2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

Building Information Modeling Application in Engineering Design Performance Prediction

[1]DEVISETTI UMA SHANKAR RAO Assistant Professor umashankar.divisetti@gmail.com
[2]GOPIDI RAM MOHAN REDDY Assistant Professor rammohan.nits@gmail.com
Department of CIVIL Engineering,
Nagole Institute of Engineering and Technology Hyderabad.

Abstract

Engineering design constitutes a critical factor in a construction project, and the process has fundamentally impacted the performance. Previous research on design performance has established the relationships between project attributes and performance measures. Recently, there is growing interested in measuring the benefits of BIM on project performance, but less attention on design performance. Evaluating design performance based on the relationships between the use of BIM inputs and outputs becomes essential. This paper presents a systematic analysis correlating BIM uses with engineering performance to better predict industrial construction projects. Applying project data collected through BIM application surveys and the statistical variable reduction techniques to develop multiple linear regression models of the engineering design performance evaluation, the best prediction was achieved and validated. The study results show that the correlation between BIM uses and engineering performance measures is significant, and the engineering design performance can be predicted from BIM uses attributes.

Index Terms—Building Information Modeling (BIM), engineering design performance, BIM Uses, performance measures

INTRODUCTION

Project performance attracts attention for industrial owners and researchers in various aspects of construction activities. With expectations of high performance, the measurement and prediction of performance constitute a successful execution and delivery of a project. The engineering design process is defined as a transformation of idea into reality from owner's expectation and requirement are considered as a significant driving force for a successful project overall performance [1]. As the fact that the engineering design process is a crucial factor impacting project life cycle, the engineering performance measurement and prediction is critical for the successful delivery of a project, and the ability to manage engineering design performance is essential. In recent years, the engineering design process has been significantly influenced the project execution workflows during the life cycle of a facility by applying Building Information Modeling (BIM) in the Architecture,Engineering, and Construction (AEC). Now, BIM application has gained a rapid interest in the AEC industry. The major challenge is allowing the stakeholders to automate project tasks in design, analysis, coordination, fabrication, construction, commissioning, operation, and maintenance processes. A study of critical success factors for BIM implementation during the period 2005 to 2015 found the factors were collaboration in design, engineering, and construction stakeholders; earlier and accurate 3D visualization of design; coordination and planning of construction works; enhancing the exchange of information and knowledge management; and improved site layout planning and site safety [2]. Research on the significant findings of BIM benefits is mainly related to 3D modeling, coordination, collaboration, process improvement, cost management, time management, risk management, resource management, facility management, and sustainability applications [3]. Results of the research also showed that the priority rankings performed for the benefits of BIM in terms of time and cost [4]. The application of BIM has proven to reduce project schedules, avoid project cost growth, and improve the overall quality of facilities, and many facility owners and developers are requiring teams to embed BIM into their projects.

Thus, BIM is seen by changing the conventional project execution model and impact how the stakeholders evaluate and predict the project and engineering performance. Therefore, there is a significant requirement to measure and predict engineering performance through project life for improving the implementation of BIM uses. This paper proposes a systemic approach to measure and predict the effectiveness of using BIM on project engineering performance. First, previous studies in engineering performance assessment and data collection are conducted. Second, find the relationship among the BIM uses identified in National BIM Guide for Owner (NBGO) by the National Institute of Building Sciences [5], and the correlation between BIM uses and engineering design. The stepwise multiple regression modeling and the assessment of the prediction model are both developed. Third, the validation where the model will be validated and implemented through real data from projects. Finally, the findings will be concluded for future works will be suggested.

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

RESEARCH METHODOLOGY

This study applied correlation analysis and regression modeling by using Minitab 18 statistical software, which is a comprehensive, predictive analytics and modeling tool. To identify the levels of influence by BIM use inputs on engineering design performance, two statistical models as shown in Fig. 1 are proposed to evaluate the relationship of the variables and develop the prediction model. The first model is separated essential and enhanced BIM uses, which considers how essential and enhanced BIM uses influence separately at stages of engineering performance measures. Model 1 applies correlation analysis to measure the strength of the relationship between 10 outputs associated with 5 inputs for the essential model and ten outputs associated with 10 inputs for the enhanced model. This model is in the establishment of the statistical correlation significance and possible connection among the inputs and the outputs. The second model considers how essential and enhanced BIM uses influence combinedly at stages of engineering performance measures. Model 2 applies multiple regression model by stepwise procedures for the output and input variables and is a screening processes to define the list of probable inputs and it is a method of fitting regression models in which the choice of predictive variables is carried out by an automatic procedure to find the final regression equations and further predict the engineering performance.

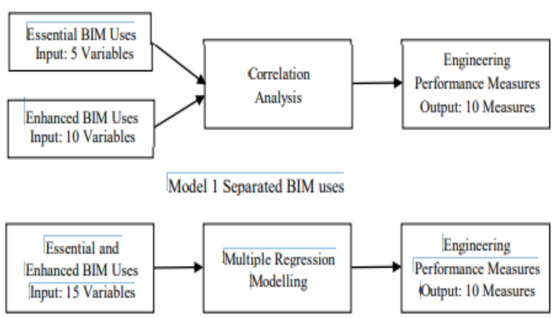


Figure 1. Separated and combined model approach

To determine and analyze the set of perceived BIM uses utilized by construction projects in the industry, four sectors were targets with the intention of the assessment of engineering design performance in BIM implementation. The four industry sectors chosen were power, oil and gas, rail and metro, and high-tech facilities. The data was collected from 55 lump sum turnkey projects world-wise from Engineering News-Record (ENR) top 10 U.S. Design-Build Firms and Top 10 U.S. Contractors [6]. The projects surveyed in this research including power plants (22%), oil and gas plants (12%), rail and metro (31%) and high-tech facilities (35%) where representing diversity spectrum of the construction industry. These projects are/were constructed by the leading companies in the U.S. industrial construction sector and U.S. leading company engineering design process for normalization purposes. The data set consisted of large-scale projects from with lump sum andtargeted price with incentives of project sizes from US$10 million to US$150 million. To construct the proposed model, a performance evaluation form was designed to find the correlation between BIM use attributes and engineering performance. As a result, these attributes that were found to be statistically significant were identified and formed the basis for constructing the engineering performance prediction models. The total 54 survey data set were divided into two groups, the first group of 52 projects was to provide sample data for model development, the second group of 2 project data for model validation. To evaluate the model, first is to compare the existing project data sets by the selection of a project of sample 36 from the first group of 52 projects. The second step was to use 2 projects for model validation.

INPUTS AND OUTPUTS

BIM Use Input Attributes

To direct the industrial facility owner to develop and implement requirements for BIM application in procedures and in contracts to plan, design, construct, and operate facilities, National Institute of Building Sciences (NIBS) published the National BIM Guide for Owners (NBGO) in January 2017 as a standard guideline. The Guide defines an approach to creating and fulfilling BIM requirements for a typical project from the owner's standpoint and assists owners in maximizing the potential of BIM on their projects.

2581-4575

International Journal For Recent Developments in Science & Technology

Crossref

A Peer Reviewed Research Journal

Cat	BIM Use Attributes	Data Collection
Essential BIM Uses	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model
	Design Authoring	BIM Software/Tool Used in Design Process
	Design Review Coordination	30/60/90%/100% Model Review Clash Detection Process
	Record Modeling	Physical and Functional Information input in model
Enhanced BIM Uses	Cost Estimating	Generate MTO and Cost Data
	Phase and 4D planning	Dimension of Time and Schedule Added
	Site Analysis-Development	GIS Tools used in Model
	Site utilization-For Construction	Communication Tool for Construction Plan Added
	Digital Fabrication	Prefabricate by using BIM Data or Information
	3D Location and Layout	Function of Utilities to Layout Assemblies
	Engineering Analysis	Engineering System Simulation used in Model
	Sustainability Analysis	Sustainable Design Elements included in Model
	Codes and Standards Compliance	Validation of Codes for Model
	Construction Systems Design	Contemporary System Analysis in Model

In NBGO, BIM uses are defined as a method of applying BIM during a facility's life cycle to achieve owner's specific objectives. The application of BIM then allows owners to use the model in multiple waysdepending on their specific requirements of the facility. As indicated in NBGO section 4.2, BIM uses are characterized as Essential BIM Users, Enhanced BIM Users, and Owner-Related Uses, where should be aligned with project goals, selected based on added value to owners. Table I shows the Essential and Enhanced BIM Uses from NBGO with data collection scale 0 to 10 for 0- 100% implemented in the projects. The owner related BIM uses include asset management, disaster planning and management, and space management in the Guide. Considering the significance of BIM uses in the construction project development and the size of the data domain, the owner-related BIM uses is not included in this research. The definition of the attributes further defined the execution method of the use variables. It provided a clear instruction of data collection criteria for the standardization of the input attributes. B. Engineering Performance Output Measures The Research Team 156 (RT-156) of Construction Industry Institute (CII) studied the industrial project data collected by CII Benchmarking and Metrics Committee and aimed at searching for approaches to improving engineering performance in industrial construction projects and developed a new and innovative approach for measuring productivity in engineering organizations by addressing the broader scheme of engineering performance [7]. The developed platform by RT-156 was used for several practical purposes, including prediction of engineering performance measures, assessment of total and relative engineering performance. On the integrated scheme by RT-156, the engineering performance measures of 10 metrics which based on the 10 outputs identified for measuring and forecasting engineering performance by Georgy, Chang and Zang [8]. This paper further expanded the definition of output measures, the output variables further defined the execution method of the use variables and provided an explicit instruction of data collection criteria for the standardization of the output variables. There are three non-numerical variables consisted of a higher degree of uncertainty or fuzziness, namely (1) design document release commitment (2) construction hours for design problem solving and filed design (3) estimated dollar saving due to constructability. These performance output variables were difficult to define and can only be depicted in vague linguistic terms. Research through a substantial collection of quantitative project performance data and univariate statistical analysis was conducted for further consideration. Based on the research, 3 variables were redefined and replaced by the more specific and measurable quantitative index, namely Detailed Designed Quantity Compared to Final Installed Quantity, to replace design document release commitment in the detailed design phase to reflect design performance. Construction Hours for Request for Information, to replace construction hours for design problem solving and filed design and Construction Hours for Field Change Request (FCR), to replace estimated dollar saving due to constructability. As shown in Table II, the revisedengineering performance output measures of total 10 variables consist of 3 replaced variables and originally defined 7 variables which are mainly divided by three categories according to the development of a construction project. The proposed engineering performance measures specify the measurable quantitative criteria definition to evaluate the output values from the owner's perspective

TABLE II. ENGINEERING PERFORMANCE OUTPUT MEASURES

2581-4575

International Journal For Recent Developments in Science & Technology

Crossref

A Peer Reviewed Research Journal

Phase	Output Measures (in %)	Definition (in %)
Detailed Design	Design Rework	Design Rework Hours/Total Design Hours
	Detailed Design Schedule Delay	Days of Design Schedule Delay/Total Design Schedule
	Detailed Design Cost Overrun	Design Cost Overrun in USD/Total Design Cost in USD
	Detailed Designed Quantity Compared to Final Installed Quantity	Issue for Construction Designed Quantity/Final Installed Quantity
Construction	Fabrication and Construction Schedule Delay due to Design Deficiencies	Days of Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction
	Fabrication and Construction Cost Overrun due to Design Deficiencies	Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD
	Construction Hours for Request for Information (RFI)	Construction Hours for Request for Information (RFI)/Total Construction Hours
	Construction Hours for Field Change Request (FCR)	Construction Hours for Field Change Request (FCR)/Total Construction Hours
Start-up	Start-up Schedule Delay due to Design Deficiencies	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up
	Start-up Cost Overrun due to Design Deficiencies	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD

FINDINDS

Correlation Analysis Correlation analysis is a statistical method to evaluate the strength of cause-effect relationship between two quantitative variables. A high correlation explains that two or more variables have a strong relationship with each other, and a weak correlation explains that the variables are hardly related. Pearson's correlation coefficient for continuous interval level data ranges from -1 to +1 is a measure of the strength of the relationships. A correlation analysis is conducted to measure the relationship between BIM use input attributes and engineering design performance measure outputs. Applying Rule of Thumb in interpreting the size of correlation coefficient, 0.9 to 1.0 (−0.9 to −1.0) represents very high positive (negative) correlation and 0.7 to 0.9 (−0.70 to −0.9) represents high positive (negative) correlation [9]. The Pearson Correlation between 0.7 to 1.0 (−0.70 to −1.0) are further be focused and reviewed in the correlation analysis. The correlation in BIM Use input attributes and engineering performance outputs. Detailed design valuescorrelate with essential BIM uses mainly on design activities including coordination, record modeling design authoring, design review, and correlate with enhanced BIM uses also influenced by design including engineering analysis, sustainability analysis and phase and 4D planning. Fabrication and construction values correlate with enhanced BIM uses, where related to construction activities including digital fabrication, site analysis development, construction system design, site utilization for construction and cost estimating. Start-up and commissioning values outputs correlate with both essential and enhanced BIM uses, where record modeling in essential use reflects record information and cost estimating, codes and standards compliance, construction system design and phase and 4D planning in enhanced BIM use significantly influence at project completion phase.Multiple Regression A prediction model is proposed to be employed for engineering design performance measurement using statistic regression techniques. This process develops a sequence of regression models, at each step adding or deleting an input variable based on F-statistic calculations to determine whether such variable is significant or insignificant. Applying the stepwise reduction technique, a multiple linear regression model was developed for each measure of engineering performance outputs. The details of the 52 project samples were applied into Minitab 18 and the models were produced as shown in Table 3 for each output measure. The predictive power of the models is rated through the statistical measurement coefficient of determination and the model goodness of fit adjusted R-square as shown in R-sq (adj) column. The F-test has the null hypothesis that the means of a given set of normally distributed populations, all having the same standard deviation, are equal. The model explains zero variance in the dependent variables, the results shown in F-Value column is highly significant, thus, it can be concluded that the model explains a significant amount of the variance. The P-value (0.000s) are much smaller than a significance level of 0.05 which is the probability of rejecting the null hypothesis, hence, the null hypothesis is rejected and concluding the model is statistically significant. From the statistical evidence, the fittest regression models with the formation of equations of inputs and outputs then produced and significantly created very reliable predictions for each engineering performance measure, as showed on the third column in Table III. TABLE III.

MULTIPLE REGRESSION

MODEL FOR OUTPUT MEASURES AND BIM USES ATTRIBUTES

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

Ph	Output Measures (in %)	Regression Model	R^2(adj)	F-Value	P-Value
Detailed Design	Design Rework	26.96 - 0.815 A4 - 1.032 A10 - 1.629 A12	80.32%	70.37	0.000
	Design Schedule Delay	12.811 - 0.303 A1 - 0.765 A3 + 0.293 A4 - 0.493 A5	73.75%	36.82	0.000
	Design Cost Overrun	27.31 - 1.202 A4 - 0.912 A10 - 1.179 A12	81.46%	75.68	0.000
	Designed Quantity Compared to Final Installed Quantity	90.823 + 0.2268 A4 + 0.3865 A7 - 0.3105 A10 + 0.2506 A11 + 0.801 A12	84.48%	56.51	0.000
Construction	Construction Schedule Delay due to Design Deficiencies	21.34 - 1.312 A8 - 1.082 A9 + 0.678 A12	68.29%	37.62	0.000
	Construction Cost Overrun due to Design Deficiencies	10.765 - 0.521 A4 - 0.755 A6 + 0.441 A14	71.25%	43.12	0.000
	Construction Hours for Request for Information (RFI)	10.096 - 0.706 A8 + 0.501 A11 - 0.611 A14	65.69%	33.55	0.000
	Construction Hours for Field Change Request (FCR)	8.811 - 0.4674 A4 + 0.3261 A5 - 0.6091 A6	71.77%	44.21	0.000
Start-up	Start-up Schedule Delay due to Design Deficiencies	10.551 - 0.467 A6 + 0.368 A13 - 0.923 A14	63.01%	29.96	0.000
	Start-up Cost Overrun due to Design Deficiencies	9.201 - 0.452 A5 - 0.3954 A6	67.77%	54.63	0.000

MODEL VALIDATION

The statistical models proposed in previous section described the measuring and predicting capabilities of the engineering design performance and the best fit model was obtained through stepwise regression modeling practices. The regression analysis techniques include maximizing the adjusted R-sq value, minimizing model variances, and only including variables in the model that have been proven to be statistically significant through Ftests and stepwise selection procedures. To validate the developed performance prediction model further, twostage test approaches was deployed to verify the accuracy of the model. As shown in Table IV, the first proposed test is applying the two project samples from the data collected pool for the comparing purpose. The second proposed test consists of two sets of a total of 2 samples. Knowing that the output measures given by the project data sets and those derived from the regression model had a linear relationship, the next step was to ascertain the strength and direction of the relationship using a correlation coefficient.

TABLE IV. MODEL VALIDATION

Ph	Engineering Performance Measures (in %)	Project Test 1-36		Project Test 2-53		Project Test 3-54	
		Model	Data	Model	Data	Model	Data
Design	Design Rework	22.6%	21%	11.2%	11%	22.4%	24%
	Detailed Design Schedule Delay	11.8%	12%	7.1%	7%	10.7%	9%
	Design Cost Overrun	22.8%	22%	10.8%	11%	23.1%	21%
	Designed Quantity Compared to Final Installed Quantity	93.8%	91%	96.5%	97%	92.6%	93%
Construction	Construction Schedule Delay due to Design Deficiencies	13.9%	12%	11.4%	11%	11.1%	10%
	Construction Cost Overrun due to Design Deficiencies	9.4%	7%	5.1%	6%	10.8%	12%
	Construction Hours for Request for Information	10.5%	10%	6.6%	6%	6.7%	5%
	Construction Hours for Field Change Request	7.5%	6%	3.8%	4%	8.3%	8%
Start-up	Start-up Schedule Delay due to Design Deficiencies	9.5%	8%	5.9%	6%	8.7%	7%
	Start-up Cost Overrun due to Design Deficiencies	8.3%	8%	5.4%	5%	5.9%	7%
Pearson Correlation Coefficient		0.9995		0.9998		0.9989	
Significant Level		0.000		0.000		0.000	

Apply Minitab, the correlation coefficients and significant levels were calculated as shown in the Table 4 by the correlation analysis between predicted model and awarded data for each engineering performance outputs. As a result, the first proposed test of two test projects for comparing to existing project data, the correlation coefficients are 0.9972 for test project sample 1 and 0.9995 for test project sample 36 with both P-value of 0.000 in more than 95% confidence interval which indicates that the correlation coefficients are significant. As the second proposed test of two test project sets, the average correlation coefficients are 0.9996 for test project set

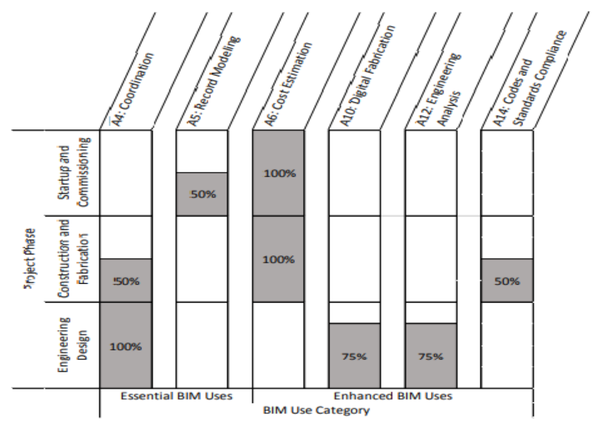
2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

1 and 0.9998 for test project set 2 with both average P-value of 0.000 in 95% confidence interval which indicates that the correlation coefficients are significant. According to Rule of Thumb, for 0.9 to 1.0 represents very high positive correlation. This meant that the correlation between the test project data and the model was a strong, positive, and linear relationships at high acceptance and desired levels. The results of the test to validate the model showed that it was reliable and able to predict an engineering performance measures that is highly correlated with awarded data from the projects.

VI. Discuss and limitations

In consolidating the findings from the proposed first separated BIM use model, the frequency of occurrence over 50% of each input by the outputs in three project phases are further reviewed. As illustrated in Fig. 2 Model 1, the essential BIM uses with five inputs, design authoring and design review present 100% by the four engineering performance measures in the engineering design phase, coordination presents 75% by the four engineering performance measures in the engineering phase and 50% in the construction phase, and 100% for record modeling by the two engineering performance measures in start-up phase. Furthermore, the enhanced BIM uses with ten inputs, phase and 4D planning and engineering analysis present 75% in the engineeringdesign phase, cost estimating, digital fabrication, and construction system design present 50% in the construction phase. In the start-up phase, phase and 4D planning, codes and standards compliance all present 100% occurrence. The first model shows the essential BIM uses are highly related to design phase activities, and the enhanced BIM uses are mainly correlated to the construction phase. Thus, Model 1 shows the engineering performance are highly influenced by BIM uses for essential and enhanced separately. In consolidating the findings from the proposed second combined BIM use model, the frequency of occurrence over 50% of each input by the outputs in three project phases are further reviewed. As illustrated in Figure 2 Model 2, the essential BIM uses with five inputs, coordination present 100% by the four engineering performance measures in engineering design phase and 50% by the four engineering performance measures in construction phase and 50% by the two engineering performance measures for record modeling in start-up phase. Furthermore, the enhanced BIM uses with 10 inputs, digital fabrication, and engineering analysis present 75% in engineering design phase, cost estimating shows 100% and codes and standards compliance present 50% in the construction phase. In the start-up phase, cost estimating presents a 100% occurrence. The second model indicates the essential BIM uses are highly related to design phase activities, and the enhanced BIM uses are mainly correlated to the construction phase. Therefore, the engineering performance are highly influenced by BIM uses for combined essential and enhanced inputs. In reviewing the frequency of percentage occurrence of total BIM uses in the project phases by the performance measures for both models, it is confirmed the BIM use input is highly significant for developed engineering performance prediction models.

Model 1



Model 2

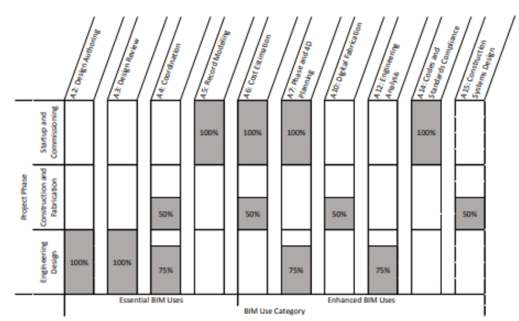


Figure 2. Models of critical BIM Uses for engineering performance

Furthermore, coordination presents in both models in the engineering design phase, and this explains coordination effort in the engineering design phase, including design authoring and review, which are significant. Coordination and cost estimating in the presence of both models in construction phase indicate coordination in construction activities and cost estimating are the main factors in construction. Recording modeling and cost estimating present in start-up phase for both models which indicate the record and cost are significant in project start-up phase. There are two limitations in the study. The chosen output measures are limited to the project phases before the operation of constructed plants. Adding performance measures depicting the operation and maintenance phases to the current measures would help create a more comprehensive prediction model. Second is the lack of data and the difficulty of collection. The data set of 54 industrial construction project samples is quite limited in terms of both data size and data quality. Although the number sample is limited, this study is nevertheless considered acceptable based on the triangulation concept, which stated that information about a single phenomenon should be collected from at least three different sources [10]. Notwithstanding the limited data, the high R-seq and high predictive power show the model is robust.

VII. CONCLUSIONS AND RECOMMENDATIONS

This paper utilized the statistical correlation and regression models as the platform for estimating engineering design performance regarding the project BIM use measures having impacts on such performance. Data and information from industrial projects contributed to the study of the targeted 10 engineering performance assessment with 15 BIM use inputs showed the promising results of the proposed model. The essence of this study intends to provide a comprehensive platform for establishing the relationships among the BIM use inputs and engineering performance measures. The approach utilized statistical correlation and regression models as the platform for estimating engineering performance regarding the project BIM use measures having impacts on such engineering performance. The study for Model 1 Separated BIM use inputs indicates a high correlationrelationship between inputs and outputs with 0.7 to 0.9 Pearson's Correlation coefficients. The multiple regression study for Model 2 combined BIM uses indicates 70% on average of high goodness of fit R-sq (adj) values and the acceptance level of the P-value of 0.000s. The prediction made through the performance prediction model in robust validation tests because of the high R-sq (adj) of 000s, the research thus validated.

AUTHOR CONTRIBUTION

The core contribution of this research is enhancing the knowledge of BIM implementation on engineering design performance and constructing a genetic model with predicting capabilities of the system while maintaining the flexibility in variable description of statistical-based modeling. The accuracy and reliability of the genetic model can further be improved by increasing the multidimensional project database used for the system. Two recommendations suggested to the construction project stakeholders who intend to measure and predict engineering performance by using BIM application in the projects. First, is to focus on the implementation of both essential and enhanced BIM use suggested in this paper and the definition of the BIM use and the defined attribute inputs provide a clear guideline on the driving factors for the engineering performance outputs. Second, to apply the performance prediction model developed in this study to predict the engineering performance so that there is a higher chance of control on the project design success. The new strategy alignment of standardization for the project engineering design process further benefits the overall project performance.

CONFLICT OF INTEREST

The author represents that the work is the author's original work. It is submitted only to this conference and has not been published before. The author also represents that, to the best of the knowledge, the work contains no libelous or unlawful statements, does not infringe on the rights of others, or contain material or instructions that might cause harm or injury. The author has no conflict of interest to declare.

REFERENCES

[1] M. E. Georgy, L. M. Chang, and L. Zang, "Prediction of engineering performance: A neurofuzzy approach," J. Constr. Eng. Manage., ASCE, vol. 131, no. 5, pp. 548-557, 2005.

[2] M. Antwi-Afari, H. Li, E. Pärn, and D. Edwards, "Critical success factors for implementing building information modeling (BIM): A longitudinal review," Automation Construction, pp. 100-110, July 2018.

[3] S. Seyis, "Pros and cons of using building information modeling in the AEC industry," J. Constr. Eng. Manage, ASCE, vol. 145, no. 8, 04019046, 2019.

[4] B. Tatum, "Construction engineering research: Integration and innovation," J. Constr. Eng. Manage., ASCE, vol. 144, no. 3, 04018005, 2018.

[5] National Institute of Building Sciences, National BIM guide for owners. Washington, DC: National Institute of Building Sciences, pp. 25-27, 2017.

[6] Engineering News-Record, The top 400 contractor's sourcebook 2017, The top 500 design firms sourcebook 2017, McGraw-Hill, New York, 2017.

[7] L. M. Chang, M. E. Georgy, and L. Zhang, "Engineering productivity measurement Research Rep. No. RT156-11," in Construction Industry Institute, Austin, Texas, 2001, pp. 100-134

[8] M. E. Georgy, L. M. Chang, and L. Zang, "Prediction of M. E. Georgy, L. M. Chang, and L. Zang, "Prediction of engineering performance: A neurofuzzy approach," J. Constr. Eng. Manage., ASCE, vol. 131, no. 5, pp. 548-557, 2005.

[9] 9-D. E. Hinkle, W. Wiersma, S. G. Jurs, Applied statistics for the behavioral sciences, 5th ed., Boston: Houghton Mifflin, 2003.
[10] M. Hammersley and P. Atkinson, Ethnography: Principles in Practice, London: Tavistock, 1983