024
Rule 8	0.007	Rule 26	0.028
Rule 9	0.014	Rule 27	0.022
Rule 10	0.011	Rule 28	0.004
Rule 13	0.024	Rule 31	0.026
Rule 17	0.020	Rule 35	0.017
Rule 18	0.015	Rule 36	0.010

Draft

Table 13 A sample of a fuzzy knowledge base

Process Variables									Membership Functions			Fuzzy Rules								
V1	V2	V4	V5	V6	V7	V8	V9	Time	C1	C2	C3									
-8.5	46	0	6.6	7	57	2	1	63	0.55	0.23	0.21	Rule 1	If C1 is	0.23	and C2 is	0.23	and C3 is	0.21	Then Time is	63.0
-15	50	0	12	5	60	2	1	53.7	0.63	0.2	0.16	Rule 2	If C1 is	0.20	and C2 is	0.20	and C3 is	0.16	Then Time is	53.7
-14.5	42	0	7.5	11	63	4	1	59.1	0.55	0.25	0.19	Rule 3	If C1 is	0.25	and C2 is	0.25	and C3 is	0.19	Then Time is	59.1
3	97	0	8	11	63	5	1	62.7	0.75	0.12	0.12	Rule 4	If C1 is	0.12	and C2 is	0.12	and C3 is	0.12	Then Time is	62.7
2.5	92	0	6.2	5	60	6	1	69.9	0.72	0.14	0.13	Rule 5	If C1 is	0.14	and C2 is	0.14	and C3 is	0.13	Then Time is	69.9
4.5	86	1	9.1	11	64	6	1	51.6	0.62	0.2	0.17	Rule 6	If C1 is	0.20	and C2 is	0.20	and C3 is	0.17	Then Time is	51.6
-4.5	48	0	14.1	11	64	6	1	48.9	0.50	0.31	0.18	Rule 7	If C1 is	0.31	and C2 is	0.31	and C3 is	0.18	Then Time is	48.9
-18.1	66	0	7	11	64	7	1	41.1	0.63	0.2	0.17	Rule 8	If C1 is	0.20	and C2 is	0.20	and C3 is	0.17	Then Time is	41.1
-6	37	0	19.9	7	57	7	1	51.6	0.55	0.27	0.17	Rule 9	If C1 is	0.27	and C2 is	0.27	and C3 is	0.17	Then Time is	51.6
-7	41	0	7.9	5	60	7	1	58.8	0.57	0.24	0.18	Rule 10	If C1 is	0.24	and C2 is	0.24	and C3 is	0.18	Then Time is	58.8

Table 14 Fuzzy knowledge base validation results

C1	C2	C3	Time(min)	Estimated Time (min)	AIP	(Ci - Ei)^2	ABS (Ci - Ei)
0.6255	0.2049	0.1696	53.7	52.9261	0.0144	0.5989	0.7739
0.5461	0.2571	0.1968	59.1	57.3813	0.0291	2.9539	1.7187
0.4422	0.3323	0.2255	62.1	65.3717	0.0527	10.7041	3.2717
0.6187	0.1751	0.2062	60.3	57.8351	0.0409	6.0757	2.4649
0.3454	0.2165	0.4381	76.2	68.3471	0.1031	61.6678	7.8529
0.1668	0.1529	0.6803	71.4	74.8541	0.0484	11.9311	3.4541
0.49	0.2588	0.2512	69.3	56.7075	0.1817	158.5717	12.5925
0.5224	0.2316	0.246	70.2	54.7342	0.2203	239.1914	15.4658
0.5254	0.2468	0.2278	55.8	57.0190	0.0218	1.4861	1.2190
0.4208	0.2456	0.3336	55.5	61.3393	0.1052	34.0975	5.8393
AIP (%)	8	AVP (%)	92	RMSE	2	MAE	5

Figure 1 The considered variables in the present study

Figure 2 Model of the concrete pouring operation

Draft

Figure 3 The data sets of concrete pouring operation

Draft

Figure 4 Statistical parameters and probability density functions

Figure 5 Fuzzy curve for Gang Size

Figure 6 Estimated vs. actual task duration

Draft