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建築資訊模型執行應用於工程設計績效評估

Building Information Modeling Application in Engineering Performance Evaluation

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國立台灣大學土木工程學系博士班

民國 112 年博士學位論文摘要

建築資訊模型執行應用於工程設計績效評估

研 究 生：邱文彬

指導教授：張陸滿

績效管理為營建工程專案重要的經營措施，目的為評核專案執行過程中的各項績效指標，例如成本、進度、品質、安全與顧客滿意度等，主要為提供經營管理者必要的決策參考、早期警示與預防措施、以及加強持續改善的機會。然而，工程績效管理所涉及的層面非常廣泛，除了對績效一詞的看法與定義不盡相同外，其決策者對於專案執行各階段中績效監督的程度，也可能依其經驗與看法不同，而採取不同的決策與措施。

工程績效評估與控制對於專案的執行具有重要的意義，正確而有效的績效評估方式是營建工程專案成功與否的關鍵。根據營建工程業經驗，在專案規劃與執行初期，工程設計的過程就影響了營建工程的生命週期，且直接影響專案執行的成敗。而營建工程中廣泛被應用的成本影響曲線，說明了工程設計執行為最能夠直接影響總造價的階段，在專案執行過程中需要仔細評估與衡量，所以工程規劃與設計對於專案的成功執行有關鍵性影響。儘管在某些營建工程專案中，工程設計成本已接近專案總造價的 20%，但至今對於工程設計績效的了解和研究仍不及施工績效普遍與深入。此外工程設計績效是工程專案成本和進度的關鍵決定因素。由於這些原因，評估工程設計以預測專案績效指標與推動持續改善至關重要。

有效而實用的工程營建績效指標必須建立，並將其應用於現行的營建工作流程，然後進一步建立工程執行績效的可預測性。多年來，許多相關研究已經提出了幾種不同的工程績效測量與預測方法，並已經建立專案執行參數變量和績效測量之間

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的因果關係。然而現在分析測量工程績效的研究和方式，大都主要集中在工時與時程的績效上，並不是一個足夠廣泛的衡量標準來評估工程績效的有效與適用性。

近年來，建築資訊模型（Building Information Modeling, BIM）已成為建築與營建工程領域中快速發展的創新技術，其應用主要是透過多維數位化模型建構與管理，對工程生命週期中的各階段作業進行各種應用分析，除了對工程的實際執行有較佳的掌握外，更能有效整合工程執行過程中的各項設計、採購與施工作業資訊，降低工程成本與錯誤，提升工程品質、效率與安全。現今許多國際工程專案已普遍使用 BIM 技術執行，國內一些重大工程也逐步導入 BIM 技術，並積極開發可以整合時程、成本、風險與績效資訊，以期達成對工程執行的有效掌控。然而在國內外各型工程專案一致朝向應用與發展 BIM 技術同時，現今學術界針對 BIM 的執行對於專案績效評估相關研究尚未發展成熟，相關研究也僅限於 BIM 執行本身的績效，未針對其專案工程設計階段績效進行評估與探討。

BIM 的應用已改變營建工程統包執行方式。基於了解應用 BIM 於專案執行所使用的輸入參數變量與專案設計績效成果之間的關係，提高預測工程設計績效的重要性，進一步了解其相對關聯性。本研究建立一套系統分析模型，透過調查收集實際來自 60 個應用 BIM 工程執行樣本的專案數據，將 BIM 使用輸入變量與工程設計績效輸出進行關聯性分析，並依相關係數來檢核 BIM 輸入因子之間及 BIM 輸入因子與輸出績效的相互關係，之後進一步採用統計變量遞減技術建立工程績效預測的多元線性回歸模型，並運用人工智慧機器學習技術，建立評估模型，以期達更好的測量和預測營建專案 BIM 的應用效益。經過嚴格的驗證流程，並採用統計方法評估模型的差異性，實現並達成了最佳的專案工程績效預測，結果證明 BIM 應用與工程設計績效指標之間存在顯著相關性，可進一步利用建立的多元線性回歸與人工智慧機器學習模型來預測工程設計績效指標，並有效且正確的應用於工程專案執行。

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ABSTRACT

Performance management is an essential task for construction projects. The primary purpose is to evaluate various indicators which impact performance in project execution, such as cost, schedule, quality, safety, and customer satisfaction. These performance indicators provide management stakeholders with necessary decision-making references, early risk warnings, preventive measures, and continuous improvement opportunities. The effective performance evaluation methodology is the key to the success of a construction project. However, engineering performance management involves a wide range of measurement and evaluation details. In addition to the different views and definitions of performance, the decision-makers may also adopt different decisions and measures based on their experience in the level of supervision of each stage at project execution.

The engineering design process has fundamentally impacted the life cycle of construction projects, and notably, engineering performance constitutes a critical factor for a project and shall be measured efficiently. The control, measurement, evaluation, and prediction of engineering performance are significant in delivering construction projects, and reliable engineering performance measurement is critical to project performance and continuous improvement. In the project execution life, the engineering design at the early stage is critical for successful execution and can significantly affect the final total cost as illustrated in cost impact curves. Even though engineering costs have increased to reaching around 20% of total installation cost on several construction projects, engineering performance is less well realized and has received less focus compares to construction performance. The implementation of the early-stage engineering design is an essential key for successful execution and the engineering performance evaluation and prediction have a substantial influence on the execution phases and effectiveness of the

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project. For above reasons, reliable and precision metrics for evaluating real-time performance to drive improvement are significant.

Applicable industry engineering performance must be recognized and applied to current engineering work processes before essential improvement and predictability of performance can be developed. Over the past years, several approaches for engineering performance measurement and evaluation methods have been proposed, and the studies have demonstrated the cause-effect relationships between project variables and performance measures. The historical research for engineering performance measurement was analyzed primarily focused on job-hour performance, represented an incomplete picture, and is not broad enough to assess the effectiveness of engineering performance.

Recently, building information modeling (BIM) application has been a rapidly developing innovative technology in architecture and construction engineering. In addition to having better control of the actual implementation of the project, BIM can integrate various design, procurement, and construction operations in the project life cycle, reduce project costs and errors, and improve project quality, efficiency, and safety. Many international engineering projects have deployed BIM technology, and some major domestic projects have also gradually introduced BIM technology and actively developed information that can integrate schedule, cost, risk, and performance to control project execution effectively. The application has reformed how owners execute the industry's engineering, construction, commissioning, and operation. While large-scale projects at home and abroad are consistently oriented towards the application of BIM technology, the current academic research on BIM implementation and project performance evaluation has not yet matured, and the relevant research is limited to the performance of BIM implementation. It has not evaluated its project engineering design stage.

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The application of BIM has changed how design-build or turnkey project are performed. Based on understanding the relationship between the application of BIM use elements and project results, the importance of predicting engineering design performance, and understanding of its relative relevance, improving project engineering performance based on the knowledge of the relationships between BIM use application and performance outcomes becomes essential. This research proposes a system analysis model to correlate BIM use input factors with engineering design performance output analysis by leveraging data from 60 samples. The statistical variable reduction techniques are deployed to develop multiple linear regression models linear regression (LR) analysis and applying artificial intelligence neural network (ANNs) machine learning multilayer perceptron (MLMP) technology of the engineering performance to establish evaluation models to measure and predict the application benefits of BIM in construction projects. The development of the prediction models is based on practical execution data from projects collected through a comprehensive BIM application survey and the best prediction was generated, validated, and implemented. After rigorous verification, the best prediction is obtained and the results prove a significant correlation between BIM application and engineering design performance outcome measures, which can be applied to predict engineering design performance measures using the established models. The study establishes a comprehensive methodology for the proposing models, and the accuracy and reliability of the models are tested validated. Moreover, engineering performance measures can be predicted by BIM uses.

Keywords: building information modeling (BIM); artificial neural networks (ANNs); Engineering, procurement, and construction (EPC); machine learning multilayer perceptron (MLMP); engineering performance

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LIST OF ABBREVIATIONS

AEC	Architecture, engineering, and construction
AI	Artificial intelligence
ANNs	Artificial neural networks
BIM	Building information modelling
CII	Construction industry institute
ENR	Engineering news record
EPC	Engineering, procurement, and construction
LR	Linear regression
ML	Machine learning
MLMP	Machine learning multilayer perceptron
NBGO	National BIM guide for owners
NIBS	National institute of building sciences
TIC	Total installation cost
F-value	The variance between the means of two populations significantly different
P-value	The value in hypothesis testing to support or reject the null hypothesis
R-sq (adj)	The coefficient of determination to show how well data points fit the line
X_i	Input variables
W_{ij}	Weighted activation function
y_k	Output measures

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1.0 Introduction

1.1 Background

The term “Performance” attracts extraordinary attention from industry stakeholders and researchers in various construction activities. In the five phases of an industrial construction project, namely, preliminary planning, engineering design, procurement, construction, and commissioning, the owner’s expectations and requirements for the engineering design process that transforms ideas into reality are considered critical driving factors for a successful project performance (Georgy, Chang, and Zhang 2005). Engineering performance has a major impact on the subsequent project execution phases, thus, potentially affecting the overall project outcome. Project owners and facility managers need a means to evaluate the engineering performance of internal design organizations or engineering contractors. Engineering contractors need the means to drive improvement in their organizations as engineering costs as a percentage of total project costs continue to rise. Since the engineering design process is critical for the project life cycle, performance measurement and prediction are very important for successful project delivery, and the ability to manage engineering performance is essential.

Cost engineering research has proven that the ability to influence and manage Total Installation Cost (TIC) is greatest at the earliest stages of a construction project. The cost curves widely used in construction engineering projects in Figure 1 (Anderson, Molenaar, and Schexnayder 2007) illustrates the concept and were fully endorsed by the Construction Industry Institute (CII). The ability to influence TIC is most significant at the beginning of the project development and design process. During the implementation of the procurement and construction phase, the ability to influence project costs declines rapidly. By the commissioning and handover phase, the impact on the cost structure is

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almost negligible. According to the relevant historical data and construction engineering experience, the engineering design stage can account for up to 20% of the project cost. However, the engineering design content and related equipment and material specifications directly affect the total TIC structure of the project.

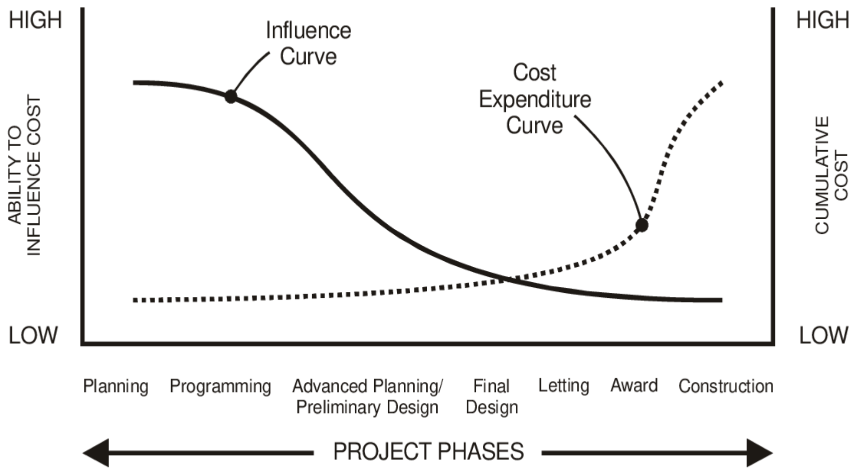

Figure 1. Cost Influence Curves

(Anderson, Molenaar, and Schexnayder 2007)

Engineering design performance is a crucial aspect of a construction project, and it plays a significant role in the overall project performance. Engineering design performance focuses on design quality, efficiency, risk mitigation, cost control, schedule management, quality assurance, stakeholder satisfaction, environmental and regulatory compliance. In comparison to project overall performance, which encompasses the entire project lifecycle, engineering design performance primarily focuses on the initial planning and conceptualization stages. However, the quality of the design has a direct and lasting impact on the overall project's success, as it sets the sequent stages for construction, procurement, commissioning, operation, and maintenance. Thus, good engineering design performance is essential for achieving favorable project performance outcomes.

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The implementation of the early-stage engineering design stage is an essential key for the project's success or failure, and its engineering design performance evaluation and prediction have a significant influence on the project execution life and execution effectiveness of a project. Reliable and accurate assessment of project performance evaluation is significant to the success of construction projects. Such prediction assists stakeholder in obtaining early warnings against potential execution issues. Thus, performance measurement and prediction constitute critical evaluations for higher performance and successful project delivery.

The engineering design process has significantly changed the project execution workflow of a facility by applying building information modeling (BIM) to the architecture, engineering, and construction (AEC) industry, thereby promoting a rapid interest in its application in the AEC industry. BIM is developing and managing parametric digital building or facility models during its execution lifecycle (Lee et al. 2006). BIM has been acknowledged as a new execution project approach that can improve productivity and quality in the construction industry for both academic research and industry application (Smith and Tardif 2009). In recent years, BIM has become increasingly vital in managing large scales of information and communication and sharing processes on collaborative aspect of construction projects. The significant evolution in BIM allows stakeholders to automate project tasks in the design, analysis, coordination, fabrication, construction, startup, operation, and maintenance processes. Most importantly, the nature and attributes of a digitally simulated facility can be the knowledge base and record information center of a construction project (Eastman et al. 2011).

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1.2 BIM Application and Engineering Performance

A study of the foremost successful factors for BIM implementation from 2005 to 2015 found elements include design collaboration, engineering and construction owners or contractors, early and precise model design visualization, construction planning and coordination, enhancing the information exchange and knowledge database management, and improved site arrangement planning and construction site safety (Antwi-Afari et al. 2018). Research on the significant benefits of the BIM application shows its usability in three-dimensional modeling, work process, coordination and collaboration improvement, quality, cost and schedule management, project potential risk monitoring, workforce and resource management, utility and supply management, and sustainable implementation (Seyis 2019). Furthermore, the study showed that effective scheduling and costing are the leading top-ranking benefits of the BIM application. An analysis of the average BIM return on investment for a project from 2005 to 2007 showed a 634% increase, indicating its potential economic benefits (Azhar 2011).

BIM applications have proven to enhance project schedules, reduce project costs, and improve the overall quality of facilities. Recently, many facility owners and developers now required teams to embed BIM in their projects (Jung and Joo 2011). Its application in the execution procedure and delivery process helps designers to develop, coordinate, and revise a current design and measure it for engineering design performance more efficiently. Also, contractors can easily extract material quantities from models and correctly develop a cost estimate for the project (Won et al. 2013). This development implies that engineering design or construction changes can be efficiently studied and evaluated for cost and schedule impacts, constructability, and engineering performance. BIM application enhances construction and startup processes efficiency by coordinating different site activities (Suermann 2009). Nowadays, the increasing application of project

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planning and analysis by implementing more integrated BIM applications and capable modeling technology has significantly improved project performance. The BIM-based off-site assembly and fabrication approach for industrial facilities also offers expanded benefits (Tatum 2018). Thus, BIM has changed the conventional project execution model and impacted how stakeholders evaluate and predict project and engineering performance.

The increasing application of BIM technology is very difficult to be sustained if the synergy among BIM, like project performance, integrated project delivery, sustainability, and risk management are not properly addressed (Kent and Becerik-Gerber 2010). In addition, deploying BIM technology requires significant technical and non-technical changes in widely adopted business practices in the AEC industry (Succar 2009; Gu and London 2010). While technological interoperability has made significant progress, but business or performance interoperability is still limited (Taylor and Bernstein 2009). An integrated performance measurement and assessment approach is needed to assist owners in assessing and aligning BIM application with their defined business strategy. Furthermore, implementing new technology creates numerous challenges, including the challenge of accurately measuring project performance is now critical. Therefore, measuring and predicting engineering performance through project life is essential to improving project performance through BIM implementation.

The application of BIM has a significant impact on project engineering performance compared to projects that do not use BIM. The project apply BIM in execution has the following major influence to engineering performance:

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- Enhanced Collaboration: BIM promotes better collaboration among engineering disciplines (civil, structural, piping, mechanical, electrical and control system) through a shared 3D model to reduce miscommunication and coordination issues.
- Real-Time Updates: BIM allows for real-time updates and changes to the design, reducing the need for manual revisions and facilitating faster decision-making.
- Clash Detection: BIM software can automatically detect clashes and conflicts in engineering systems, reducing errors and rework in the construction phase.
- Data Integration: BIM integrates engineering data, specifications, and material information, streamlining the design, construction, operation, and maintenance processes.
- Visualization: Engineers can visually assess the design, making it easier to identify design flaws and optimize system performance. The constructability and the requirements of operation and maintenance can be further reviewed.
- Energy Efficiency: BIM enables engineers to simulate and optimize building systems for energy efficiency, which is essential for sustainable and high-performance buildings and facilities.
- Cost Estimation: BIM can provide more accurate cost estimations for engineering components, helping engineers stay within budget.

As for the projects do not apply BIM in execution, the engineering has the major impact on:

- Limited Collaboration: In non-BIM projects, collaboration between engineering disciplines may be less efficient and coordination with construction and operation can be difficult, leading to communication challenges and coordination issues.

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- Manual Clash Detection: Engineers must manually detect clashes and conflicts in design, which can be time-consuming and prone to errors.
- Data Fragmentation: Engineering data, material specifications, and cost information may be stored in separate documents or systems, making integration and updates more challenging.
- Visualization Challenges: Non-BIM projects often rely on 2D drawings, which may not provide a clear visual representation of the design, potentially leading to oversight of engineering issues and less coordination with construction and operation.
- Energy Efficiency Challenges: Achieving energy efficiency and sustainable design may be more challenging without BIM tools for simulations and optimizations.
- Cost Estimation Uncertainty: Cost estimations in non-BIM projects may be less precise, leading to potential cost overruns.

From above comparison, BIM application can significantly improve engineering performance by enhancing collaboration, reducing errors, enabling real-time updates, and providing tools for better visualization, analysis, and optimization. However, the projects that do not apply BIM may encounter challenges related to communication, coordination, and efficiency in the engineering and the subsequent phases.

1.3 Research Motivation

A reliable engineering performance evaluation is a critical component in the project execution and improvement processes. Applicable industry engineering performance systems shall be developed and then applied to project execution processes before the improvement and predictability of performance can be implemented. Furthermore, a based technique for evaluating engineering performance can enhance the benchmarking effort on both an internal and external basis of the business outcome (Hanna 2016).

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Several approaches for engineering performance measurement have been proposed for the past two decades. These historical approaches for measuring engineering performance mostly focus on job hours expended on deliverables, the completion number of drawings, and the specifications verse schedules. Several apparent issues, including subjective weighting to address the complexity of each deliverable, costly data collection effort on all hours expended on each deliverable, drawing scale changes that may increase the number of deliverables, and the base of performance calculation are not adequately presented and reported.

Recently, BIM application has reformed how owners execute the industry's engineering, construction, commissioning, and operation. Research on integration and innovation for construction engineering suggested taking significant benefits from computer automation modeling processes from project planning, executing, and closing. The study also suggested that the constructed BIM models and planning, design, construction, and startup processes provide a critical opportunity for the research related to engineering and construction execution. However, most previous studies have concentrated on the advantages of BIM use in projects. Until now, linking quantitative studies connecting BIM use to improved engineering design performance has been lacking. Moreover, the definition of performance study is limited in cost, schedule, quality, and customer satisfaction because of the difficulty in measuring these terms. Further issues are the difficulty of measuring and collecting the input and output variables and the data complexity of construction projects.

There is increasing interest among industry practitioners to evaluate potential benefits of BIM and accurately present the BIM's influence on executing projects. Recently, many researchers have proposed case studies to describe how to be applying BIM for application can improve project performance. Several research have found the value of

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specific case studies or isolated BIM application projects. However, the research findings that may be expended across the construction industry still need to be discovered. There has been an increasing focus on finding the benefits of BIM use on project performance. However, a minor priority has been given to engineering performance. Improving engineering performance based on the knowledge of the relationships between BIM inputs and project performance outcomes becomes essential.

Based on the above reasons, which represent an incomplete picture and is not a broad enough measure to assess the effectiveness of the engineering performance in project execution applying BIM. It is necessary to contribute to the study of the effect of the BIM application on engineering performance of engineering, procurement, and construction (EPC) approach projects. Accurately measuring the engineering performance of BIM applications and implementation is essential to facilitate early responsive action to adjust or correct project performance, increasing the possibility of successful BIM implementation in EPC project execution. This research proposes a systematic statistical analysis that correlates the BIM uses with engineering performance, a machine learning multilayer perceptron (MLMP) model, and a liner regression (LR) model to have better engineering performance control evaluation and measurement and prediction in industrial EPC approach projects.

1.4 Goals and Objectives

The goals and objectives are the aims and specific targets guiding this research process in BIM application in engineering design performance. The primary goals are intended to develop a generic system for BIM application on engineering performance that aids the industry in the following ways:

- Enhancing engineering design performance by effectively utilizing BIM applications.

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- Bridging the gap between BIM application potential and practical performance implementation in engineering design processes.
- Optimizing engineering design efficiency, accuracy, cost-effectiveness, and sustainability in EPC projects by BIM application.
- Leveraging data-driven insights and advanced technologies to improve design performance outcomes by applying regression and ANN deep learning methods.
- Applying the validated prediction model to evaluate the outcomes and developing control procedures to ensure the desired engineering performance.
- Contributing to the body of knowledge and best practices in BIM application for engineering design performance.

To achieve above research goals, the following research objectives were identified:

- To assess the current BIM adoption and utilization level in engineering design processes and to understand past and current practices in engineering performance assessment. To go through and summarize research on engineering performance assessment and further define the performance.
- To investigate the relationship among the BIM uses identified in the National BIM Guide for Owners (NBGO), identify key design performance metrics, and develop measurement methodologies for quantifying them. Find the correlation between BIM use inputs and engineering design performance measures.
- To analyze the collected data and to construct a framework that allows uniform application of evaluation of engineering. To evaluate the impact of BIM applications on design performance, such as efficiency, accuracy, and cost-effectiveness.

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- To analyze data and apply ANN machine learning models to identify patterns, relationships, and predictive capabilities to build the machine learning multilayer perceptron (MLMP) method and linear regression (LR) stepwise modeling and develop an assessment of the prediction models.
- The prediction models can be validated and implemented by applying the actual data from selected and targeted projects for laying out the suggestions of project successful factors. To validate the developed models and findings through independent data sets to monitor and evaluate the outcomes of the implemented models and assess their impact on design performance.
- To apply and communicate the research process, methodologies, and findings to contribute to the field of BIM application in engineering design performance.

The research process becomes focused, purposeful, and aligned with the desired outcomes by establishing clear goals and objectives. These goals and objectives guide the research activities, analysis, and implementation, ensuring that the research improves design performance and advances the field of BIM application in engineering.

1.5 Research Scope

Based on the goals and objectives identified above, the research scope for investigating the application of BIM application in engineering design performance can be structured and developed from the following key aspects:

- Evaluation of BIM application adoption: evaluate the current level of BIM adoption in the engineering and construction industry, including the extent to which BIM application is utilized in engineering design processes, the awareness and understanding of BIM among professionals, and the challenges faced in implementing and integrating BIM applications.

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- Investigation and identification of BIM use factors and engineering performance measures: identify and define key design performance metrics that can be influenced or improved through the effective use of BIM. These metrics may include design efficiency, accuracy, constructability, collaboration, cost-effectiveness, sustainability, and overall project success.
- Data collection and best practices: conduct in-depth data collection and studies of construction projects that have successfully utilized BIM applications to improve design performance. Analyze the project workflows, implementation strategies, challenges faced, and lessons learned to identify best practices and success factors in utilizing BIM effectively.
- Construct, implement, apply and control: Utilize the MLMP model and LR stepwise model and develop an assessment of the prediction models, and apply the models to current execution projects.
- Recommendations for future knowledge: based on the research findings, develop recommendations and knowledge for engineering firms and professionals to maximize the benefits of BIM applications in design performance. Provide practical strategies for integrating BIM into design workflows, addressing interoperability issues, and enhancing skills and knowledge in BIM utilization.
- Future trends and opportunities: Explore emerging trends, technologies, and advancements in BIM that have potential to enhance engineering design performance. Investigate topics such as artificial intelligence and machine learning integration, automation, and digital twins, and assess their implications for design processes.

By focusing on these research areas within the scope of BIM application in engineering design performance, the study can provide valuable insights, guidance, and

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recommendations to bridge the gap between BIM potential and its practical implementation in improving design outcomes. Recently, artificial neural network (ANNs) applications have commonly been used in the industry to model performance and productivity using intelligent information that learns and imitates from data and training samples. As parts of ANNs, machine learning (ML) algorithms simulate human thinking processes and apply computational methodologies to understand information and experience. The method is applied to model constructions from the measuring, learning, and predictive effectiveness of ML (Portas and AbouRizk 1997).

This research proposes a comprehensive performance evaluation model for BIM application EPC approach projects. First, the study summarizes previous research on engineering performance assessment, BIM application and ANNs machine learning and the required research data collection based on benchmarking and a previous study of critical successful factors. Second, the study investigated the relationship among the BIM uses identified in the NBGO by the National Institute of Building Sciences (NIBS 2017). The correlation between BIM use inputs and engineering design performance was used to evaluate effective implementation, which included the benchmarking concept and the BIM key performance indicators. Next, the study presented the MLMP method and a LR stepwise modeling and developed an assessment of the prediction models. Furthermore, the developed prediction models are validated by the training data and implemented by applying the actual data from selected and targeted projects. The validity of the BIM application engineering performance evaluation models was verified for multicriteria statistical methods including coefficient of determination adjusted R-square and variance value F-value of F-test from the test projects. Recommendations of the findings from the research process, and the conclusions and suggestions for future works were proposed.

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2.0 Literature Review

This research begins with summarizing previous studies in engineering design performance, building information modeling, artificial neural network, and ANNs machine learning. The progress of the most updated research on the relative subjects has been reviewed and served as a base knowledge for this research.

2.1 Engineering Design Performance

Engineering design performance is an inconsistent term interpreted by many practitioners in the construction industry. When thinking and applying engineering design, involvers cannot limit themselves only to the tangible outcomes of the engineering and design activities. Engineering provides the process and procedure to transform owner expectations and requirements into engineered deliverables, specifications, and documents. Engineering design can be ideas, images, sketches, drawings, specifications, or physical models. Regardless of the neatness and timeliness of engineering outcomes, and unless the owner is satisfied with how these engineering outcomes perform down the road in the project life cycle, the engineering job cannot be described as successful.

For decades, engineering performance has been studied and applied to define the best evaluation and measurement metrics or indicators to interoperate performance. According to the study by Tucker and Scarlett (1986), the most common indicator of engineering performance in the construction industry is the ratio of engineering design work hours per deliverable or drawing. Few researchers, however, have investigated more reliable engineering performance measures. The most common to these studies is the introduction of engineering performance in the form of value-added function, although implementation varies between one study and another.

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A study introduced the owner satisfaction as a main based of measuring engineering performance through the major success factors project execution such as cost, schedule, and quality (Chalabi, Beaudin, and Salazar 1987). This approach can be formally represented as a multi-attribute value function. The concept assumes that the owner makes single comparisons between actual and specified performance on attribute designating value to the stakeholders, then accumulates the single evaluations to determine a comprehensive value of satisfaction measured by a function. Tucker and Scarlett (1986) pursued another research activity, which addresses measuring engineering performance by applying the concept of design effectiveness. An objective matrix method was used to list, categorize, and weight design criteria having significant project impact. As an evaluation procedure, this method is commonly used to measure and improve the performance of difficult-to-measure functions. The objective matrix comprises four main components: criteria, importance ratings and weights, performance scale, and performance index. The requirements define what is to be measured and the weights determine the relative importance of the criteria to another and to the overall performance measurement objectives. The performance scale compares the project-measured value of the benchmark to past performance and future goals. The performance index is calculated to evaluate and track performance using these three components.

The definition of design effectiveness criteria constitutes the core of the research by Tucker and Scarlett (1986) in the report SD-16 by Construction Industry Institute (CII). Fourteen criteria were originally identified for the overall evaluation of design effectiveness. Based on the quantitative nature, data availability, and timing of this availability, the original list was refined to include only seven criteria to evaluate design effectiveness. The criteria chosen are accuracy of design deliverables or drawings, applicability of design documents, total design costs, constructability of designed facility,

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design economy, performance against schedule, and ease of facility startup. After interviewing several construction industry personnel, the research team assigned weights indicating the relative importance of each criterion to the remaining set of criteria. The criteria with their assigned weights were used to construct an objective matrix with a 0-10 scale corresponding to each criterion. This scale uses 10 as an indicator of optimal performance, 0 as an indicator of poor performance, and 3 as an indicator of average performance. For any project to be judged under this method, each criterion is evaluated and assigned a value on the scale. A cumulative design effectiveness index is calculated based on the values and weights of the different criteria. Each criterion can be assessed based on subjective or quantitative measures. For instance, the accuracy of design deliverables can be evaluated by measuring the number of rework or the number of revisions per total amount of drawings. Using an objective matrix also allows each criterion to be measured using a separate sub-matrix. A sub-matrix employs sub-criteria to evaluate a specific criterion. This makes a sub-matrix final index correspond to a single value entry in the original objective matrix. Using of sub-matrices allows for a far better evaluation of a single criterion compared with a one-step approach.

Improving engineering performance has been one of the major considerations for most contractors in AEC to minimize rework and manage risks. As the frontline construction workforce, the contractors are working to transform design concepts to physical facilities, the effective engineering approach is their major focus. Finding effective strategies to manage engineering performance improvement has been concerned and presented in several industry reviews (Mottahedin 2003). In these studies, proactive evaluate and measure performance like selecting a capable contractor is fundamental to secure the performance (Konchar and Sanvido 1998; Kashiwagi and Byfield 2002). Several researchers proposed that contractors performance depends on the factors of the

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experience of contractors, financial capability, and feasibility and availability of resources. The study proposed the project performance can be effectively predict by staffing capability, company scale, experience, financial status, and quality control (Wong 2004; Ling and Liu 2004) and suggested that past performance of contractor, relationships with the local authority, and the level of mechanization are major performance predictors. Some performance prediction models based on these suggested predictors had been proposed to assist the contractor selection at the pre-contract stage (Molenaar and Songer 1998; Ng et al. 2002).

Research focus on the project performance of the efficiency process is another study to understand the relationship of efficiency and performance. The relative study is mainly focuses on the time consuming, man-hours expenditure, or cost of production. A study proposed the average man-hours spent for erecting formwork as a major performance measure for civil work (Thomas and Napolitan 1995). Another study predicted the contractors' performance in tunneling projects by examining the monthly site activities progress rates (Touran 1997). Nevertheless, the researchers argued that the strong supporters focus on efficiency may encourage contractors to stay with old engineering assumptions (Crawford and Bryne 2003). The study pointed out the action restrict their innovation and insensitivity to client needs changes, thus sacrificing effectiveness in return. Regarding the concerns, the study suggested using performance indication to represent both efficiency and effectiveness in evaluating and measuring for performance prediction. Therefore, the study proposed the effectiveness of contractors of work can be measured by their ability to complete customer requirements and propose innovative ideas for the project execution (Cheung et al. 2005). As such, recently, the progressive development of project performance evaluation systems has made measuring the performance of contractors in terms of both efficiency and possible effectiveness

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(Crawford and Bryne 2003). In this connection, historical data from project performance evaluation systems were considered for predicting contractors' performance as the project progress (Wong and Cheung 2005).

A systematic and analytical scheme that measures and predicts engineering performance is essential for industrial projects. The concept of engineering performance strengthens the understanding of the measurability of the required inputs and expected output variables (Maloney 1990). The study by the Construction Industry Institute (CII) research team 156 (RT-156) identified 25 engineering inputs and 10 engineering design performance outputs. CII RT-156 proposed a genetic algorithm, the ANN integrated search model, which developed the relationships between the 25 inputs and 10 outputs (Chang, Georgy, and Zhang 2001). This model searched the engineering inputs directly targeting the engineering performance, which is a part of the basis of this research. The study used neuro-fuzzy systems to measure project engineering performance by identifying project attributes and execution status that positively or negatively influenced the performance (Georgy, Chang, and Zang 2005).

2.2 Building Information Modeling

Measuring and predicting project performance by implementing the BIM application is complicated. Previous studies indicated that 55% and 58% of survey responses agreed that the BIM application could lower project costs and overall project schedule, respectively (Becririk-Gerber and Rice 2010). A strong positive relationship was found and suggested among project schedule, cost, quality performance, and BIM implementation (Azhar 2011; Barlish and Sullivan 2012; Bryde, Broquetas, and Volm 2013). The benefits of BIM adoption show that 52% of the surveyed information suggested reduced errors and omissions, 48% reduced rework, 39% reduced cycle time

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for specific workflows, 37% reduced project duration, and 32% reduced construction costs (Bernstein and Jones 2012). A study showed that project cost is the most significant influence attribute for BIM application in project success. Other factors are execution communication, work coordination improvement, and quality assurance and control (Bryde, Broquetas, and Volm 2013). By surveying project data from 200 more projects via multiple regression analysis, a strong relationship emerged between the BIM application and the project delivery time and perceived project quality performance when controlling project execution complexity. This quantitative study examined whether the project's overall performance was influenced by BIM use implementation and BIM execution planning in the project delivery method (Franz and Messner 2019).

Measuring the influence of BIM application on project performance for a single project is a challenging work (Yuan et al. 2009). Deployment of applying management strategies for predicting BIM impact on all projects in an organization is even more challenging. For providing some guidance, several previous studies applied industry surveys to identify and analyze the perception of construction project participants regarding the benefits and return on investment that can be achieved through BIM application (Jones et al. 2015; Zuppa, Issa, and Suermann 2009). A study found that 55% of survey respondents thought that BIM application was associated with lower project total costs, and 58% replied that the overall schedule was reduced (Becerik-Gerber and Rice 2010). Research has also been proposed and studied by using detailed interview analysis (Vass and Gustavsson 2014) and industry workshops (Stowe et al. 2014), the findings from the studies generally supported the perceptions of practitioners received from surveys. Moreover, several detailed case studies have compared BIM and non-BIM application projects. These studies suggested a strong positive relationship between the application of BIM and cost, schedule, and quality considerations. The other research

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identified cost and schedule improvements in hospital construction attributable to adopting BIM application and a comprehensive integrated project delivery method. The study reported a US$ 9 million cost savings of over 9% of total project cost and a 6-month schedule saving of approximately 15% of total project schedule (Khanzode, Fischer, and Reedn 2008).

While the above study examples offer some viewpoints into the extensive literature on the benefits of BIM application, researchers have struggled to find solid quantitative evidence connecting BIM use to improved project performance. Several reasons have been suggested for this lack of evidence: (1) the difficulty in accurately measuring the specific performance areas impacted by BIM and distinguishing them from other factors like changes in delivery methods, (2) inconsistencies in measuring BIM use, including the varying extent of adoption for each application and the maturity of the organizations implementing the technology, and (3) the inherent uniqueness and complexity of each construction project. The focus of this study was to examine the impact of implementing one or multiple BIM uses on a project. A BIM use is defined as a method or strategy of applying BIM throughout a facility's life cycle to achieve specific objectives (Kreider and Messner 2013). Different approaches have been used to define BIM use variables (Kreider 2013). The BIM Project Execution Planning Guide (CIC 2011) outlines 25 distinct BIM uses across various stages, including planning, design, construction, and operation. For this research, the study specifically utilizes a subset of these BIM uses, emphasizing those that have been widely adopted (Kreider, Messner, and Dubler 2010).

In recent years, numerous researchers have employed illustrative case studies to present how the application of BIM for specific purposes can enhance project performance. A notable study conducted by Franz and Messner in 2019 places particular emphasis on evaluating the impact of BIM on project performance and quantifying the

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benefits it brings. This research presents the findings of a quantitative study aimed at examining the influence of BIM use adoption and BIM Execution Planning (BEP) on project performance across various project delivery methods. The study revealed that BEP participation plays a significant role as a predictor of BIM use adoption. Projects that implemented BEP, either with a designer-contractor team or involving the entire project team, demonstrated a higher adoption rate of BIM compared to projects that did not employ BEP. Furthermore, the results indicated a substantial positive correlation between BIM use adoption and the speed of project delivery, perceived facility quality, and group cohesion within the project team, even when accounting for project complexity. Despite the critical insights gained from this research, it also shed light on the need for a fresh approach to capturing process data across projects to enable more detailed and comprehensive analysis in the future. The industry stands to benefit from additional studies that focus on obtaining and leveraging a dataset specifically designed for the application of BIM and BEP processes. It is important to note that the existing dataset applied in this study was initially collected to observe project-level trends in performance resulting from variations in project delivery methods. The data analysis provided empirical support for three out of the five project benefits of BIM, as perceived by practitioners: faster delivery, enhanced collaboration, and improved quality. However, there was a lack of information concerning how each specific BIM use was implemented and how the BEP was utilized to integrate these uses into design and construction workflows. Furthermore, the study did not include information on the observed performance improvements at the process level, such as the number of Requests for Information (RFIs) and the percentage of rework, while both factors are critical to impact the performance.

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Recent advancements in BIM have significantly contributed to enhanced productivity and improved quality within the AEC industry. In this context, Mom and Hsieh (2012) have proposed a systematic and practical method for assessing BIM technology implementations at the corporate level. Their research framework comprises four models: BIM perception, adoption, performance, and capability maturity. These models were derived and consolidated from various existing BIM frameworks and approaches utilized within the AEC industry.

The BIM perception model plays a crucial role in assisting management in evaluating the perceived benefits, costs, and risks associated with their investments in BIM technology. Through this model, management can evaluate the potential benefits against the costs and risks involved in implementing the BIM technology, with the return on investment (ROI) technique serving as the best practice evaluation method. Moreover, the BIM adoption model aids in formulating a strategic BIM execution plan by identifying the critical success factors (CSFs) relevant to the identified BIM performance areas (Bassioni, Price, and Hassan, 2004). Several approaches, such as the strength, weakness, opportunities, and threats method (Luu et al. 2008), performance objectives, and cause-and-effect linkage (Kaplan and Norton 1996), can be employed to achieve this objective. Additionally, the BIM performance model plays a key role in establishing benchmarks for important performance reference using key performance indicators (KPIs). The model aims to utilize specific KPIs for BIM performance measurement. These metrics should be tailored to the unique requirements of each project and organization while maintaining adaptability to be applicable across the entire construction industry. Notably, there is currently no consensus on KPI measures among existing performance measurement frameworks in construction (Bassioni, Price, and Hasssan 2005), allowing BIM adopters to choose a suitable framework based on their specific requirements. Furthermore, the

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performance measures should be concise and flexible enough to accommodate changes as needed. It is worth noting that organizations rarely suffer from having too few steps in the process (Kaplan and Norton 1996). Various techniques can be applied to predict, measure, or evaluate project or company performance within the context of BIM implementation. These techniques include a scoring system (Yu et al. 2007; Ling and Peh 2005), a regression model (El-Mashaleh, O'Brien, and Minchin Jr 2006; Elyamany, Basha, and Zayed 2007), factor analysis (Isik et al. 2010), data envelopment analysis (El-Mashaleh, Minchin Jr, and O'Brien 2007; Horta, Camanho, and Da Costa 2010), a utility-function model (Georgy, Chang, and Zhang 2005), and a value model (Sullivan 1998). These techniques provide valuable tools for accurately assessing the effectiveness and impact of BIM implementation on project and organizational performance.

The BIM capability maturity model serves as a framework to determine the BIM performance levels within an organization. It offers an assessment procedure that guides the evaluation process. This approach aims to provide a practical and feasible solution for systematically assessing an organization's BIM application performance, considering both technical and non-technical aspects. The model revolves around the diffusion of BIM technology within the organization and evaluates the interaction between BIM capability and BIM maturity. As proposed by Mom, Tsai, and Hsieh in 2011, the study includes a comparison between the definitions of BIM adoption stages and an analysis of the maturity levels based on maturity models and BIM performance maturity. This comparison helps in gauging the organization's progress and effectiveness in adopting and utilizing BIM, ultimately contributing to a more comprehensive understanding of its BIM capabilities.

Now, there is an increasing understanding in the industry that BIM is operated and maintained by facility owners. Thus, the NIBS released the NBGO in 2017 as a guideline

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for implementing projects for contractors, designers, and owners. The primary aim of the NBGO is to provide building owners with a comprehensive outline for developing and implementing BIM application requirements in their internal policies, procedures, and contracts. This includes guidance on utilizing BIM for planning, designing, constructing, and operating buildings. The McGraw Hill Construction Smart Market Reports indicate that the business value of BIM use in construction projects has continuously increased (BuildingSMART Alliance 2015). The business value of BIM trend study and user surveys from 2007 to 2012 suggests that BIM implementation increased from 17% in 2007 to 71% in 2012, and 62% of responses from the construction industry recognized a positive return on their BIM application investment. The 2014 BIM business value for owners identified 68% of the facility owners in the U.S. as either deploying or applying BIM for their current and planning projects. Now, BIM implementation is widely deployed in the industry, and there is an increasing need among owners, stakeholders, and contractors to evaluate the advantages of BIM applications more precisely (Succar 2010; Sher, and Willaims 2012 and 2013).

Research on integration and innovation for construction engineering (Tatum 2018) was emphasized that leveraging computer automation modeling in project planning and execution offers significant potential benefits. The study also highlighted how BIM models and the various stages of planning, design, construction, and startup present a crucial opportunity for advancing research in construction engineering execution. The research program's results, based on case studies of innovative projects, provided valuable insights, enabling a better understanding of construction innovation and its effectiveness. This increased understanding led to significant findings concerning innovative design and construction organizations and projects. Moreover, the study underscored the importance of practical applications, particularly the application of BIM technology, to foster the

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expansion and acceleration of innovation within the construction industry (Yu et al. 2007). Ultimately, the research findings contribute to the core body of knowledge in construction engineering activities and highlight their essential role in enhancing project performance across critical aspects such as cost management, schedule adherence, safety, quality, and sustainability objectives.

2.3 Artificial Neural Network and Machine Learning

Artificial Neural Networks (ANNs) and machine learning techniques have emerged as powerful tools within the field of BIM, enabling engineers to leverage data-driven insights and optimize design processes. This literature review explores the applications of ANNs and machine learning in the context of BIM for engineering design performance. Research in AI and ML has provided reliable tools for the construction industry. ML algorithms improve the implementation performance since the data samples available for the learning process increase. Recently, ANNs in AI have provided robust systems and introduced promising management techniques that improve current automation processes in the construction business. ANNs have become integral in enhancing engineering performance through their application in various machine learning tasks. In the literature, numerous studies highlight the efficacy of ANNs in optimizing engineering processes. Researchers have extensively explored the use of ANNs for predictive modeling, demonstrating their capability to forecast complex engineering outcomes with high accuracy. Machine learning, including ANNs, has also been leveraged in optimization problems within engineering design. From parameter tuning to the layout optimization of complex systems, ANNs offer innovative solutions that significantly streamline the design process and improve overall performance.

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In the work by Moselhi, Hegazy, and Fazio (1991), the fundamental neural network architectures and their potential applications in construction engineering and management were explored, focusing on the usage and potential of ANNs in civil engineering. The study offered a graphical representation of ANNs' functioning and demonstrated their effectiveness in detecting various civil engineering issues (Flood and Kartam 1994). Moreover, the research by Sonmez and Rowings (1998) proposed the development of a model to evaluate the labor productivity using multilayer feedforward neural networks trained with a backpropagation algorithm. This approach allowed for the presentation of a complex mapping of factors affecting labor productivity. These studies shed light on the utility and potential of ANNs in the field of civil engineering, proposing their ability to address various construction-related challenges and improve labor productivity modeling. The evaluation performance models were proposed and implemented at two actual power plant construction projects by examining the influential factors and creating an ANN to evaluate labor productivity (Heravi and Eslamdoost 2015). The above studies have reported the application and use of ANNs or ML to measure labor productivity and engineering performance in some areas.

Multiple regression and ANNs have become common tools for developing prediction models in various fields. For instance, A study utilized multiple regression approach to forecast the unit costs and predict the construction progress and speed in design and build projects (Konchar and Sanvido 1998). Similarly, a study used multiple regression to forecast project cost, schedule growth, conformance to expectations, and user satisfaction levels (Molenaar and Songer 1998). Wong (2004) employed multiple regression to predict contractors' performance in meeting client requirements. However, not all prediction models yield satisfactory results. The reason might be caused by the assumption of linear characteristic nature between predictors and performance in the

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multiple regression approach as pointed out in the research. To overcome this limitation, serval researchers turned to ANN as an alternative approach. The study used ANN to predict the construction quality of design and build projects (Ling and Liu 2004). Similarly, Georgy, Chang, and Zhang (2005) developed an ANN model to predict the performance of civil engineering projects. In another study, ANN was applied with input parameters such as contractor's financial capability, technical expertise, and project experience to predict the organizational effectiveness and overall contractor performance. Despite producing satisfactory prediction results, ANN's black-box computation process sometimes poses challenges in interpreting the implications of the models (Dikmen, Birgonul, and Ataoglu 2005).

While the literature recognizes the potential of ANNs in engineering and BIM, ongoing research is dedicated to addressing challenges such as interpretability, robustness, and the need for large datasets. Future endeavors are likely to focus on refining these aspects to further enhance the integration of ANNs and machine learning techniques into engineering and BIM practices.

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3.0 Research Framework and Approaches

A comprehensive methodology is developed as a framework and an approach for this research. The framework builds a structure of the phases of this research and provides the planned outputs at each phase. The research approach lay outs the processes and methods of this study, including target industry sector for data collection and model development methodology. The concept of deep machine learning of multilayer perception techniques is introduced and finally the proposed models is validated and implemented.

3.1 Framework

This research proposes a three-phase main framework, as illustrated in Figure 2. The three phases are approached as phase 1: define and measure, phase 2: analysis and modeling, and phase 3: validation and implementation.

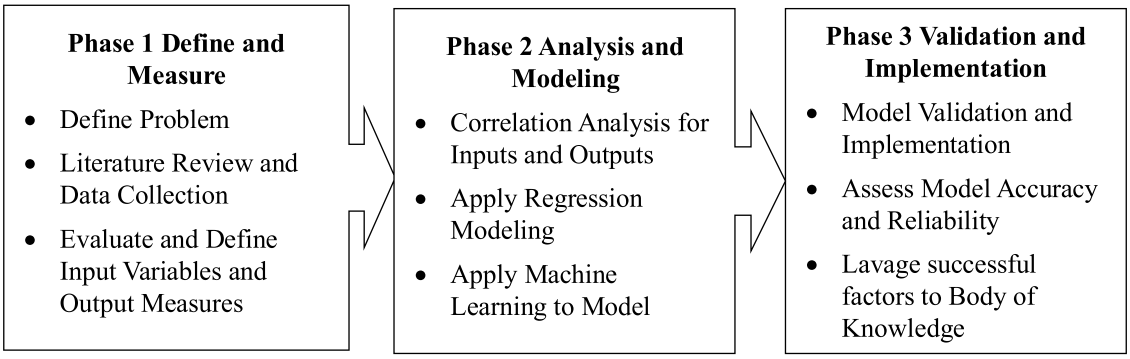

Figure 2. Research Framework

At phase 1 of define and measure, the study first articulates the problem for baseline industry requirements. Clearly defines the research goals, objectives, and scope of the study related to BIM application in engineering design performance. Previous studies are reviewed to form a body of knowledge as a foundation for this research. Next, identify the key variables and metrics that are used to measure engineering design performance, such as efficiency, accuracy, cost-effectiveness, or sustainability. Determine the data

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collection methods and sources, and this step involves collecting data from BIM models, project records, surveys, or other relevant sources from target industry sectors. Finally, develop a methodology to quantify and measure the identified engineering design performance measures. This step involves establishing performance indicators, developing evaluation criteria, or defining measurement scales. The output of this phase is defined 15 BIM use input variables and 10 selected engineering performance output measures.

Phase 2 analysis and modeling is to analyze the collected data using appropriate statistical or analytical techniques, including descriptive statistics, correlation analysis, regression analysis, and machine learning algorithms. Two stages are proposed to approach phase 2. Stage 1 is to find the relationship between input variables and output measures by correlation analysis and examine the interaction of the factors. Stage 2 is to apply linear regression and machine learning models to the data to identify patterns, relationships, or predictive capabilities. Train the models on the available data to develop robust and accurate models. Explore the relationship between the identified design performance metrics and other variables to gain insights into the factors influencing engineering design performance. This analysis can help identify significant predictors or drivers of engineering design performance. The outputs of this phase are correlation analysis for inputs, inputs, and outputs, the LR model, and the MLMP model.

Phase 3 of validation and implementation is to validate and apply the developed models by testing their predictive capabilities using independent data sets. This step helps to assess the accuracy and reliability of the models. Compare the model's predictions or recommendations with actual engineering design performance outcomes to evaluate its effectiveness. This step ensures that the models are providing valuable insights and contributing to improved design performance. Implement the validated models or

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findings in practical engineering scenarios. This step involves integrating the models into BIM software tools, decision support systems, or design workflows. Assess the impact of the implemented models on design performance by monitoring and evaluating the outcomes. This step helps determine the practical implications and benefits of utilizing the developed models in real-world engineering projects. The outputs of this stage are model validation and implementation, further application of the model and monitoring and control, discussion of the findings, core contribution, and suggestions of the body of knowledge.

Throughout each planned phase, it is essential to document and communicate the research methodology, data analysis techniques, and findings clearly and transparently. This enables future researchers to replicate or build upon the research and contribute to advancing BIM applications in engineering design performance. These outputs serve as valuable contributions to the field of BIM application in engineering design performance. They provide insights, recommendations, and actionable information for engineers, designers, and stakeholders to improve engineering process efficiency, accuracy, cost-effectiveness, and sustainability. Additionally, the knowledge of the research process and findings allows for transparency, replication, and advancements in the field.

3.2 Approaches

Under the three-phase framework structure, the approach lays out this research's main steps. Four target industry sectors were selected to establish the scope of the investigation, and the survey data was collected from the targeted sectors. This research is primarily centered around projects that employ the EPC approach during their planning and execution phases. The primary focus of this study is to examine and analyze the performance of surveyed projects by utilizing BIM. The data is obtained through

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surveying projects that fall within specific industry sectors. These surveys are conducted to gather valuable information and insights from the projects operating within these sectors. By gathering survey data from targeted industry sectors, the study aims to offer a detailed analysis and assessment of how BIM application in EPC projects perform within these specific domains. To conduct this research, a key emphasis is placed on projects that implement EPC practices during their execution phases. Through the collection of survey data from chosen industry sectors, the study aims to deliver sector-specific findings and conclusions that can benefit practitioners and stakeholders in those industries. The methodology of model development is introduced as the base of the study.

3.2.1 Targeted Industrial Sectors

The primary goal of this research was to gain a comprehensive understanding of the applications and effectiveness of BIM in large-scale construction projects. By focusing on four distinct industry sectors, this research aimed to shed light on the diverse ways in which BIM was being utilized across different domains, from power generation to high-tech facility construction.

- Industry Sectors: The choice of the four industry sectors, namely power, oil and gas, rail and metro, and high-tech facilities, was strategic. Each of these sectors has its unique challenges and requirements, and the study sought to determine how BIM was adapted to address the specific needs of each.

- Types of Projects Considered: Within each of these industry sectors, various types of industrial projects were taken into consideration. This means that BIM's implementation was assessed across a range of project types, from power plants to high-tech facilities.

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- Data Sources: Data for the study was sourced from 60 projects conducted by prominent U.S. companies. These companies were chosen based on their ranking in the 2017 ENR lists of top design-build firms and top contractors. The selection of these companies adds a level of credibility to the research as it draws upon real-world practices of industry leaders.

- Project Diversity: By including a wide variety of projects within the selected sectors, the research encompassed a broad cross-section of construction endeavors. This ensured that the findings would be applicable to a range of project types, not limited to a single niche within each sector.

- Scale of Projects: The research focused on projects with substantial financial investments, ranging from US$ 750 million to US$ 3 billion. This deliberate choice of scale allowed the researchers to explore how BIM was employed in significant construction efforts, where the stakes are high, and the complexities are considerable.

- Data Summary: The research collected data from different sources and summarized in Table 1. The table shows the distribution of the sampled projects among the four industry sectors: 13 from power plants, 7 from oil and gas plants, 19 from rail and metro, and 21 from high-tech facilities.

This study sought to provide a robust analysis of BIM implementation in the construction industry by examining a variety of sectors and project types. The inclusion of data from top U.S. firms and the emphasis on large-scale projects make the findings relevant to major players in the industry and offer insights into the adaptation of BIM technology to diverse construction challenges.

The following methods were performed to ensure the diversity of the data sets to reach more accurate and reliable models: (1) Descriptive statistics provide insights into

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the central tendency and variability of the data and identify potential outliers. (2) Correlation analysis identifies the strength and direction of relationships between variables to identify potential confounding variables that need to be controlled for in the modeling process. (3) Data visualization identifies patterns to identify potential gaps in the data before modeling. (4) Data sampling applies to ensure a diverse range of data for modeling to ensure equal representation of different subgroups. (5) Data transformation for normalization ensures the data is in a suitable format for modeling to prevent biases due to differences in different variable ranges.

Table 1. Project Survey Summary

Industry Sector	**Total Project Samples**	**Model Development Training Set**			**Model Validation Test Set**		
		Project Number	**%**	**Average TIC (US$ in mil)**	**Project Number**	**%**	**Average TIC (US$ in mil)**
Power Plants	13	11	21%	2,850	2	25%	2,500
Oil and Gas Plants	7	5	10%	2,650	2	25%	2,600
Rail and Metro	19	17	33%	1,450	2	25%	1,420
High Tech Facility	21	19	37%	800	2	25%	760
Total	60	52	100%	1,938	8	100%	1,820

3.2.2 Data Collection

This research developed a comprehensive data collection method to collect the performance information of the targeted construction projects to build the proposed models. Next, the study designed and distributed a project performance evaluation package to collect required information and determine the relationship between BIM use inputs and engineering performance measures. The survey package consists of three forms is designed to explain the purpose of the research is to evaluate the impact of BIM uses on engineering design performance and ask the evaluator's experience of how BIM uses in the project affects the engineering performance.

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The first section collects feedback on the acceptance level of output engineering measures to understand the performance perspective from either project directors or managers. This section consists of two parts, part 0 is the information for the inputter including name, title, company, industry experiences, and BIM uses in years. And part 1 is the acceptance level in the percentage of 15 engineering performance measures according to BIM use the standard of application experience. The second section in the survey package is to evaluate the relationship between BIM use inputs and engineering performance outputs by measuring the significant levels on a five-point Likert scale, where 5 represents very significant, 4 is significant, 3 is moderate, 2 is little significant, 1 is not significant, and 0 is no relationship. The purpose is to understand the experience and perspective of BIM use application in relation to performance. The third section assesses the inputs of BIM uses on implementation levels and the engineering performance by using a 10-point scale in percentage, where 0 represents 0% implemented, and 10 represents 100% implemented. Moreover, the project information of the above survey input includes the project name, project sector, project location, contract type, contract value, and project schedule. The third section is the primary data sets to conduct the prediction models. By using 15 input variables of BIM application and 10 output variables of engineering performance, the relationships are reviewed by AI and statistical methods. This survey package with a data collection plan comprises three sections as attached in Appendix 2.

The data collection was a rigorous process to ensure the quality of the survey and the reliability of the data. After the necessary data collection, these data were applied to evaluate the statistical key results to obtain the significant levels of the input and output variables. These confirmed important variables were formed to construct the correlation analysis and the assessment MLMP and LR prediction models. Data preparation is a

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crucial step in preparing the original data for machine learning. This process involves selecting the relevant data and applying various pre-processing steps to transform the raw data into a format suitable for training and validating machine learning models. The data is split into multiple parts, with one part used as the training set for model development, and the other part as the test set for model validation and implementation. Three project samples with a data collection plan of three sections of survey package as attached in Appendix 3. Some of information are protected for the project required confidential and commercial reasons.

In this study, a total of 60 data samples are grouped into two sets: the training set, which is essential for training the deep model to understand and apply concepts, design rules, and produce accurate results; and the test set, which is used to evaluate the effectiveness of the predictive model trained with the training set. During the training process, the model is adjusted by fitting parameters, which involves adjusting weights to optimize the model's performance. The test set, on the other hand, is not used during training but is utilized in the validation process to inform the choice of parameters and input features. Once the final model is selected, the test data set serves as a final test, providing the best possible estimate of the model's success when applied to entirely new data. This step ensures the reliability and generalizability of the predictive model for future data.

Data mining is applied to improve efficiency and productivity by identifying patterns, trends, and insights to optimize data preparation processes. Preprocess and clean the data to ensure the quality and suitability for data mining before applying it to build the models. By analyzing data from previous BIM application and engineering design processes, the patterns and trends are used to optimize processes for better BIM application and

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engineering performance, reduced costs, shorter design cycles, and increased customer satisfaction (Hao, Zhien, and Zhao 2019).

3.2.3 Model Development Method

To identify the influence levels of BIM use inputs on engineering performance measure outputs, two approaches were proposed, as shown in Figure 3, to evaluate the relationship between the inputs and outputs and develop the performance prediction models. The first approach is separated essential and enhanced BIM uses, which considers how essential and enhanced BIM uses influence separately at different phases of engineering performance measures. This is defined as the separated BIM use model, which applies correlation analysis to evaluate the relationship strength between 10 performance outputs associated with 5 BIM use inputs for the essential model and 10 performance outputs related to 10 BIM use inputs for the enhanced model. This method establishes the statistical correlation significance and possible connection among the inputs and outputs. The second approach with 2 stages is the combined BIM use approach, which combines the essential and enhanced BIM uses and considers how essential and enhanced BIM uses jointly influence different phases of engineering performance measures. Stage 1 is to construct the MLMP model, and stage 2 is to construct the LR model. In approach 2, both were built to evaluate the collected output measures and input variables from the data survey and collection, find regression and activation equations, and predict the engineering performance.

MiniTab 18 statistical software package is selected and deployed for the data analysis in this research. MiniTab is a comprehensive, robust data mining, predictive analytics, and modeling tool for performing statistical analysis, including correlation,

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hypothesis testing, regression, and ANOVA. The main features used in this study are basic statistics, regression, ANOVA, and control charts under statistical analysis modules.

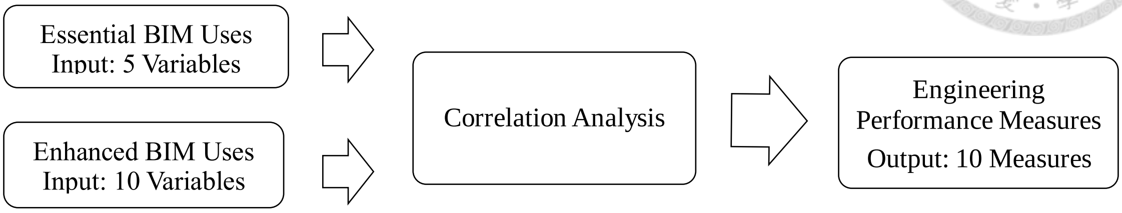
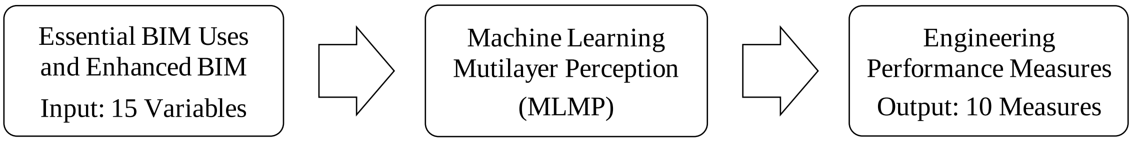


Figure 3. (a) Approach 1 Separated BIM Uses



(b) Approach 2 Stage 1 Combined BIM Uses for MLMP Model

(c) Approach 2 Stage 2 Combined BIM Uses for LR Model

Figure 3. (b) and (c) Approach 2 Combined BIM Uses

BIM applications were implemented in the life cycles of the 60 surveyed project samples with valid data points. These survey datasets were separated into two groups training set and a test set. The first group of 52 projects applied sample data as a training set for required model development, and the second group of 8 project data as a test set for model validation and implementation. The second group of 8 project samples of the test set was selected from the four sectors near the mean TIC average statistical points for model validation and implementation, as indicated in Table 1. The first compared the

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existing project datasets by selecting two projects from the two most populated sectors. Project sample 1 from the rail and metro sector and Project sample 36 from the high-tech facility from the first group of 52 project sample training sets. The second step uses 8 project sample test sets from four sectors and two from each sector divided into two test sets for model validation. The separation of samples aims to spread the data among sectors to ensure the diverse spectrum of the projects.

3.3 ML Multilayer Perception Techniques

An MLMP technique is a feedforward ANNs that creates a group of outputs from a group of inputs for function approximation. MLMP is a type of artificial neural network that consists of multiple layers of nodes or neurons, and this network helps to obtain information about the underlying reasons in the advanced models of deep learning. It is commonly used in machine learning for various tasks like classification, regression, and pattern recognition.

MLMP is widely used in machine learning and can be applied to various tasks, including engineering performance analysis and prediction is commonly used in simple regression problems. A multilayer perceptron strives to remember patterns in sequential data. Because of this, it requires many parameters to process multidimensional data. It is characterized by multiple layers of input nodes connected as a directed connection between the input and output layers. MLMP consists of the input, hidden, and output layers.

Figure 4 shows a diagram of a neuron in an MLMP network, also called Node i. It includes a summer and nonlinear activation function g. This study applies the Karas source Python library to develop and evaluate the proposed deep learning models. Keras is a high-level deep learning library written in Python. It provides a user-friendly and

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intuitive interface for building and training neural networks, including MLMPs. Multilayer feedforward networks use several training techniques, the significant portions of a feedforward network's learning and training process with a backpropagation algorithm (Svozil, Kvsanicka, and Pospichal 1997).

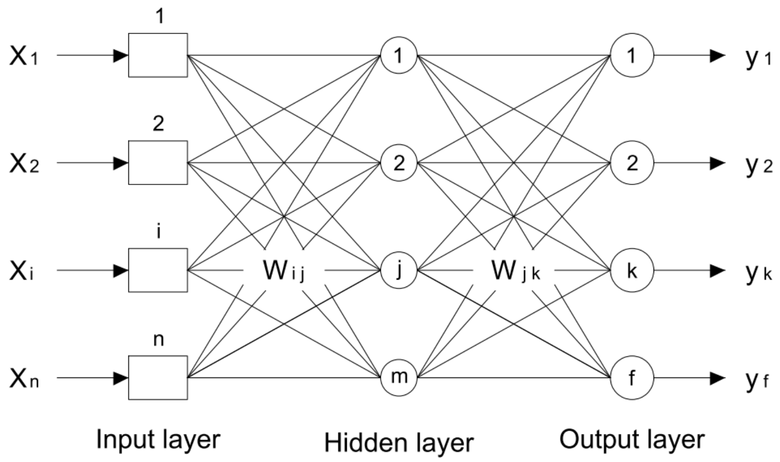

Figure 4. Multilayer Perceptron Feedforward Neural Network

In MLMP, the information flows from the input layer through the hidden layers to the output layer in MLMP. Each neuron in a layer process its inputs and passes the result to the next layer. The weights and biases are parameters that the network learns during training, they are adjusted to minimize the difference between predicted and actual outputs. MLMP is trained using a supervised learning approach, it involves feeding input data forward through the network, calculating the error, and adjusting weights and biases using backpropagation. Backpropagation is an optimization algorithm that minimizes the error by adjusting weights backward through the network. It involves computing the gradient of the error with respect to the weights.

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The applications of MLMP are pattern recognition, classification and regression, function approximation, time series prediction and natural language processing. MLMP is applied in tasks like language translation, sentiment analysis, and text classification. MLMP's strength lies in its ability to model complex non-linear relationships in data. Its architecture and training process make it a foundational building block for more advanced neural network architectures used in contemporary machine learning applications. MLMP is proposed to apply to this research by using it’s regression feature to enhance performance.

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4.0 Input Variables and Output Measures

This section explains the input variables and output measures applied to this research. The input variables are the BIM use, and the output measures are the engineering performance outputs. The definitions of input variables and output measures are investigated, reviewed, discussed, and defined for correlation analysis and model development purposes.

4.1 BIM Use Input Variables

The National Institute of Building Sciences (NIBS) launched and published a National BIM Guide for Owners (NBGO) in January 2017. The applicability of NBGO can vary depending on the specific country and jurisdiction, as different countries may have their own guidelines and standards for BIM implementation in the construction and real estate industries. The NBGO is typically designed to assist building owners and operators in effectively implementing and using BIM throughout the lifecycle of a construction project. It provides guidance on how to specify BIM requirements, set expectations, and establish protocols for information exchange with project teams and stakeholders. The key points to consider regarding the applicability of a NBGO are:

- Local Regulations: Different country or region has specific regulations or guidelines related to BIM implementation. In some countries, BIM requirements are mandated for public projects, and these requirements may align with a national BIM guide.
- Project Type: The applicability of the guide depends on the type and scale of the construction project. Larger, more complex projects are more likely to benefit from comprehensive BIM guidelines, but the principles can be adapted for smaller projects as well.

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- Industry Standards: Consider industry-specific standards and guidelines. For example, organizations like the BuildingSMART International have developed global standards for BIM that can be used in conjunction with or in place of national guides.
- Organizational Requirements: Even if there is no specific national guide, a BIM guide for owners can be developed at the organizational level to ensure consistency and best practices for BIM implementation.
- Collaboration: Collaboration with architects, engineers, contractors, and other stakeholders is crucial. The applicability of a BIM guide is often tied to the willingness of all parties involved to adopt BIM processes.

It is essential to understand the specific requirements and guidelines in different region and for the type of project. BIM can offer numerous benefits in terms of improved project coordination, reduced costs, and enhanced facility management, so it is worth considering its implementation and referring to relevant guides and standards for guidance. BIM guides and standards can vary significantly from one country to another. These variations are often influenced by factors such as local regulations, construction practices, and the level of BIM adoption within a specific region. A general comparison of BIM guides in different countries:

- United States National BIM Standard (NBIMS): The United States has a National BIM Standard, which provides a framework for BIM implementation. It includes guidelines and templates for BIM execution plans, standards for data exchange, and classification systems like COBie (Construction-Operations Building information exchange).
- United Kingdom BS 1192 and PAS 1192: The UK has been a pioneer in BIM adoption with its BS 1192 and PAS 1192 standards. These standards provide detailed guidance

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on BIM processes, information exchange, and common data environments. The UK also introduced a BIM Level 2 mandate for government projects.

- Canada CAN/CSA Z195: Canada has the CAN/CSA Z195 standard for BIM, which outlines processes and guidelines for BIM implementation. Provinces like Ontario have also developed their own BIM standards and guidelines.
- Australasian BIM Framework: Australia has the Australasian BIM Framework, which provides guidance for BIM implementation in the Australian and New Zealand context. The framework includes principles for BIM use in various project stages.
- Singapore BCA BIM Guide: The Building and Construction Authority (BCA) in Singapore has developed a comprehensive BIM guide. It includes guidelines for BIM standards, project collaboration, and BIM submission requirements.
- Germany: DIN 69910-1 and VDI 2552: Germany has DIN 69910-1 and VDI 2552 standards that provide guidance on BIM processes and information modeling. These standards are widely used in the German construction industry.
- China: China has its own BIM standards and guidelines that align with the country's specific construction practices and regulations. These standards are developed by organizations such as the China BIM Alliance.
- Netherlands: The Netherlands has a BIM Loket, which serves as a national platform for BIM development. They have their own guidelines and standards, including the Netherlands Standard for Building Specifications (STABU) and the Netherlands Information Model (NL/SfB).

The application of specific BIM guides and standards varies from country to country and often depends on local regulations, industry practices, and project requirements. There is no single universally adopted BIM guide or standard that applies worldwide.

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However, some guides and standards have gained broader recognition and use in various regions. The following standards provide general practice and application for most of the locations.

- ISO 19650: ISO 19650 is an international standard for BIM that provides a framework for managing information over the entire life cycle of a built asset using BIM. It has gained global recognition and serves as a foundation for BIM implementation in many countries.
- UK BIM Standards (BS 1192 and PAS 1192): The United Kingdom's BIM standards, including BS 1192 and PAS 1192, were influential in the early adoption of BIM practices and have been widely used as a reference in many countries.
- National BIM Standard (NBIMS) in United States: The NBIMS in the United States, developed by the National Institute of Building Sciences (NIBS), provides guidance for BIM implementation in the U.S. It has been used as a reference point for BIM practices in North America.
- Australasian BIM Framework: The Australasian BIM Framework is well-recognized in Australia and New Zealand and has influenced BIM practices in the region.
- Local Standards and Guidelines: Many countries have developed their own BIM standards and guidelines tailored to their specific construction industry and regulatory environment. These local standards are often more widely used for projects within their respective countries.

It is important that BIM adoption and the use of specific guides and standards can change over time, and new standards may have emerged. When embarking on a BIM project, it is essential to identify the most current and relevant BIM guides and standards for the specific region and project type. Additionally, project owners and stakeholders

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should consult with local authorities and industry organizations to ensure compliance with the latest regulations and best practices. In this research, the NBIMS of the United States developed by the NIBS, provides more general practice guidance for BIM implementation in the U.S. It has been used as a reference point for BIM practices in North America, is applied to this study.

The NBGO intended to direct facility owners to apply and implement the BIM application requirements in execution procedures and contracts to plan, design, build, startup, operate, and maintain the facilities. The Guide defines a method for developing and implementing the BIM application requirements for a construction project from the viewpoint of facility owner. It assists them in maximizing the potential opportunities of BIM implementation in their projects. The Guide further indicates that the BIM application can facilitate the owner's communication of decision-making processes, design concept, details integration, project-wise coordination across different stages, improved project overall schedule and cost control, after-construction facility management and maintenance, building automation, monitoring, and many other benefits. Notably, BIM implementation in the U.S. keeps increasing since owners benefit the most by applying BIM as a control tool to maximize a facility's value during its overall execution phase.

The BIM uses defined in NBGO are a standard criterion for implementing BIM applications, enabling the facility's overall life cycle to reach specific objectives expected by the owner. The implementation of BIM empowers facility owners to utilize the integrated model in various applications tailored to their specific requirements. To ensure a successful project execution, a well-defined project execution plan is essential, outlining the project deliverables to be provided to the facility owner upon the turnover after test and commissioning. The defined deliverables encompass a design intent model, a

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construction model, and comprehensive operations and maintenance data, as illustrated in Figure 5. To avoid any ambiguities or misunderstandings, the content of each deliverable should be explicitly specified within the contract documents involved in project. The BIM use input variables identified to apply in this study are included in the deliverables as described in the following processes.

- Design Intent Model: This model captures the intended design, and serves multiple purposes, including project BIM execution, digital design mock-ups, decision support, and design coordination.
- Construction Model: Developed based on criteria relevant to the facility's fabrication and construction, these models stem from the design intent model during construction coordination. Cross-platform 3D model viewing software is often used to combine the files to accommodate various subcontractor file formats and provide a higher level of detail.
- As-Built Model: This model captures the status of the project upon its completion. Initially based on the design intent model, it progressively incorporates project information as construction progresses.
- Record Model: Prepared for operations and maintenance purposes, the record model typically utilizes the design intent model as a baseline and is then updated to reflect all changes made during construction and testing. The goal is to create a lightweight model with sufficient detail for facilities management operations, without being overly detailed. It contains accurate attribute data on major equipment and systems, supporting facilities management documentation. The model is utilized during commissioning or updated to reflect commissioning data.

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- Operations and Maintenance Data: This deliverable comprises asset inventory with asset names, classifications, and locations. For critical components, attributes such as make, model, and serial number are considered. Throughout the project phases, the project BIM team must provide a formal report confirming the completion of consistency checks. This report is discussed as part of the review process and addresses any identified interferences and constructability issues.

As depicted in Figure 5, the collaborative process between design and construction professionals involves the creation of design intent models to generate accurate construction documents. These design intent models serve as a foundation for developing construction models during the construction phase. As construction progresses, these models evolve to capture project data, forming the basis for an as-built model that depicts more detailed construction task conditions. Throughout construction, the integration of various construction models culminates in the development of the as-built model. This model, along with ongoing project information exchanged with design professionals, facilitates the updating of design intent models into a record model. To cater to the specific needs of operations and maintenance, the record model is derived from the design intent model, providing a lightweight version without compromising essential information. Overall, the record model, along with the as-built model and project data, offers facilities management personnel a diverse array of information in multiple formats, effectively supporting various facilities management uses and activities. The seamless interaction between design intent models, construction models, as-built models, and record models ensures a comprehensive and streamlined approach to facility management.

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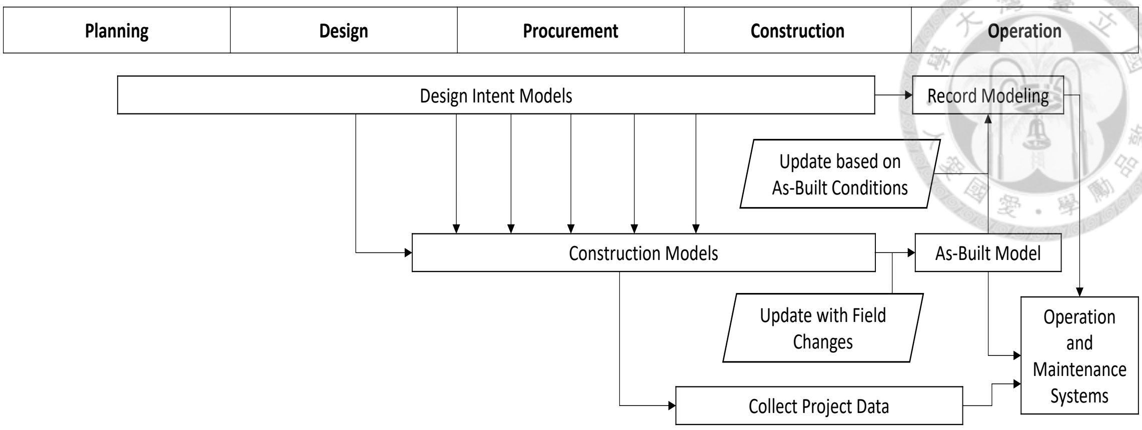

Figure 5. Sample Process for Life Model Requirements

From section 4.2 BIM uses of the NBGO, a BIM use refers to the application of BIM throughout the lifecycle of a facility to achieve specific objectives. The versatile nature of BIM technology enables various owners to utilize the model in diverse ways, tailoring its implementation to suit their project's distinct requirements. As the project progresses through different phases, the information constructed within the BIM expands both in quantity and detail. These BIM uses can be categorized into three main types: essential BIM, enhanced BIM, and owner-related uses. Each of these categories represents specific functionalities and purposes of BIM, providing owners with valuable tools to optimize their project management and decision-making processes. The essential BIM uses identify a minimum key requirement to apply BIM in the project, and the enhanced BIM uses identify an extension of essential BIM use to reinforce the application of BIM use. The owner-related uses are mainly the usage of BIM identified by the owner to include the required information related to operation and maintenance after project turnover. NGBO suggests that it is very important that the BIM uses should align with project goals and execution plans.

The guild establishes a minimum requirement for the five essential BIM uses indicated in Table 2, second column from X1 to X5, namely X1: existing conditions, X2:

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design authoring, X3: design review, X4: three-dimensional (3D) coordination, and X5: record modeling. As shown in Figure 6, the minimum BIM example suggests the five essential BIM uses applications in the five phases of an industrial construction project life cycle. The main application applies to a project phase indicated in solid boxes and the extension applications in dotted boxes. From applying the five essentials is in the project phases, as shown in Figure 6, the interaction and the overlapping of the BIM use expended in the five phases of the project cycle explicitly explains the correlation among these BIM uses input variables.

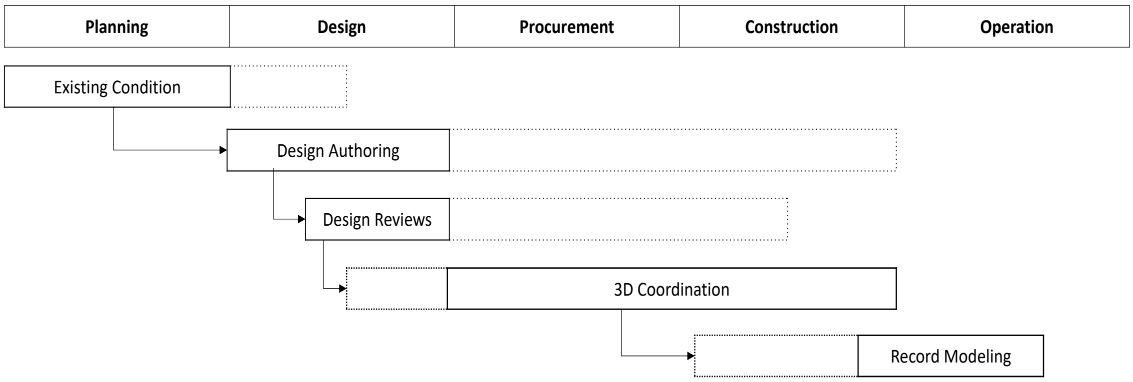

Figure 6. Minimum BIM Use in Project Phases

Project conditions classify the enhanced BIM uses, and the owner-related BIM uses in the Guide, the Enhanced BIM Uses as described in Table 2 from X6 to X15, namely X6: cost estimating, X7: phase and 4D planning, X8: site analysis-development, X9: site utilization-for construction, X10: digital fabrication, X11: 3D location and layout, X12: engineering analysis, X13: sustainability analysis, X14: codes and standards compliance, and X15: construction systems design. The definition of the essential and enhanced BIM use defined in NBGO is listed in Table 2 to identify the actual practice and to provide the application guidelines. The owner-related BIM uses, including asset management, disaster planning and management, and space arrangement in NGBO, are suggested in the Guide to confidently include the operation of manufacture for vertical and horizontal

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phase information. Owner-related uses represent the culmination of the BIM journey, emphasizing the owner's specific needs during the operation and maintenance phase. This phase involves the integration of crucial information identified by the owner to facilitate seamless operation and maintenance post-project turnover. By tailoring BIM to these owner-centric requirements, the technology becomes a powerful asset, contributing to effective facility management and long-term sustainability. In essence, the tripartite classification of BIM applications aligns with the distinct demands of design, construction, and operation, offering a comprehensive approach to project optimization. Considering that the size of the data domain for the collection and analysis from the owner is complicated, the owner-related BIM uses are excluded from this study.

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Table 2. BIM Use in NBGO

Category	BIM Uses	Definition in NBGO Section 4.2
Essential BIM Uses	Existing Conditions	A process of geometry and information of the existing conditions and facilities on a site
	Design Authoring	A process is used or implemented to develop a BIM of the engineering design
	Design Review	A quality process is used to allow stakeholders to verify design and reviews can resolve design issues
	Coordination	A process for elements can be coordinated, and clash detection or conflicts can be identified
	Record Modeling	A process contains an accurate depiction of the physical and functional conditions of a facility
Enhanced BIM Uses	Cost Estimating	A process used to generate a quantity takeoff and cost estimate and provide cost effects of changes
	Phase and 4D Planning	4D used to effectively plan the phased occupancy in a renovation, and the construction sequence with space requirements
	Site Analysis-Development	BIM and GIS tools are used to evaluate properties to determine the most optimal site location
	Site utilization for Construction	For Construction (See Phase and 4D Planning)
	Digital Fabrication	Machine technology to prefabricate directly. model is used as input into manufacturing for production of components and assemblies
	3D Location and Layout	Utilizes a model to lay out the building assemblies and produce 2D/3D component drawings used during site construction
	Engineering Analysis	The integrated tools that allow the physical and material properties of elements, assemblies, and systems within for analysis and simulation
	Sustainability Analysis	The integrated tools that allow the physical and material properties of elements, assemblies, and systems for developing sustainable elements
	Codes and Standards Compliance	A process in which validation to check the model parameters against applicable codes and standards
	Construction Systems Design	A process to design and analyzes the contemporary systems

The brief description of BIM uses extracted from NBGO section 4.2 is shown in the third column in Table 2 to provide the general practices of each input. The definition of BIM use provides standard guidelines to 15 suggested applications for facility owners or BIM users to follow in both essential and enhanced BIM uses. Based on the brief description of BIM inputs from NBGO, the definitions of input variables are enhanced and specified to reflect the actual practices for data collection purposes indicated in the

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fourth column in Table 3. In the third section of the survey package, to evaluate the implementation of each 10-input attribute, the application level is indicated as a scale of 0 to 10 to represent 0 to 100% implementation, where 0 represents 0% implemented, and 10 represents 100% implemented for the surveying project. The application of BIM uses is suggested to apply in this study to provide comprehensive understanding of analysis and must be aligned with construction project goals, based on added value to the facility owner. The definition of the BIM inputs is defined as the execution method of the used variables, and it provides explicit instruction on data collection criteria for the standardization of the BIM use input variables.

Table 3. BIM Use Input Variables

Category	**BIM Use Attributes**		**Attributes of Data Collection (Scale 0 to 10 for 0-100% implemented)**
Essential BIM Uses	X1	Existing Conditions	Existing site and facilities geometry information to be included in BIM model
	X2	Design Authoring	BIM Software/Tool used in the engineering design process
	X3	Design Review	30/60/90%/100% Model Review in the design execution
	X4	Coordination	Clash detection and resolution execution in BIM model
	X5	Record Modeling	Physical and functional information input in the elements of the model
Enhanced BIM Uses	X6	Cost Estimating	Generate material quantity takeoff and cost data
	X7	Phase and 4D Planning	Dimension of time and schedule information used in the model
	X8	Site Analysis Development	GIS tools used in model
	X9	Site utilization for Construction	Communication tool for construction plan added in the model
	X10	Digital Fabrication	Prefabricate by using BIM data or information
	X11	3D Location and Layout	Function of utilities to layout assemblies
	X12	Engineering Analysis	Engineering system simulation used in model
	X13	Sustainability Analysis	Sustainable design elements included in model
	X14	Codes and Standards Compliance	Validation of codes for model
	X15	Construction Systems Design	Contemporary system analysis in Model

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4.2 Engineering Performance Output Measures

As discussed in the previous section, the term “performance” can be viewed and evaluated from different perspectives. The evaluation of engineering performance in the industrial sector is paramount, and the contentment of owners and facility developers with engineering outcomes has been recognized as a fundamental criterion in this regard. Alongside the satisfaction factor, scholarly literature and insights from industry experts corroborate that numerous measures can be deployed to evaluate engineering performance across each phase of the project life cycle. This comprehensive approach aims to ensure a holistic assessment and continual improvement of engineering processes throughout the entire facility development process.

The CII RT-156 studied and analyzed the data collected from targeted projects using the CII benchmarking and metric committee to have a valid, reliable, and easy-to-use system for measuring engineering performance (Chang, Georgy, and Zhang 2001). The research found systematic processes and procedures and developed a new and innovative approach for measuring productivity in engineering organizations by addressing the broader scheme and improving engineering performance. A utility-based neuro-fuzzy approach was established by constructing the connections between engineering inputs and performance outputs, and multiple utility functions were applied to integrate the collective assessments of performance measures (Georgy 2000). This developed integrated platform by RT-156 was used for several practical purposes, including performance output assessment and prediction and sensitivity analysis of individual inputs. The platform encompasses developing analytical methods that impact performance and techniques to quantify the resulting engineering performance.

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From the knowledge encoded in an integrated scheme by RT-156, several areas have been highlighted as influential in driving engineering performance in construction projects. RT-156 identified the engineering performance measures with 10 metrics and 10 outputs to measure and forecast engineering performance (Georgy et al. 2005). A total of 10 distinct measures have been discerned to represent the engineering performance across three pivotal phases of the project: detailed design, procurement and construction, and startup and commissioning. These identified 10 measures encapsulate essential indicators of engineering efficacy during each respective phase. For a comprehensive overview, please refer to Table 4, which presents the specific engineering performance measures considered for design, construction, and startup in project life.

Table 4. List of Measures of Engineering Performance by CII RT-156

Category	Engineering Performance Measure	Significant Variables
Detailed Design Value	Design Rework (%)	Completeness of scope definition Change communication system
	Design document release commitment	Split engineering practices Completeness of objectives and priorities Change communication system
	Detailed design schedule delay (%)	Completeness of objectives and priorities Change communication system
	Detailed design cost overrun (%)	Designer qualifications and capacity
Fabrication and Construction Value	Fabrication and construction schedule delay due to design deficiencies (%)	Completeness of objectives and priorities Change communication system
	Fabrication and construction cost increase due to design deficiencies (%)	Split engineering Newness of process technology to designer Change communication system
	Construction hours for design problem solving and field design	Completeness of basic design data Use of 3D computer aided design modeling
	Estimated dollar savings due to constructability	Relative size of project Design schedule Completeness of scope definition Use of electronic data interchange Change communication system
Start-up and Commissioning Value	Startup schedule delay due to design deficiencies (%)	Newness of process technology to owner Design–construction overlap
	Startup cost increase due to design deficiencies (%)	Completeness of objectives and priorities

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As reported in RT-156, the evaluation of engineering performance during the operational and maintenance phase necessitates several years of full production of the industrial facility. Therefore, for the purpose of the research by RT-156, the definition of engineering performance was restricted to the project phases leading up to the full operation of the facility. A comprehensive set of 10 output measures had been identified to signify the engineering performance during the detailed design, procurement, and construction, and the startup and commissioning phases of the project. To gather data for system training and validation, a questionnaire survey was utilized, focusing on industrial projects within the targeted industry sectors in the United States. The data set comprised information from 50 industrial projects, meticulously selected to include a diverse representation of the industry. These projects were undertaken by prominent companies within the U.S. industrial construction targeted sector and encompass a wide range of project types, including grassroots and greenfield additions to existing facilities, with varying contractual arrangements, from lump sum to targeted price with incentives, and project sizes ranging from US$ 1 million to over US$ 130 million.

Upon reviewing Table 4, a diverse range of numerical and non-numerical variables became evident. Numerical variables were characterized by precise or near-exact values, while non-numerical variables were often described using semantic scales, introducing varying degrees of imprecision or fuzziness in their descriptions. To address this variability, different strategies were employed in representing the variables. For numerical variables, a steep change in the triangular membership function was adopted, reflecting their lower level of uncertainty or fuzziness. In contrast, non-numerical or linguistic variables are typically defined on semantic or ordinal scales. To ensure consistency, a term set divided into five points is employed to represent the various non-numerical variables within the system. Given that non-numerical variables exhibit a

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higher degree of uncertainty or fuzziness, their membership functions should transition more gradually than those used for numerical variables. Consequently, any value for a non-numerical variable can simultaneously belong to multiple linguistic terms. Employing hedges like "about," "not," and "very" enables the development of appropriate representations for these linguistic variables. Such an approach accommodates the inherent imprecision in linguistic descriptions, facilitating a more nuanced and accurate fuzzy representation of the variables of the system.

The selection of performance measures for this study based on the findings from CII RT-156 , and the focus is on performance measures related to the phases leading up to a facility's full operation, which typically includes project planning, construction, and initial operation. The report mentions that while it would be beneficial to include performance measures for the operation and maintenance phase of the facility, as well as the decommissioning phase. The task is currently challenging, and this is primarily due to the lack of readily available data for these phases. Gathering data for the project phases leading up to full operation is already time-consuming, and collecting data for the entire life cycle of projects from initial planning to demolition is even more challenging. The passage highlights that integrating measures for these later phases is currently unfeasible because of these data limitations. In essence, it emphasizes the practical constraints of collecting comprehensive data for all project phases, which is why the focus remains on the earlier phases leading up to facility operation in the study.

The data set comprising 60 industrial construction projects is relatively limited in terms of both data size and data quality. Despite encountering challenges in data collection, the acquisition of data for 60 projects has been relatively successful. However, from a statistical standpoint, this sample size may not be sufficient for robust model validation. Furthermore, the data used in this study encompass various industrial facility

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types, including chemical manufacturing, oil refining, power generation, among others. As industrial facilities are bespoke entities, the amalgamation of mixed project data representing different facility types may introduce diverse patterns that can hinder the effective learning of the neuro-fuzzy system.

After reviewing the study by RT-156, the output variables defined the execution method for using the variables and provided explicit instructions on data collection criteria standardizing of the output variables. As indicated in this study, the numerical expression did not represent three variables, since these variables rated by general depict the impression levels. A review of the output performance measures in the study shows that the three variables not represented by numerical expression consisted of high levels of imprecise expression, namely (1) commitment to engineering design document release or issue, (2) construction time spent on engineering design issues or interference and field engineering coordination, and (3) construction cost-saving for constructability study. These performance output variables were difficult to define and could only be described and expressed in fuzzy linguistic terms. Therefore, the three measures are suggested to replace by quantitative items for better and more accurate data analysis (Chiu and Chang 2022).

The research focused on quantitative performance indicators from management's construction perception and asserted that quantitative units of measurement should remain simple and easy to apply (Cox, Issa, and Ahrens 2003). For control and monitoring purposes, quantifying of metrics and trend provides more solid decision-making processes and opportunities for improvement. A significant collection of performance information obtained from the quantity project data and a comprehensive statistical study were conducted for future consideration. Furthermore, a survey of benchmark performance metrics for integrated project delivery suggested the impact of the request

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for information (RFIs) and change management in quantitatively evaluating overall performance. From the results of the above research on the performance measures, three variables were redefined and replaced by the more specific and measurable quantitative index. Namely, Y4 detailed designed quantity compared to the final installed quantity replaced the commitment of engineering design document release or issue in the detailed engineering design phase to reflect engineering performance; Y7 construction hours for RFIs replaced construction spent time for engineering design issue or interference and field engineering coordination; Y8 construction hours for field change request (FCR) replaced construction cost-saving for constructability study. Both Y7 and Y8 are in the construction phase to reflect construction performance as shown in Table 5.

Table 5. Engineering Performance Output Measures

Category	Variables		Definition (in %)
Detailed Design Value	Y1	Design Rework	Design Rework Hours/Total Design Hours
	Y2	Detailed Design Schedule Delay	Days of Design Schedule Delay/Total Design Schedule Days
	Y3	Detailed Design Cost Overrun	Design Cost Overrun in USD/Total Design Cost in USD
	Y4	Detailed Designed Quantity Compared to Final Installed Quantity	Issue for Construction Designed Quantity/Final Installed Quantity
Fabrication and Construction Value	Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days
	Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD
	Y7	Construction Hours for Request for Information (RFI)	Construction Hours for Request for Information (RFI)/Total Construction Hours
	Y8	Construction Hours for Field Change Request (FCR)	Construction Hours for Field Change Request (FCR)/Total Construction Hours
Start-up and Commissioning Value	Y9	Start-up Schedule Delay due to Design Deficiencies	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days
	Y10	Start-up Cost Overrun due to Design Deficiencies	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD

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From the second column in Table 5, the revised engineering performance output measures of 10 variables consist of three replaced variables and seven defined initially defined variables that are mainly divided into three categories according to the development of a construction project, engineering design phase, construction and fabrication phase, startup, and commissioning phase, where spans over the life cycle. As each output measure's definition is clearly defined and specified, the proposed engineering performance measures with the measurable quantitative criteria to evaluate the output measures by using the percentage to identify the values.

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5.0 Model Development

The correlation analysis for BIM use inputs and engineering performance measure outputs is first be reviewed for the base of model development. And later the two prediction models are proposed for engineering design performance measurement using statistic regression processes and machine learning techniques. LR and MLMP models are developed by applying the identified BIM use input variables and engineering performance output measures. After the models are developed, the comparison and findings are discussed.

5.1 Correlation Analysis

The engineering performance evaluation is a continuous task throughout a project's life, from the planning phase to the operation and maintenance phase. As the project progresses through various phases in its execution life, the interpretation of engineering performance measures shall be different by pre-defined input variables. For example, if the design rework rate (performance output measure Y1) is high in the design phase means differently compared to measurement in the procurement or construction phases, and the required corrective action to be considered to resolve the issues shall be different. On the other hand, when measuring engineering performance at different project phase, some of the inputs are not available, or the values are partial for measurement. For example, the detailed designed quantity compared to the final installed quantity rate (performance output measures Y4) is unavailable until construction is finished. In the design phase, the designed quantity is developed at the conceptual, preliminary, and detailed design stage. Therefore, the equipment and materials quantities are finalized at issue for construction (IFC) stage, and quantities may be revised in the following procurement, construction, and commissioning phases. This explains that there shall exist

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a relationship among the input variables and between input variables and output measures. The correlation analysis is required to understand the strength of the relationships and how they interact.

Pearson's correlation coefficient for continuous interval level data from −1 to +1 was applied to evaluate the strength of the association for variables. The positive correlation indicates that both variables decrease or increase simultaneously, whereas the negative correlation indicates that as one variable decreases, the other increases, and vice versa. From the rule of thumb for interpreting the correlation coefficient size, 0.9 to 1.0 (−0.9 to −1.0) represents a very high positive (negative) correlation, and 0.7 to 0.9 (−0.7 to −0.9) represents a high positive (negative) correlation (Hinkle, Wiersma, and Jurs 2003). Therefore, the Pearson's coefficient helps quantify how closely two variables are related in a linear relationship. It is a useful tool in statistics and data analysis to understand relationships between data points. The interpretation of Pearson's correlation coefficients in terms of the strength of the relationship is based on empirical observations and statistical conventions. Many studies in various fields have supported these interpretations over the years. Researchers and statisticians have found that these general guidelines for assessing the strength of correlations are broadly applicable. Therefore, the Pearson correlation between 0.7 to 1.0 (−0.7 to −1.0) is suggested to consider a strong relationship in this research and further reviewed in the two correlation analyses.

This study applies a statistical method for correlation analysis to evaluate the strength of a cause-effect relationship for quantitative variables and measures. Here, two correlation analyses were performed to measure the relationship between the BIM use inputs and that between BIM use inputs and engineering performance outputs. Apply correlation analysis module in MiniTab 18 statistical software package by inputting BIM use variables from X1 to X15 and engineering performance output measures from Y1 to

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Y10, and the relationships of all Xs and Ys are generated as shown in Appendix 4. The results showed that a strong correlation indicates that two or more variables have a strong relationship, whereas a weak correlation shows that the variables are hardly related.

5.2 Correlation among BIM Use Input Variables

As discussed in session 4.1 and indicated in Figure 6, the input variables are extended through project phases, and relationships exist among the 15 BIM inputs. This analysis intends to find the facts of the relationships among the BIM use variables to understand the significant levels of each input and how they interact with other inputs.

After applying correlation analysis in MiniTab, the result is shown in Table 6. The correlation in BIM use input variables for essential and enhanced BIM Uses, there is a high correlation with essential BIM uses related to design phase activities including design review (0.897), design authoring (0.879), coordination (0.731), record modeling (0.704) and existing conditions (0.704). Also, essential BIM uses highly correlate with enhanced BIM uses in sustainability analysis (0.859), codes and standards compliances (0.846), and phase and 4D planning (0.816), which indicate the enhanced BIM use activities related to design efforts. For enhanced BIM uses, there is a high correlation in digital fabrication (0.888), construction systems design (0.888), cost estimation (0.874), 3D location and layout (0.869), and site utilization for construction (0.869), where implies the enhanced BIM uses are mainly influenced related to construction activities.

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Table 6. Correlation Analysis for BIM Use Input Variables

Category	BIM Uses		Essential BIM Uses			Enhanced BIM Uses		
			BIM Uses		Pearson Coefficient	BIM Uses		Pearson Coefficient
Essential BIM Uses	X1	Existing Conditions	X5	Record Modeling	0.704	X13	Sustainability Analysis	0.859
	X2	Design Authoring	X3	Design Review	0.897	X7	Phase and 4D Planning	0.712
			X4	Coordination	0.731			
	X3	Design Review	X2	Design Authoring	0.879	X7	Phase and 4D Planning	0.753
			X4	Coordination	0.716			
	X4	Coordination	X2	Design Authoring	0.731	X7	Phase and 4D Planning	0.702
	X5	Record Modeling	X1	Existing Conditions	0.704	X7	Phase and 4D Planning	0.816
						X13	Sustainability Analysis	0.771
						X14	Codes and Standards Compliance	0.846
Enhanced BIM Uses	X6	Cost Estimating	N/A			X10	Digital Fabrication	0.874
						X15	Construction Systems Design	0.870
	X7	Phase and 4D Planning	X2	Design Authoring	0.712	X14	Codes and Standards Compliance	0.752
			X3	Design Review	0.879			
			X5	Record Modeling	0.816			
	X8	Site Analysis-Development	N/A			N/A		
	X9	Site utilization-For Construction	N/A			X11	3D Location and Layout	0.869
	X10	Digital Fabrication	N/A			X6	Cost Estimating	0.874
						X15	Construction Systems Design	0.888
	X11	3D Location and Layout	N/A			X9	Site utilization-For Construction	0.869
	X12	Engineering Analysis	N/A			N/A		
	X13	Sustainability Analysis	X1	Existing Conditions	0.859	X14	Codes and Standards Compliance	0.815
			X5	Record Modeling	0.771			
	X14	Codes and Standards Compliance	X5	Record Modeling	0.846	X7	Phase and 4D Planning	0.752
			X7	Phase and 4D Planning	0.752	X13	Sustainability Analysis	0.815
	X15	Construction Systems Design	N/A			X10	Digital Fabrication	0.888

5.3 Correlation between Input Variables and Output Measures

As discussed in session 4.1 and indicated in Figure 5, the deliverables of the BIM application are models at five project execution phases. The deliverables are extended through project phases, and relationships exists between the 15 BIM inputs and 10

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engineering outputs. This analysis intends to find the facts of the relationships between inputs and outputs to understand the significant levels of inputs and outputs and how they interact with each other.

After applying correlation analysis in MiniTab, the result is shown in Table 7 for the correlation between BIM use inputs and engineering performance outputs. The results show that detailed design values correlate with essential BIM uses mainly in design activities, including coordination (-0.8093), record modeling (-0.7545), design authoring (-0.7434), and design review (-0.7432). Furthermore, it correlates with enhanced BIM uses also influenced by design, including engineering analysis (-0.7336), sustainability analysis (-0.7308), and phase and 4D planning (-0.7304). Fabrication and construction values correlate with enhanced BIM uses, and were related to construction activities, including digital fabrication (-0.7487), site analysis development (-0.7398), construction system design (-0.737), site usage for construction (-0.7285), and cost estimation (-0.7277). Values of the startup and commissioning outputs correlated with both essential and enhanced BIM uses. Here, record modeling in essential use concerned recording information and cost estimation (-0.7661). In contrast, codes, and standards compliance (-0.6961), construction system design (-0.7107), and phase and 4D planning (-0.7039) in enhanced BIM use significantly influenced the project completion stage.

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Table 7. Correlation Analysis for Engineering Performance Outputs and BIM Uses

Category	Engineering Performance Measures (%)	Essential BIM Uses		Enhanced BIM Uses	
		BIM Uses	**Pearson Coefficient**	**BIM Uses**	**Pearson Coefficient**
Detailed Design Value	Design Rework	Design Authoring	-0.7478	Phase and 4D Planning	-0.7089
		Design Review	-0.7148	Engineering Analysis	-0.7336
		Coordination	-0.8093	N/A	
	Detailed Design Schedule Delay	Existing Conditions	-0.7361	Sustainability Analysis	-0.7308
		Design Authoring	-0.7144	Codes and Standards	-0.7167
		Design Review	-0.7056	N/A	
		Record Modeling	-0.7545		
	Detailed Design Cost Overrun	Design Authoring	-0.7434	Phase and 4D Planning	-0.7304
		Design Review	-0.7432	Digital Fabrication	-0.7069
		Coordination	-0.8496	Engineering Analysis	-0.7041
	Detailed Designed Quantity Compared to Final Installed Quantity	Design Authoring	0.74228	Phase and 4D Planning	0.70217
		Design Review	0.70178	Engineering Analysis	0.81397
		Coordination	0.74514	N/A	
Fabrication and Construction Value	Fabrication and Construction Schedule Delay due to Design Deficiencies	N/A		Site Analysis-Development	-0.7398
				Site Utilization for Construction	-0.7285
				3D Location and Layout	-0.7179
	Fabrication and Construction Cost Overrun due to Design Deficiencies	Coordination	-0.7001	Cost Estimating	-0.7277
				Digital Fabrication	-0.7487
				Construction Systems Design	-0.737
	Construction Hours for Request for Information (RFI)	Existing Conditions	-0.7106	Sustainability Analysis	-0.7296
		Record Modeling	-0.7042	Codes and Standards Compliance	-0.7372
	Construction Hours for Field Change Request (FCR)	Coordination	-0.7179	Cost Estimating	-0.7284
				Digital Fabrication	-0.709
				Construction Systems Design	-0.7131
Start-up and Commissioning Value	Start-up Schedule Delay due to Design Deficiencies	Record Modeling	-0.7022	Cost Estimating	-0.7032
				Phase and 4D Planning	-0.7028
				Codes and Standards	-0.7156
	Startup Cost Overrun due to Design Deficiencies	Record Modeling	-0.7661	Cost Estimating	-0.756
				Phase and 4D Planning	-0.7039
				Digital Fabrication	-0.7012
				Codes and Standards Compliance	-0.6961
				Construction Systems Design	-0.7107

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5.4 Linear Regression Model

This iterative process involves constructing a series of regression models, wherein input variables are systematically added or removed based on F-statistic calculations to decide their significance or insignificance. The stepwise reduction technique was deployed to develop multiple linear regression models for each measure of engineering performance outputs. The details of the 52 project samples were applied to MiniTab 18 statistical software, and the models were produced as shown in Table 8 for each performance output measure.

The predictive effectiveness of the models is assessed using statistical metrics, including the coefficient of determination adjusted R-square of the model, as indicated in the R-sq (adj) column. The F-test is employed to test the null hypothesis, which assumes that the means of a specified set of normally distributed populations, all sharing the same standard deviation, are equal. In regression analysis, the F-value serves to determine the overall statistical significance of a regression model. When a regression model includes multiple predictor variables (independent variables), the F-value helps to assess whether the model as a whole explains a significant portion of the variance in the dependent variable (the variable trying to predict). A high F-value in regression analysis implies that the model is statistically significant and that the independent variables collectively contribute to explaining the variation in the dependent variable. The model explains zero variance in the dependent variables, the results shown in the F-value column are highly significant. Thus, it can be concluded that the model explains a significant amount of the variance. The P-value of 0.000s is much smaller than a significance level of 0.05, which is the normal probability of rejecting the null hypothesis in statistical practice. Hence, the null hypothesis is rejected, concluding the model is statistically significant. From the statistical evidence, the fittest regression models with the formation of equations of inputs

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and outputs then produced and significantly created very reliable predictions for each engineering performance measure, as shown in the third column in Table 8.

Table 8. Multiple Regression Model for Output Measures and Input Variables

Category	Output Measures		Linear Regression Model (LR)	R-sq(adj)	F-Value	P-Value
Detailed Design phase	Y1	Design Rework	26.96 - 0.815 X4 - 1.032 X10 - 1.629 X12	80.32%	70.37	0.000
	Y2	Detailed Design Schedule Delay	12.811 - 0.303 X1 - 0.765 X3 + 0.293 X4 - 0.493 X5	73.75%	36.82	0.000
	Y3	Detailed Design Cost Overrun	27.31 - 1.202 X4 - 0.912 X10 - 1.179 X12	81.46%	75.68	0.000
	Y4	Detailed Designed Quantity Compared to Final Installed Quantity	90.823 + 0.2268 X4 + 0.3865 X7 - 0.3105 X10 + 0.2506 X11 + 0.801 X12	84.48%	56.51	0.000
Fabrication and Construction Phase	Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies	21.34 - 1.312 X8 - 1.082 X9 + 0.678 X12	68.29%	37.62	0.000
	Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies	10.765 - 0.521 X4 - 0.755 X6 + 0.441 X14	71.25%	43.12	0.000
	Y7	Construction Hours for Request for Information	10.096 - 0.706 X8 + 0.501 X11 - 0.611 X14	65.69%	33.55	0.000
	Y8	Construction Hours for Field Change Request	8.811 - 0.4674 X4 + 0.3261 X5 - 0.6091 X6	71.77%	44.21	0.000
Start-up Phase	Y9	Start-up Schedule Delay due to Design Deficiencies	10.551 - 0.467 X6 + 0.368 X13 - 0.923 X14	63.01%	29.96	0.000
	Y10	Start-up Cost Overrun due to Design Deficiencies	9.201 - 0.452 X5 - 0.3954 X6	67.77%	54.63	0.000

The analysis is a method of fitting regression models in which an automatic procedure carried the choice of predictive variables to find the final regression equations and further predict the engineering performance. An example of output measures for Y1 and Y2 regression models generated by stepwise regression analysis from Minitab 18 is illustrated in Figure 7.

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Regression Analysis: Y1 versus X1, X2, X3, X4, X5, X6, X7, ... 3, X14, X15

Stepwise Selection of Terms
α to enter = 0.1, α to remove = 0.1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	2591.9	863.96	70.37	0.000
X4	1	125.6	125.63	10.23	0.002
X10	1	306.2	306.21	24.94	0.000
X12	1	253.7	253.66	20.66	0.000
Error	48	589.3	12.28		
Total	51	3181.2			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3.50401	81.47%	80.32%	78.61%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	26.96	1.20	22.44	0.000	
X4	-0.815	0.255	-3.20	0.002	2.55
X10	-1.032	0.207	-4.99	0.000	1.56
X12	-1.629	0.358	-4.55	0.000	1.87

Regression Equation
Y1 = 26.96 - 0.815 X4 - 1.032 X10 - 1.629 X12

Regression Analysis: Y2 versus X1, X2, X3, X4, X5, X6, X7, ... 3, X14, X15

Stepwise Selection of Terms
α to enter = 0.1, α to remove = 0.1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	592.23	148.057	36.82	0.000
X1	1	17.53	17.528	4.36	0.042
X3	1	75.93	75.927	18.88	0.000
X4	1	17.12	17.116	4.26	0.045
X5	1	51.05	51.046	12.69	0.001
Error	47	189.00	4.021		
Total	51	781.23			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.00533	75.81%	73.75%	70.49%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	12.811	0.740	17.32	0.000	
X1	-0.303	0.145	-2.09	0.042	2.42
X3	-0.765	0.176	-4.35	0.000	2.87
X4	0.293	0.142	2.06	0.045	2.42
X5	-0.493	0.138	-3.56	0.001	2.43

Regression Equation
Y2 = 12.811 - 0.303 X1 - 0.765 X3 + 0.293 X4 - 0.493 X5

Figure 7. Example of Output Measure Model from MiniTab 18 Stepwise Regression

The output variable Ys represent output measures, and Xs represent the BIM use input attributes in regression analysis. Analysis of variance indicates the equality of variances between factor levels, where a P-value 0.000 explains that the association

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between the responses and the inputs is statistically significant, and F-value indicates 70.37 associated with the response high significant level. Model summary shows how the model goodness-of-fit with the data, R-sq (adj) 80.32% indicates a high percentage of variation in output explained by the model. The coefficients describe the size and direction of the relationship between inputs and outputs and the regression coefficient of each input variable. Finally, the regression equations are generated, and the complete regression analysis report for all performance outputs is attached in Appendix 5.

The LR procedure generates a series of regression models by adding or deleting an input attribute, followed by F-statistic evaluations to decide whether such input attributes are significant at each step. Applying the statistical stepwise reduction method showed that the LR models were well constructed for each output attribute of the engineering performance outputs.

5.5 MLMP Model

The engineering performance measurement prediction models in this study were developed using the MLMP technique. MLMP networks represent feedforward multilayer neural networks trained with a backpropagation learning algorithm. These networks consist of computational neurons organized into separate output and hidden layers, with the connections between neurons characterized by weighting. Each neuron incorporates an activation function that maps its summed input to its output, and bias is another parameter calculated with the weighted inputs of the neuron.

For the implementation of MLMP, Python Keras was employed. Keras is a high-level neural networks API written in Python, offering a powerful and user-friendly open-source library for developing and evaluating deep learning models. It leverages efficient numerical computation libraries, enabling the definition and training of neural network

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models with minimal lines of code. Additionally, Keras supports both convolutional networks and recurrent networks, as well as combinations of both. The modeling steps using Keras, as depicted in Figure 8, involve loading the data, defining the MLMP model, compiling the model, fitting the model to the data, evaluating the model's performance, and predicting the outputs. This comprehensive approach utilizing MLMP with Python Keras facilitates efficient and effective development, evaluation, and application of the engineering performance prediction models. In the implementation process, the following steps are performed using Python Keras:

- Data Loading: Functions and classes are defined to load and prepare the data for the subsequent modeling stages.
- Model Definition: The MLMP model is structured as a sequence of layers, and layers are added one by one to construct the network architecture.
- Model Compilation: The MLMP model is compiled, utilizing the efficient numerical libraries (backend). The backend automatically selects the most optimized representation for network training and predictions.
- Model Fitting: The compiled model is executed on the chosen dataset, undergoing training and adaptation to the data.
- Model Evaluation: The network's performance is assessed on the dataset, which is separated into train and test datasets to facilitate both model training and evaluation.
- Model Prediction: Predictions are generated using the trained model on the dataset.

These steps in the MLMP implementation facilitate the seamless development and evaluation of the neural network model, ensuring its accuracy and efficiency in predicting engineering performance outcomes. Please refer to Appendix 6 for the coding of ML in Python.

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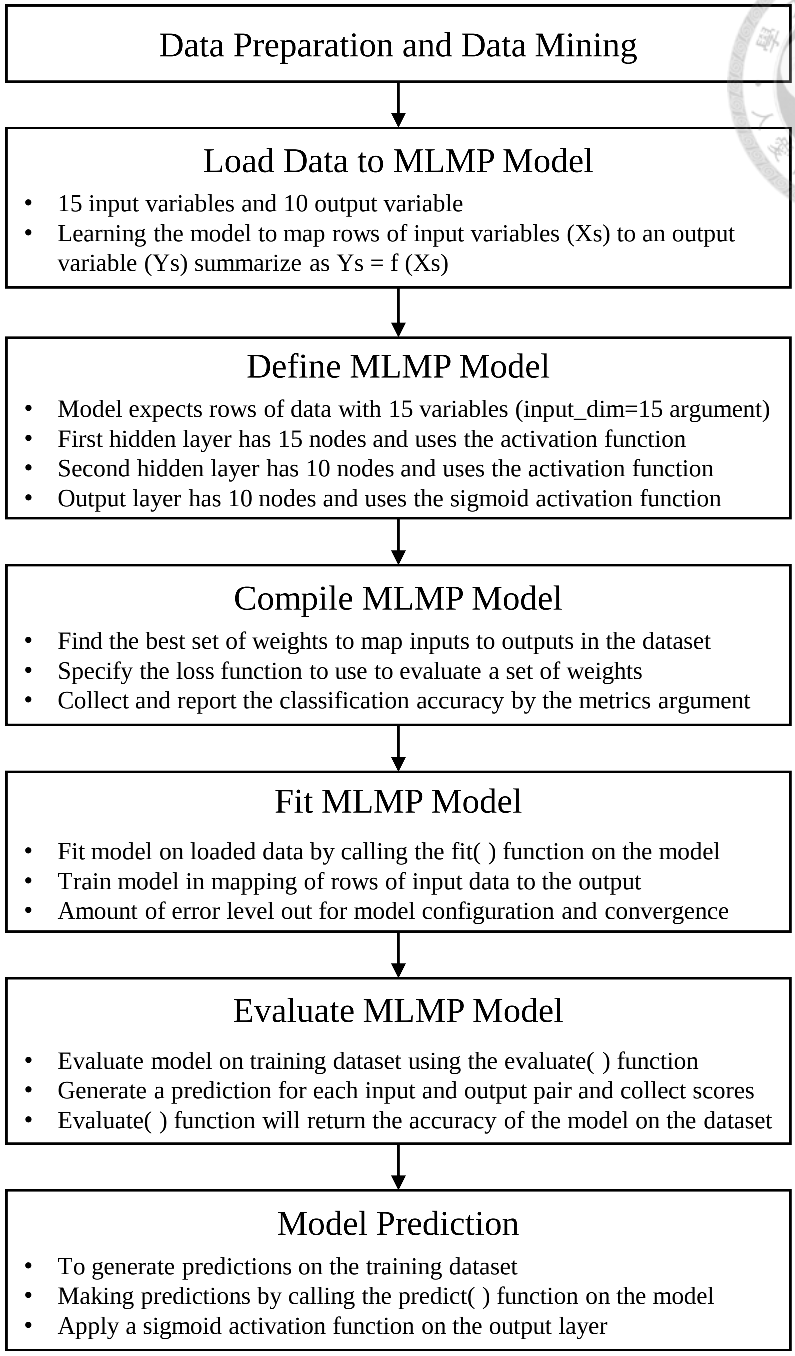

(Note: fit ( ), evaluate ( ), predict ( ) are function coding in ML Python)

Figure 8. MLMP Modeling by Python Kears

The machine learning processes develop a sequence of MLMP models for each performance output measures. The details of the 52 project samples were applied to ANN machine learning software, and the models were produced as shown in Table 9 for each output measure.

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Table 9. MLMP Models for Engineering Performance Measures

Machine Learning Multilayer Perception Models (MLMP)

Multilayer Perception Model Equation

$Yi = b + w1X1 + w2X2 + w3X3 + w4X4 + w5X5\ w6X6 + w7X7 + w8X8 + w9X9 + w10X10\ w11X11 + w12X12 + w13X13 + w14X14 + w15X15$

Example of Y1:

$Y1 = 27.038 + 0.0135\ X1 - 0.2319\ X2 - 0.0191\ X3 - 0.5388\ X4 - 0.1186\ X5 - 0.5342\ X6 - 0.4048\ X7 + 0.1821\ X8 - 0.4287\ X9 + 0.6430\ X10 + 0.4047\ X11 - 1.4968\ X12 - 0.5825\ X13 + 1.1374\ X14 + 0.1325\ X15$

	w1	*w2*	*w3*	*w4*	*w5*	*w6*	*w7*	*w8*	*w9*	*w10*	*w11*	*w12*	*w13*	*w14*	*w15*	*b*
Y1	0.01349	-0.2319	-0.0191	-0.5388	-0.1186	-0.5342	-0.4048	0.01821	-0.4287	-0.643	0.4047	-1.4968	-0.5825	1.13739	0.13249	27.038
Y2	-0.0673	-0.5109	-0.4272	0.16636	-0.0403	-0.1771	-0.1248	-0.3583	0.3233	-0.2121	0.16962	0.44196	-0.2281	0.02956	0.18	12.2983
Y3	0.38059	-0.2112	-0.246	-1.098	0.12459	-0.6543	-0.0956	-0.4173	-0.4059	-0.8977	0.81747	-0.7299	-0.498	0.44507	0.64442	27.02
Y4	-0.0157	-0.0218	0.0819	0.22759	0.216	-0.1692	0.27186	-0.056	0.03011	-0.3615	0.26321	0.80139	0.07409	-0.0661	0.14425	90.6198
Y5	0.44247	0.60359	-1.0421	0.44261	0.08645	0.51568	-0.1935	-1.2661	-0.7252	-1.1098	-0.3743	0.63631	-0.2692	0.27083	0.29693	20.7583
Y6	-0.2035	-0.2068	0.21423	-0.3404	0.0089	-0.5915	-0.0831	0.07228	0.15036	-0.1411	-0.0989	-0.2243	0.00214	0.64735	-0.1614	10.7497
Y7	-0.2057	-0.045	-0.403	-0.1495	-0.2657	-0.0268	0.25541	-0.5147	-0.1704	-0.1949	0.5333	0.44704	0.15154	-0.566	0.36798	10.9574
Y8	0.3827	-0.1241	-0.2996	-0.3431	-0.0597	-0.2884	0.28753	-0.0454	-0.0373	-0.2765	0.21216	0.08611	-0.1959	0.22807	-0.115	8.39781
Y9	0.27258	0.10541	-0.501	-0.0668	-0.2392	-0.2818	-0.0854	-0.1862	0.56097	-0.3315	-0.3928	0.4013	0.27751	-0.6077	0.28677	10.4929
Y10	0.25237	-0.384	-0.2049	0.02596	-0.3379	-0.0606	0.06843	-0.0743	0.34536	-0.4778	-0.2034	0.43302	0.27096	-0.4603	0.12916	9.38364

The evaluation of MLMP models for regression tasks, the F-value, while important in the context of statistical analysis and regression, but it is not typically used for directly evaluating the performance of MLMP models. Instead, when assessing MLMP for regression tasks, the evaluation metrics R-sq (adj) are employed. R-sq (adj) measures the

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proportion of the variance in the dependent variable that is explained by the independent variables in the model. It quantifies the goodness of fit of the regression model. R-sq (adj) values range from 0% to 100%, with higher values indicating a better fit of the model to the data. R-sq (adj) is particularly relevant when assessing the performance of MLMP models in predicting continuous numerical values. A higher R-sq (adj) value suggests that the model is doing a better job of explaining the variability in the dependent variable. Now, the predictive power of the models is determined through the statistical measurement coefficient of determination and the model goodness of fit adjusted R-square of the model as shown in the R-sq (adj) column. From the statistical evidence, the models with the formation of equations of inputs and outputs then produced and significantly created very reliable predictions for each engineering performance measure, as shown in the third column in Table 10.

Table 10. MLMP Model for Output Measures

<table>
<tr><th>Category</th><th colspan="2">Output Measures</th><th>Machine Learning Multilayer Perception Model
(MLMP)</th><th>R-sq(adj)</th></tr>
<tr><td rowspan="4">Detailed Design phase</td><td>Y1</td><td>Design Rework</td><td rowspan="10">Machine Learning Multilayer Perception Model Equation
$Yi = b + w1X1 + w2X2 + w3X3 + w4X4 + w5X5\ w6X6 + w7X7 + w8X8 + w9X9 + w10X10 + w11X11 + w12X12 + w13X13 + w14X14 + w15X15$

Example of Y1:
$Y1 = 27.038 + 0.0135\ X1 - 0.2319\ X2 - 0.0191\ X3 - 0.5388\ X4 - 0.1186\ X5 - 0.5342\ X6 - 0.4048\ X7 + 0.1821\ X8 - 0.4287\ X9 + 0.6430\ X10 + 0.4047\ X11 - 1.4968\ X12 - 0.5825\ X13 + 1.1374\ X14 + 0.1325\ X15$</td><td>99.89%</td></tr>
<tr><td>Y2</td><td>Detailed Design Schedule Delay</td><td>99.85%</td></tr>
<tr><td>Y3</td><td>Detailed Design Cost Overrun</td><td>98.94%</td></tr>
<tr><td>Y4</td><td>Detailed Designed Quantity Compared to Final Installed Quantity</td><td>99.86%</td></tr>
<tr><td rowspan="4">Fabrication and Construction Phase</td><td>Y5</td><td>Fabrication and Construction Schedule Delay due to Design Deficiencies</td><td>99.48%</td></tr>
<tr><td>Y6</td><td>Fabrication and Construction Cost Overrun due to Design Deficiencies</td><td>99.88%</td></tr>
<tr><td>Y7</td><td>Construction Hours for Request for Information</td><td>99.80%</td></tr>
<tr><td>Y8</td><td>Construction Hours for Field Change Request</td><td>99.80%</td></tr>
<tr><td rowspan="2">Startup Phase</td><td>Y9</td><td>Start-up Schedule Delay due to Design Deficiencies</td><td>99.82%</td></tr>
<tr><td>Y10</td><td>Start-up Cost Overrun due to Design Deficiencies</td><td>99.66%</td></tr>
</table>

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An example of output measures and regression models generated by machine learning is illustrated in Table 10. The output variable Y represents output measures, and Xs represent the BIM use input variables in machine learning analysis. Model summary shows how the model goodness-of-fit with the data, R-sq (adj) of 99.89% indicates a high percentage of variation in output explained by the model. Finally, the MLMP equations are generated and well-constructed for each output attribute of the engineering performance outputs.

5.6 Comparison of MLMP and LR Models

In compression of MLMP and LR models, Table 11 summarizes the performance output measures, MLMP and LR models with the predicting equations and statistical results. The Table lists the coefficient of determination R-sq (adj) to indicate the statistically significant to MLMP and LR models respects the 10 performance outputs.

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Table 11. Summary of MLMP and LR Models

Category	Engineering Performance Measures	Machine Learning Multilayer Perception Models (MLMP)		Linear Regression Models (LR)		
		Predict Equation	R-sq (adj)	Predict Equation	R-sq (adj)	F-value
Detailed Design Value	Design Rework	Machine Learning Multilayer Perception Model Equation $Yi = b + w1X1 + w2X2 + w3X3 + w4X4 + w5X5\ w6X6 + w7X7 + w8X8 + w9X9 + w10X10\ w11X11 + w12X12 + w13X13 + w14X14 + w15X15$	99.89%	Y1 = 26.96 − 0.815 X4 − 1.032 X10 − 1.629 X12	80.32%	70.37
	Detailed Design Schedule Delay		99.85%	Y2 = 12.811 − 0.303 X1 − 0.765 X3 + 0.293 X4 − 0.493 X5	73.75%	36.82
	Detailed Design Cost Overrun		98.94%	Y3 = 27.31 − 1.202 X4 − 0.912 X10 − 1.179 X12	81.46%	75.68
	Detailed Designed Quantity Compared to Final Installed Quantity		99.86%	Y4 = 90.823 + 0.2268 X4 + 0.3865 X7 − 0.3105 X10 + 0.2506 X11 + 0.801 X12	84.48%	56.51
Fabrication and Construction Value	Fabrication and Construction Schedule Delay due to Design Deficiencies		99.48%	Y5 = 21.34 − 1.312 X8 − 1.082 X9 + 0.678 X12	68.29%	37.62
	Fabrication and Construction Cost Overrun due to Design Deficiencies		99.88%	Y6 = 10.765 − 0.521 X4 − 0.755 X6 + 0.441 X14	71.25%	43.12
	Construction Hours for Request for Information		99.80%	Y7 = 10.096 − 0.706 X8 + 0.501 X11 − 0.611 X14	65.69%	33.55
	Construction Hours for Field Change Request		99.80%	Y8 = 8.811 − 0.4674 X4 + 0.3261 X5 − 0.6091 X6	71.77%	44.21
Startup Value	Startup Schedule Delay due to Design Deficiencies		99.82%	Y9 = 10.551 − 0.467 X6 + 0.368 X13 − 0.923 X14	63.01%	29.96
	Startup Cost Overrun due to Design Deficiencies		99.66%	Y10 = 9.201 − 0.452 X5 − 0.3954 X6	67.77%	54.63

The results developed by the MLMP system showed fewer deviations with much higher R-sq (adj) of outputs than the LR models, as illustrated in Figure 9. The observed output results were anticipated due to the inherent limitation of the LR models, which fail to account for the nonlinear nature of the engineering design performance prediction process. Both the accuracy of MLMP and LR models was affected by the constrained dataset used in their construction. To enhance the efficacy of the models presented in this study for potential industry applications, a critical aspect would involve augmenting the size of the actual project data set to improve their performance.

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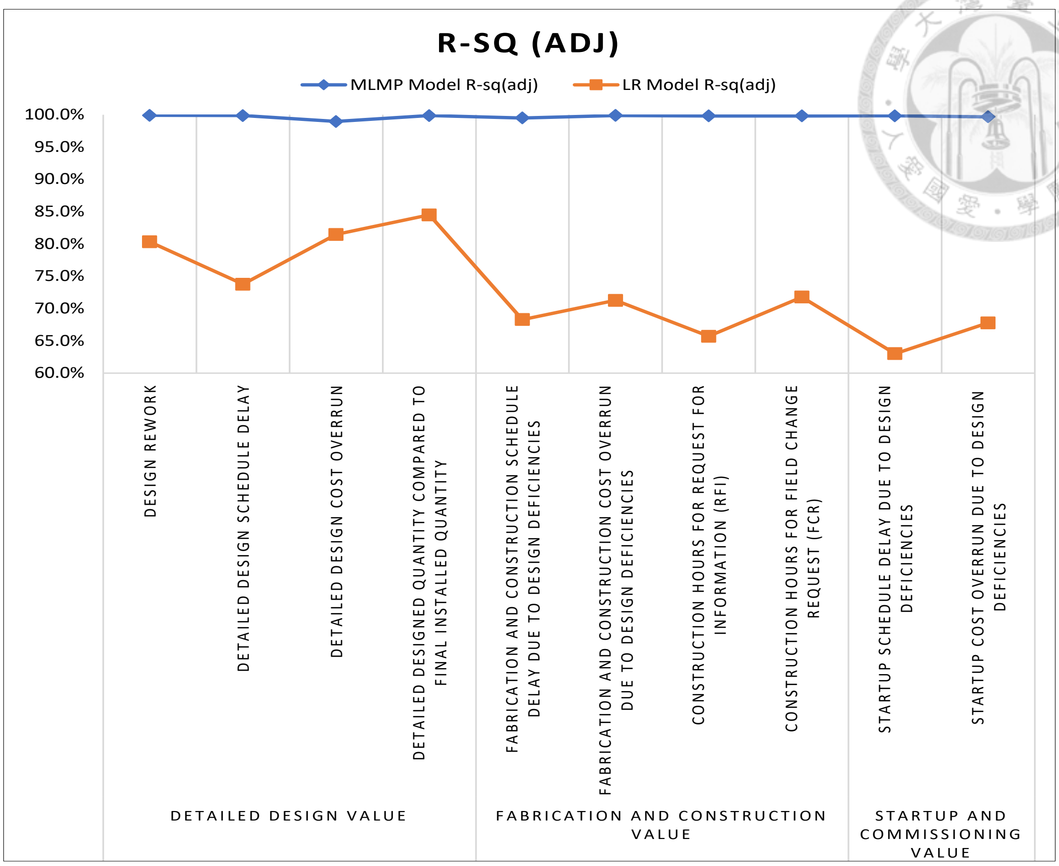

Figure 9. R-sq (adj) for MLMP and LR Models

5.7 Findings of LR and MLMP Models

In this study, the evaluation and prediction of engineering performance were approached using regression and machine learning systems, considering their merits in handling fault tolerance, modeling nonlinearity, and effectively addressing linguistic variables. To enable a comprehensive comparison, this section explores and evaluates both sets of models, namely linear regression models and machine learning techniques, to be applied for engineering performance prediction in the identified four target industrial construction sectors.

ML results in more accurate predictions and outcomes than the LR method, automating complex tasks and processes to improve efficiency and time savings. ML can adapt and learn from new data, making them more flexible and adaptable to changing

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conditions than LR methods. It can be easily scaled up or down to accommodate varying levels of complexity, making them suitable for handling big data and complex problems compared to LR methods. ML makes predictions and forecasts based on historical data, allowing for proactive decision-making and planning. This predictive capability is advantageous compared to conventional methods that may rely on past experiences or assumptions with limited ability to predict future performance outcomes. ML uncovers patterns, trends, and insights from datasets that may not be easily identifiable through conventional methods.

Due to the substantial number of BIM use input variables, it becomes impractical to develop regression models encompassing the entire set of inputs. To address this, screening procedures, commonly known as exploratory variable reduction techniques, are employed to identify potentially significant variables. In this study, the forward stepwise procedure, widely acknowledged in practice, is used for this purpose (Neter, Wasserman, and Kutner 1990). This approach iteratively constructs regression models, assessing the significance of each input variable based on F-statistic calculations to determine inclusion or exclusion.

In several study cases, the machine learning system exhibits less deviations from the actual performance outputs compared to regression models. This outcome is reasonable an as the expectation, as regression models do not account for the possible nonlinearity inherent in the engineering performance prediction process. Regardless of the approach used, the accuracy of the models, whether employing ANNs or statistical regression, is influenced by the limited dataset availability during model development. To enhance the functionality of the models presented in this paper for potential industry applications, increasing the capacity of actual project data is crucial for consideration in future research and industry practices.

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From the statistical evidence, the MLMP and LR models, with the formation of input and output equations, produced and significantly created a reliable scientific foundation for validation of proposed models for each engineering performance measure, as shown in Table 11.

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6.0 Model Validation and Implementation

The prediction models of the engineering performance presented in the above sections of this paper has shown that the best-fit models were obtained through the MLMP and LR analysis procedures and processes. The adjusted R-sq value maximization, model variance minimization, and the selected attributes in the best-evaluated model are statistically significant using F-tests and stepwise selection processes.

Figure 10 shows the process map for model validation and implementation and, later the applications of the models. As depicted in the flowchart, three distinct data sets - the training set, the validation set, and the pilot test set are employed for various stages, including model training, fine-tuning, and testing. This approach ensures rigorous model validation, implementation, and application. The dataset is divided into multiple parts, enabling the model to be trained on one portion and its effectiveness to be tested on another.

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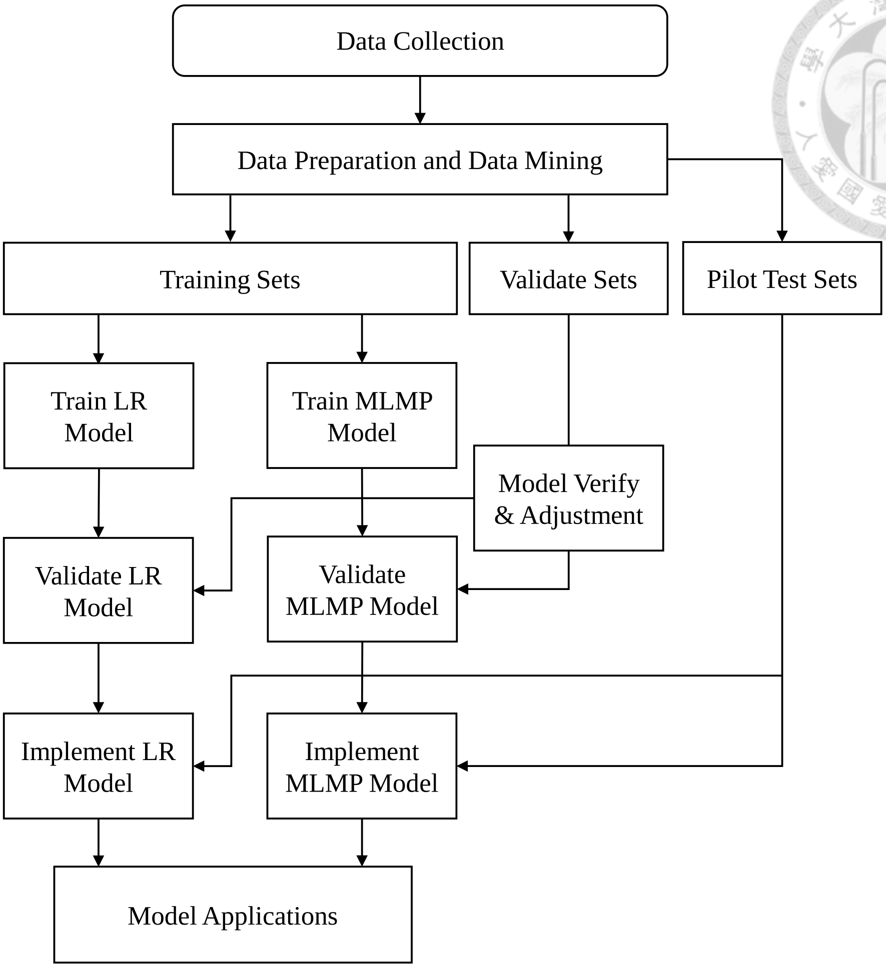

Figure 10. Process Map for Model Validation and Implementation

6.1 Model Validation

The purpose of model validation is to validate the developed models by testing their predictive capabilities using independent data sets and to assess the accuracy, and by applying statistical F-test method to verify the reliability of the models. The next step is the predictions and recommendations of the models with actual engineering performance outcomes to evaluate its effectiveness to ensure that the models provide valuable insights and contribute to improved engineering performance.

Two-stage test approaches were deployed to verify the accuracy of the models and validate the developed performance prediction model. The first stage test uses the two projects (sample 1 and 36) from the project dataset collected for comparison and the

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second stage consists of two test sets balancing the project type (sample 52 to 60) with four test project data for each group, used for validation. Understanding that the output measures provided by the project datasets and the data derived from the LR and MLMP models indicated linear and nonlinear correlations for LR and MLMP, the following steps were developed to evaluate the strength and direction of the correlation relationship by representing a correlation coefficient.

Apply Minitab to calculate the correlation coefficients and significant levels, as shown in Table 12, using the correlation analysis between the predicted models and actual awarded data for each engineering performance output. Thus, in the first stage of both test projects (sample 1 and 36) for comparing existing project data, the correlation coefficients were 0.99912 for LR and MLMP for the test project sample 1 and 0.99989 for LR and MLMP for test project sample 36 with both P-values of 0.000s in more than 95% confidence interval, showing that the correlation coefficients are significant.

To verify the reliability of the developed models, the F-test is applied to access the variance of the LR and MLMP models. The F-test is a statistical test used to compare the variances of two or more populations and the test is used to assess whether the variances of two groups are equal or they differ significantly. The F-value, also known as the F-statistic, is the test statistic generated by the F-test. It represents the ratio of the variances between two or more groups being compared. The F-value is calculated by dividing the variance between groups by the variance within groups. The significance of the F-value is assessed by comparing it to a critical F-value from a probability distribution, typically an F-distribution. A high F-value suggests that the variances between groups are significantly larger than the variances within groups, indicating that there may be a significant difference between the groups being compared. In contrast, a low F-value suggests that the variances between groups are similar, and there is no significant

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difference. Therefore, if the calculated F-statistic is greater than the critical F-value, the null hypothesis of the alternative hypothesis is rejected, suggesting that one model is significantly better than the other. On the other hand, if the calculated F-statistic is less than the critical F-value, the null hypothesis is failed to reject, indicating that there is no significant difference between the two models.

Table 12. LR and MLMP Model Validation

Category	**Engineering Performance Measures (%)**	**Compare to Existing Project Data Project No 1 and No 36**					
		Project $_{\text{Test 1 No 1}}$			**Project $_{\text{Test 2 No 36}}$**		
		LR	**MLMP**	***Data**	**LR**	**MLMP**	***Data**
Detailed Design Value	Design Rework	23.5%	27.0%	25%	22.6%	22.5%	21%
	Detailed Design Schedule Delay	10.4%	10.2%	8%	11.8%	12.6%	12%
	Detailed Design Cost Overrun	24.0%	24.4%	20%	22.8%	24.0%	22%
	Detailed Designed Quantity Compared to Final Installed Quantity	92.9%	92.8%	95%	93.8%	93.6%	91%
Fabrication and Construction Value	Fabrication and Construction Schedule Delay due to Design Deficiencies	9.8%	10.7%	10%	13.9%	14.3%	12%
	Fabrication and Construction Cost Overrun due to Design Deficiencies	12.1%	13.2%	15%	9.4%	9.4%	7%
	Construction Hours for Request for Information	4.1%	5.8%	3%	10.5%	11.2%	10%
	Construction Hours for Field Change Request	8.3%	9.2%	8%	7.5%	8.3%	6%
Startup Value	Startup Schedule Delay due to Design Deficiencies	6.3%	7.7%	7%	9.5%	10.1%	8%
	Startup Cost Overrun due to Design Deficiencies	7.9%	7.6%	6%	8.3%	8.9%	8%
Pearson Correlation Coefficient		0.99912		N/A	0.99989		N/A
Significant Level		0.000			0.000		

*Data: The data is actual collected from the survey

To verify the validity of the developed models to check the variance of the engineering performance output measures between MLMP, and LR models and compare

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the actual performance data from the survey, Figure 11 identifies the 15 performance outputs at project design, construction, and startup phases by inputting test data set of test sample project #1 into models. It compares to the variance to the actual data value from the survey. The Figure shows the facts that the performance output measure prediction for MLMP and LR for test project 1 (Project #1) is precisely matched and almost the same value as the actual performance data from the survey.

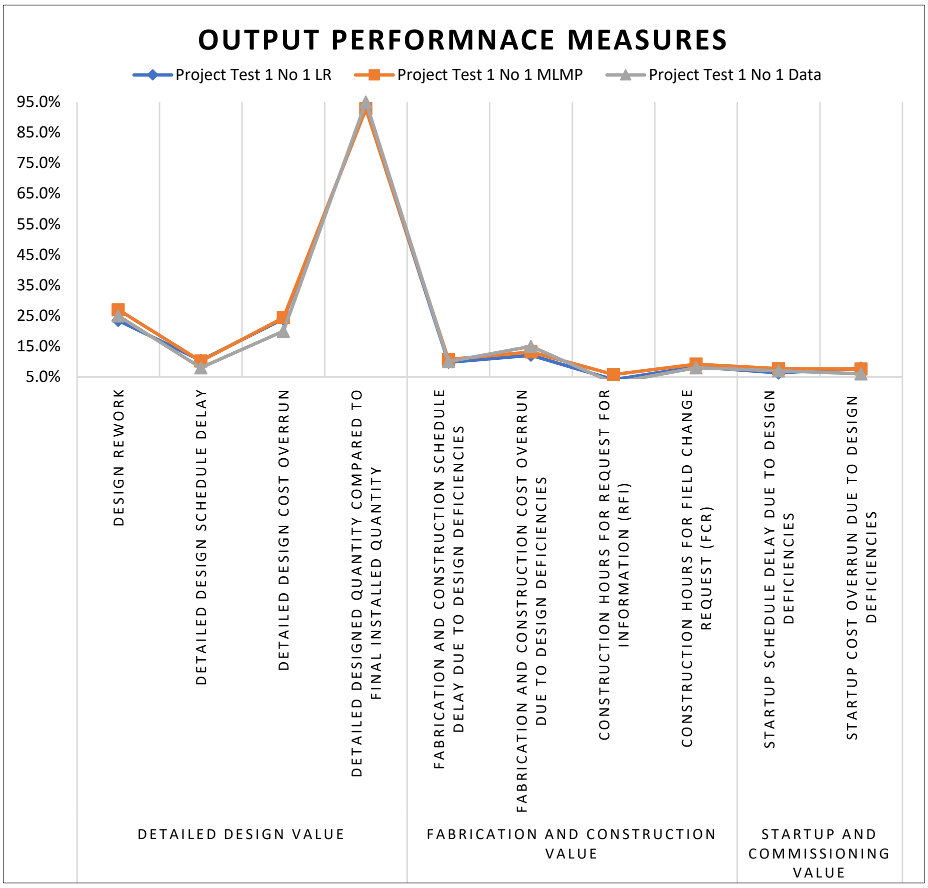

Figure 11. Output Performance Measures for Test Project 1 in 1st Stage Validation

Figure 12 identifies the 15 performance outputs at project design, construction, and startup phases by inputting test data set of test sample project #36 into models. It compares to the variance to the actual data value from the survey. The Figure shows the facts that the performance output measure prediction for MLMP and LR for test project

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2 (Project #36) is precisely matched and almost the same value as the actual performance data from the survey.

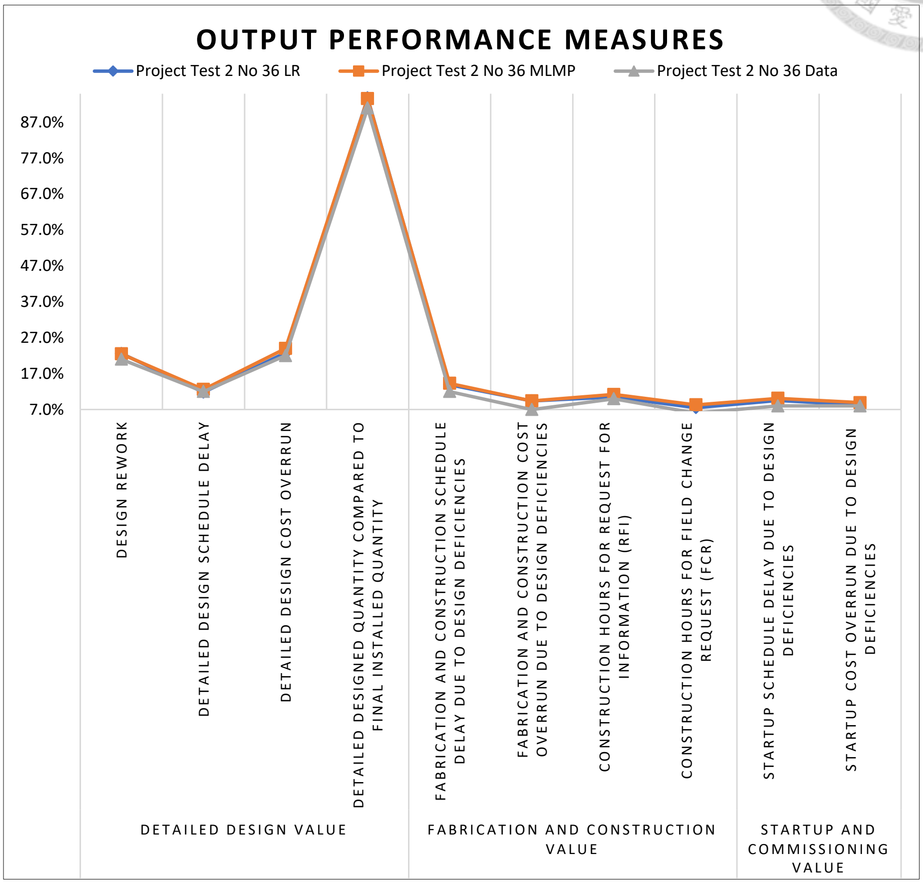

Figure 12. Output Performance Measures for Test Project 2 in 1st Stage Validation

By applying F-test in Minitab, the F-value is calculated to verify the variance between the LR models and MLMP models. As shown in Figure 13, based on the comparison of F-statistic is 1.01805 and critical F-value is 3.17889 for test project test sample 1, the calculated F-statistic is less than the critical F-value with the significance level of 5%, indicating that there is no significant difference between the two models and the conclusion about the relative performance of the two models. Thus, the acceptance of reliability of the LR and MLMP models is reached.

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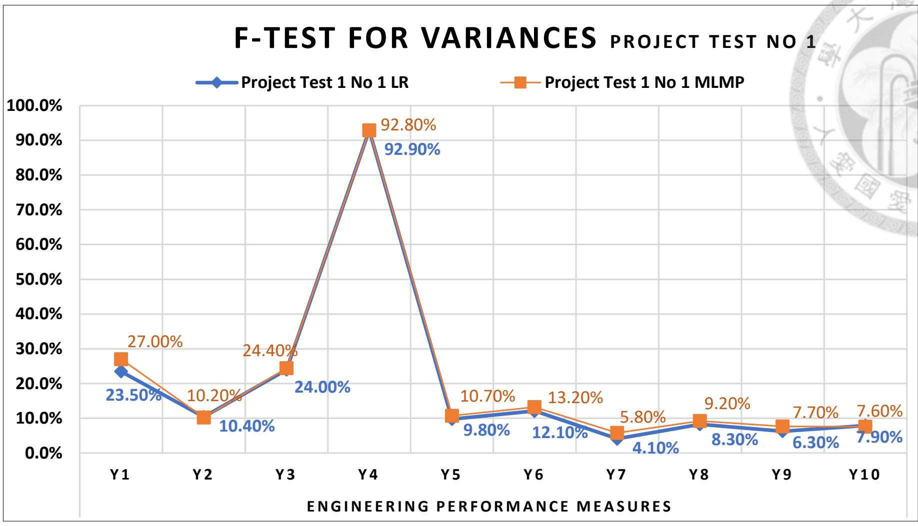

F-Test Two-Sample for Variances

Project Test No 1

	LR Outputs	MLMP Outputs
Mean	0.1993	0.2086
Variance	0.070278011	0.069032267
Observations	10	10
df	9	9
F	1.018045828	
P(F<=f) one-tail	0.48959128	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test No 1

	LR Outputs	MLMP Outputs
LR Outputs	1	
MLMP Outputs	0.99911627	1

Figure 13. F-test and Correlation for LR and MLMP Models for Project Test 1

For test project sample 36 as shown in Figure 14, the comparison of F-statistic is 1.01803 and critical F-value is 3.17889, the calculated F-statistic is less than the critical F-value with the significance level of 5%, indicating that there is no significant difference between the two models and the conclusion about the relative performance of the two models. Thus, the acceptance of reliability of the LR and MLMP models is reached.

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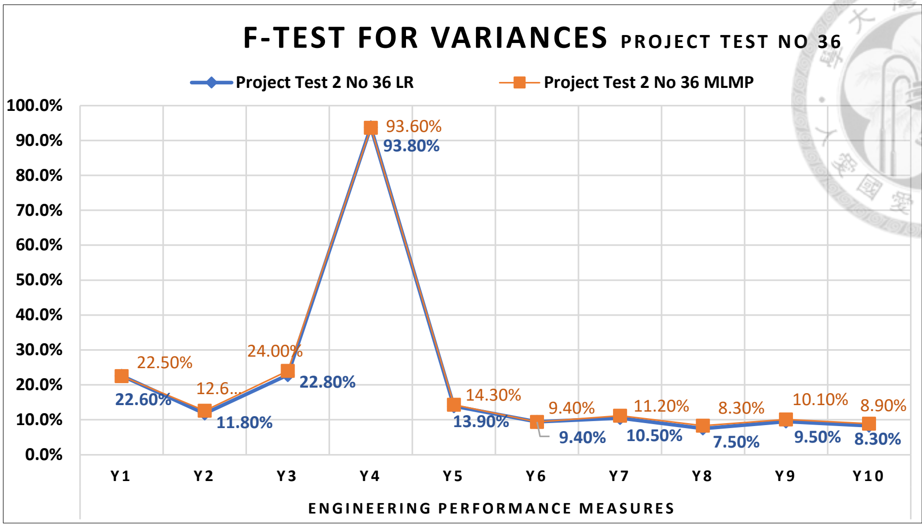

F-Test Two-Sample for Variances

Project Test No 36

	LR Outputs	MLMP Outputs
Mean	0.2101	0.2149
Variance	0.068458767	0.067246322
Observations	10	10
df	9	9
F	1.0180299	
P(F<=f) one-tail	0.489600384	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test No 36

	LR Outputs	MLMP Outputs
LR Outputs	1	
MLMP Outputs	0.999889582	1

Figure 14. F-test and Correlation for LR and MLMP Models for Project Test 36

Appling Minitab to calculate the correlation coefficients and significant levels, Table 13 summarizes the results using the correlation analysis between the predicted models and actual awarded data for each engineering performance output. The Table shows the second stage test for validation, which uses the two sets of test projects (samples 53 to 60) from the project dataset collected for comparison. In the second stage of the two test project sets (samples 53 to 60), the average correlation coefficients were 0.99987 for LR and MLMP for test project set 1 and 0.99991 for LP and MLMP for test project set 2 with both average P-value of 0.000 in 95% confidence interval, showing that the correlation coefficients are significant. As mentioned in the correlation analysis, the rule of thumb

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states that 0.9 to 1.0 represents a very high positive correlation (Hinkle, Wiersma, and Jurs 2003), the correlation relationship between the test project data and developed models is strong, positive, and linear at high acceptance and desired levels. The test outcomes to validate the regression model showed high reliability and capability of assessing the engineering performance measures significantly correlated with actual project data. The stronger positive relationships for MLMP than LP explain why the MLMP models predict more reliable results than LR.

Table 13. LR and MLMP Model Validation

Category	Engineering Performance Measures	Model Validation from Project Data No 53 to No 60					
		Test Set 1 Projects in Average			Test Set 2 Projects in Average		
		LR	MLMP	*Data	LR	MLMP	*Data
Detailed Design Value	Design Rework	14.2%	15.3%	15%	11.3%	10.6%	11%
	Detailed Design Schedule Delay	7.6%	7.5%	7%	7.1%	7.1%	7%
	Detailed Design Cost Overrun	14.1%	14.3%	14%	11.4%	11.1%	11%
	Detailed Designed Quantity Compared to Final Installed Quantity	95.8%	95.7%	96%	96.5%	96.6%	96%
Fabrication and Construction Value	Fabrication and Construction Schedule Delay due to Design Deficiencies	11.4%	11.1%	11%	11.0%	11.3%	11%
	Fabrication and Construction Cost Overrun due to Design Deficiencies	6.7%	7.2%	8%	5.7%	5.2%	5%
	Construction Hours for Request for Information	6.3%	6.1%	6%	6.5%	6.7%	7%
	Construction Hours for Field Change Request	5.0%	5.0%	5%	4.5%	4.3%	4%
Startup Value	Startup Schedule Delay due to Design Deficiencies	6.2%	6.0%	6%	6.6%	7.0%	7%
	Startup Cost Overrun due to Design Deficiencies	5.9%	5.5%	5%	5.5%	5.9%	6%
Pearson Correlation Coefficient		0.99987		N/A	0.99991		N/A
Significant Level		0.000			0.000		

*Data: The data is actual collected from the survey

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In the second stage of the validation process, to verify the validity of the developed models and to check the variance of the engineering performance output measures between MLMP and LR models, and compare the actual performance data from the survey, Figure 15 identifies the 15 performance outputs at project design, construction, and startup phases by inputting test data set of average test sample project from #52 to #56 into models. It compares to the variance to the actual data value from the survey. The Figure shows the facts that the performance output measure prediction for MLMP and LR for test projects average is precisely matched and almost the same value as the actual performance data from the survey.

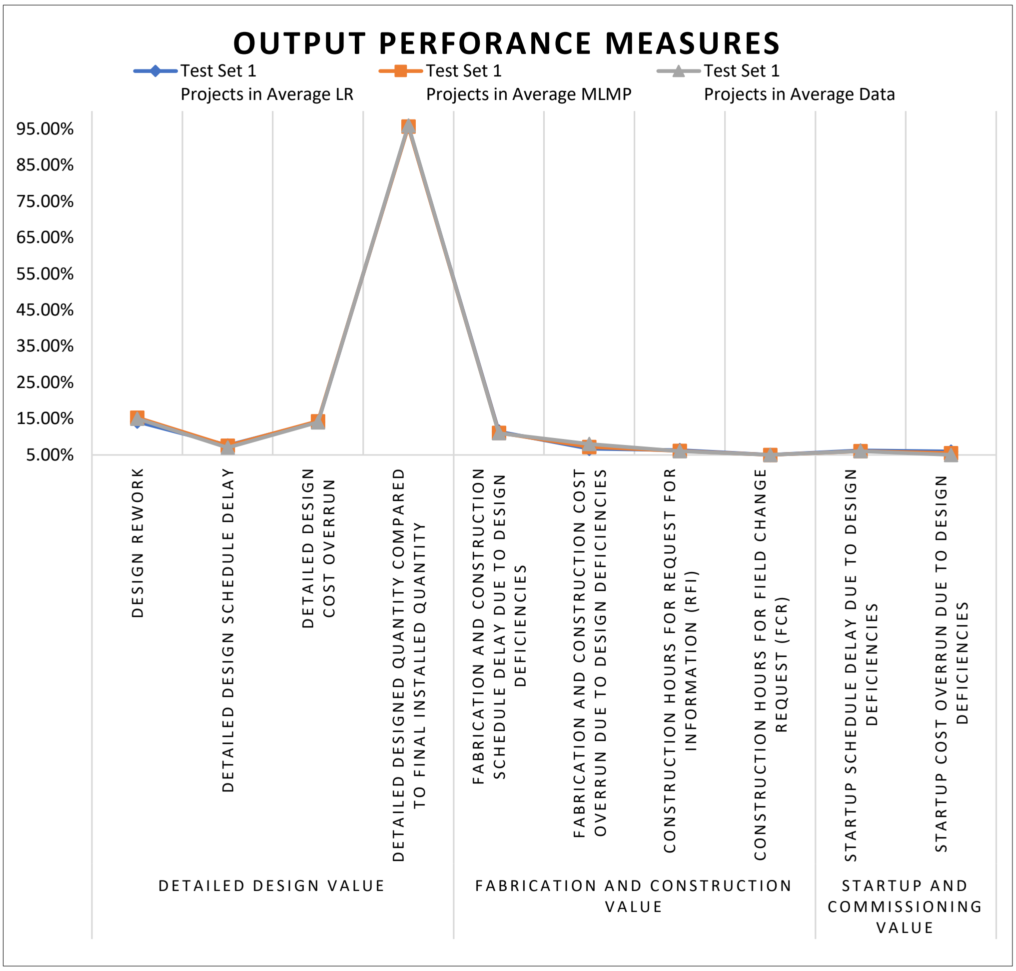

Figure 15. Output Performance Measures for Test Project Set 1 in 2nd Stage Validation

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Similarly, in the second stage of the validation process, to verify the validity of the developed models and to check the variance of the engineering performance output measures between MLMP and LR models and compare the actual performance data from the survey, Figure 16 identifies the 15 performance outputs at project design, construction, and startup phases by inputting test data set of average test sample project from #57 to #60 into models. It compares to the variance to the actual data value from the survey. The Figure shows the facts that the performance output measure prediction for MLMP and LR for test projects average set 2 is precisely matched and almost the same value as the actual performance data from the survey.

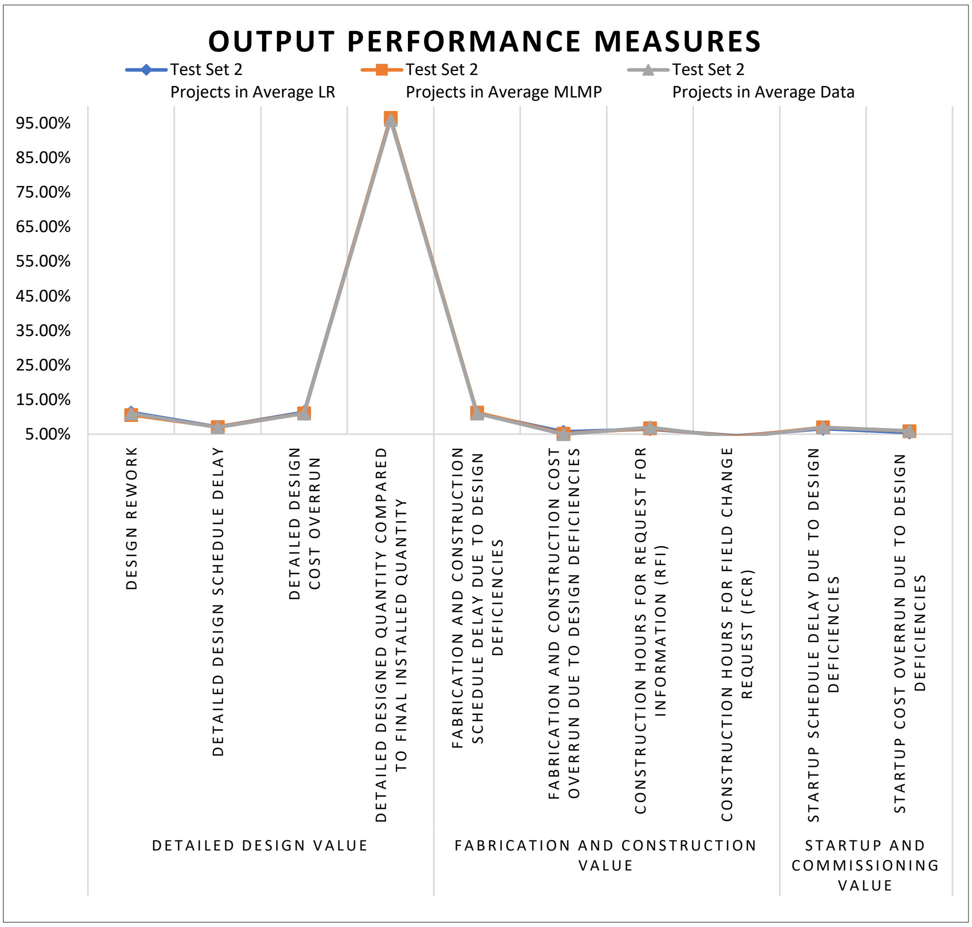

Figure 16. Output Performance Measures for Test Project Set 2 in 2nd Stage Validation

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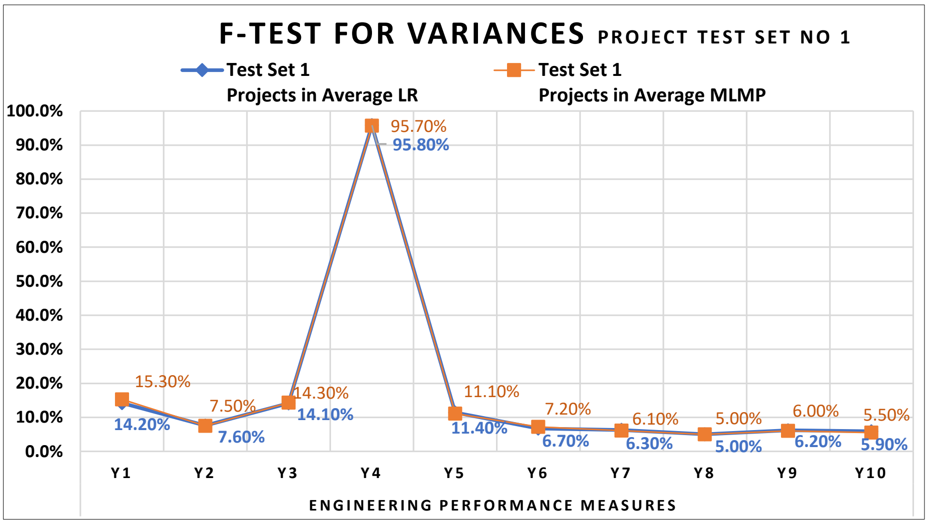
By applying F-test in Minitab, the F-value is calculated to verify the variance between the LR models and MLMP models. As shown in Figure 17, based on the comparison of F-statistic is 1.00132 and critical F-value is 3.17889 for test project test set 1, the calculated F-statistic is less than the critical F-value with the significance level of 5%, indicating that there is no significant difference between the two models and the conclusion about the relative performance of the two models. Thus, the acceptance of reliability of the LR and MLMP models is reached.



F-Test Two-Sample for Variances

Project Test Set No 1

	LP Outputs in Average	MLMP Outputs in Average
Mean	0.1732	0.1737
Variance	0.077209067	0.077107344
Observations	10	10
df	9	9
F	1.001319229	
P(F<=f) one-tail	0.499232646	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test Set No 1

	LP Outputs in Average	MLMP Outputs in Average
LR Outputs	1	
MLMP Outputs	0.999868813	1

Figure 17. F-test and Correlation for LR and MLMP Models for Project Test Set 1

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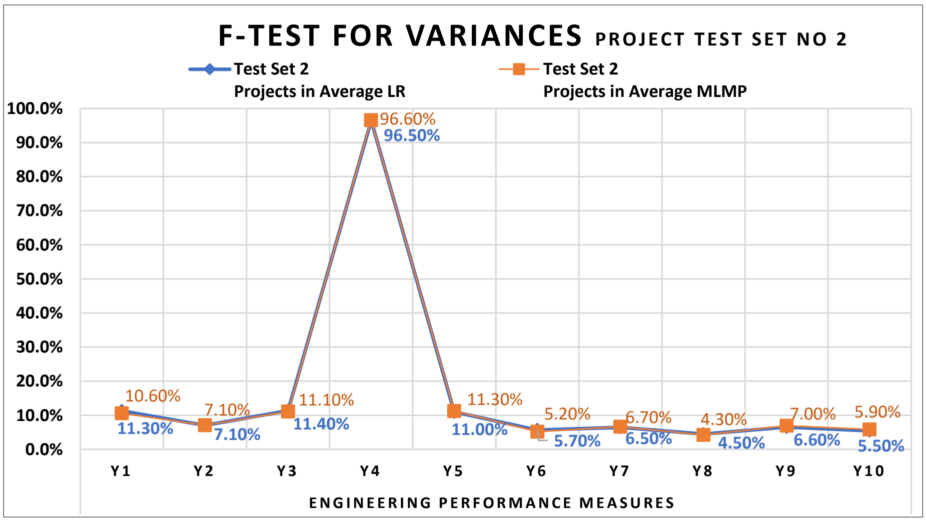
For test project set 2 as shown in Figure 18, the comparison of F-statistic is 0.99731 and critical F-value is 3.14575, the calculated F-statistic is less than the critical F-value with the significance level of 5%, indicating that there is no significant difference between the two models and the conclusion about the relative performance of the two models. Thus, the acceptance of reliability of the LR and MLMP models is reached.



F-Test Two-Sample for Variances

Project Test Set No 2

	LP Outputs in Average	MLMP Outputs in Average
Mean	0.1661	0.1658
Variance	0.079457656	0.079672178
Observations	10	10
df	9	9
F	0.997307439	
P(F<=f) one-tail	0.498430679	
F Critical one-tail	3.145749062	

Correlation Analysis

Project Test Set No 2

	LP Outputs in Average	MLMP Outputs in Average
LR Outputs	1	
MLMP Outputs	0.999908671	1

Figure 18. F-test and Correlation for LR and MLMP Models for Project Test Set 2

The accuracy of the models is evaluated by applying surveyed project samples to both LR and MLMP models as indicated in Appendix 7. This assessment involves

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evaluating their predictive capabilities using independent data sets. Furthermore, the reliability of the models is established through a rigorous statistical analysis. The F-test method is applied to assess the variances and significance levels of both the LR and MLMP models. Following these validation methods, it is confirmed that both accuracy and reliability meet acceptable standards, thus validating the models.

6.2 Model Implementation

Model implementation aims to implement the validated models and findings in practical engineering scenarios. This step involves integrating the models into BIM applications, decision support systems, and design workflows to assess the impact of the implemented models on engineering performance by monitoring and evaluating the outcomes. This step helps to determine the practical implications and benefits of utilizing the developed models in real-world construction projects.

The primary objective of training the system with a limited dataset is to create a platform capable of capturing the underlying relationships between project BIM use input variables and the output of engineering performance. This enables the system to estimate or predict performance measures when presented with a new set of input variables from the project, leveraging the knowledge encoded in the network structure. To validate the system's effectiveness, two separate sets of projects were chosen for testing. Notably, none of these projects were utilized during the system's training phase. The selection of these projects was deliberately varied to represent diverse project conditions and corresponding performances. It is essential to acknowledge that the use of only 60 projects in the system's development had an impact on the reliability and accuracy of predicted engineering performance output measures. With a more extensive dataset for

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training, the deviations from the targeted values could have been minimized. The limitations of the dataset are presented in discussion section later.

As the performance models have been validated and meet the desired performance criteria, the models are proposed to be implemented in practical applications. This could involve integrating the model into software tools, decision support systems, or simulation platforms used in engineering design processes. Continuously monitor the performance model in real-world applications. Collect new data and periodically retrain or update the model to ensure accuracy and reliability. Monitor the model's predictions and compare them to actual performance outcomes to identify areas for improvement or recalibration. Engage in collaborative efforts with domain experts, designers, and stakeholders to refine the performance model. Gather feedback, incorporate new knowledge, and iterate on the model to enhance its effectiveness and relevance.

Implementing of a performance model in engineering design aims to provide valuable insights, predictions, or evaluations to support decision-making, optimize designs, and improve overall performance. By leveraging data and modeling techniques, engineers better understand of the factors that impact performance and make informed decisions to achieve desired outcomes.

A pilot study is recommended before full implementing of the validated models. A pilot is the trial implementation of the identified solution of the proposed models on a reduced scale. In order the verify the models after validation, two pilot test projects are chosen to be implemented by inputting the BIM use input data to the developed models. As discussed in the definition of BIM input variables, the data represent the inputs of BIM uses on implementation levels using a 10-point scale in percentage, where 0 represents 0% implemented, and 10 represents 100% implemented. After inputting the BIM use

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input data to validate the MLMP model, the performance output measures are generated. Table 14 shows the implementation of the MLMP model with BIM use inputs and performance outputs. As illustrated in the Table, 15 BIM use inputs for pilot test 1 generate 10 performance outputs measures, and the same process applies to pilot test 2.

Table 14. MLMP Model Implementation

Input Variables		**Test 1**	**Test 2**	
X1	Existing Conditions	4	5	Project Implementation
X2	Design Authoring	6	6	
X3	Design Review	6	6	
X4	Coordination	5	7	
X5	Record Modeling	4	4	
X6	Cost Estimating	5	5	
X7	Phase and 4D Planning	5	5	
X8	Site Analysis-Development	4	6	
X9	Site utilization-For Construction	4	6	
X10	Digital Fabrication	4	5	
X11	3D Location and Layout	4	5	
X12	Engineering Analysis	2	4	
X13	Sustainability Analysis	4	5	
X14	Codes and Standards Compliance	4	3	
X15	Construction Systems Design	5	5	

Output Measures		**MLMP**	**Test 1**	**Test 2**
Y1	Design Rework	Machine Learning Multilayer Perception Model Equation $Yi = b + w1X1 + w2X2 + w3X3 + w4X4 + w5X5\ w6X6 + w7X7 + w8X8 + w9X9 + w10X10\ w11X11 + w12X12 + w13X13 + w14X14 + w15X15$	16.2	8.2
Y2	Detailed Design Schedule Delay		6.3	7.0
Y3	Detailed Design Cost Overrun		15.4	9.1
Y4	Detailed Designed Quantity Compared to Final Installed Quantity		95.5	97.3
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies		13.2	9.5
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies		6.9	4.4
Y7	Construction Hours for Request for Information		5.9	6.5
Y8	Construction Hours for Field Change Request		4.8	3.8
Y9	Startup Schedule Delay due to Design Deficiencies		5.0	7.5
Y10	Startup Cost Overrun due to Design Deficiencies		4.3	6.6

The same implementation process applies to the LR model. After inputting the BIM use input data to validate the LR model, the performance output measures are generated. Table 15 shows the implementation of LR model with BIM use inputs and performance

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outputs. As illustrated in the Table below, 15 BIM use inputs for pilot test 1 generate 10 performance output measures, and the same process applies to pilot test 2.

Table 15. LR Model Implementation

Input Variables		Pilot Test 1/2	
X1	Existing Conditions	4	5
X2	Design Authoring	6	6
X3	Design Review	6	6
X4	Coordination	5	7
X5	Record Modeling	4	4
X6	Cost Estimating	5	5
X7	Phase and 4D Planning	5	5
X8	Site Analysis-Development	4	6
X9	Site utilization -For Construction	4	6
X10	Digital Fabrication	4	5
X11	3D Location and Layout	4	5
X12	Engineering Analysis	2	4
X13	Sustainability Analysis	4	5
X14	Codes and Standards Compliance	4	3
X15	Construction Systems Design	5	5

Project Implementation

Output Measures		LR Model	Test 1	Test 2
Y1	Design Rework	Y1 = 26.96 − 0.815 X4 − 1.032 X10 − 1.629 X12	14.7	9.7
Y2	Detailed Design Schedule Delay	Y2 = 12.811 − 0.303 X1 − 0.765 X3 + 0.293 X4 − 0.493 X5	6.7	7.0
Y3	Detailed Design Cost Overrun	Y3 = 27.31 − 1.202 X4 − 0.912 X10 − 1.179 X12	14.5	9.5
Y4	Detailed Designed Quantity Compared to Final Installed Quantity	Y4 = 90.823 + 0.227 X4 + 0.387 X7 − 0.311 X10 + 0.251 X11 + 0.801 X12	95.5	96.8
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies	Y5 = 21.34 − 1.312 X8 − 1.082 X9 + 0.678 X12	12.6	8.8
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies	Y6 = 10.765 − 0.521 X4 − 0.755 X6 + 0.441 X14	6.2	4.9
Y7	Construction Hours for Request for Information	Y7 = 10.096 − 0.706 X8 + 0.501 X11 − 0.611 X14	6.4	6.1
Y8	Construction Hours for Field Change Request	Y8 = 8.811 − 0.4674 X4 + 0.3261 X5 − 0.6091 X6	4.6	4.0
Y9	Startup Schedule Delay due to Design Deficiencies	Y9 = 10.551 − 0.467 X6 + 0.368 X13 − 0.923 X14	5.3	7.1
Y10	Startup Cost Overrun due to Design Deficiencies	Y10 = 9.201 − 0.452 X5 − 0.3954 X6	5.4	5.3

Now, the emphasis is on the successful implementation and maintaining the gains achieved. The question is trying to answer, “How can we guarantee performance?” From the pilot test project process above, the engineering design performance measures are

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generated for required actions for stakeholders to assist in obtaining warnings against potential problems. Predicting of the performance constitutes critical evaluations for higher performance outcomes and successful project execution and delivery.

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7.0 Discussion

7.1 Evaluation of Correlation Analysis

In synthesizing the findings from the proposed first separated BIM use, which applied the correlation method to analyze the influence of essential and enhanced BIM uses on engineering performance measures separately, the study further reviews the frequency of occurrence of more than 50% of each input by the outputs in three project phases. Figure 19 shows that the essential BIM uses with five inputs, design authoring, and design review and coordination obtained 100% and 75% for the four engineering performance measures in the engineering design phase, 50% in the construction stage, and 100% for record modeling for both engineering performance measures in the startup phase. As for enhanced BIM uses with ten inputs, phase and 4D planning and engineering analysis achieved 75% in the engineering design phase, cost estimating, digital fabrication, and construction system design achieved 50% in the construction phase. Finally, phase and 4D planning and codes and standards compliance all attained 100% occurrence in the startup phase.

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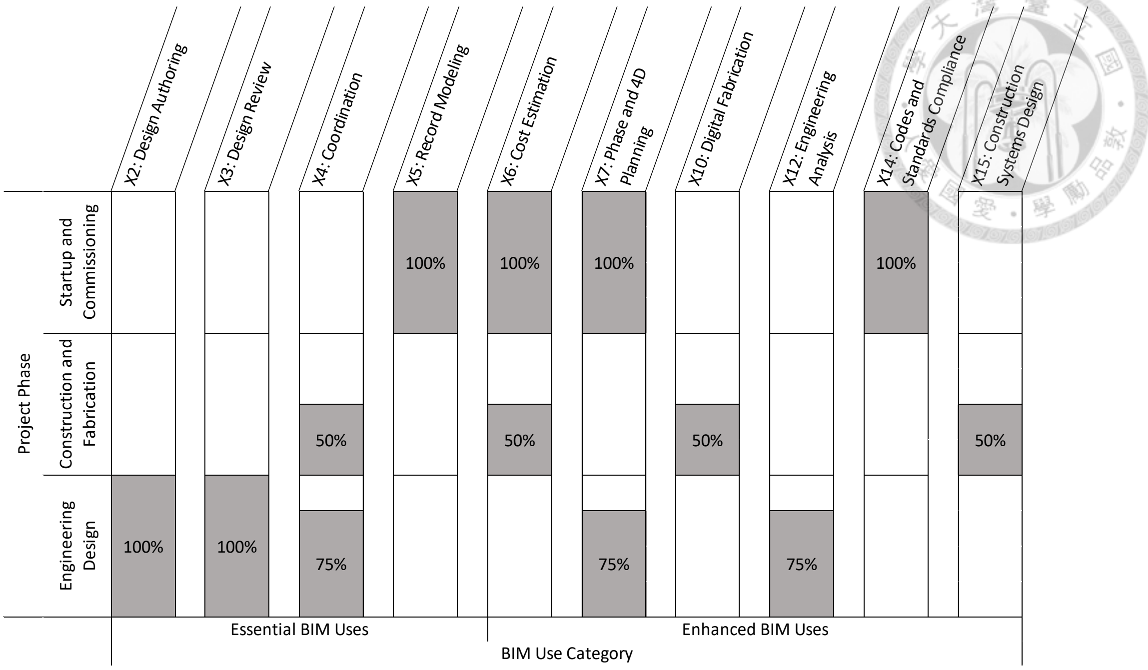

Figure 19. Critical BIM Uses for Engineering Performance

This first approach applied a correlation method to analyze the separated BIM use. The results show that the essential BIM uses are highly related to design phase activities, and the enhanced BIM uses are mainly correlated with the construction phase. Figure 20 shows the essential and enhanced BIM uses highly influences the engineering performance separately. Essential BIM meticulously addresses the foundational requirements, chiefly concentrated on the design phase, serving as a pivotal framework for implementing BIM. It sets the stage by establishing a minimum key requirement to ensure BIM's effectiveness in guiding the project through the intricacies of the design process.

The correlation analysis for BIM use input is to find the relationships of the 15 variables by two categories of 5 essential BIM uses and 10 enhanced BIM uses and to understand their interaction. As shown in Figure 20, the high correlative BIM use inputs for both essential and enhanced expansion at the main three phases of project execution, and the high correlative inputs describe the influence level of the phases. The result

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confirms the suggestions in NGBO, as shown in Figure 6. The main findings are discussed in the following section.

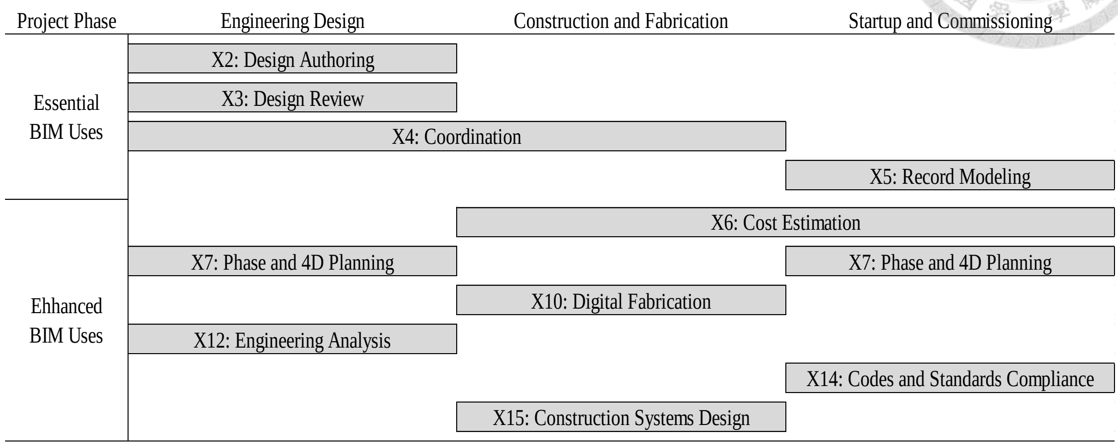

Figure 20. Expansion of BIM Use Inputs at Project Phases

7.2 Evaluation of Models

In synthesizing the findings from the proposed second combined BIM use approach, which applied MLMP and LR methods to analyze the influence of combined essential and enhanced BIM uses on engineering performance measures integrally, the frequency of occurrence over 50% of each input by the outputs in three project phases were reviewed. From Figure 21, the essential BIM uses with five inputs show that coordination attained 100% and 50% for the four engineering performance measures in the engineering design and construction phases, respectively, and 50% for the two engineering performance measures for record modeling in the startup phase. For the enhanced BIM uses with 10 inputs, digital fabrication and engineering analysis achieved 75% in the engineering design phase, cost estimating was 100%, and codes and standards compliance showed 50% in the construction phase. In the startup phase, cost estimating attained a 100% occurrence.

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The second approach of the MLMP and LR methods showed that the essential BIM uses are highly related to design phase activities. The enhanced BIM uses are mainly correlated with the construction phase. From Figure 21, the engineering performance is highly influenced by BIM uses for combined essential and enhanced inputs. Enhanced BIM seamlessly extends beyond the design phase, delving into the construction phase with a focus on reinforcing BIM applications. This phase expands on the essential BIM functions, aligning them with the intricacies of the construction process. It provides an enriched set of tools and functionalities, enhancing collaboration and efficiency during the physical realization of the project.

Reviewing the frequency of percentage occurrence of the total BIM uses in the project phases by the performance measures for both models confirms that BIM use inputs are highly significant for developing engineering performance prediction models. Furthermore, coordination was presented in both models in the engineering design phase, explaining that coordination efforts in the engineering design phase, including design authoring and review, are significant. Coordination and cost estimation in both models in the construction phase indicate that coordination in construction activities and cost estimation are the main factors in construction. Recording modeling and cost estimation were present in the startup phase for both models, demonstrating that recording and costs are significant in the project startup phase.

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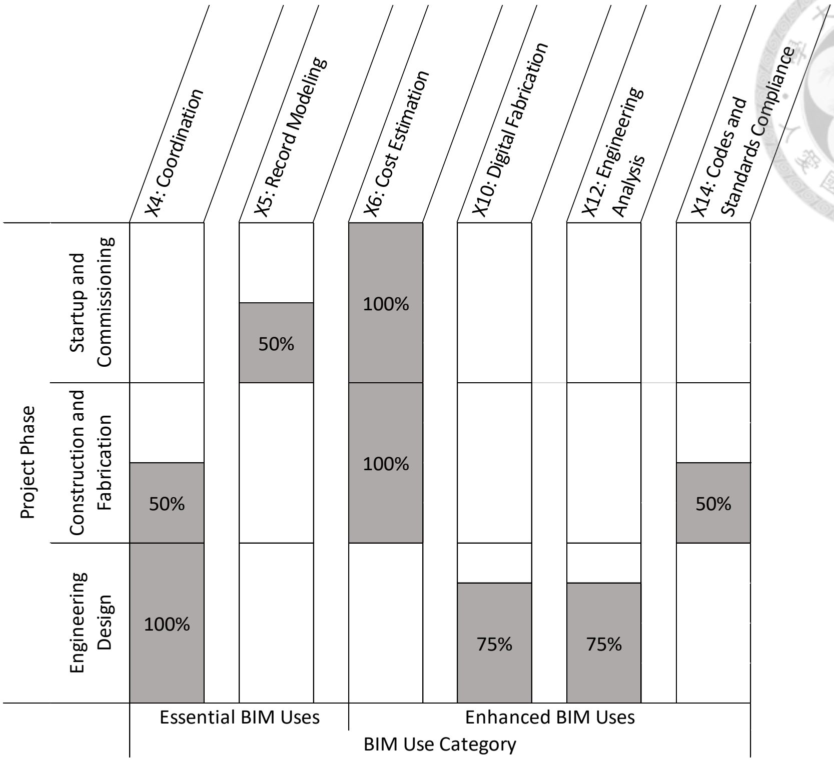

Figure 21. Critical BIM Uses for Engineering Performance

The models for BIM use input are to find the relationships of the 15 variables in two categories of 5 essential BIM uses and 10 enhanced BIM uses and the 10 output performance measures in three categories of 4 detailed design values, 4 fabrication and construction values and 2 start-up and commissioning values to understand their interaction. As shown in Figure 22, the high correlative BIM use inputs for both essential and enhanced expand at the main three phases of project execution, and the high correlative inputs describe the influence level of the phases. The result confirms the suggestions in NGBO shown in Figure 6. The main findings are discussed in the following section.

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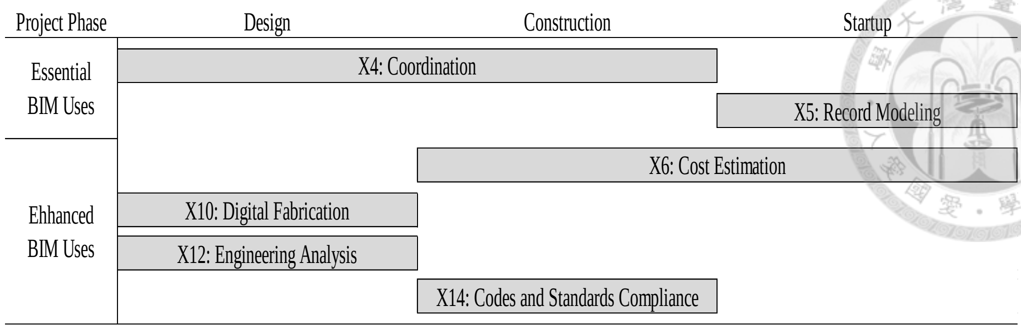

Figure 22. Expansion of BIM Use Inputs at Project Phases

Facilitating the performance prediction models involves ensuring that the developed models are effectively utilized in real-world project execution scenarios to address practical challenges and improve the decision-making process. The application of the developed models involves two processes, performance monitoring and performance controls.

7.3 Application for Performance Monitoring Management

Facilitating the performance prediction models involves ensuring that the developed models are effectively utilized in real-world project execution scenarios to address practical challenges and improve the decision-making process. The application of the developed models involves two processes, performance monitoring and performance controls. Figure 23 shows the suggested application process.

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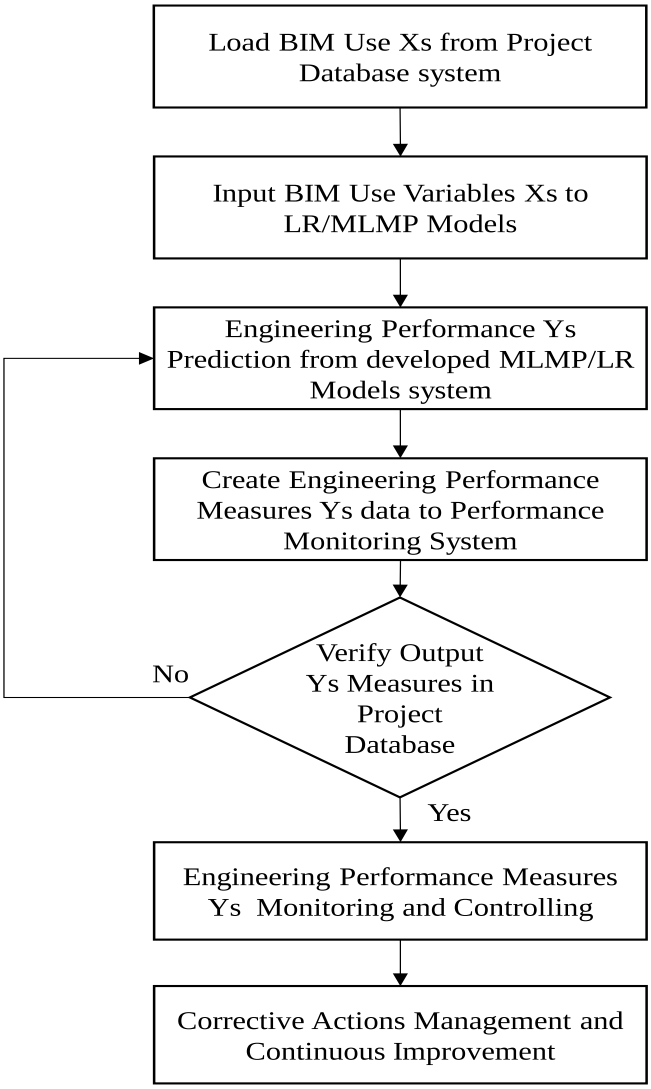

Figure 23. Model Application Process

The suggested process aims to integrate these models into real-world systems or project execution scenarios. This task often requires collaboration with IT teams to ensure a seamless transition. The project data and predictions are continuously fed back into the models, allowing them to adapt and improve over time. This iterative process helps in addressing practical challenges. The predictions generated by these models should be effectively utilized to support decision-making processes, and this involves creating dashboards, reports, or alerts for decision-makers to use. Establishing a feedback loop with end-users and stakeholders is essential and the input helps in fine-tuning the models and making them more practical and aligned with the project's goals. Based on feedback

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and changing project requirements, models are required to be adapted, retrained, or improved to maintain their relevance and effectiveness. It is important to document the models and provide training to relevant team members, ensuring that the team understand how to interpret the predictions and make informed decisions. Thus, facilitating performance prediction models involves a comprehensive approach that integrates data science with real-world project execution, constant feedback, and adaptation to ensure the models effectively address practical challenges and enhance decision-making.

Implement performance monitoring to track the accuracy and effectiveness of models over time and regularly assess how well the model's prediction aligns with real-world outcomes and make necessary adjustments. This section shows that the real-world project data was applied to the validated engineering performance models for implementation pilot tests. From the implementation process of a pilot test and has had a chance to ensure the performance is under control and continue. The application of performance control allows the project team or stakeholder to identify what is essential to improve and maintain the current performance levels based on the research.

Table 16 shows the application of the goal and acceptance levels for each engineering performance output measures for pilot test 1. As illustrated in the Table, the engineering performance output are listed with the definition of each measurement. Two control targets are identified as the goal of aiming result and the acceptance level of desired control limit. After applying BIM use variables X1 to X15 to MLMP and LR models, the performance measure output Y1 to Y10 can be generated as indicated in Table 16 of pilot test 1. Further applications or recommendations can be developed for performance control purposes.

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Table 16. Pilot Test 1 Application

Engineering Performance Output Measures			Target		Pilot Project 1	
Measures		Definition	Goal (%)	Acceptance Level (%)	MLMP (%)	LR (%)
Y1	Design Rework	Design Rework Hours/Total Design Hours	0	2.5	16.2	14.7
Y2	Detailed Design Schedule Delay	Days of Design Schedule Delay/Total Design Schedule Days	0	0.0	6.3	6.7
Y3	Detailed Design Cost Overrun	Design Cost Overrun in $/Total Design Cost in $	0	0.0	15.4	14.5
Y4	Detailed Designed Quantity Compared to Final Installed Quantity	Issue for Construction Designed Quantity/Final Installed Quantity	100	95.0	95.5	95.5
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/ Total Fabrication and Construction Days	0	0.0	13.2	12.6
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies	Fabrication and Construction Cost Overrun due to Design Deficiencies in $/Total Fabrication and Construction Cost in $	0	0.0	6.9	6.2
Y7	Construction Hours for Request for Information	Construction Hours for Request for Information/ Total Construction Hours	0	5.0	5.9	6.4
Y8	Construction Hours for Field Change Request	Construction Hours for Field Change Request/Total Construction Hours	0	2.5	4.8	4.6
Y9	Start-up Schedule Delay due to Design Deficiencies	Days of Start-up Schedule Delay due to Design Deficiencies/ Total Start-up Days	0	2.0	5.0	5.3
Y10	Start-up Cost Overrun due to Design Deficiencies	Start-up Cost Overrun due to Design Deficiencies in $/Total Start-up Cost in $	0	0.0	4.3	5.4

To have better compassion of the goal, acceptance level and the actual engineering performance output measures, Figure 24 shows the variation of the pilot test 1. The engineering performance output measures of Y1 to Y10 are shown in X-axis and actual values are shown in Y-axis. The results show that the strength of performance prediction for MLMP and LR models is almost the same. The acceptance level and the control target are also identified to display the variation of actual performance measurements.

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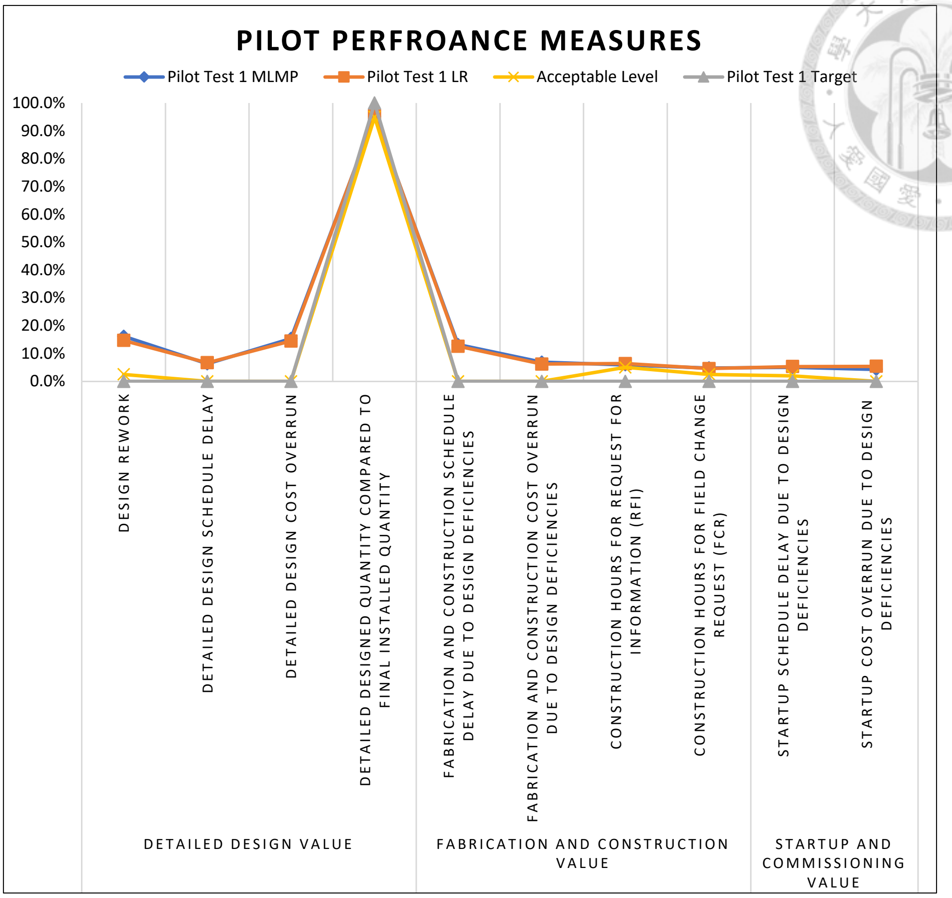

Figure 24. Pilot Test 1 for Performance Measures for MLMP and LR Models

In Figure 24, each predicted output measure value generated by the model has two reference points for applying engineering performance measures. These reference points are the acceptance level and the target values. The acceptance level represents the level of performance that can be tolerated, while the target is the ideal control goal. For instance, consider the engineering performance output measure Y1, which is design rework calculated by comparing design rework hours to total design hours. In the Figure, the acceptance level is set at 2.5%, and the control target is 0%. During the evaluation and measurement, the MLMP generated a value of 16.2%, while LR generated 14.7%, indicating a high level of rework hours at current evaluating period. In real-world applications, corrective actions are necessary to mitigate the high design rework risk.

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Continuous monitoring of the performance moving range after corrective efforts with the acceptance level and control limit is suggested in the design execution and management.

Table 17 shows the application of the goal and acceptance levels for each engineering performance output measures for pilot test 2. As illustrated in the Table, the engineering performance output are listed with the definition of each measurement. Two control targets are identified as the goal of aiming result and the acceptance level of desired control limit. After applying BIM use variables X1 to X15 to MLMP and LR models, the performance measure output Y1 to Y10 can be generated as indicated in Table 17 of pilot test 2. Further applications or recommendations can be developed for performance control purposes.

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Table 17. Pilot Test 2 Application

Engineering Performance Output Measures			Target		Pilot Project 2	
Measures		Definition	Goal (%)	Acceptance Level (%)	MLMP (%)	LR (%)
Y1	Design Rework	Design Rework Hours/Total Design Hours	0	2.5	8.2	9.7
Y2	Detailed Design Schedule Delay	Days of Design Schedule Delay/Total Design Schedule Days	0	0.0	7.0	7.0
Y3	Detailed Design Cost Overrun	Design Cost Overrun in $/Total Design Cost in $	0	0.0	9.1	9.5
Y4	Detailed Designed Quantity Compared to Final Installed Quantity	Issue for Construction Designed Quantity/Final Installed Quantity	100	95.0	97.3	96.8
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/ Total Fabrication and Construction Days	0	0.0	9.5	8.8
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies	Fabrication and Construction Cost Overrun due to Design Deficiencies in $/Total Fabrication and Construction Cost in $	0	0.0	4.4	4.9
Y7	Construction Hours for Request for Information	Construction Hours for Request for Information/ Total Construction Hours	0	5.0	6.5	6.1
Y8	Construction Hours for Field Change Request	Construction Hours for Field Change Request/Total Construction Hours	0	2.5	3.8	4.0
Y9	Start-up Schedule Delay due to Design Deficiencies	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days	0	2.0	7.5	7.1
Y10	Start-up Cost Overrun due to Design Deficiencies	Start-up Cost Overrun due to Design Deficiencies in $/Total Start-up Cost in $	0	0.0	6.6	5.3

To have better compassion of the goal, acceptance level and the actual engineering performance output measures, Figure 25 shows the variation of the pilot test 2. The engineering performance output measures of Y1 to Y10 are shown in X-axis and actual values are shown in Y-axis. The results show that the strength of performance prediction for MLMP and LR models is almost the same. The acceptance level and the control target are also identified to display the actual performance measurements.

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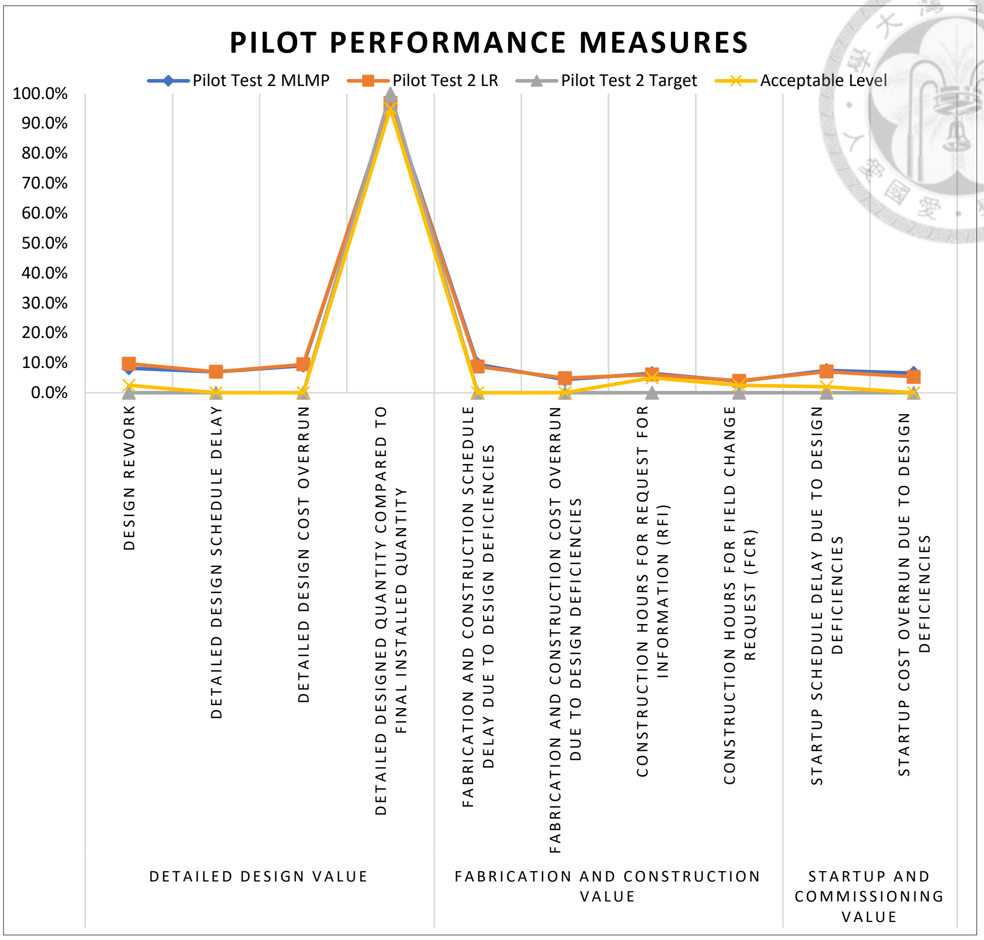

Figure 25. Pilot Test 2 for Performance Measures for MLMP and LR Models

As shown in Figure 25, for instance, the two reference points, acceptance level and target values are also applicable to engineering performance output measure Y4. The measure Y4 represents the detailed design quantity compared to the final construction installed quantity, measuring the effectiveness of the design quantity. In this case, the Figure displays an acceptance level of 95% and a control target of 100%. During the evaluation and measurement, the MLMP generated 97.3%, and LR generated 96.8%, indicating good design quality at the current evaluating period, surpassing the acceptance level but still falling short of the control target. In real-world implementations, corrective actions should be considered to address the accuracy of design and construction quantity. Continuous monitoring of the performance moving range after corrective efforts with the acceptance level and control limit is suggested in the quantity control and management.

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7.4 Application for Performance Control Management

The engineering performance control is proposed to interpretate the ongoing monitoring or process controls needed to ensure that process owners sustain the gains of the engineering performance prediction process. The effective and precision performance control also plays a crucial part in fulfilling the requirements for strengthening the ability of project to keep the solutions in place. The control chart is general applied as a practical management tool to performance control. The control chart as specialized run chart is recommended to control and monitor the performance and provide a systematic way to evaluate engineering performance continuously by monitoring key performance metrics and enabling data driven decision-making (McCary et al. 2005). By maintaining a stable process and addressing variations as they arise, the decision makers can optimize the engineering operations for better quality and efficiency. Facilitating control charts to effectively manage a process involves various steps and considerations. To facilitate the use of control charts for process management, the major consideration and steps are,

- Select the Engineering Performance Metric: Identify metrics that align with project goals and customer requirements. Consider both leading and lagging performance indicators, focusing on what is most critical and collaborate with stakeholders to define which metrics are most relevant.

- Collect Project Data: Set up a data collection process with defined data sources and methods. Ensure the data quality and consistency by using standardized measurement procedures and collect data at regular intervals, but do not overwhelm the process with excessive data points.

- Determine Control Limits: Consider the process stability and available historical data when setting control limits. Choose the appropriate control chart type, such as X-bar

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and R-chart, X-bar and S-chart, or individual/moving range (I-MR) charts based on the data characteristics. Understand that control limits may need adjustment over time as the process improves.

- Create the Control Chart: Use specialized software or templates to create accurate and visually clear control charts. Ensure the chart is accessible to relevant team members through a centralized platform. Consider implementing automated data collection and chart generation for real-time monitoring.

- Define Responsibilities: Clearly outline the responsibility for data collection, chart maintenance, and problem-solving. Designate roles for reviewing and analyzing the chart, including a process owner or champion. Encourage team members to take ownership of their roles and be proactive in maintaining the chart.

- Regular Monitoring: Choose the appropriate review frequency based on the process's nature and the criticality of the metric. Schedule regular meetings or check-ins to review the chart, share insights, and track progress. Develop a standardized process for reviewing data and reacting to out-of-control situations.

- Data Analysis: Implement statistical analysis tools to identify trends, cycles, or special causes of variation. Apply statistical process control techniques like control chart pattern recognition. Conduct hypothesis testing if necessary to confirm the significance of observed variations.

- Root Cause Analysis: Utilize methods 5 Whys or Fishbone cause and effect diagrams to identify the underlying causes of process variations. Encourage cross-functional teams to collaborate in root cause analysis. Focus on addressing root causes rather than just the symptoms of a problem.

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- Take Corrective Actions: Develop an action plan to address identified root causes and bring the process back into control. Track the progress and effectiveness of corrective actions and adjust them as needed. Ensure communication and accountability for implementing corrective actions.

- Continual Improvement: Encourage a culture of continuous improvement within the team. Share best practices, lessons learned, and successful improvements across the organization. Consider process reengineering or major changes based on the cumulative insights from control charts.

- Documentation: Maintain a comprehensive and easily accessible record of all control chart data, findings, and actions taken. Use documentation to track the historical performance of the process and reference it for future analysis and audits.

- Communication: Establish regular communication channels to keep team members informed about control chart status and updates. Encourage open dialogue and feedback to address concerns or suggestions for improvement. Share success stories and achievements related to process management through control charts.

The control chart as specialized run chart is recommended to control and monitor the performance. In a control chart, the Y axis is the metric of output measures, and the X axis is the time or sample point in time series. There are three statistically calculated lines are imposed for control propose, a center line in an average of output measures, upper or lower control limits to identify acceptance levels, and a target line to specify the control targets.

Figure 26 illustrates the example of the performance control for output measure Y2. The definition of output measure Y2 is a detailed design schedule delay and calculated by the days of design schedule delay divided by total design schedule days. The chart

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shows the variation of performance measure output Y2 from the beginning of the project in term of sample # where the measurement frequency of cycle can be defined by the control and monitoring propose. The blue dotted line is the average of the performance measure output during the evaluation period and can be compared to the variation of each measurement. The red solid line is the control limit, where specifies the acceptance level at performance measure output. The green line is the control target of the measurement, which identify the aim of the control result. This pilot project applies the performance measure output Y2 from the prediction of the MLMP model by inputting BIM use variables X1 to X15 as indicated in MLMP model implementation in Table 14. The performance of detailed design delay varied from 6.3% to 2.4%. Here, 6.3% is above control limit 6.0%, and 2.4% is under control limit, and the performance moving over a 10 checking points is approaching the target at 0.0%. The pilot application indicates that the project takes the required actions to control the performance to the desired outcome.

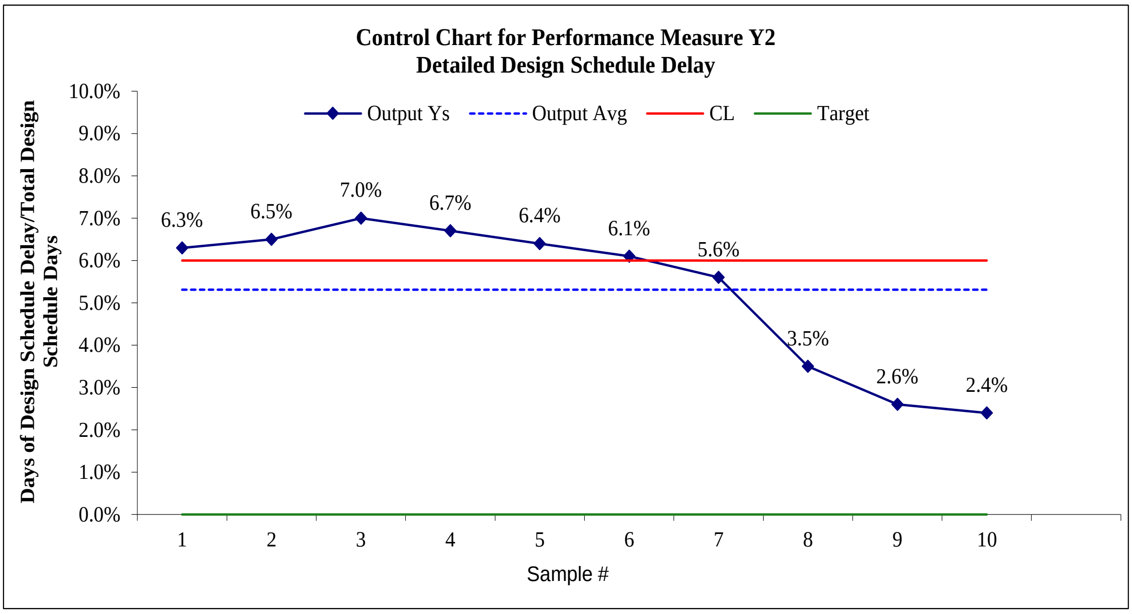

Figure 26. Control Chart Performance Measures Y2

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Figure 27 shows the example of the performance control for output measure Y4. The definition of output measure Y4 is a detailed designed quantity compared to the final installed quantity and calculated by the issue for construction designed quantity divided by the final installed quantity. The chart shows the variation of performance measure output Y4 from the beginning of the project in terms of sample number, where the measurement frequency of the cycle can be defined by the control and monitoring purpose. This pilot project applies the performance measure output Y4 from the prediction of the MLMP model by inputting BIM use variables X1 to X15 as indicated in LR model implementation in Table 15. The performance of the detailed designed quantity compared to the final installed quantity varied from 95.5% to 101.0%. Here, 95.5% is above control limit of 95.0%, and 101% is above control limit, and the performance moving over 10 checking points is approaching the target at 100.0%. The pilot application indicates that the project takes the required actions to control the performance to the desired outcome.

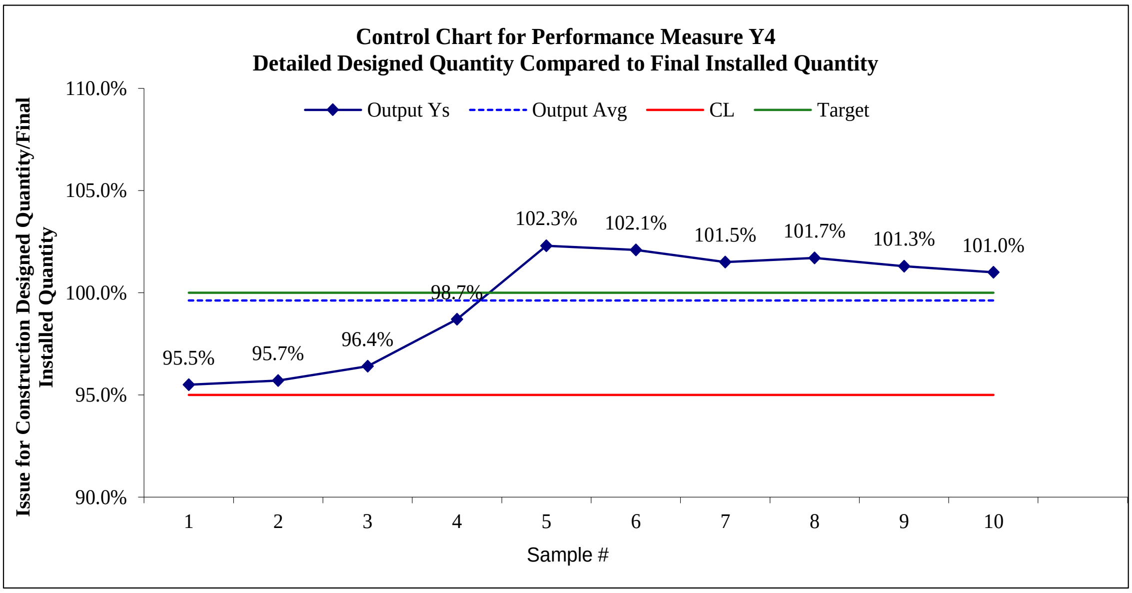

Figure 27. Control Chart Performance Measures Y4

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7.5 Statistical and Hypothesis Tests

This research utilizes the use of statistical and hypothesis tests for model validation, specifically highlighting the adjusted R-squared coefficient of determination and the F-test for variance. This discussion sets the stage for a deeper exploration of these tests in the following sections, emphasizing their importance and relevance in the context of regression analysis and the linear regression and machine learning models.

7.5.1 Adjusted R-squared

R-squared also known as the coefficient of determination, is a statistical measure to assess the goodness of fit of a regression model. It quantifies the proportion of the variance in the dependent variables (Ys) that can be explained by the independent variables (Xs) in a linear regression model. It helps to understand how well the independent variables can account for the variations in the dependent variable. R-squared is between 0 and 1, representing the percentage of the variation in the dependent variable Y that is explained by the independent variables X. An R-squared value of 0 means that the independent variables do not explain any of the variation in Y, while an R-squared value of 1 means that all the variation in Y can be explained by the independent variables (Downing and Clark 2003).

In LR model, $Y = a + bX1 + cX2 + dX3 + ... + Xn$ is a multiple linear regression model. Here 'a' represents the intercept or constant term, and 'b', 'c', 'd', ..., 'Xn' are the coefficients associated with each of the independent variables. These coefficients indicate the strength and direction of the relationship between each X variable and the dependent variable Y. Now, an R-squared value of 90% as in LR model, it means that 90% of the variability in the dependent variable Y can be attributed to the influence of the independent variables X1, X2, X3, ..., Xn. In other words, these independent variables

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collectively account for a significant portion of the observed variations in Y. It considers the trade-off between model complexity and goodness of fit.

In this research, the adjusted R-squared is used to evaluate the developed models. An adjusted R-squared is a modified version of the standard R-squared that considers the number of independent variables in a regression model. Adjusted R-squared is calculated using the same principles as R-squared, but it incorporates the number of independent variables in the model. It is designed to balance the need for a good fit with the risk of overfitting. While R-squared defines how well the independent variables explain the variance in the dependent variable, adjusted R-squared offers a more nuanced view by penalizing the inclusion of unnecessary or irrelevant independent variables. A higher adjusted R-squared suggests that a larger proportion of the variation in the dependent variable is explained by the independent variables while penalizing the inclusion of unnecessary variables. When comparing models, a higher adjusted R-squared indicates a better model fit.

When comparing different regression models, the adjusted R-squared is a helpful criterion. A model with a higher adjusted R-squared, indicating a better fit while considering the number of independent variables included. Adjusted R-squared is not a definitive measure for model selection. It should be used in conjunction with other model evaluation techniques and domain knowledge. It assumes that all variables included in the model are relevant and correctly specified. An adjusted R-squared is a valuable tool for assessing the goodness of fit of a regression model while considering the trade-off between model complexity and model performance. It helps address the issue of overfitting by penalizing models with excessive independent variables. When comparing models, a higher adjusted R-squared indicates a better model fit while considering the number of independent variables in the model. However, it should be used in combination

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with other evaluation metrics and domain knowledge to make well-informed decisions about model selection and refinement.

7.5.2 F-Test in Machine Learning

The F-test is typically used in the context of statistical hypothesis testing to compare the variances of two or more groups or to compare the fits of different models. In machine learning, it can be used for certain tasks, but its application is different from traditional statistical hypothesis testing. The F-test can be used to assess the relevance of different variables in the machine learning model and the F-statistic and associated F-value can be computed to determine whether a particular feature significantly contributes to the predictive power of the model (Downing and Clark 2003).

In this research, the two developed models applied F-test to assess whether the differences in their performance are statistically significant. It is important that the application of the F-test in machine learning often depends on the specific problem and context. However, the application of F-test is tailored to the specific needs and objectives of machine learning evaluation with Pros and Cons.

The Pros of using F-test in machine learning:

- Feature Selection: The F-test can help identify which features are most relevant for a predictive model, allowing to reduce the dimensionality of the data and potentially improve model performance and interpretability.
- Model Comparison: It provides a statistical basis for comparing the performance of different models or distinct groups of features, helping to make informed decisions in model selection.

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- ANOVA for Regression Analysis: In regression analysis, the F-test allows to determine whether groups of predictor variables collectively have a significant impact on the target variable, providing insights into the overall importance of feature groups.
- Statistical Significance: It helps to determine whether observed differences between groups or models are statistically significant, which can be important for making robust and data-driven decisions.

The Cons of using F-test in machine learning:

- Assumptions: The F-test relies on certain assumptions, such as the assumption of normally distributed errors and homoscedasticity. Homoscedasticity is the spread of data points is consistent throughout a regression analysis, indicating a stable level of variance, and this assumption is important for reliable linear regression models. Violations of these assumptions can lead to incorrect results or interpretations.
- Limited to Linear Models: The F-test is commonly associated with linear models, and its applicability to more complex and nonlinear models like deep neural networks may be limited. For such models, other methods like cross-validation may be more appropriate for model comparison. Cross-validation is a technique used in machine learning and statistics to assess how well a predictive model can perform on an independent dataset. This process is repeated several times, and the performance metrics are averaged to help in obtaining a more robust estimate of a model's performance and reduces the risk of overfitting.
- Subjectivity: Determining the appropriate significance level for the F-test can be subjective and may lead to different results based on the chosen significance level.
- Multiple Comparisons: If the multiple F-tests is performed on different variables or models, it need to adjust for multiple comparisons to control the multiplicity error rate

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to avoid of making a Type I error (false positive). The adjustments help maintain an acceptable overall significance level when conducting multiple tests, reducing the likelihood of incorrectly rejecting a null hypothesis in any individual test.

- Model Overfitting: Over-reliance on the F-test for variable selection can lead to overfitting if not used judiciously. Removing features solely based on F-scores can lead to loss of valuable information.

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8.0 Conclusions and Recommendations

This dissertation presents a comprehensive exploration of engineering productivity knowledge, encompassing motivation, background, and methodology. Through fruitful collaboration with industry stakeholders, the study successfully achieved several key objectives. As defined at the beginning of this research included the assessment of current BIM utilization in engineering processes and the identification of performance, development of methodologies for quantifying and correlating of BIM use and performance, application of machine learning models to identify predictive capabilities and the MLMP and LR modeling and development an assessment of the prediction, validation and implantation of the developed models, and application to contribute the findings. The conclusions drawn from the awareness of constraints and the potential impact with limitations defined. The research findings are summarized herein, shedding light on significant insights and implications for the field with inherent constraints and boundaries that affect the research. Additionally, the dissertation offers recommendations for future research endeavors, highlighting areas where investigation could yield valuable contributions to the domain of engineering performance knowledge.

Through this scholarly work, the research aims to enrich the understanding of engineering performance and its multifaceted dynamics. By collaborating closely with industry partners, this study seeks to bridge the gap between academia and practice, fostering a more holistic and evidence-based approach to enhance project engineering performance. The conclusions and recommendations provided herein aim to inspire and guide future researchers in their pursuit of continued advancement in this vital area.

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8.1 Limitations

Several limitations were observed in the proposed BIM implementation. The first limitation is the selection criteria of the engineering performance output measures. These chosen performance output measures were insufficient during the project execution cycle before the actual operation of the completed plants or facilities. Practically, it is almost difficult and time-consuming to obtain comprehensive lifecycle data for projects from the planning phase through the operation and maintenance period. Thus, adding performance attributes and measures depicting the operation and maintenance phases to the existing dataset of variables to develop a more accurate engineering performance assessment prediction model is necessary.

The second limitation is the inadequate applicable data and the difficulty of data collection. The dataset of 60 industrial construction project samples used in this study is minimal for total data amount and valuable quality. However, the group of 60 project sample data was considered very successful despite the data collection difficulties. Although the samples were limited, this study remains acceptable by the triangulation concept (Hammersley and Atkinson 2007). The concept explains that the information on a single phenomenon should be collected from at least three distinct and separated sources to recognize the difference in the information. The project data applied in the study were collected from 4 distinct industry sectors of power, oil and gas, transportation, and high-tech facility, which represented different specific types of facilities over different regions. Since these industrial facilities for data collection are highly specialized functions for different industrial purposes, various project types exist in different modes. Notwithstanding the limited data, the high R-sq (adj) and high assessment power indicated the applicability of the models.

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The third limitation pertains to the restricted application of the developed models, which are primarily recommended for EPC projects that implement BIM right from the planning stage. Since the engineering prediction models rely on data collected from EPC projects utilizing BIM as a management tool, when dealing with projects that either don't use BIM or use it only partially, the absence of complete BIM data inputs may result in deviations, potentially leading to inaccurate performance predictions. This limitation underscores the importance of a comprehensive BIM adoption within EPC projects, as it forms the foundation for accurate performance predictions using the developed models. In cases where BIM is not fully integrated, the quality and completeness of data inputs may suffer, and this deficiency can compromise the precision of the output performance forecasts. The limitation underscores a critical dependency on the consistent and comprehensive use of BIM in EPC projects. When BIM is not universally embraced, there is a higher likelihood of disparities in data collection, and this, in turn, can introduce errors or inaccuracies in the performance predictions derived from the engineering models. It is essential to recognize that the efficacy of the developed models is contingent on the extent to which BIM is employed in EPC projects. The models may not yield accurate predictions for projects that do not fully embrace BIM, potentially leading to deviations in performance expectations due to incomplete or inconsistent data inputs. The third limitation emphasizes that the success of the developed models hinges on the pervasive utilization of BIM in EPC projects. When BIM adoption is partial or absent, there is a risk of encountering discrepancies in the collection of BIM-related data, which can introduce inaccuracies in the performance predictions, highlighting the need for a standardized BIM approach in these projects.

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8.2 Conclusions

Evaluating and predicting project performance in construction projects is essential for all stakeholders to deliver to the facility owners. During a project's life cycle, the engineering design process plays a critical role and is regarded as a significant driving force for the overall project performance. BIM use is now considered a substantial factor in the project execution outcomes. With the implementation of BIM use in project execution to facilitate the engineering process recently, adding BIM applications to the engineering design performance evaluation is necessary.

Previous research on this related study has been insufficient because of the imprecision definition of project performance and the complexity of data collection for studying engineering performance. The purpose of this study was to establish a generic framework for constructing comprehensive relationships between BIM use and the overall engineering project performance.

The first objective of the study was to explore generic models that could delineate the statistical correlation between engineering input variables by using BIM and overall project performance output measures through MLMP and LR. The model could further examine the influential degree of project input variables by using BIM on output engineering performance measure. Existing data from 60 industrial finished projects with 15 BIM use input variables and targeted 10 engineering performance output measures were utilized to construct the proposed models.

The modeling results indicate a high correlation between input variables and output measures with 0.7 to 0.9 Pearson's positive correlation coefficients or -0.7 to -0.9 Pearson's negative correlation coefficients as shown in Table 7. The method of correlating MLMP and LR with combined BIM-use results in 70% on average of high

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goodness of fit R-sq (adj) values and an acceptable level of P-value of 0.000s. Table 11 summarizes MLMP and LR models with the prediction equations and their statistical results, MLMP is in the range of 99.48%~99.94% while LR is in the range of 63.01%~84.48%. Figure 9 depicts that MLMP shows fewer deviations with much higher R-sq (adj) of outputs than the LR models'.

Moreover, the graphical evaluation shows that the essential BIM uses are highly related to design activities, and the enhanced BIM uses are correlated with construction phase as indicated in Figure 19 of the critical BIM uses for engineering performance. Moreover, Figure 20 of the expansion of BIM uses at project phase demonstrates the high correlative BIM use inputs for both essential and enhanced expansion at the three phases of project execution, and the influence level of the phases.

The second objective of the study was verifying the validity and reliability of the proposed models and to check the variance of the engineering performance output measures through MLMP and LR models and compare their actual performance data with the data of overall 60 projects.

The validation process contains two stages. the F-test was applied to access the variances of the LR and MLMP models in the 1st stage. The average values of 15 output performance measures identified at project design, construction, and startup phases from two selected individual project #1 and project #36 were input into proposed models separately. Their variances were compared. Figure 11 and Figure 12 depict that they are highly matched. Furthermore, F-test clearly indicates that there is no significant difference between the proposed model and the individual project's as shown in Figure 13 and Figure 14. The results are significantly equivalent on 95% confidence level of reliability.

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In the second stage of validation process, the average values of 15 output performance measures identified at project design, construction, and startup phases from the original 60 project data set were compared with average values of two testing sample group projects of #52 to #56 and from #57 to #60. By the same token, signified in Table 13, Figure 15, Figure 16, Figure 17 and Figure 18, there is no significant difference between the proposed model and the group project's. Thus, the models in this research are validated.

In conclusion, the prediction of engineering performance emerges as a vital component for effective project control and management. Previous attempts in this research areas were somewhat limited, largely due to the inherent complexity and imprecision in engineering performance. This study employed machine learning systems, specifically ANNs, to estimate engineering performance by considering various project attributes and conditions affecting performance. The utilization of ANNs allowed for both learning capabilities and flexible variable descriptions within AI-based modeling.

The implemented system focused on the identified target industrial sector in this study, and the application of ANNs for predicting engineering performance demonstrated promising results. The reliability and accuracy of the models can be enhanced by expanding the project database. Additionally, these models hold potential for practical applications, including performance comparisons, risk identification, sensitivity analyses of project attributes and conditions, tradeoff evaluations, and more.

By leveraging the power of machine learning and ANNs, the research can take significant strides in refining the understanding of engineering performance prediction. These advancements could contribute to more informed decision-making and ultimately

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may lead to more efficient and successful project outcomes within the construction industry.

Future research and data collection efforts in this area could theoretically enrich the knowledge and strengthen the applicability of AI-based models in construction project management. The experience and knowledge can be applied to the future new projects.

8.3 Recommendations

This dissertation presents a pragmatic approach to constructing engineering performance evaluation models, investigating the correlation between BIM use and performance measures, and implementing and applying performance prediction. The study offers valuable recommendations for construction stakeholders seeking to measure and predict engineering performance using BIM applications in project execution. Despite limitations due to the sample size of the data, the following action items are proposed:

- Focus on Implementing Essential and Enhanced BIM Uses: Emphasize the adoption of both essential and enhanced BIM uses identified in this study. The clear guidelines provided by the BIM use inputs will drive engineering performance outcomes.
- Examine the Relative Importance of Influence Factors: Future research is suggested to explore the relative importance of factors affecting engineering performance. Due to the limited data sample size and missing values in this study, a comprehensive multivariate analysis could not be conducted. Enhancing the dataset will enable more in-depth analysis to facilitate benchmarking efforts.
- Apply Prediction Models for Performance Monitoring: Utilize the prediction model to measure and evaluate engineering performance during project execution. Real-time

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project progress and performance monitoring will enable proactive measures to address issues promptly, enhancing the overall success of engineering design.

- Improve Decision-Making and Risk Management: Incorporate performance models to predict and evaluate design outcomes, leading to improved performance and efficiency in engineering projects. Quantifying the potential impact of design choices on project performance will enhance decision-making and risk management processes.
- Scalable and Adaptable Solutions: Performance models can be applied across various engineering and construction projects and industries. These models provide scalable and adaptable solutions, optimizing resource allocation and cost management, ensuring project efficiency while adhering to budget constraints.

By following these recommendations, construction stakeholders can leverage the power of BIM applications and performance models to achieve enhanced project outcomes, improved decision-making, and more efficient resource management. The ongoing pursuit of data collection and analysis will further strengthen the effectiveness of these models in project execution and performance evaluation within the construction industry. The findings suggest several key research questions and recommendations as follows:

- Prioritizing BIM Use Factors and Engineering Performance Measures: How can BIM use factors and engineering performance measures be effectively prioritized to enhance engineering performance evaluation and prediction efforts?
- Data Acquisition and Weighting During Project Life Cycle: What methods can be employed to acquire data throughout the project life cycle, and how should the weighting of data from different phases be determined?

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- Measuring BIM Use Factors and Engineering Performance Measures: How can the measurement of BIM use factors and engineering performance measures be consistently applied during each phase of a project execution cycle, considering their varying values?
- Applying Performance Analysis Results to Improve Project Management: How can the analysis results of engineering performance correlations be practically applied to enhance project management and decision-making throughout project life cycles?
- Applicability of Performance Models Across Industry Sectors: How can the performance models be effectively applied to various industry sectors while maintaining reliable and trustworthy prediction capabilities?

Addressing these research questions will not only contribute to advancing the field of engineering performance evaluation and prediction but also provide valuable insights for practical application in diverse construction projects and industry sectors. Future research is suggested to base on the questions and recommendations to extent this study and further contribute to the body of knowledge.

8.4 Research Contributions

This research constitutes a structured and comprehensive approach in collaboration with construction industry practitioners to synthesize BIM use factors and engineering performance metrics, encompassing diverse measures, and employs these metrics to construct predictive models that enrich the body of knowledge. This study offers significant contributions to both research and practical applications in the realm of BIM application for engineering performance within the construction industry, achieved through the development of genetic models with predictive capabilities. The specific contributions are outlined below:

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- Development of High-Level BIM Use Factors and Engineering Performance Indices: The research successfully developed high-level BIM use factors and engineering performance indices, enabling the synthesis of metrics with distinct units to facilitate effective management of engineering performance.
- Unpacking the Complexity of Engineering Performance: Through comprehensive analysis, the study revealed insights into the complex relationships between engineering performance and BIM use factors, advancing the understanding of engineering performance factors and their interdependencies.
- Knowledge for Engineering Performance Improvement: The investigation encompassed a systematic exploration of information dependencies among BIM use factors and engineering performance, identification of quantifiable measures for future research, and knowledge the direct impact of BIM use factors on project performance, all contributing to enhancing engineering performance.
- Implementation of MLMP and Statistical-Based Models: The research effectively presented the application of MLMP statistical-based systems utilizing the surveyed and collected project dataset, offering two models for predicting engineering performance outcomes in the industrial construction projects.
- Potential for Future Improvement: The research highlights the potential for refining the developed genetic models by augmenting the multi-dimensional project database, which could enhance the accuracy and reliability of the predictive models.

Overall, the contributions of this study enable engineers and designers to make more informed decisions, optimize design processes, enhance project performance, and foster sustainable and efficient construction practices. The integration of BIM performance models has the potential to revolutionize the engineering industry, making it more data-

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driven, collaborative, and capable of delivering innovative and successful projects. By leveraging the predictive capabilities of the proposed models, the construction industry can embark on a transformative journey towards improved project outcomes and heightened project performance. The experience gained in this research can be applied and beneficial to new projects.

8.5 Future Research

In pursuing of an effective and user-friendly engineering performance prediction model, future research endeavors will be directed towards encapsulating the developed generic model into a software package. This approach aims to invite BIM users to test the model using their project data, thereby ensuring practical applicability and user acceptance. A pilot test of the engineering performance prediction software has already been conducted with selective EPC or contractors who participated in the survey, and the preliminary feedback has been positive. To optimize the model's performance, specific guidance shall be provided for collecting data from various construction tasks. While raw data may exist in some form, it must undergo distillation and tailoring before being fed into the predictive model. Future research is suggested to conduct and interpret test results and unlock the full potential of BIM as a valuable tool in construction tasks, promoting wider implementation across the industry.

Future efforts are suggested to focus on addressing the limitations identified in current proposed study. The collection of life-cycle data of construction projects will be contingent on data availability and facility owners' willingness to release such data. In cases where the model scope is limited to project phases preceding the operation phase, a practical plan of project data collection and data mining can be developed. With ample data from construction projects of the similar facility type, the ML method could be better

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trained, leading to more reliable and precise predictions. The system's customization, including appropriate input and output variables selection, can facilitate both internal and external benchmarking of facility owners and AEC companies. However, the validity of predicted engineering performance measures remains subject to the consolidation of more tailored project data in the future.

Enhancing engineering performance validation and reliability forecasts through BIM uses will be a focal point of future research. One approach is to apply artificial intelligence methods and deep learning algorithms to enable computers to simulate thinking processes and learn directly from data without relying on pre-defined models. As the number of data samples for the learning process increases, these algorithms can improve implementation performance. Advanced AI methods can be applied by enhancing predictive capabilities and optimizing system parameters. The technique enables the model to learn complex patterns, adapt to changing conditions, and provide more accurate assessments of performance in diverse engineering scenarios. Another area of investigation is the application of cross-validation for the developed models. This technique, widely used in machine learning, assesses the predictive accuracy and reliability of the models by dividing the data into multiple subsets and iteratively training and testing the model on different subsets. Cross-validation can ensure that the model generalizes well to new data and help identify potential data issues, thus enhancing the predictive accuracy and reliability of the models. Lastly, including a multi-dimensional data structure in the evaluation model will be explored. The current study excluded owner-related BIM uses such as asset management, disaster planning and management, and space management. Incorporating these aspects into the engineering performance model through lifecycle data integration could provide valuable insights and benefit analysis.

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The future research agenda aims to elevate the field of engineering performance prediction by leveraging cutting-edge methodologies, optimizing data utilization, and expanding the scope of BIM applications to enhance construction practices and project outcomes.

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APPENDICES

Appendix 1 Top 100 Contractor List

Appendix 2 Survey of Engineering Performance of BIM Implementation

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Appendix 4 Correlation Analysis MiniTab Report

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Appendix 6 Deep Learning Model in Python with Keras

Appendix 7 F-test and Correlation for LR and MLMP Models

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Appendix 1
Top 100 Contractor List (1/2)

ENR 2017 Top 400 Contractors 1-100

Companies are ranked by construction revenue in 2016 in ($) millions. Those with subsidiaries (†) are listed by company rank, which may be found on the ENR website at www.ENR.com. Firms not ranked last year are designated as **. Some markets may not add up to 100% due to omission of the "other" miscellaneous market category. NA = "not available." Page 1 of 2

RANK 2017	RANK 2016	FIRM
1	1	BECHTEL, San Francisco, Calif.†
2	2	FLUOR CORP., Irving, Texas†
3	3	THE TURNER CORP., New York, N.Y.
4	4	CB&I LLC, The Woodlands, Texas†
5	6	AECOM, Los Angeles, Calif.†
6	5	KIEWIT CORP., Omaha, Neb.†
7	7	SKANSKA USA INC., New York, N.Y.†
8	8	PCL CONSTRUCTION ENTERPRISES INC., Denver, Colo.†
9	10	TUTOR PERINI CORP., Sylmar, Calif.†
10	9	THE WHITING-TURNER CONTRACTING CO., Baltimore, Md.
11	11	THE WALSH GROUP LTD., Chicago, Ill.†
12	15	CLARK GROUP, Bethesda, Md.†
13	14	GILBANE BUILDING CO., Providence, R.I.
14	12	BALFOUR BEATTY US, Dallas, Texas†
15	17	STRUCTURE TONE, New York, N.Y.†
16	20	DPR CONSTRUCTION, Redwood City, Calif.
17	24	SWINERTON INC., San Francisco, Calif.
18	18	MORTENSON CONSTRUCTION, Minneapolis, Minn.†
19	19	HENSEL PHELPS, Greeley, Colo.†
20	25	MCCARTHY HOLDINGS INC., St. Louis, Mo.†
21	13	JACOBS, Dallas, Texas
22	22	ZACHRY GROUP, San Antonio, Texas†
23	26	JE DUNN CONSTRUCTION GROUP, Kansas City, Mo.
24	21	LENDLEASE, New York, N.Y.†
25	30	HOLDER CONSTRUCTION CO., Atlanta, Ga.
26	27	SUFFOLK CONSTRUCTION CO., Boston, Mass.†
27	23	TURNER INDUSTRIES GROUP LLC, Baton Rouge, La.†
28	28	GRANITE CONSTRUCTION INC., Watsonville, Calif.†
29	35	BARTON MALOW CO., Southfield, Mich.
30	29	BRASFIELD & GORRIE LLC, Birmingham, Ala.
31	**	DRAGADOS NORTH AMERICA, New York, N.Y.†
32	16	KBR, Houston, Texas†
33	37	AUSTIN INDUSTRIES, Dallas, Texas†
34	31	ALBERICI-FLINTCO, St. Louis, Mo.†
35	33	PRIMORIS SERVICES CORP., Dallas, Texas†
36	34	MICHELS CORP., Brownsville, Wis.
37	42	CHINA CONSTRUCTION AMERICA/PLAZA CONSTR., Jersey City, N.J.†
38	46	CLAYCO INC., Chicago, Ill.†
39	36	THE YATES COS. INC., Philadelphia, Miss.†
40	56	DEVCON CONSTRUCTION INC., Milpitas, Calif.
41	40	BLACK & VEATCH, Overland Park, Kan.†
42	43	OHL USA INC., College Point, N.Y.†
43	52	WEBCOR CONSTR. DBA WEBCOR BUILDERS, San Francisco, Calif.†
44	71	AMEC FOSTER WHEELER, Atlanta, Ga.†
45	38	PERFORMANCE CONTRACTORS INC., Baton Rouge, La.
46	**	WOOD GROUP, Houston, Texas†
47	44	MANHATTAN CONSTRUCTION GROUP, Naples, Fla.†
48	62	HATHAWAY DINWIDDIE CONSTRUCTION CO., San Francisco, Calif.
49	47	HOFFMAN CORP., Portland, Ore.†
50	41	WALBRIDGE, Detroit, Mich.†

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Appendix 1
Top 100 Contractor List (2/2)

ENR 2017 Top 400 Contractors 1-100		
Companies are ranked by construction revenue in 2016 in ($) millions. Those with subsidiaries (†) are listed by company rank, which may be found on the ENR website at www.ENR.com. Firms not ranked last year are designated as **. Some markets may not add up to 100% due to omission of the "other" miscellaneous market category. NA = "not available." Page 2 of 2		
RANK 2017	**RANK 2016**	**FIRM**
51	51	RYAN COS. US INC., Minneapolis, Minn.
52	45	LANE INDUSTRIES INC., Cheshire, Conn.†
53	57	LAYTON CONSTRUCTION CO. LLC, Sandy, Utah
54	53	COLAS INC., Morristown, N.J.†
55	68	HITT CONTRACTING INC., Falls Church, Va.
56	49	MATRIX SERVICE CO., Tulsa, Okla.†
57	59	SHAWMUT DESIGN AND CONSTRUCTION, Boston, Mass.
58	75	BL HARBERT INTERNATIONAL, Birmingham, Ala.
59	60	MESSER CONSTRUCTION CO., Cincinnati, Ohio
60	39	DAY & ZIMMERMANN, Philadelphia, Pa.†
61	**	MOSS & ASSOCIATES LLC, Fort Lauderdale, Fla.
62	32	DAVID E. HARVEY BUILDERS INC., Houston, Texas†
63	50	FLATIRON CONSTRUCTION CORP., Broomfield, Colo.†
64	67	PEPPER CONSTRUCTION GROUP, Chicago, Ill.†
65	64	HUNTER ROBERTS CONSTRUCTION GROUP LLC, New York, N.Y.
66	**	CENTURI CONSTRUCTION GROUP, Phoenix, Ariz.†
67	79	CONSIGLI BUILDING GROUP INC., Milford, MA
68	66	GRAY CONSTRUCTION, Lexington, Ky.†
69	82	EMJ CORP., Chattanooga, Tenn.†
70	65	THE WEITZ CO., Des Moines, Iowa†
71	70	KOKOSING INC., Westerville, Ohio†
72	93	ARCO CONSTRUCTION COS., St. Louis, Mo.†
73	55	BURNS & MCDONNELL, Kansas City, Mo.
74	61	THE BECK GROUP, Dallas, Texas
75	91	CHOATE CONSTRUCTION CO., Atlanta, Ga.
76	89	BIG-D CONSTRUCTION CORP., Salt Lake City, Utah†
77	78	ROBINS & MORTON, Birmingham, Ala.
78	74	POWER CONSTRUCTION CO. LLC, Chicago, Ill.
79	85	CROSSLAND CONSTRUCTION CO. INC., Columbus, Kan.
80	72	THE BOLDT CO., Appleton, Wis.
81	63	FERROVIAL US CONSTRUCTION CORP., Austin, Texas†
82	134	CLUNE CONSTRUCTION CO., Chicago, Ill.
83	86	SELLEN CONSTRUCTION CO., Seattle, Wash.
84	88	AVALONBAY COMMUNITIES INC., Arlington, Va.
85	101	OKLAND CONSTRUCTION CO. INC., Salt Lake City, Utah
86	**	CORE CONSTRUCTION GROUP, Phoenix, Ariz.
87	104	MIRON CONSTRUCTION CO. INC., Neenah, Wis.
88	83	JAMES G. DAVIS CONSTRUCTION CORP., Rockville, Md.
89	98	THE MCSHANE COS., Rosemont, Ill.†
90	81	PJ DICK - TRUMBULL - LINDY PAVING, Pittsburgh, Pa.†
91	112	ALSTON CONSTRUCTION, Atlanta, Ga.
92	73	AEGION CORP., Chesterfield, Mo.
93	69	AMES CONSTRUCTION INC., Burnsville, Minn.
94	54	M+W GROUP, Albany, N.Y.
95	58	S&B ENGINEERS AND CONSTRUCTORS LTD., Houston, Texas†
96	129	E.E. REED CONSTRUCTION LP, Sugar Land, Texas†
97	77	SUNDT CONSTRUCTION INC., Tempe, Ariz.
98	90	LEVEL 10 CONSTRUCTION, Sunnyvale, Calif.
99	160	FORTIS CONSTRUCTION INC., Portland, Ore.
100	96	WEEKS MARINE INC., Cranford, N.J.†

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Appendix 2

Survey of Engineering Performance of BIM Implementation (1/3)

Survery of Engineering Performance Assessment of BIM Implementation

Purpose of the Research

This research is studing the imapct of BIM uses on engineering design performance. Recent years, BIM application has changed how we approach design, construction, and operations in the construction industry. This study is asking your experience of how BIM uses in the project affects the engineering performance. By using 15 input variavles of BIM application and 10 output variables of engineering performance, the relationships will be reviewed by AI and statisic methods. There are 3 parts of survery, please input you responses and help the research.

Part 0. Please input your Information

Name:

Title:

Company:

Experience in Industry (Years):

Experience in BIM Uses (Years):

Part 1. Please input the acceptance according to your experience

Output Variables Engineering Performance Measures			Target	Acceptance Level	Example
Output Variables		Variable Desceiption			
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	0%		5%
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	0%		15%
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	0%		10%
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	0%		5%
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	0%		3%
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	0%		3%
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	0%		2%
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	0%		1%
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	0%		2%
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	0%		2%

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Appendix 2

Survey of Engineering Performance of BIM Implementation (2/3)

Survery of Engineering Performance Assessment of BIM Implementation

Part 2. Please input the significant level according to your experience

Please evaluate the relation between inputs and outputs, input the significant levels in scale of 5,
5= Very Significant
4= Significant
3= Moderate
2= Little Significant
1= Not Significant
0= No Relationship

		Input Variables BIM Virables	Variable Description	Y1 Design Rework (%)	Y2 Detailed Design Schedule Delay (%)	Y3 Detailed Design Cost Overrun (%)	Y4 Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Y5 Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Y6 Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Y7 Construction Hours for Request for Information (RFI) (%)	Y8 Construction Hours for Field Change Request (FCR) (%)	Y9 Start-up Schedule Delay due to Design Deficiencies (%)	Y10 Start-up Cost Overrun due to Design Deficiencies (%)
Input Variables- BIM Uses	X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model										
	X2	Design Authoring	BIM Software/Tool Used in Design Process										
	X3	Design Review	30/60/90%/100% Model Review										
	X4	Coordination	Clash Detection Process										
	X5	Record Modeling	Physical and Functional Information input in Model										
	X6	Cost Estimating	Generate MTO and Cost Data										
	X7	Phase and 4D Planning	Dimension of Time and Schedule Added										
	X8	Site Analysis-Development	GIS Tools used in Model										
	X9	Site utilization-For Construction	Communication Tool for Construction Plan Added										
	X10	Digital Fabrication	Prefabricate by using BIM Date or Information										
	X11	3D Location and Layout	Function of Utilities to Layout Assemblies										
	X12	Engineering Analysis	Engineering System Simulation used in Model										
	X13	Sustainability Analysis	Sustainable Design Elements included in Model										
	X14	Codes and Standards Compliance	Validation of Codes for Model										
	X15	Construction Systems Design	Contemporary System Analysis in Model										

Output Variables- Engineering Performance Measures: Y1–Y10

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Appendix 2

Survey of Engineering Performance of BIM Implementation (3/3)

Survery of Engineering Performance Assessment of BIM Implementation

Part 3. Please input the scales according to your project involved

Input Variables- BIM Uses

Input Variables		Variable Description	Scale (0-10)
X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	
X2	Design Authoring	BIM Software/Tool Used in Design Process	
X3	Design Review	30/60/90%/100% Model Review	
X4	Coordination	Clash Detection Process	
X5	Record Modeling	Physical and Functional Information input in Model	
X6	Cost Estimating	Generate MTO and Cost Data	
X7	Phase and 4D Planning	Dimension of Time and Schedule Added	
X8	Site Analysis-Development	GIS Tools used in Model	
X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	
X10	Digital Fabrication	Prefabricate by using BIM Date or Information	
X11	3D Location and Layout	Function of Utilities to Layout Assemblies	
X12	Engineering Analysis	Engineering System Simulation used in Model	
X13	Sustainability Analysis	Sustainable Design Elements included in Model	
X14	Codes and Standards Compliance	Validation of Codes for Model	
X15	Construction Systems Design	Contemporary System Analysis in Model	

Implementation Scale (0-10)

0	Not Implemented
1~10	10~100% implemented

Output Variables- Engineering Performance Measures

Output Variables		Variable Desceiption	Project Implemented (%)
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	

Project Information

Project Name:	
Project Sector: (Power, Chem/Gas, Metro, Industrial)	**Project Location:**
Project Contract Type: (Lump Sum, Cost Plus, Unit Price)	**Proejct Contract Value (USD):**
Project Schedule:	

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Appendix 3
Survey Samples (Project Sample 1-1)

Survery of Engineering Performance Assessment of BIM Implementation Part 1 of 3

Purpose of the Research

This research is studing the imapct of BIM uses on engineering design performance. Recent years, BIM application has changed how we approach design, construction, and operations in the construction industry. This study is asking your experience of how BIM uses in the project affects the engineering performance. By using 15 input variavles of BIM application and 10 output variables of engineering performance, the relationships will be reviewed by AI and statisic methods. There are 3 parts of survery, please input you responses and help the research

Part 0. Please input your Information

Name: Oliver Su
Title: Project Manager
Company: ABC
Experience in Industry (Years): 25
Experience in BIM Uses (Years): 20

Part 1. Please input the acceptance according to your experience

Output Variables Engineering Performance Measures			Target	Acceptance Level	Example
	Output Variables	Variable Desceiption			
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	0%	**10%**	5%
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	0%	**5%**	15%
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	0%	**5%**	10%
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	0%	**5%**	5%
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	0%	**3%**	3%
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	0%	**3%**	3%
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	0%	**1%**	2%
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	0%	**3%**	1%
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	0%	**3%**	2%
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	0%	**3%**	2%

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Appendix 3
Survey Samples (Project Sample 1-2)

Survery of Engineering Performance Assessment of BIM Implementation Part 2 of 3

Part 2. Please input the significant level according to your experience

Please evaluate the relation between inputs and outputs, input the significant levels in scale of 5,
5= Very Significant
4= Significant
3= Moderate
2= Little Significant
1= Not Significant
0= No Relationship

Input Variables- BIM Uses		Input Variables BIM Virables	Variable Description	Y1 Design Rework (%)	Y2 Detailed Design Schedule Delay (%)	Y3 Detailed Design Cost Overrun (%)	Y4 Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Y5 Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Y6 Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Y7 Construction Hours for Request for Information (RFI) (%)	Y8 Construction Hours for Field Change Request (FCR) (%)	Y9 Start-up Schedule Delay due to Design Deficiencies (%)	Y10 Start-up Cost Overrun due to Design Deficiencies (%)
	X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	2	2	3	3	2	2	3	3	0	0
	X2	Design Authoring	BIM Software/Tool Used in Design Process	4	3	3	5	5	2	4	4	2	2
	X3	Design Review	30/60/90%/100% Model Review	2	4	5	4	4	5	2	3	4	4
	X4	Coordination	Clash Detection Process	4	4	4	4	4	4	4	4	4	4
	X5	Record Modeling	Physical and Functional Information input in Model	3	3	3	3	3	3	3	3	3	3
	X6	Cost Estimating	Generate MTO and Cost Data	3	2	5	4	2	4	2	2	2	2
	X7	Phase and 4D Planning	Dimension of Time and Schedule Added	2	2	2	2	2	2	2	2	2	2
	X8	Site Analysis-Development	GIS Tools used in Model	2	2	2	2	1	1	0	0	0	0
	X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	1	0	0	0	0	2	2	1	1	1
	X10	Digital Fabrication	Prefabricate by using BIM Date or Information	2	2	2	2	4	4	3	2	1	1
	X11	3D Location and Layout	Function of Utilities to Layout Assemblies	3	2	2	3	4	4	4	4	2	2
	X12	Engineering Analysis	Engineering System Simulation used in Model	3	3	3	4	4	4	3	3	2	2
	X13	Sustainability Analysis	Sustainable Design Elements included in Model	3	3	3	4	3	3	2	2	2	2
	X14	Codes and Standards Compliance	Validation of Codes for Model	5	5	5	5	5	5	5	5	5	5
	X15	Construction Systems Design	Contemporary System Analysis in Model	4	4	4	3	3	3	3	3	2	2

doi: 10.6342/NTU202304540

Appendix 3
Survey Samples (Project Sample 1-3)

Survery of Engineering Performance Assessment of BIM Implementation Part 3 of 3

Part 3. Please input the scales according to your project involved

Input Variables- BIM Uses				Output Variables- Engineering Performance Measures			
	Input Variables BIM Virables	**Variable Description**	**Scale (0-10)**		**Output Variables**	**Variable Desceiption**	**Project Implemented (%)**
X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	**6**	Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	**8%**
X2	Design Authoring	BIM Software/Tool Used in Design Process	**8**	Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	**8%**
X3	Design Review	30/60/90%/100% Model Review	**10**	Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	**12%**
X4	Coordination	Clash Detection Process	**8**	Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	**2%**
X5	Record Modeling	Physical and Functional Information input in Model	**6**	Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	**2%**
X6	Cost Estimating	Generate MTO and Cost Data	**9**	Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	**1%**
X7	Phase and 4D Planning	Dimension of Time and Schedule Added	**3**	Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	**1%**
X8	Site Analysis-Development	GIS Tools used in Model	**1**	Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	**1%**
X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	**3**	Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	**3%**
X10	Digital Fabrication	Prefabricate by using BIM Date or Information	**5**	Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	**2%**
X11	3D Location and Layout	Function of Utilities to Layout Assemblies	**8**		**Project Information**		
X12	Engineering Analysis	Engineering System Simulation used in Model	**6**		**Project Name:** Data Center Project		
X13	Sustainability Analysis	Sustainable Design Elements included in Model	**7**		**Project Sector:** High Tech	**Project Location:** Taiwan	
X14	Codes and Standards Compliance	Validation of Codes for Model	**9**		**Project Contract Type:** Ceiling Price	**Proejct Contract Value (USD):** $20M (TIC)	
X15	Construction Systems Design	Contemporary System Analysis in Model	**7**		**Project Schedule:** 26 months		

Implementation Scale (0-10)
0-Not Implemented, 1-10% Implemented, 2-20% Implemented, 3-30% Implemented, 4-40% Implemented, 5-50% Implemented,
6-60% Implemented, 7-70% Implemented, 8-80% Implemented, 9-90% Implemented, 10-100% Implemented,

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Appendix 3

Survey Samples (Project Sample 2-1)

Survery of Engineering Performance Assessment of BIM Implementation Part 1 of 3

Purpose of the Research

This research is studing the imapct of BIM uses on engineering design performance. Recent years, BIM application has changed how we approach design, construction, and operations in the construction industry. This study is asking your experience of how BIM uses in the project affects the engineering performance. By using 15 input variavles of BIM application and 10 output variables of engineering performance, the relationships will be reviewed by AI and statisic methods. There are 3 parts of survery, please input you responses and help the research

Part 0. Please input your Information

Name: Tom Lee

Title: Project Manager

Company: ABC

Experience in Industry (Years): 25

Experience in BIM Uses (Years): 8

Part 1. Please input the acceptance according to your experience

Output Variables Engineering Performance Measures			Target	Acceptance Level	Example
Output Variables		Variable Desceiption			
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	0%	**5%**	5%
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	0%	**10%**	15%
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	0%	**10%**	10%
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	0%	**5%**	5%
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	0%	**0%**	3%
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	0%	**3%**	3%
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	0%	**2%**	2%
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	0%	**1%**	1%
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	0%	**0%**	2%
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	0%	**0%**	2%

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Appendix 3
Survey Samples (Project Sample 2-2)

Survery of Engineering Performance Assessment of BIM Implementation Part 2 of 3

Part 2. Please input the significant level according to your experience

Please evaluate the relation between inputs and outputs, input the significant levels in scale of 5,
5= Very Significant
4= Significant
3= Moderate
2= Little Significant
1= Not Significant
0= No Relationship

				Output Variables- Engineering Performance Measures									
				Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
				Design Rework (%)	Detailed Design Schedule Delay (%)	Detailed Design Cost Overrun (%)	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Field Change Request (FCR) (%)	Start-up Schedule Delay due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies (%)
Input Variables- BIM Uses	Input Variables BIM Virables		Variable Description										
	X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	3	1	3	0	3	2	1	2	1	1
	X2	Design Authoring	BIM Software/Tool Used in Design Process	3	1	4	4	2	4	4	4	3	3
	X3	Design Review	30/60/90%/100% Model Review	3	1	3	4	3	3	4	4	3	3
	X4	Coordination	Clash Detection Process	4	4	4	3	2	2	3	3	2	2
	X5	Record Modeling	Physical and Functional Information input in Model	1	1	1	1	1	1	2	2	1	1
	X6	Cost Estimating	Generate MTO and Cost Data	1	1	1	4	2	2	2	2	2	2
	X7	Phase and 4D Planning	Dimension of Time and Schedule Added	1	1	1	2	3	3	1	1	3	3
	X8	Site Analysis-Development	GIS Tools used in Model	1	1	1	1	2	1	1	1	2	1
	X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	1	1	3	1	2	2	1	1	2	2
	X10	Digital Fabrication	Prefabricate by using BIM Date or Information	1	1	3	1	1	1	1	1	1	1
	X11	3D Location and Layout	Function of Utilities to Layout Assemblies	3	3	3	2	3	2	3	3	3	2
	X12	Engineering Analysis	Engineering System Simulation used in Model	3	3	3	1	3	3	1	1	3	3
	X13	Sustainability Analysis	Sustainable Design Elements included in Model	1	3	3	1	1	1	1	1	1	1
	X14	Codes and Standards Compliance	Validation of Codes for Model	1	1	3	1	1	2	1	1	1	1
	X15	Construction Systems Design	Contemporary System Analysis in Model	1	1	3	1	1	2	1	1	1	1

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Appendix 3
Survey Samples (Project Sample 2-3)

Survery of Engineering Performance Assessment of BIM Implementation Part 3 of 3

Part 3. Please input the scales according to your project involved

Input Variables- BIM Uses				Output Variables- Engineering Performance Measures			Project Implemented (%)
Input Variables BIM Virables		Variable Description	Scale (0-10)	Output Variables		Variable Desceiption	
X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	3	Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	25%
X2	Design Authoring	BIM Software/Tool Used in Design Process	1	Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	8%
X3	Design Review	30/60/90%/100% Model Review	1	Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	20%
X4	Coordination	Clash Detection Process	1	Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	95%
X5	Record Modeling	Physical and Functional Information input in Model	2	Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	10%
X6	Cost Estimating	Generate MTO and Cost Data	1	Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	15%
X7	Phase and 4D Planning	Dimension of Time and Schedule Added	1	Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	3%
X8	Site Analysis-Development	GIS Tools used in Model	6	Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	8%
X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	4	Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	7%
X10	Digital Fabrication	Prefabricate by using BIM Date or Information	1	Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	6%
X11	3D Location and Layout	Function of Utilities to Layout Assemblies	4	**Project Information**			
X12	Engineering Analysis	Engineering System Simulation used in Model	1	**Project Name: K City Underground Station**			
X13	Sustainability Analysis	Sustainable Design Elements included in Model	5	**Project Sector: Transportation**		**Project Location: Taiwan**	
X14	Codes and Standards Compliance	Validation of Codes for Model	6	**Project Contract Type: LS**		**Proejct Contract Value (USD): 0.3 M**	
X15	Construction Systems Design	Contemporary System Analysis in Model	1	**Project Schedule: 84 months**			

Implementation Scale (0-10)
0-Not Implemented, 1-10% Implemented, 2-20% Implemented, 3-30% Implemented, 4-40% Implemented, 5-50% Implemented,
6-60% Implemented, 7-70% Implemented, 8-80% Implemented, 9-90% Implemented, 10-100% Implemented,

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Appendix 3
Survey Samples (Project Sample 3-1)

Survery of Engineering Performance Assessment of BIM Implementation Part 1 of 3

Purpose of the Research
This research is studing the imapct of BIM uses on engineering design performance. Recent years, BIM application has changed how we approach design, construction, and operations in the construction industry. This study is asking your experience of how BIM uses in the project affects the engineering performance. By using 15 input variavles of BIM application and 10 output variables of engineering performance, the relationships will be reviewed by AI and statisic methods. There are 3 parts of survery, please input you responses and help the research

Part 0. Please input your Information
Name: Leo Kung
Title: BIM Center Manager
Company: ABC
Experience in Industry (Years): 7.5
Experience in BIM Uses (Years): 7.5

Part 1. Please input the acceptance according to your experience

Output Variables Engineering Performance Measures			Target	Acceptance Level	Example
Output Variables		Variable Desceiption			
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	0%	**8%**	5%
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	0%	**10%**	15%
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	0%	**15%**	10%
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	0%	**10%**	5%
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	0%	**5%**	3%
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	0%	**5%**	3%
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	0%	**10%**	2%
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	0%	**3%**	1%
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	0%	**3%**	2%
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	0%	**5%**	2%

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Appendix 3
Survey Samples (Project Sample 3-2)

Survery of Engineering Performance Assessment of BIM Implementation Part 2 of 3

Part 2. Please input the significant level according to your experience

Please evaluate the relation between inputs and outputs, input the significant levels in scale of 5,
5= Very Significant
4= Significant
3= Moderate
2= Little Significant
1= Not Significant
0= No Relationship

	Input Variables BIM Virables	Variable Description	Y1 Design Rework (%)	Y2 Detailed Design Schedule Delay (%)	Y3 Detailed Design Cost Overrun (%)	Y4 Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Y5 Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Y6 Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Y7 Construction Hours for Request for Information (RFI) (%)	Y8 Construction Hours for Field Change Request (FCR) (%)	Y9 Start-up Schedule Delay due to Design Deficiencies (%)	Y10 Start-up Cost Overrun due to Design Deficiencies (%)
X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	4	2	2	1	4	4	4	4	1	1
X2	Design Authoring	BIM Software/Tool Used in Design Process	5	4	4	5	3	3	4	4	1	1
X3	Design Review	30/60/90%/100% Model Review	5	4	4	1	1	1	1	1	1	1
X4	Coordination	Clash Detection Process	5	4	4	1	1	1	1	1	1	1
X5	Record Modeling	Physical and Functional Information input in Model	0	3	3	1	1	1	2	2	4	4
X6	Cost Estimating	Generate MTO and Cost Data	2	2	5	5	4	5	2	2	1	1
X7	Phase and 4D Planning	Dimension of Time and Schedule Added	0	4	1	1	4	1	3	3	1	1
X8	Site Analysis-Development	GIS Tools used in Model	3	3	1	1	1	1	2	2	0	0
X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	0	0	0	0	4	4	3	3	1	1
X10	Digital Fabrication	Prefabricate by using BIM Date or Information	3	3	1	5	5	5	3	3	0	0
X11	3D Location and Layout	Function of Utilities to Layout Assemblies	1	1	1	3	3	3	4	4	2	2
X12	Engineering Analysis	Engineering System Simulation used in Model	4	3	2	1	1	1	1	1	1	1
X13	Sustainability Analysis	Sustainable Design Elements included in Model	3	3	3	1	3	3	0	0	0	0
X14	Codes and Standards Compliance	Validation of Codes for Model	1	3	2	5	4	4	0	0	4	4
X15	Construction Systems Design	Contemporary System Analysis in Model	3	3	3	1	4	4	3	3	0	0

Input Variables- BIM Uses

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Appendix 3

Survey Samples (Project Sample 3-3)

Survery of Engineering Performance Assessment of BIM Implementation Part 3 of 3

Part 3. Please input the scales according to your project involved

Input Variables- BIM Uses

	Input Variables BIM Virables	Variable Description	Scale (0-10)
X1	Existing Conditions	Existing Site/Facilities Geometry and Information included in Model	**7**
X2	Design Authoring	BIM Software/Tool Used in Design Process	**10**
X3	Design Review	30/60/90%/100% Model Review	**8**
X4	Coordination	Clash Detection Process	**8**
X5	Record Modeling	Physical and Functional Information input in Model	**8**
X6	Cost Estimating	Generate MTO and Cost Data	**7**
X7	Phase and 4D Planning	Dimension of Time and Schedule Added	**4**
X8	Site Analysis-Development	GIS Tools used in Model	**0**
X9	Site utilization-For Construction	Communication Tool for Construction Plan Added	**2**
X10	Digital Fabrication	Prefabricate by using BIM Date or Information	**1**
X11	3D Location and Layout	Function of Utilities to Layout Assemblies	**1**
X12	Engineering Analysis	Engineering System Simulation used in Model	**2**
X13	Sustainability Analysis	Sustainable Design Elements included in Model	**5**
X14	Codes and Standards Compliance	Validation of Codes for Model	**6**
X15	Construction Systems Design	Contemporary System Analysis in Model	**4**

Output Variables- Engineering Performance Measures

	Output Variables	Variable Desceiption	Project Implemented (%)
Y1	Design Rework (%)	Design Rework Hours/Total Design Hours (%)	**40%**
Y2	Detailed Design Schedule Delay (%)	Days of Design Schedule Delay/Total Design Schedule Days (%)	**30%**
Y3	Detailed Design Cost Overrun (%)	Design Cost Overrun in USD/Total Design Cost in USD (%)	**30%**
Y4	Detailed Designed Quantity Compaired to Final Installed Quantity (%)	Issue for Construction Designed Quantity/Final Installed Quantity (%)	**10%**
Y5	Fabrication and Construction Schedule Delay due to Design Deficiencies (%)	Days of Fabrication and Construction Schedule Delay due to Design Deficiencies/Total Fabrication and Construction Days (%)	**5%**
Y6	Fabrication and Construction Cost Overrun due to Design Deficiencies (%)	Fabrication and Construction Cost Overrun due to Design Deficiencies in USD/Total Fabrication and Construction Cost in USD (%)	**7%**
Y7	Construction Hours for Request for Information (RFI) (%)	Construction Hours for Request for Information (RFI)/Total Construction Hours(%)	**10%**
Y8	Construction Hours for Field Change Request (FCR) (%)	Construction Hours for Field Change Request (FCR)/Total Constrction Hours(%)	**15%**
Y9	Start-up Schedule Delay due to Design Deficiencies (%)	Days of Start-up Schedule Delay due to Design Deficiencies/Total Start-up Days (%)	**2%**
Y10	Start-up Cost Overrun due to Design Deficiencies (%)	Start-up Cost Overrun due to Design Deficiencies in USD/Total Start-up Cost in USD (%)	**2%**

Project Information

Project Name: R City Metro	
Project Sector: Rail	**Project Location: KSA**
Project Contract Type: Lump Sum	**Proejct Contract Value (USD): 3.0B**
Project Schedule: 2013~2020	

Implementation Scale (0-10)
0-Not Implemented, 1-10% Implemented, 2-20% Implemented, 3-30% Implemented, 4-40% Implemented, 5-50% Implemented,
6-60% Implemented, 7-70% Implemented, 8-80% Implemented, 9-90% Implemented, 10-100% Implemented,

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Appendix 4

Correlation Analysis MiniTab Report (1/2)

Correlation: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15, Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8, Y9, Y10

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15
X2	0.6000														
	0.0000														
X3	0.5150	0.8970													
	0.0000	0.0000													
X4	0.2110	0.7310	0.7160												
	0.1320	0.0000	0.0000												
X5	0.7040	0.6200	0.5590	0.4460											
	0.0000	0.0000	0.0000	0.0010											
X6	0.3610	0.5400	0.5860	0.5620	0.6780										
	0.0090	0.0000	0.0000	0.0000	0.0000										
X7	0.4510	0.7120	0.7530	0.7020	0.8160	0.6950									
	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000									
X8	0.4340	0.3670	0.3050	0.1970	0.3160	0.1960	0.2800								
	0.0010	0.0070	0.0280	0.1620	0.0220	0.1640	0.0450								
X9	-0.1450	0.0680	0.0070	0.1410	-0.1810	-0.0090	-0.0630	0.6090							
	0.3060	0.6340	0.9630	0.3180	0.1990	0.9470	0.6570	0.0000							
X10	0.3940	0.5390	0.5260	0.5940	0.6230	0.8740	0.6670	0.2550	0.0870						
	0.0040	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0690	0.5410						
X11	-0.0680	0.0420	-0.0390	0.0310	-0.1460	-0.0720	-0.0900	0.6290	0.8690	0.0120					
	0.6330	0.7680	0.7820	0.8270	0.3000	0.6100	0.5270	0.0000	0.0000	0.9340					
X12	0.3020	0.6630	0.6240	0.6780	0.3540	0.2900	0.5750	0.0980	-0.0680	0.3420	-0.1830				
	0.0290	0.0000	0.0000	0.0000	0.0100	0.0370	0.0000	0.4900	0.6300	0.0130	0.1940				
X13	0.8590	0.5810	0.5310	0.2970	0.7710	0.4870	0.5990	0.4940	-0.1000	0.4480	-0.0350	0.3250			
	0.0000	0.0000	0.0000	0.0330	0.0000	0.0000	0.0000	0.0000	0.4810	0.0010	0.8040	0.0190			
X14	0.6670	0.5290	0.5700	0.3750	0.8460	0.6190	0.7520	0.2700	-0.2830	0.5120	-0.2230	0.3610	0.8150		
	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0000	0.0530	0.0420	0.0000	0.1120	0.0090	0.0000		
X15	0.3720	0.5850	0.5550	0.6500	0.6440	0.8700	0.6810	0.2450	0.0930	0.8880	0.0680	0.2740	0.4440	0.5500	
	0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0800	0.5130	0.0000	0.6340	0.0490	0.0010	0.0000	
Y1	-0.3570	-0.7480	-0.7180	-0.8090	-0.5180	-0.6580	-0.7090	-0.2510	-0.1160	-0.7080	0.0310	-0.7340	-0.4210	-0.4060	-0.6490
	0.0090	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0730	0.4140	0.0000	0.8260	0.0000	0.0020	0.0030	0.0000
Y2	-0.7360	-0.7140	-0.7060	-0.3750	-0.7540	-0.5800	-0.6610	-0.4110	0.1780	-0.5160	0.1270	-0.3380	-0.7310	-0.7160	-0.5170
	0.0000	0.0000	0.0000	0.0060	0.0000	0.0000	0.0000	0.0030	0.2060	0.0000	0.3710	0.0140	0.0000	0.0000	0.0000
Y3	-0.3220	-0.7430	-0.7430	-0.8500	-0.5260	-0.6840	-0.7300	-0.2880	-0.0990	-0.7070	0.0540	-0.7040	-0.4270	-0.4580	-0.6470
	0.0200	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0380	0.4870	0.0000	0.7030	0.0000	0.0020	0.0010	0.0000
Y4	0.3610	0.7420	0.7020	0.7450	0.4920	0.2990	0.7020	0.2950	0.1270	0.3110	0.0870	0.8140	0.4240	0.4410	0.3680
	0.0090	0.0000	0.0000	0.0000	0.0000	0.0310	0.0000	0.0340	0.3700	0.0250	0.5410	0.0000	0.0020	0.0010	0.0070
Y5	-0.0600	-0.0790	-0.0960	0.0030	0.0280	-0.0380	-0.0260	-0.7400	-0.7290	-0.1460	-0.7180	0.1580	-0.1020	0.0740	-0.0940
	0.6750	0.5780	0.4990	0.9840	0.8460	0.7870	0.8560	0.0000	0.0000	0.3030	0.0000	0.2630	0.4710	0.6020	0.5050
Y6	-0.2140	-0.5600	-0.5320	-0.7000	-0.4060	-0.7280	-0.5380	-0.1000	-0.1010	-0.7490	0.0020	-0.4330	-0.2400	-0.2460	-0.7370
	0.1270	0.0000	0.0000	0.0000	0.0030	0.0000	0.0000	0.4790	0.4770	0.0000	0.9900	0.0010	0.0870	0.0790	0.0000
Y7	-0.7110	-0.5630	-0.6000	-0.3080	-0.7040	-0.5010	-0.5700	-0.4680	0.0870	-0.4350	0.1210	-0.2560	-0.7300	-0.7370	-0.4100
	0.0000	0.0000	0.0000	0.0260	0.0000	0.0000	0.0000	0.0000	0.5380	0.0010	0.3920	0.0670	0.0000	0.0000	0.0030
Y8	-0.0790	-0.5400	-0.5840	-0.7180	-0.3380	-0.7280	-0.5230	-0.1010	-0.1080	-0.7090	0.0390	-0.3790	-0.2000	-0.2730	-0.7130
	0.5800	0.0000	0.0000	0.0000	0.0140	0.0000	0.0000	0.4780	0.4470	0.0000	0.7860	0.0060	0.1540	0.0500	0.0000
Y9	-0.3870	-0.4880	-0.5860	-0.4090	-0.7020	-0.7030	-0.7030	-0.2090	0.1780	-0.5930	0.1150	-0.2300	-0.4760	-0.7160	-0.6100
	0.0050	0.0000	0.0000	0.0030	0.0000	0.0000	0.0000	0.1370	0.2070	0.0000	0.4150	0.1020	0.0000	0.0000	0.0000
Y10	-0.4380	-0.5500	-0.5700	-0.4220	-0.7660	-0.7560	-0.7040	-0.1960	0.1570	-0.7010	0.1080	-0.2090	-0.4820	-0.6960	-0.7110
	0.0010	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000	0.1630	0.2660	0.0000	0.4470	0.1360	0.0000	0.0000	0.0000

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Appendix 4
Correlation Analysis MiniTab Report (2/2)

Correlation: Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8, Y9, Y10									
	Y1	**Y2**	**Y3**	**Y4**	**Y5**	**Y6**	**Y7**	**Y8**	**Y9**
Y2	0.5540								
	0.0000								
Y3	0.9510	0.5620							
	0.0000	0.0000							
Y4	-0.7010	-0.4250	-0.6820						
	0.0000	0.0020	0.0000						
Y5	0.0970	0.1730	0.1370	-0.0220					
	0.4920	0.2210	0.3330	0.8770					
Y6	0.8260	0.3730	0.7900	-0.3800	0.0360				
	0.0000	0.0060	0.0000	0.0050	0.7990				
Y7	0.3810	0.8260	0.4590	-0.3370	0.1460	0.2590			
	0.0050	0.0000	0.0010	0.0150	0.3010	0.0640			
Y8	0.7920	0.4030	0.8380	-0.3440	0.1040	0.8970	0.3220		
	0.0000	0.0030	0.0000	0.0130	0.4630	0.0000	0.0200		
Y9	0.4560	0.7390	0.5240	-0.2770	0.0880	0.4300	0.6950	0.4920	
	0.0010	0.0000	0.0000	0.0470	0.5340	0.0010	0.0000	0.0000	
Y10	0.4770	0.7660	0.5100	-0.2780	0.0770	0.4540	0.6680	0.5090	0.8870
	0.0000	0.0000	0.0000	0.0460	0.5880	0.0010	0.0000	0.0000	0.0000

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Appendix 5
Regression Analysis MiniTab Report (1/5)

Regression Analysis: Y1 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.1, α to remove = 0.1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	2591.9	863.96	70.37	0.000
X4	1	125.6	125.63	10.23	0.002
X10	1	306.2	306.21	24.94	0.000
X12	1	253.7	253.66	20.66	0.000
Error	48	589.3	12.28		
Total	51	3181.2			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3.50401	81.47%	80.32%	78.61%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	26.96	1.20	22.44	0.000	
X4	-0.815	0.255	-3.20	0.002	2.55
X10	-1.032	0.207	-4.99	0.000	1.56
X12	-1.629	0.358	-4.55	0.000	1.87

Regression Equation

Y1 = 26.96 - 0.815 X4 - 1.032 X10 - 1.629 X12

Fits and Diagnostics for Unusual Observations

Obs	Y1	Fit	Resid	Std Resid	
3	20.00	13.27	6.73	2.06	R
21	3.00	11.04	-8.04	-2.37	R
31	2.00	9.36	-7.36	-2.14	R

R Large residual

Regression Analysis: Y2 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.1, α to remove = 0.1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	592.23	148.057	36.82	0.000
X1	1	17.53	17.528	4.36	0.042
X3	1	75.93	75.927	18.88	0.000
X4	1	17.12	17.116	4.26	0.045
X5	1	51.05	51.046	12.69	0.001
Error	47	189.00	4.021		
Total	51	781.23			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.00533	75.81%	73.75%	70.49%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	12.811	0.740	17.32	0.000	
X1	-0.303	0.145	-2.09	0.042	2.42
X3	-0.765	0.176	-4.35	0.000	2.87
X4	0.293	0.142	2.06	0.045	2.42
X5	-0.493	0.138	-3.56	0.001	2.43

Regression Equation

Y2 = 12.811 - 0.303 X1 - 0.765 X3 + 0.293 X4 - 0.493 X5

Fits and Diagnostics for Unusual Observations

Obs	Y2	Fit	Resid	Std Resid	
52	16.000	11.835	4.165	2.17	R

R Large residual

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Appendix 5

Regression Analysis MiniTab Report (2/5)

Regression Analysis: Y3 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	2697.7	899.25	75.68	0.000
X4	1	273.4	273.42	23.01	0.000
X10	1	239.1	239.14	20.13	0.000
X12	1	132.8	132.80	11.18	0.002
Error	48	570.3	11.88		
Total	51	3268.1			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3.44699	82.55%	81.46%	79.65%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	27.31	1.18	23.12	0.000	
X4	-1.202	0.251	-4.80	0.000	2.55
X10	-0.912	0.203	-4.49	0.000	1.56
X12	-1.179	0.353	-3.34	0.002	1.87

Regression Equation

Y3 = 27.31 - 1.202 X4 - 0.912 X10 - 1.179 X12

Fits and Diagnostics for Unusual Observations

Obs	Y3	Fit	Resid	Std Resid	
17	13.00	20.41	-7.41	-2.23	R
31	3.00	9.92	-6.92	-2.05	R

R Large residual

Regression Analysis: Y4 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	345.052	69.010	56.51	0.000
X4	1	8.438	8.438	6.91	0.012
X7	1	32.038	32.038	26.23	0.000
X10	1	21.702	21.702	17.77	0.000
X11	1	17.976	17.976	14.72	0.000
X12	1	53.667	53.667	43.94	0.000
Error	46	56.179	1.221		
Total	51	401.231			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.10512	86.00%	84.48%	82.26%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	90.823	0.497	182.71	0.000	
X4	0.2268	0.0863	2.63	0.012	2.94
X7	0.3865	0.0755	5.12	0.000	2.64
X10	-0.3105	0.0737	-4.22	0.000	2.00
X11	0.2506	0.0653	3.84	0.000	1.10
X12	0.801	0.121	6.63	0.000	2.14

Regression Equation

Y4 = 90.823 + 0.2268 X4 + 0.3865 X7 - 0.3105 X10 + 0.2506 X11 + 0.801 X12

Fits and Diagnostics for Unusual Observations

Obs	Y4	Fit	Resid	Std Resid	
27	100.000	97.889	2.111	2.01	R
36	91.000	93.794	-2.794	-2.63	R

R Large residual

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Appendix 5

Regression Analysis MiniTab Report (3/5)

Regression Analysis: Y5 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	1773.06	591.02	37.62	0.000
X8	1	401.96	401.96	25.58	0.000
X9	1	254.44	254.44	16.19	0.000
X12	1	79.17	79.17	5.04	0.029
Error	48	754.17	15.71		
Total	51	2527.23			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
3.96382	70.16%	68.29%	64.79%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	21.34	1.66	12.85	0.000	
X8	-1.312	0.259	-5.06	0.000	1.64
X9	-1.082	0.269	-4.02	0.000	1.63
X12	0.678	0.302	2.24	0.029	1.04

Regression Equation

Y5 = 21.34 - 1.312 X8 - 1.082 X9 + 0.678 X12

Fits and Diagnostics for Unusual Observations

Obs	Y5	Fit	Resid	Std Resid	
28	5.00	13.74	-8.74	-2.38	R

R Large residual

Regression Analysis: Y6 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	495.12	165.040	43.12	0.000
X4	1	89.60	89.603	23.41	0.000
X6	1	162.22	162.215	42.38	0.000
X14	1	51.48	51.483	13.45	0.001
Error	48	183.71	3.827		
Total	51	678.83			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.95633	72.94%	71.25%	68.09%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	10.765	0.673	16.00	0.000	
X4	-0.521	0.108	-4.84	0.000	1.46
X6	-0.755	0.116	-6.51	0.000	2.04
X14	0.441	0.120	3.67	0.001	1.62

Regression Equation

Y6 = 10.765 - 0.521 X4 - 0.755 X6 + 0.441 X14

Fits and Diagnostics for Unusual Observations

Obs	Y6	Fit	Resid	Std Resid	
3	10.000	5.007	4.993	2.68	R
4	5.000	0.528	4.472	2.38	R
34	5.000	8.888	-3.888	-2.05	R

R Large residual

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Appendix 5
Regression Analysis MinitTab Report (4/5)

Regression Analysis: Y7 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	419.65	139.883	33.55	0.000
X8	1	81.66	81.657	19.59	0.000
X11	1	34.60	34.596	8.30	0.006
X14	1	107.50	107.497	25.79	0.000
Error	48	200.10	4.169		
Total	51	619.75			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.04176	67.71%	65.69%	62.17%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	10.096	0.822	12.28	0.000	
X8	-0.706	0.160	-4.43	0.000	2.34
X11	0.501	0.174	2.88	0.006	2.28
X14	-0.611	0.120	-5.08	0.000	1.49

Regression Equation

Y7 = 10.096 - 0.706 X8 + 0.501 X11 - 0.611 X14

Fits and Diagnostics for Unusual Observations

Obs	Y7	Fit	Resid	Std Resid	
24	4.000	8.670	-4.670	-2.40	R
43	2.000	7.735	-5.735	-2.93	R
52	14.000	9.075	4.925	2.51	R

R Large residual

Regression Analysis: Y8 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	330.24	110.082	44.21	0.000
X4	1	71.35	71.354	28.66	0.000
X5	1	28.96	28.956	11.63	0.001
X6	1	98.26	98.262	39.47	0.000
Error	48	119.51	2.490		
Total	51	449.75			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.57788	73.43%	71.77%	69.45%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	8.811	0.531	16.58	0.000	
X4	-0.4674	0.0873	-5.35	0.000	1.48
X5	0.3261	0.0956	3.41	0.001	1.87
X6	-0.6091	0.0969	-6.28	0.000	2.19

Regression Equation

Y8 = 8.811 - 0.4674 X4 + 0.3261 X5 - 0.6091 X6

Fits and Diagnostics for Unusual Observations

Obs	Y8	Fit	Resid	Std Resid	
4	3.000	-0.040	3.040	2.02	R
31	2.000	5.201	-3.201	-2.05	R
34	4.000	7.126	-3.126	-2.04	R

R Large residual

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Appendix 5
Regression Analysis MiniTab Report (5/5)

Regression Analysis: Y9 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	481.91	160.637	29.96	0.000
X6	1	77.91	77.910	14.53	0.000
X13	1	22.03	22.032	4.11	0.048
X14	1	99.00	99.004	18.46	0.000
Error	48	257.40	5.362		
Total	51	739.31			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.31569	65.18%	63.01%	60.33%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	10.551	0.627	16.84	0.000	
X6	-0.467	0.122	-3.81	0.000	1.62
X13	0.368	0.181	2.03	0.048	2.99
X14	-0.923	0.215	-4.30	0.000	3.69

Regression Equation

Y9 = 10.551 - 0.467 X6 + 0.368 X13 - 0.923 X14

Fits and Diagnostics for Unusual Observations

Obs	Y9	Fit	Resid	Std Resid	
14	3.000	8.050	-5.050	-2.25	R
33	7.000	7.267	-0.267	-0.13	X
44	18.000	9.529	8.471	3.76	R
52	18.000	9.529	8.471	3.76	R

R Large residual
X Unusual X

Regression Analysis: Y10 versus X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15

Stepwise Selection of Terms

α to enter = 0.05, α to remove = 0.05

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	326.85	163.424	54.63	0.000
X5	1	56.24	56.237	18.80	0.000
X6	1	49.01	49.013	16.38	0.000
Error	49	146.59	2.992		
Total	51	473.44			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.72966	69.04%	67.77%	64.55%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	9.201	0.442	20.83	0.000	
X5	-0.452	0.104	-4.34	0.000	1.85
X6	-0.3954	0.0977	-4.05	0.000	1.85

Regression Equation

Y10 = 9.201 - 0.452 X5 - 0.3954 X6

Fits and Diagnostics for Unusual Observations

Obs	Y10	Fit	Resid	Std Resid	
14	2.000	6.095	-4.095	-2.50	R
28	1.000	4.401	-3.401	-2.08	R
44	12.000	8.354	3.646	2.16	R
52	12.000	8.354	3.646	2.16	R

R Large residual

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Appendix 6
Coding of Machine Learning Modeling in Python with Keras (1/6)

The code is to establish the main equation of MLMP and predict after the MLMP equation is established.

```
# cnn_pecl.py
# coding: utf-8
import os
import numpy as np
from private.pecl.common_pecl import load_data, getTrainAndTestData, getTrainAndTestData6
from keras.utils import np_utils
from keras.models import load_model
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
import pandas as pd
from private.pecl.common_pecl import show_train_history

if __name__ == '__main__':

np.random.seed(10)
pathName = os.path.dirname(os.path.dirname(os.path.dirname(os.path.abspath(__file__)))) + "\\source\\"
dirName = "peclSave\\"
fileName = pathName + dirName + "data.pickle"
x, yy1, yy2, yy3, yy4, yy5, yy6, yy7, yy8, yy9, yy10 = load_data(fileName)
y = [yy1, yy2, yy3, yy4, yy5, yy6, yy7, yy8, yy9, yy10]
index = 9
outputValue = 5
(x_train, y_train), (x_test, y_test) = getTrainAndTestData(x,y[index], probility=0.85)
# (x_train, y_train), (x_test, y_test) = getTrainAndTestData6(x,y[index], probility=0.85)
x_train4D = x_train.reshape(x_train.shape[0],3,5,1).astype('float32')
x_test4D = x_test.reshape(x_test.shape[0],3,5,1).astype('float32')
print(x_train4D.shape, x_test4D.shape)

x_train4D_normalize = x_train4D
x_test4D_normalize = x_test4D
y_trainOneHot = np_utils.to_categorical(y_train)
y_testOneHot = np_utils.to_categorical(y_test)

# model = load_model(pathName + dirName + "y" + str(index + 1) + "model.h5")

model = Sequential()

model.add(Conv2D(filters=16, kernel_size=(2,2), padding='same', input_shape=(3,5,1), activation='relu'))
model.add(MaxPooling2D(pool_size=(1,1)))
```


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```
model.add(Conv2D(filters=16, kernel_size=(2,2), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(1,1)))

model.add(Dropout(0.05))

model.add(Flatten())

model.add(Dense(units=32, activation='relu'))

model.add(Dropout(0.05))

model.add(Dense(units=outputValue, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

train_history = model.fit(x=x_train4D_normalize, y=y_trainOneHot, validation_split=0.2, epochs=2000,
batch_size=5000, verbose=2)

model.save(pathName + dirName + "y" + str(index + 1) + "model.h5")

show_train_history(train_history, 'acc', 'val_acc', pathName + dirName + "y" + str(index + 1) + "_acc.jpg")
show_train_history(train_history, 'loss', 'val_loss', pathName + dirName + "y" + str(index + 1) + "_loss.jpg")

# scores = model.evaluate(x_test4D_normalize, y_testOneHot)
# print()
# print('accuracy = ', scores[1])

# prediction = model.predict_classes(x_test4D_normalize)
predictionAll = model.predict_classes(x.reshape(x.shape[0],3,5,1).astype('float32'))
print(x.shape, predictionAll)
np.savetxt(pathName + dirName + "y" + str(index + 1) + "_prediction.txt", predictionAll)
```


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Appendix 6
Coding of Machine Learning Modeling in Python with Keras (2/6)

The code is created to include:

1. Read the original data (the original EXCEL data has been converted into a pickle file)
2. Divide the original data into training data and test data for MLMP training
3. Establish various verification methods (such as least square method R-square, mean square error MSE, root mean square error RMSE)

```
# common_pecl.py
# coding: utf-8
import os, pickle
import numpy as np
import matplotlib.pylab as plt
from keras import backend as K

def load_data(fileName):
    with open(fileName, 'rb') as f:
    x, y1, y2, y3, y4, y5, y6, y7, y8, y9, y10 = pickle.load(f)
    return x, y1, y2, y3, y4, y5, y6, y7, y8, y9, y10

def load_rawdata(fileName):
    with open(fileName, 'rb') as f:
    x, y = pickle.load(f)
    return x, y

def getTrainAndTestData(x, y, probility=0.85):
    msk = np.random.rand(len(x)) < probility
    x_train = x[msk]; y_train = y[msk]
    x_test    = x[~msk]; y_test = y[~msk]
    return (x_train, y_train), (x_test, y_test)

def getTrainAndTestData6(x, y, probility=0.85):
    xx = np.concatenate((x[1:14], x[15:]))
    yy = np.concatenate((y[1:14], y[15:]))
    msk = np.random.rand(len(yy)) < probility
    x_train = np.concatenate((xx[msk], x[[0]])); y_train = np.concatenate((yy[msk], y[[0]]))
    x_test    = np.concatenate((xx[~msk], x[[14]])); y_test = np.concatenate((yy[~msk], y[[14]]))

    return (x_train, y_train), (x_test, y_test)

def show_train_history(train_history, train, validation, saveName):
    plt.plot(train_history.history[train])
    plt.plot(train_history.history[validation])
    plt.title('Train History')
    plt.ylabel(train)
    plt.xlabel('Epoch')
    plt.legend(['train', 'validation'], loc='upper left')
    # plt.show()
```


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```
    plt.savefig(saveName, dpi=300, bbox_inches='tight')

def r_square(y_true, y_pred):
    SS_res =    K.sum(K.square(y_true-y_pred))
    SS_tot = K.sum(K.square(y_true - K.mean(y_true)))
    return (1 - SS_res/(SS_tot + K.epsilon()))

def rsqrt(y_true, y_pred):
    correlation_matrix = np.corrcoef(y_true, y_pred)
    correlation_xy = correlation_matrix[0,1]
    r_squared = correlation_xy**2
    return r_squared

def mse(y_true, y_pred):
    return np.sum(np.power((y_true.reshape(-1,1) - y_pred.reshape(-1,1)),2))/len(y_true.reshape(-1,1))

def rmse(y_true, y_pred):
    return np.sqrt(mse(y_true, y_pred))

def mae(y_true, y_pred):
    return np.sum(np.abs(y_true.reshape(-1,1) - y_pred.reshape(-1,1)))/len(y_true.reshape(-1,1))

if __name__ == '__main__':
    pathName = os.path.dirname(os.path.dirname(os.path.dirname(os.path.abspath(__file__)))) +
"\\source\\"
    dirName = "peclSave\\"
    fileName = pathName + dirName + "data.pickle"
    x, y1, y2, y3, y4, y5, y6, y7, y8, y9, y10 = load_data(fileName)
    y = y6
    (x_train, y_train), (x_test, y_test) = getTrainAndTestData6(x, y, probility=0.85)

    print(x_train.shape, y_test.shape)
```


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Appendix 6

Coding of Machine Learning Modeling in Python with Keras (3/6)

The code is to import the original data of the EXCEL file and convert the data into a pickle file for subsequent modeling (the main reason is that it is time-consuming to read the EXCEL file).

```
# DataProcessing.py
# coding: utf-8
import os, pickle
import numpy as np

def getFormat():
    a = 0
    return a

def getTrainAndTestData(x, y, probility=0.85):

    msk = np.random.rand(len(x)) < probility
    x_train = x[msk]; y_train = y[msk]
    x_test    = x[~msk]; y_test = y[~msk]
    return (x_train, y_train), (x_test, y_test)

if __name__ == "__main__":

pathName = os.path.dirname(os.path.dirname(os.path.dirname(os.path.abspath(__file__)))) + "\\source\\"
    dirName    = "pecl\\"
    outputFileDir    = "peclSave\\"
    outputFileName = "data.pickle"
    fileName = "data.txt"

    with open(pathName + dirName + fileName, 'r') as file:
        lines = file.readlines()

    x    = []; y1 = []; y2 = []; y3 = []; y4 = []; y5 = []
    y6 = []; y7 = []; y8 = []; y9 = []; y10 = []
    for idx, line in enumerate(lines):
        x.append([float(i) for i in line.split(",")[0:15]])
        y1.append(float(line.split(",")[15]))
        y2.append(float(line.split(",")[16]))
        y3.append(float(line.split(",")[17]))
        y4.append(float(line.split(",")[18]))
        y5.append(float(line.split(",")[19]))
        y6.append(float(line.split(",")[20]))
        y7.append(float(line.split(",")[21]))
        y8.append(float(line.split(",")[22]))
        y9.append(float(line.split(",")[23]))
```


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```
        y10.append(float(line.split(",")[24]))

  x = np.array(x); y1 = np.array(y1); y2 = np.array(y2); y3 = np.array(y3)
y4 = np.array(y4); y5 = np.array(y5); y6 = np.array(y6); y7 = np.array(y7)
y8 = np.array(y8); y9 = np.array(y9); y10 = np.array(y10)

with open(pathName + outputFileDir + outputFileName, 'wb') as handle:
        pickle.dump((x, y1, y2, y3, y4, y5, y6, y7, y8, y9, y10), handle)

with open(pathName + outputFileDir + outputFileName, 'rb') as f:
        xx, yy1, yy2, yy3, yy4, yy5, yy6, yy7, yy8, yy9, yy10 = pickle.load(f)

(x_train, y_train), (x_test, y_test) = getTrainAndTestData(xx, yy1, probility=0.9)

print(x_train.shape, y_train.shape)
```


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Appendix 6
Coding of Machine Learning Modeling in Python with Keras (4/6)

The code is to save all the parameters into the file (.h5) after completing the MLMP simulation and perform multiple verifications to find the best MLMP model (the main reason is that the random distribution of the normal distribution is placed at the beginning of the establishment of the MLMP model. The numerical value is not the best MLMP mode after one training is completed, so it is necessary to find the final MLMP mode after multiple calculations).

```
# LinearRegression.py
#coding = utf-8
# Multilayer Perceptron, MLP
import os
from private.pecl.common_pecl import load_rawdata, getTrainAndTestData, rsqrt, mse, rmse, mae
import numpy as np
from keras.models import load_model
from keras.models import Sequential
from keras.layers import Dense

if __name__ == "__main__":

    np.random.seed(29999)
    pathName = os.path.dirname(os.path.dirname(os.path.dirname(os.path.abspath(__file__)))) +
"\\source\\"
    dirName = "peclSave\\"
    fileName = pathName + dirName + "rawdata.pickle"

    x, y = load_rawdata(fileName)
    (x_train, y_train), (x_test, y_test) = getTrainAndTestData(x,y, probility=0.95)

    print(x_train.shape, x_test.shape)
    print(y_train.shape, y_test.shape)

# model = load_model(pathName + dirName + "linear_regression_model.h5")

model = Sequential()
model.add(Dense(output_dim=10,input_dim=15))
# model.add(Dense(units=15, input_shape=(15,), activation='relu'))
# model.add(Dense(units=40, activation='relu'))
# model.add(Dense(units=10, activation='relu'))

# model.compile(loss='mse',optimizer='adam', metrics=[r_square])
model.compile(loss='mse',optimizer='sgd')

print("start training")
for step in range(100001):
    cost = model.train_on_batch(x_train, y_train)
    if step % 2000 == 0:
        print("train cost: {}".format(cost))
```


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```
print("start testing")
cost = model.evaluate(x_test, y_test, batch_size=4000)
print("test cost: {}".format(cost))
W , b = model.layers[0].get_weights()
print("Weights = {}, bias = {}".format(W,b))

model.save(pathName + dirName + "linear_regression_model.h5")

y_pred = model.predict(x) # y predict
print(y_test.shape, y_pred.shape)
print("y_pred = {}".format(y_pred))

print("R2 = {}, MSE = {}, RMSE = {}, MAE = {}".format(rsqrt(y, y_pred), mse(y, y_pred), rmse(y, y_pred),
mae(y, y_pred)))
```


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Appendix 6
Coding of Machine Learning Modeling in Python with Keras (5/6)

```
# LinearRegressionTest.py
#coding = utf-8
import numpy as np
from keras.models import Sequential
from keras.layers import Dense
from private.pecl.common_pecl import r_square

np.random.seed(1337)
X1 = np.linspace(-10,10,200)
np.random.shuffle(X1)
X2 = np.linspace(-20,5,200)
np.random.shuffle(X2)
Y1 = 0.5 * (X1 + X2) + 2 + np.random.normal(0, 0.05, (200,))
Y2 = 0.5 * (X1 + X2) *0.15 + np.random.normal(0, 0.05, (200,))

X = np.concatenate(([X1],[X2]), axis=0)
X = X.T
Y = np.concatenate(([Y1],[Y2]), axis=0)
Y=Y.T
print(X.shape, Y.shape)
X_train, Y_train = X[:160], Y[:160]
X_test, Y_test = X[160:], Y[160:]

model = Sequential()
model.add(Dense(output_dim=2,input_dim=2))

model.compile(loss='mse',optimizer='adam', metrics=[r_square])

print("start training")
for step in range(10001):
    cost = model.train_on_batch(X_train, Y_train)    #
    if step % 500 == 0: print("train cost: {}".format(cost))

print("start testing")
cost = model.evaluate(X_test, Y_test, batch_size=40)
print("test cost: {}".format(cost))
W , b = model.layers[0].get_weights()
print("Weights = {}, bias = {}".format(W,b))

Y_pred = model.predict(X_test) # Y predict
```


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Appendix 6
Coding of Machine Learning Modeling in Python with Keras (6/6)

```
# RawdataProcessing.py
# coding: utf-8
import os, pickle
import numpy as np

def getTrainAndTestData(x, y, probility=0.85):
    msk = np.random.rand(len(x)) < probility
    x_train = x[msk]; y_train = y[msk]
    x_test    = x[~msk]; y_test = y[~msk]
    return (x_train, y_train), (x_test, y_test)

if __name__ == "__main__":

    pathName = os.path.dirname(os.path.dirname(os.path.dirname(os.path.abspath(__file__)))) +
"\\source\\"
    dirName    = "pecl\\"
    outputFileDir    = "peclSave\\"
    outputFileName = "rawdata.pickle"
    fileName = "rawdata.txt"

    with open(pathName + dirName + fileName, 'r') as file: lines = file.readlines()

    x    = []; y = []
    for idx, line in enumerate(lines):
        x.append([float(i) for i in line.split(",")[0:15]])
        y.append([float(i) for i in line.split(",")[15:]])

    x = np.array(x); y = np.array(y)
    print(x)
    print(y)
    with open(pathName + outputFileDir + outputFileName, 'wb') as handle:
        pickle.dump((x, y), handle)

    with open(pathName + outputFileDir + outputFileName, 'rb') as f:
        xx, yy = pickle.load(f)

    (x_train, y_train), (x_test, y_test) = getTrainAndTestData(xx, yy, probility=0.9)

    print(x_train.shape, y_train.shape)
    print(x_test.shape, y_test.shape)
```


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Appendix 7

F-test and Correlation for LR and MLMP Models (1/2)

F-Test Two-Sample for Variances

Project Test No 1

	LR Outputs	MLMP Outputs
Mean	0.1993	0.2086
Variance	0.070278011	0.069032267
Observations	10	10
df	9	9
F	1.018045828	
P(F<=f) one-tail	0.48959128	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test No 1

	LR Outputs	MLMP Outputs
LR Outputs	1	
MLMP Outputs	0.99911627	1

F-Test Two-Sample for Variances

Project Test No 36

	LR Outputs	MLMP Outputs
Mean	0.2101	0.2149
Variance	0.068458767	0.067246322
Observations	10	10
df	9	9
F	1.0180299	
P(F<=f) one-tail	0.489600384	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test No 36

	LR Outputs	MLMP Outputs
LR Outputs	1	
MLMP Outputs	0.999889582	1

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Appendix 7
F-test and Correlation for LR and MLMP Models (2/2)

F-Test Two-Sample for Variances

Project Test Set No 1

	LP Outputs in Average	MLMP Outputs in Average
Mean	0.1732	0.1737
Variance	0.077209067	0.077107344
Observations	10	10
df	9	9
F	1.001319229	
P(F<=f) one-tail	0.499232646	
F Critical one-tail	3.178893104	

Correlation Analysis

Project Test Set No 1

	LP Outputs in Average	MLMP Outputs in Average
LR Outputs	1	
MLMP Outputs	0.999868813	1

F-Test Two-Sample for Variances

Project Test Set No 2

	LP Outputs in Average	MLMP Outputs in Average
Mean	0.1661	0.1658
Variance	0.079457656	0.079672178
Observations	10	10
df	9	9
F	0.997307439	
P(F<=f) one-tail	0.498430679	
F Critical one-tail	3.145749062	

Correlation Analysis

Project Test Set No 2

	LP Outputs in Average	MLMP Outputs in Average
LR Outputs	1	
MLMP Outputs	0.999908671	1

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