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FORECASTING THE NET COSTS TO ORGANISATIONS OF BUILDING INFORMATION MODELLING (BIM) IMPLEMENTATION AT DIFFERENT LEVELS OF DEVELOPMENT (LOD)

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SUMMARY*: Numerous frameworks and tools have been proposed in the literature to assess the performance of BIM implementation in the Architecture, Engineering and Construction (AEC). However, there is yet a lack of ex-ante evaluation methods that forecast BIM implementation costs. This study aims to propose an ex-ante evaluation method to forecast the net costs of BIM implementation at different Level of Development (LOD). The proposed method is expected to assist decision makers to find the most cost-saving LOD when investing resources for implementing BIM, from an organisational perspective. The proposed method relies on an Artificial Neural Network (ANN) for each type of implementation costs and benefits. The findings suggest that decision makers need to evaluate an organisation's competency and their implemented BIM applications when choosing the BIM implementation level of BIM. Furthermore, the results show that a higher BIM implementation level does not often secure more benefits. Over 30 features were included in the ANNs with results indicating the possibility of expanding the feature set to obtain more accurate results.*

KEYWORDS: *BIM implementation, Ex-ante evaluation, BIM benefit, BIM cost*

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1 INTRODUCTION

As one of the key Information Technology (IT) developments in the construction industry, Building Information Modelling (BIM) has been gaining immense growth in its applications, particularly due to its advantages in improving construction efficiency and minimising design error (Keskin et al., 2019). Earlier research on BIM functions and applications tend to focus more on visualising the project design in a multi-dimensional environment (Azhar, 2011; Inyim et al., 2015), and on the cost and benefit analysis regarding BIM implementation (Lu et al., 2014; Barlish et al., 2012). Several studies attempted to evaluate BIM implementation performance from different perspectives, including Return on Investment (ROI) and the maturity of BIM implementation (National Institute of Building Sciences 2007).

There are two types of evaluation methods for BIM adoption, depending on when the evaluation is performed. Ex-ante (predictive) evaluation is performed to forecast and evaluate the impact of future occurrences on decision making (Remenyi et al., 2012). In comparison, ex-post evaluation assesses the value of existing occurrences on the decisions that are to be made (Myrdal, 1939). Ex-post evaluation of BIM implementation has been frequently reported via case studies, for example in Ham et al. (2018) and Manning et al. (2008) Ex-ante evaluation plays a critical role in project initiation and project success evaluation (European Commission 2001), yet has not been adopted for evaluation of BIM implementation.

Previous studies have proposed numerous metrics to evaluate BIM performance, including project-based metrics (Sacks et al., 2005) and technological or organisational maturity metrics (Sebastian et al., 2010; Succar et al., 2015). Du et al. (2014) proposed a qualitative tool to assess BIM performance by analysing the frequencies of deriving project data among project stakeholders. Level of Development (LOD) is one of the most frequently used criteria to describe the detail level embedded in digital building models created via BIM (American Institute of Architect 2007). A higher LOD can result in more computational costs, due to high volumes of information (NATSPEC, 2013); while, a lower LOD has restrictions on performing further building analysis, for example, life-cycle assessment (Santos et al., 2017). In addition, public projects in some countries have specific requirements for LOD implementation (UK Cabinet Office, 2011). Hence, choosing a suitable BIM implementation level can be a problem for decision makers. In addition, literature suggests that different BIM applications (i.e. project design and procurement management) have different levels of requirement when it comes to model's data richness (Song et al., 2017; Grytting et al., 2017). Therefore, this study aims to propose an ex-ante evaluation method for decision-makers to assess the level at which BIM should be implemented, subject to the utilisation of specific BIM applications.

In this work, artificial neural networks (ANNs) will be utilised to make predictions of the organisations' level of implementation of BIM, through specifying the LOD level to focus on. The use of ANN offers a number of advantages, compared to other approaches such as support vector machines (SVMs). Firstly, the ANN is a parametric model whereas most SVMs are non-parametric (Smeraldi, 2002), hence the SVM models can be very complexed as the training data increased. Secondly, artificial neural network have the advantage of being able to solve complex non-linear problems (Boussabaine, 1996; Rumelhart et al., 1994). As a result, ANNs are a better option when the research data does not indicate strong linear relationships.

ANNs have been used previously in different domains of AEC research to predict key project performance indicators, including costs of construction projects (Wilmot Chester et al., 2005). In this study, through using ANNs as a prediction tool, a generic approach is derived to conduct cost-benefit analysis for BIM implementation at organisations. Given the high expenses of BIM implementation and its low ROI (Bernstein et al., 2015), the ex-ante evaluation method developed in this study can assist decision-makers in choosing an appropriate LOD to invest in maintaining on their BIM projects, in order to maximise the ROI of BIM implementation. Rather than using a dollar value of costs associated with different aspects of BIM implementation, this study estimates the generic *Net Cost* of BIM implementation. This is because: i) assigning a dollar value to intangible benefits and costs is challenging (Zheng et al., 2019). ii) Dollar value of benefits and costs could vary significantly across different sized projects undertaken by an organization. The latter issue is well demonstrated in the three case studies on BIM implementation, with different levels of organisation size and project characteristic, reported by Giel et al. (2013) which showed a wide range of ROI values, ranging between 16% and 1654%.

This paper starts with a literature review which summarises the implementation benefits and costs of BIM. Section 3 presents an overview of ANNs, and briefly summarises the processes to obtain key elements used to train a

ANNs; while, the detailed processes are explained in Section 4. Section 5 presents the case study testing results, and concluding remarks are presented at the end. Fig. 1 summarises the structure of this paper.

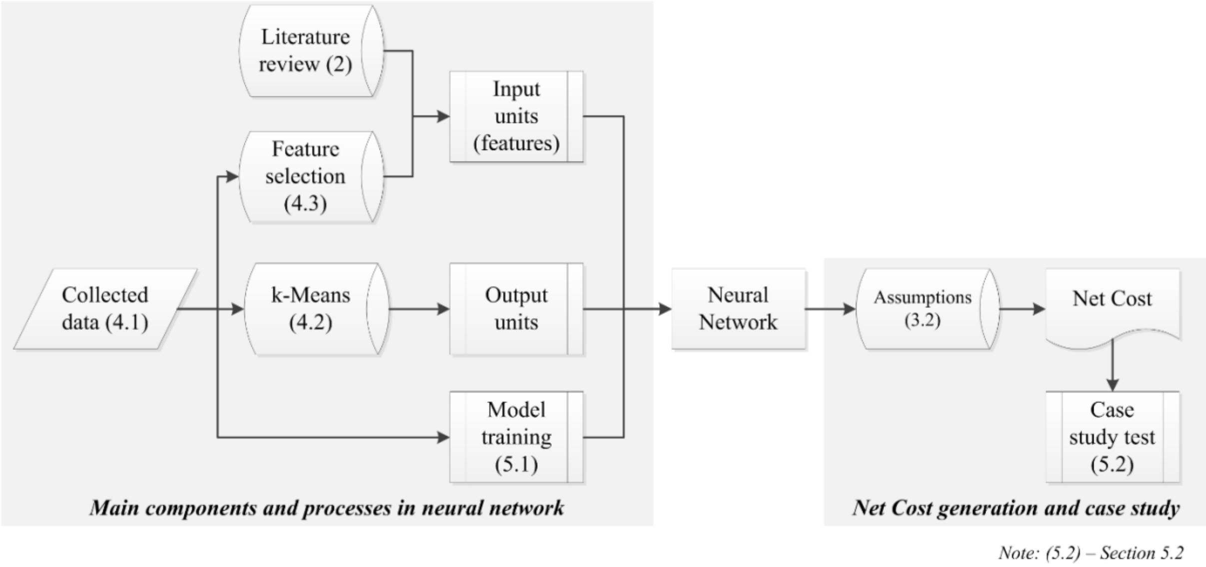


FIG. 1 Paper's structure

2 LITERATURE REVIEW

Benefits associated with BIM implementation, including impacts on productivity, are considered as one of the main motivations for many Architectural, Engineering and Construction (AEC) to adopt the technology (Xu et al., 2014). BIM benefits can be grouped into *Productivity* improvements and *Intangible* improvements. However, the cost associated with BIM implementation hinders BIM adoption for most firms (Li et al., 2017). According to existing studies, this study summarised the *Implementation Costs* into *Training Costs, Installation and Maintenance Costs,* and *Adaptation Costs.*

"Productivity" is the amount of goods and services produced by a productive factor in a unit of time, which could be improved through improving construction planning and scheduling, site supervision and engineering design (Arditi, 1985). The most frequently reported benefit is *Productivity Improvement* which encompasses, but is not limited to, shortened project period (Jang et al., 2018), reduced project costs (Seadon et al., 2019), improved field labour productivity control (Lee et al., 2017), and improved design productivity (Zhang et al., 2018). The implementation of information technology is often associated with intangible benefits, which are difficult to be quantified in monetary terms (Murphy et al., 2002). Previous studies demonstrated the improved management via BIM usage, including project management (Ghaffarianhoseini et al., 2017) and data management (Gerrish et al., 2017). These intangible improvements are critical (Borhani et al., 2017), but challenging to quantify (Zheng et al., 2019), since intangible benefits impact the company's profitability indirectly (Remenyi et al., 1993). There are other *Intangible Improvement* that can not be neglected when considering BIM implementation, including improved external relationships with other project participants (Cao et al., 2017), and improved project participants' collaboration (Bozoglu, 2016).

Although the benefits of BIM implementation are attractive, the costs for implementing BIM may hinder many AEC companies from adopting BIM. Dakhil et al. (2019) and Garcia et al. (2018) emphasised the importance of *Training Costs* associated with BIM implementation. In addition, training staff from novice to intermediate or to a more advanced level is one of the major investments of BIM users in the short-term (Hanna et al., 2013). *Installation and Maintenance Cost* is one of the major costs in BIM implementation, which include license purchasing fees (Holzer, 2016) and upgrading costs of hardware and software (Liu et al., 2017). Since BIM implementation relates to several subsequent matters including suitability and interoperability, the availability of technical support during BIM implementation is critical (Nuttens et al., 2018). In this study, *Adaptation Cost* is considered as a type of indirect cost or loss of income, which may occur at the very early stage of BIM implementation (Beach et al., 2017). The occurrence of adaptation costs is caused by the change of workflow, learning curve's influences, and people's psychological resistance (Lu et al., 2012).

Previous studies modelled the BIM adoption process and examined the effects of various critical factors when it comes to BIM adoption (Wang et al., 2017; Xu et al., 2014). In addition, researchers also proposed frameworks that can help an organisation to plan its BIM implementation from different perspectives, for instance, based on people management (Liao et al., 2018) and contractual management (Chong et al., 2017). Although these models and frameworks are important to assist decision-makers in assessing BIM adoption strategically, the information may not be sufficient for decision makers to tell whether BIM implementation can bring any benefits. This study aims to evaluate the *Net Cost* (*Implementation Costs* minus *Implementation Benefits*) associated with BIM implementation, through evaluation of *Implementation Benefits* and *Implementation Costs*.

In the following sections, the *Implementation Benefits* and *Implementation Costs* reported in the literature will be used as proxies to measure the generic *Net Cost* of BIM implementation. Twenty-two features are used to represent the proxies listed (summarised in the Appendix), and these are fed into the standard ANNs to predict an organisation's selection of LOD to use when implementing BIM. Section 3 explains the data collection process and presents a brief introduction on ANNs.

3 DATA COLLECTION AND ASSUMPTIONS

3.1 Data collection

A 7-point Likert scale questionnaire was developed to collect the data. The collected numbers of the 7-point scale were one of the main sources of ANNs input. Apart from 7-point scale questions, there are also some questions about the respondent's basic information, including organisation's size, frequently used contract types, business category, and main project types; this basic information were collected as categorical features that act as an additional source of ANNs input.

Research participants were asked to select a single number that best characterises their opinion/experience with regards to the features that represent implementation benefits and costs (starting at 1 = strongly disagree to 7 = strongly agree). The following selection criteria for participants were specified: 1) they must have at least 5 years of work experience in the construction industry; 2) they must have some basic BIM knowledge, for example being aware of BIM and knowing how BIM can be used in construction projects; exposure to at least a workshop or a project where BIM is utilised would deem the respondent as having satisfied this requirement. A total of 307 research participants were involved in this survey, where 62% are contractors, 19% are engineers, 18% are architects, and 1% are consultants. Fig. 2 summarises other key information about survey respondents. The questionnaire used in this study was previously published in (Hong et al., 2019).

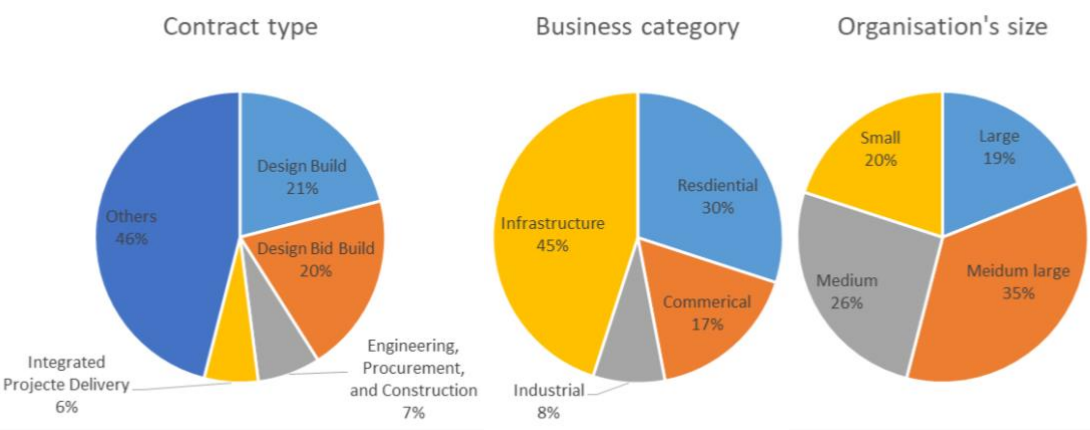


FIG. 2: Respondents key information

3.2 Overview of ANNs

This subsection aims to provide an overview of how the proposed ANN is used to predict an organisation's BIM implementation LOD; the section also describes two main assumptions relating to the calculation of *Net Cost*. Fig. 3 presents a simplified architecture of feedforward ANNs used in this study. The key elements within a feedforward ANNs frame are the input units (x_j), hidden units (z_h), output units (Y_i), weights (w_{hj}, v_{ih}), and the activation function (Alpaydin, 2014; Boussabaine, 1996). In this study, the input units are the features/proxies collected from the questionnaire, including the features of each *Implementation Benefits* and *Costs*, along with the relevant categorical features which will be further discussed in Section 4; the output units are different LODs (i.e. LOD100, LOD 200, LOD 300, LOD 350, LOD 400), which will be elaborated on in Section 4. Hidden units and weights will be derived during the ANNs training process. The rectified linear unit (ReLU) is adopted as the activation function in the hidden layers herein, since it is efficient in optimising the error (Pan et al., 2016).

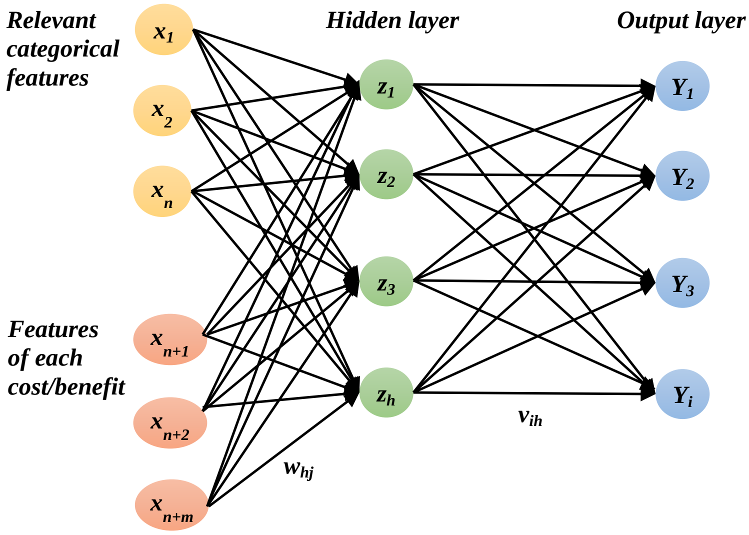


FIG. 3: A simplified feedforward ANN architecture

Computation experiments indicated that the ANNs was sensitive to the 7-point scale used in the survey (Alpaydin, 2014; Ng, 2017). Therefore, before ANNs training, this study normalised the input by subtracting sample mean and dividing by sample standard deviation. In addition, the normalisation could speed up the training process of the network, and to reduce the possibility of the network being stuck in a local solution (Rafiq et al., 2001). Meanwhile, the whole dataset was separated into three sets, which are train set, validation set, and test set. The ANNs training process includes two essential steps, namely forward propagation and backpropagation. Forward propagation calculates the value of output units ($p(x_j)$) based on known input units (x_j) and randomly generated weights (w_{hj}, v_{ih}). Backpropagation carries the error from output units back to input units and minimises the total errors, where the weights of the network are updated (Rumelhart et al., 1986).

Selection of the LOD to adopt can be formulated as a multi-class classification problem which assigns an instance with a single label from a set of disjoint labels (Trohidis et al., 2008). As a result, softmax function, a function used for multiclass classification, is adopted as the activation function in the output layer (Goodfellow et al., 2016). Softmax function is used in the output layer of the ANNs to find the instance's (organisation's) class from all five classes considered. By feeding the output units ($p(x_j)$) into the softmax function, the maximum value of $s(x_j)$ will be assigned with a positive label (Alpaydin, 2014).

3.3 Assumptions

By using the softmax function in the output layer, the predicted results ($p(x_j)$) in each class follows a multinoulli distribution and represents the probability of each class being identified as 'positive' (Chong et al., 2009). Therefore, the outputs of ANNs cannot be directly interpreted as the generic costs of BIM implementation. Two assumptions are made to convert the ANNs outputs into the generic *Net Costs* of BIM implementation.

Assumption 1: Since the output of the softmax function follows a multinoulli distribution, this study assumes that the lower *Implementation Costs*, the higher the possibility that the organisation will implement BIM at a higher LOD. The higher *Implementation Benefits*, the higher the possibility that the organisation will implement BIM at a higher LOD.

Assumption 2: Given that the input of the trained ANNs have been normalised, the average value of normalised inputs is adopted ($\overline{x_j}$) to determine whether the organisation finds it more/less challenging to invest BIM implementation. If $\overline{x_j} > 0$, the selected organisation experiences greater challenges in *Adaptation Cost* compared to other types of costs (i.e. *Training Cost*), when contrasted against other industrial counterparts. Consequently, more costs would be incurred to the organisation.

Training Cost, *Installation and Maintenance Cost*, *Intangible Improvement*, and *Productivity Improvement* associated with LOD level implementation ($r(x_j)$) are expressed as follows, Eq. (1):

$$r(x_j) = [p(x_j) - s(x_j)] \times (-\overline{x_j}) \times 10 \qquad \text{Eq. (1)}$$

where $p(x_j)$ denotes predicted value of output unit(s) and $s(x_j)$ denotes threshold value in multi-class classification obtained from the softmax function.

Adaptation Cost associated with LOD level implementation $r(x_j)$ is expressed as follows, Eq. (2):

$$r(x_j) = [p(x_j) - s(x_j)] \times (\overline{x_j}) \times 10 \qquad \text{Eq. (2)}$$

Given the equations above, the implementation cost ($r(x_j)$) will be 0 for organisation's implemented LOD, because $p(x_j) = s(x_j)$. But with the involvement of $\overline{x_j}$, $r(x_j)$ would be negative, if the organisation finds less challenging to implement BIM; vice versa. Table 1 summarises the details of variables mentioned above.

Table 1: List of Notations

Notation	Description
x_j	Input unit(s), $j = 0,1,\ldots,J$, with x_0 being the bias unit in the input layer
$\overline{x_J}$	The average value of the input unit(s)
z_h	Hidden units, $h = 0,1,\ldots,H$, z_0 is the bias unit in the hidden layer
Y_i	True (known) label of output unit(s), $i = 0,1,\ldots,I$
$p(x_j)$	Predicted value of output unit(s)
w_{hj}	Weights in the first layer
v_{ih}	Weights in the second layer
$s(x_j)$	Threshold value in multi-class classification obtained from softmax function
$r(x_j)$	Units of costs of instance $x_j$in LOD selection
$J(\theta)$	Value of cost function in k-Means
k	Number of clusters in k-Means

4 DATA

Data used in this study was collected through a survey. The questions (or inputs) included in the questionnaire were selected by focusing on the important factors related to BIM implementation as obtained from an extensive literature review (Section 2). Different thoughts exist when it comes to defining LOD, for example, LOD defined by American Institute of Architect (2007) and LOD defined by British Standards Institution (2013). Therefore, an unsupervised clustering learning – k-Means analysis is employed to determine organisations' LOD, rather than asking respondents from different parts of the world where LOD terminology slightly differs, to identify their organisations' LOD. The k-Means analysis utilised is a simple algorithm that can converge to the local optima efficiently (Jain, 2010). Another important step before training the ANNs is feature selection. The purpose of feature selection is to improve model performance and produce a more cost-effective model (Saeys et al., 2007). This section starts with the data collection its preparation for use by the ANNs, followed by a k-Means analysis to identify organisations' LOD. Feature selection is presented at the end of this section.

4.1 k-Means

As highlighted earlier, this study used k-Means analysis to reduce the effects of respondents' misunderstanding of LOD (as it may differ across regions). The process of k-Means analysis can be summarised into three steps: Step 1, reviewing different versions of LOD definitions and identifying relevant features by using domain knowledge; Step 2, involves feeding the collected data and features into the k-Means model and determining number of clusters k; and Step 3, which involves matching a level of development to a cluster by using domain knowledge. This study utilised the LOD definitions proposed by the American Institute of Architect (2007) (summarised in Fig. 4).

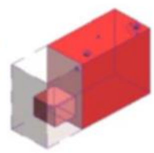
LOD	Definition	Example
LOD 100 Conceptual	The Model Element may be graphically represented in the Model with a symbol or other generic representation but does not satisfy the requirements for LOD 200.	
LOD 200 Approximate Geometry	The Model Element is graphically represented within the Model as a generic system, object, or assembly with approximate quantities, size, shape, location, and orientation.	
LOD 300 Precise Geometry	The Model Element is graphically represented within the Model as a specific system, object or assembly in terms of quantity, size, shape, location, and orientation.	
LOD 400 Fabrication	The Model Element is graphically represented within the Model as a specific system, object or assembly in terms of quantity, size, shape, location, and orientation with detailing, fabrication, assembly, and installation information.	
LOD 500 As-built	The Model Element is a field verified representation in terms of size, shape, location, quantity, and orientation.	

FIG. 4: LOD definitions (derived from American Institute of Architect (2007))

Through reviewing the definition of LOD summarised in Fig 4, it is noticed that the key difference between different LODs is the availabity of data (either graphic or non-graphic) that can be used throughout the project life-cycle. Therefore, this study assesses LOD of BIM implementation by organisation's purpose of using BIM (i.e. modelling software and communication tool), and the functionality of geometric information contained in BIM models. Table 2 summarises the main features that will be used in k-Means to cluster different LODs and their data type.

After identifying the inputs of the k-Means analysis, the following step involves choosing a reasonable number of clusters (*k*). The elbow method is adapted to determine *k*. In the elbow method, the moment when the cost function value $J(\theta)$ drops dramatically and then plateaus (even temporarily) indicates that the ideal *k* is reached (Kodinariya et al., 2013). Fig. 5 presents the relationship between $J(\theta)$ and *k*. According to the elbow method, five clusters are sufficient in this study.

Table 2: Features used in k-Means

Features		Data type
F1	The implementation of 3D visualisation	Boolean (0 = False, 1 = True)
F2	The implementation of building performance analysis	Boolean
F3	The implementation of design plan integration	Boolean
F4	The implementation of design optimisation	Boolean
F5	The implementation of lifecycle maintenance	Boolean
F6	The implementation of quantity take-off	Boolean
F7	The implementation of cost estimation	Boolean
F8	The implementation of facility management	Boolean
F9	The implementation of clash detection	Boolean
F10	The implementation of procurement management	Boolean
F11	Willingness to integrate BIM for project communication purpose	Ordinal (from 1 = extremely unwillingly to 7 = extremely willingly)
F12	Organisation's understanding of BIM	Nominal (1 = BIM is a 2D drafting tool; 2 = BIM is a 3D/4D modelling software; 3 = BIM is a database that stores project data; 4 = BIM can be used to manage building design throughout the lifecycle; 5 = BIM is a digital representation of the facility)

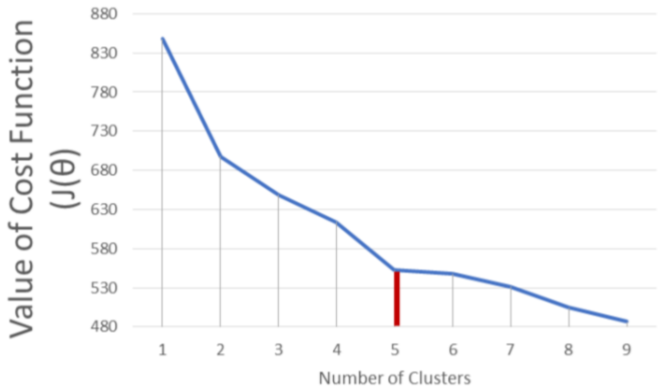


FIG. 5: Determining the number of clusters (k)

Since k-Means analysis is classified as unsupervised learning, the results obtained do not directly refer to a specific LOD. Therefore, domain knowledge was involved to assign a LOD to each cluster. The mean and median values of features used in the k-Means analysis are analysed and compared to allocate a specific LOD level to a cluster (Table 3). As shown in Table 3, F1 to F10 are Boolean variables, while F11 and F12 are nominal/ordinal variables. Table 3 indicates the mean value of F1 to F10 and the median value of F11 and F12. Cluster K4 shows a strong preference for implementing the applications which require more model details (including procurement management, facility management, and lifecycle maintenance) compared to other clusters. In addition, K4 strongly favours the integration of BIM for communication purposes. As a result, it can be concluded that K4 refers to the highest LOD level among these five clusters. In contrast, cluster K1 shows the weakest preference to implement the applications which require more model details, along with the weakest willingness to integrate BIM for communication purpose. Therefore, it can be concluded that K1 refers to the lowest LOD level among all five clusters. As summarised in Fig. 4, LOD 350 requires more interfaces with other building systems. Hence K0 is labelled as LOD 350, given its emphasis in design optimisation (F4), design plan integration (F3), and building performance analysis (F2). Compared with K2, K3 tend to have a more detailed model specification, in order to perform building performance analysis (F2) and project coordination (F11). The assignment of LOD to each label is summarised in Table 3.

Table 3: Mean and median values of features in different clusters

Features		K0	K1	K2	K3	K4
F1 – mean	The implementation of 3D visualisation	0.38	0.48	0.41	0.56	0.84
F2 – mean	The implementation of building performance analysis	0.37	0.10	0.31	0.59	0.36
F3 – mean	The implementation of design plan integration	0.26	0.24	0.16	0.11	0.36
F4 – mean	The implementation of design optimisation	0.38	0.33	0.36	0.65	0.38
F5 – mean	The implementation of lifecycle maintenance	0.13	0.10	0.17	0.19	0.22
F6 – mean	The implementation of quantity take-off	0.44	0.29	0.40	0.40	0.86
F7 – mean	The implementation of cost estimation	0.48	0.24	0.33	0.24	0.66
F8 – mean	The implementation of facility management	0.27	0.10	0.14	0.13	0.46
F9 – mean	The implementation of clash detection	0.32	0.33	0.24	0.04	0.74
F10 – mean	The implementation of procurement management	0.13	0.00	0.09	0.07	0.20
F11 – median	Willingness to integrate BIM for project communication purpose	5	1	4	6	7
F12 – median	Organisation's understanding of BIM	4	3	3	3	4
Assigned LOD		***LOD 350***	***LOD 100***	***LOD 200***	***LOD 300***	***LOD 400***

4.2 Feature selection

Kohavi et al. (1997) categorised feature selection techniques into two groups: filter method and wrapper method. Filter method only relies on the general characteristics of the training data to select features, while wrapper method uses the inductive algorithm (i.e. Expectation Maximisation algorithm) to estimate the value of a given subset (Sánchez-Maroño et al., 2007; Talavera, 2005). Compared with the wrapper method, the filter method is less computationally expensive (Weston et al., 2000). Therefore, this study uses the filter method to select features. Applicable approaches within the frame of filter method include chi-square test, mutual information, and information gain. Chi-square is the most effective measure (Yang et al., 1997); whereas mutual information could lead to an NP-hard optimisation problem (Venkateswara et al., 2015). As a result, this study uses chi-square test for feature selection.

Table 4 summarises the results of the chi-square test with confidence interval 90%. According to the results presented in Table 4, the respondent's position and the organisation's project do not have significant impacts on LOD; while, organisation's size, organisation's business category, and frequently used contract type are significant when determining the LOD to implement. Organisation's size, business category, and contract type are included as inputs in the ANNs training. The last two columns in Table 4 show the chi-square test results of the impacts of BIM applications on LOD selection. As presented in Table 4, the majority of BIM applications (except lifecycle maintenance) have significant impacts on LOD. Therefore, the respondent's preference toward BIM application should be included as inputs in the ANNs. It is important to note that in order to maintain the brevity of the discussion, a limited set of BIM applications have been included in Table 4, with the same analysis still applicable was the application set be expanded.

Table 4: Chi-square test

Relevant categorical features	Significant level (p)	Relevant categorical features	Significant level (p)
Organisation's frequently used contract	0.004***	3D visualisation	0.000***
Organisation's size	0.008***	Environmental analysis	0.000***
Organisation's business category	0.054*	Design plan integration	0.006***
Respondent's position	0.472	Design plan optimisation	0.000***
Organisation's project type	0.817	Lifecycle maintenance	0.612
		Quantity take-off	0.000***
		Cost estimation	0.000***
		Facility management	0.000***
		Clash detection	0.000***
Note: *** (p<0.01), ** (p<0.05), * (p<0.1)		Procurement management	0.059*

5 CASE STUDY

The investigated case study is a medium-sized (Grade 2) construction company that specialises in commercial building construction. The most frequently used contract in the investigated case study is Design-Bid-Build contract. A project manager in the investigated case study participated in the survey. The investigated case study implemented cost estimation, facility management, and clash detection at LOD 350. This section is organised as follows: Section 5.1 summarises the ANNs tuning approaches used in this study, followed by the ANNs prediction results (Section 5.2). The next section (Section 5.3) tests the effects of different applications on the choice of LOD, while discussions are presented at the end (Section 5.4).

5.1 Neural network training

To achieve an optimal ANNs structure, a constructive approach is adopted, which starts with a small network and adds units/layers gradually to improve the ANNs performance (Alpaydin, 2014). As discussed in Section 3.2, the whole dataset was separated into three sets during the training process. The tuning process stops when the loss in validation set (i.e. validation loss) reaches a minimum.

L2 regularisation was adopted to avoid overfitting the ANNs (Liu et al., 2011). Another frequently used regularisation method is L1, which could result in a solution that is sparser (Goodfellow et al., 2016). In addition, the 'he-normal' initialiser is used in this study, since it is an initialiser designed for ReLU (activation function utilised in the ANNs) (He et al., 2015). The optimiser used is RMSprop developed by Tieleman et al. (2012), which adapts the learning rates of model parameters and has better performances in non-convex settings. Table 5 summarises the loss and accuracy of the proposed ANNs.

Table 5: Loss and Accuracy

	Productivity Improvement	**Intangible Improvement**	**Training Cost**	**Installation and Maintenance Cost**	**Adaptation Cost**
Train loss	1.5281	1.5507	1.5602	1.5280	1.4778
Validation loss	1.7184	1.6017	1.6705	1.7149	1.7110
Test accuracy	0.6757	0.6892	0.6757	0.7297	0.6757

5.2 Prediction

Once an ANN is trained, the responses of the investigated case study are fed into the trained ANN. Table 6 summarises the generic costs and benefits for the case study to implement BIM at different LOD. As presented in Table 6, implementing BIM at LOD 300 is the most beneficial choice for the case study in terms of *Productivity Improvement* (1.85) and *Training Cost* (-4.42). LOD 350 appears to be the most economical choice when it comes to *Adaptation Cost* and *Installation and Maintenance Cost* (both 0). The *Net Cost* of BIM implementation suggests that implementing BIM at LOD 300 (-6.39) could maximise the organisation's benefits.

Table 6: Net Cost

LOD	**Productivity Improvement**	**Intangible Improvement**	**Training Cost**	**Installation and Maintenance Cost**	**Adaptation Cost**	**Net Cost**
LOD100	1.57	1.84	-4.06	1.52	2.48	-4.65
LOD200	0.08	0.50	-3.53	0	1.55	-4.51
LOD300	1.85	0.79	-4.42	1.90	2.71	-6.39
LOD350	0	0	-1.47	0	0	-1.47
LOD400	0.68	0.96	0	0.31	0.26	1.07

5.3 Effects of applications

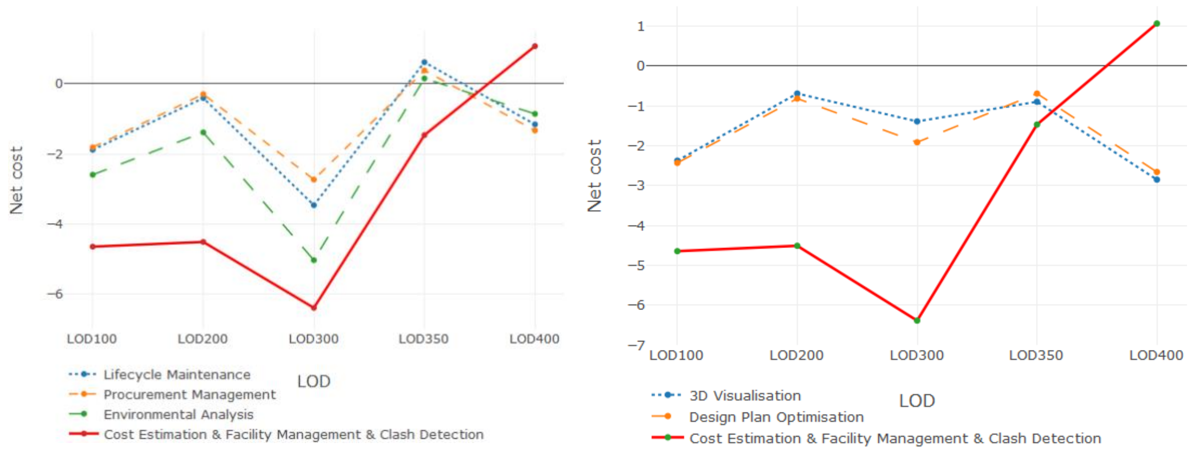
As highlighted earlier, the investigated case study implemented cost estimation, facility management, and clash detection. However, previous studies suggested that different BIM applications have different levels of requirement when it comes to the model's data richness. For example, LOD 400 is critical for daily work orders and BIM-based bill of materials related to non-prefabricated materials (Song et al., 2017). LOD 300 is more frequently seen in project design, in particular at the detailed design stage (Grytting et al., 2017). Therefore, in this section, the effect of different BIM applications on the LOD selection process is estimated. The original responses (input) of the case study are set as the control group; in the experiment group, all responses (input) remain the same, except the preference for different BIM applications. The experiment group includes eleven samples: three samples prefer to implement one BIM application, three samples prefer to implement two BIM applications, and five samples prefer to implement a BIM application that has not yet been implemented.

Fig. 6 presents the estimated *Net Cost* of the experiment samples that implement only one application. According to Fig. 6, the most cost-saving LOD remains LOD 300. However, implementing an application at LOD 400 could be less expensive than implementing at LOD 350. Fig. 7 presents the estimated *Net Cost* of the experiment samples that implement two applications. Fig. 7 demonstrates a similar result, where the most cost-saving LOD remains LOD 300. Implementing two applications at LOD 400 would be more expensive than implementing one application at the same level. For a lower LOD (i.e. LOD 200), implementing one application could be costlier than implementing two applications, due to the expensive upfront costs to set up the BIM implementation and less benefits from a lower LOD.

FIG. 6: Net Cost (1)

FIG. 7: Net Cost (2)

There are some applications have not been implemented by the case study. The following figures present the *Net Cost* for implementing these applications. Fig. 8(a) summarises the *Net Cost* while implementing lifecycle maintenance, procurement management, and building performance analysis. Similar to the results highlighted above, LOD 300 remains the most cost-saving option. However, 3D visualisation and design plan optimisation tend to reach the most cost-saving point at LOD 400, followed by LOD 100 (Fig. 8(b)). 3D visualisation has been considered as one of the BIM applications with lower technical requirements (Ismail et al., 2017); hence, 3D visualisation may not worth to be implemented at a higher level. However, Jupp (2017) suggested that, for complex projects, visualisation is implemented as an assistant application to facilitate the time and space relationships of construction activities. Design plan optimisation may involve many parameters, for example building materials and room size (Liu et al., 2018). Therefore, a more detailed building model could improve the benefit significantly.



(a) (b)

FIG 8: Net Cost (3)

5.4 Insights

The ANNs prediction results indicate that a higher level of LOD does not guarantee more benefits. Another finding is that LOD selection also depends on the implemented applications, since some applications (for example, design plan optimisation) could achieve the most cost-saving point at LOD 400. The role of government initiatives is critical, in terms of demanding and fostering the introduction of BIM (Borrmann et al., 2018). In particular, the British Government began mandating Level 2 for all public construction projects from 2016 (UK Cabinet Office, 2011). However, a higher level of BIM implementation does not secure a better result, in particular for small firms (Dainty et al., 2017). Although BIM implementation level may be requested within the contract, especially for public projects (Vass et al., 2017), it is not suggested to implement BIM at the highest level across all the projects. Researchers have been arguing about the BIM implementation approach. The case study reported by Arayici et al. (2011) illustrates that a bottom-up implementation approach has advantages in engaging project participants. In addition, Vass et al. (2017) believe that a bottom-up approach could be more effective to solve intra-organisational challenges. The results of this study encourage decision-makers to initiate a bottom-up implementation approach, in particular for those projects without contractual requirements. When the organisations are initiating the BIM implementation, more emphasises should be placed on assessing the organisation’s competency and the purpose to use BIM.

6 CONCLUSION

An ex-ante evaluation method was proposed in this study to assist organisations in estimating the costs and benefits of implementing BIM at different LOD. Collected data was trained using ANNs to predict the LOD level that is likely to be implemented by the organisations. Following that, a case study was selected to test the performance of the trained ANNs. This study aims to provide decision-makers with an evaluation tool to assess which LOD is more suitable for the organisations, given their implemented BIM applications. The investigated case study had implemented BIM at LOD 350. Although the *Net Costs* of the current implementation level (LOD 350) are desirable, the results suggest that LOD 300 results in more cost-savings. However, if the investigated case study tends to move towards more collaborative and interactive BIM applications (for example, design plan optimisation), a higher LOD will appear to be the best option. Therefore, the results of this study suggested that rather than pursuing a higher BIM implementation level, an organisation is suggested to evaluate the organisation's competency and the implemented applications.

A number of limitations exist in this study. First, although 22 'benefit and cost' features and 13 categorical features are included in the ANNs model, there are other factors and BIM applications that could affect BIM implementation and have not been fully considered in this study. Second, literature specified that LOD may vary across different project phases; however, this study did not estimate whether the optimal LOD selection would be affected by project phases. Future studies should also account for clients' demand when considering BIM implementation, in order to design a more practical BIM implementation plan for decision-makers.

7 APPENDIX

Question	Response
Productivity improvement	
BIM adoption reduces the project's overall costs.	7
BIM adoption reduces the project duration.	4
BIM improves project information management.	3
BIM improves stakeholders' understanding of the project scope.	5
Using BIM reduces conflicts in the project	5
Intangible improvement	
The decision of adopting BIM is/was strongly affected by building competitive advantage over other competitors.	6
The decision of adopting BIM is/was strongly affected by the need to streamline organisation's management process.	3
BIM improves project collaboration among participants.	6
Training cost	
No or little additional knowledge/training is invested to implement BIM in the organisation.	6
Costs and efforts required to link information from other sources are insignificant.	3
Costs and efforts required to create, annotate, and refine project documentation via BIM are insignificant.	7
The organisation will provide/provides proper training to staff before implementing BIM.	5
Installation and maintenance cost	
Costs and efforts required to upgrade BIM operation hardware are insignificant.	5
BIM implementation requires high investing expenses.	6
Professional guidance is/was available to the organisation in the selection of BIM tools.	7
Costs and efforts required to maintain BIM models are insignificant.	4
Costs and efforts required to maintain BIM central files are insignificant.	6
A specific technical centre (or a technician) is/was available for assistance with BIM implementation.	5
Adaptation cost	
BIM implementation is associated with the increasing of project cost, due to workflow changes;	3
The use of BIM gives rise to project communication issues with other project participants	7
The use of BIM brings about project schedule delays due to lack of experience in using BIM	4
The use of BIM reduces working efficiency temporarily due to people's resistance to change	6

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