Generic Model for Measuring Benefits of BIM as a Learning Tool in Construction Tasks

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Abstract: Over the past years, people's understanding of building information modeling (BIM) in the architecture, engineering, and construction (AEC) industry has improved significantly. Building information modeling can be diversely recognized as a virtual design and construction environment, a communication vehicle among stakeholders, a lifelong information model, or an education platform that can be used in universities and colleges. Building information modeling can also be used as a learning tool that can aid project teams in familiarizing themselves with a construction task before commencement of the task on-site. Yet, little effort has been made to measure the benefits of this kind. The aim of this research is to empirically measure the benefits of BIM as a learning tool in real-life construction tasks. The learning curves of two situations—construction tasks with and construction tasks without BIM—are identified by following a series of analytical processes. The two learning curves are compared and the learning effects contributed by BIM are modeled as $L_{eff\mathrm{BIM}}$. By inputting their own data, practitioners may use this generic model to measure learning effects contributed by BIM in their own projects. The model can be used to encourage potential BIM users by showing empirical evidence of BIM's benefits. It is also hoped that the model can join the concerted efforts to promote BIM's value in the AEC industry. **DOI:** **10.1061/(ASCE)CO.1943-7862.0000585.** © *2013 American Society of Civil Engineers.*

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Introduction

Recent years have seen burgeoning research agenda on building information modeling (BIM) in the architecture, engineering, and construction (AEC) industry. Despite a wide range of BIM definitions, certain consensus is reached that BIM is not a simple three-dimensional (3D) model, but a process to improve the performance through the whole life cycle of buildings. Based on these understandings, BIM can be used for a wide range of purposes, e.g., design and construction integration, project management, and facilities management (Azhar et al. 2008; Bazjanac 2008; Schlueter and Thesseling 2009). Building information modeling is argued to be a useful tool for reducing the construction industry's fragmentation, improving its efficiency/effectiveness, and lowering the high costs of inadequate interoperability (Succar 2009). Building information modeling is also recognized as a virtual design and construction (VDC) environment, a vehicle facilitating communications amongst stakeholders, an information model that can be used throughout the project life cycle, or an education platform that can be used in universities or colleges (Lu and Li 2011). It is changing the traditional AEC practices in a broad sense in terms of people, processes, working culture, communication, and business models. Some even advocate that the traditional AEC practices are facing a paradigm shift with the application of BIM (Lu and Li 2011).

Nonetheless, a widespread adoption of BIM is largely dependent on how the industry perceives its genuine benefits. Users who are to adopt BIM need to be encouraged by using empirical evidence. Investors also need to justify their investment of time and budget in BIM by discerning clear proof of its benefits. Research has shown that one of the major hurdles for adopting BIM is the justification of the additional cost and benefits (Li et al. 2009). In this light, a number of studies have been conducted to identify and measure BIM's benefits. Kaner et al. (2008) revealed clear improvement in engineering design quality, in terms of error-free drawings, and a steadily increasing improvement in labor productivity by applying BIM to four detailed case studies. Sacks et al. (2005) found that the potential benefit of adopting BIM is estimated to be in the range of 2.3–4.2% of total project cost for precast-concrete companies. Sacks and Barak (2008) reported that BIM helps gain an increase of productivity ranging from 15–41% for cast-in-place reinforced-concrete structures in the drawing phase. Patrick and Raja (2007) conducted a questionnaire survey and found that quality, on-time completion, and units per staff-hour were ranked as the highest benefits from BIM. Comparing it with traditional methods, Azhar et al. (2008) stated that a case project with BIM in place has helped save an estimated $600,000 in extras and avoid months of potential delays. On the basis of 32 major projects using BIM, Stanford University Center for Integrated Facilities Engineering (CIFE) (CIFE 2007) logged several benefits contributed by BIM, such as up to 40% elimination of unbudgeted change, cost-estimation accuracy within 3%, up to 80% reduction

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in time taken to generate a cost estimate, savings of up to 10% of the contract value, and up to 7% reduction in project time.

In addition to its applications in real-life projects, BIM is also recognized as a virtual environment in colleges for teaching and learning, e.g., architecture, engineering, construction, and operation. Building information modeling presents an opportunity for students to acquire necessary skills by closely mimicking the real-life practices in the industry, instead of going to real sites every time. Some researchers have advocated that design and construction education using BIM should be tied closely to the curriculum in schools (Ibrahim and Rahimian 2010; Peterson et al. 2011; Sacks and Barak 2010). The learning effects of BIM in this instance have been frequently assessed. For example, Dennis (2006) conducted a survey to investigate the learning effects relating to a curriculum for the Construction Management Department at California State University and found that BIM appeared to have a small but positive influence on plan-reading skills. Later, Dennis (2007) conducted a similar survey and found that BIM appeared to have a positive influence on estimating. Hedges and Denzer (2008) found that BIM promotes clearly defined roles in the group-based classroom-management approach of team learning, which encourages the students to pursue more rigorous investigations of design alternatives.

A closer investigation of the previously noted references reveals that few have actually examined BIM's further use as a tool for organizational learning in real-life construction projects. "Learning by doing" can be conducted in BIM as a virtual environment, which is supposed to be less expensive than building a physical structure. This is particularly useful considering that physical construction is often expensive and difficult, if not completely impossible, to reverse. Learning from the virtual environment in advance is expected to benefit the erection of the physical construction at a later stage. Li et al. (2009) reported a case of a high-rise building in Hong Kong for which BIM was adopted to rehearse and optimize the construction plan for a typical floor, which normally accounts for an N-day cycle. Building information modeling as a learning tool has also been applied in other construction activities, such as training field staff, occupational heath and safety (OHS), operation of construction machinery, and logistics planning (Becerik-Gerber and Kensek 2010; Eastman et al. 2008; Fox and Hietanen 2007; Sacks et al. 2009, 2010a, b). Building information modeling has also been reported to be used in constructability analysis and process identification, which contain learning processes per se (Li et al. 2008a, b). The learning effects might be phenomenal in many repetitive construction field operations ranging from smaller ones, such as fixing, molding, and concreting, to larger ones, including the construction of a standard floor. Unfortunately, these learning effects contributed by BIM have rarely been identified and measured.

The main purpose of this research is to empirically model the learning effects contributed by BIM in real-life construction tasks. Instead of focusing on a particular piece of a construction task, this paper aims to develop a generic model $L_{eff\text{BIM}}$ that allows BIM users to assess learning effects by inputting their own project data. The model can be used to convince AEC practitioners by showing empirical evidence of BIM's benefits. The model also enables BIM users to justify the investment in BIM. It is hoped that the model, by identifying and measuring BIM's benefits, can join the concerted efforts to promote BIM's value in the AEC industry. The paper subsequently comprises four sections. From a methodological point of view, "Learning Curve" reviews the literature on the learning curve and explores its implications for this research. "Methodology and Learning Effects Model of BIM" describes the methodology for measuring the learning effects contributed by BIM. With the aid of mathematical language and graphic tools, a series of six analytical processes are introduced to derive the generic model $L_{eff\text{BIM}}$. Using a case study, "Case Study for Illustrating $L_{eff\text{BIM}}$ Application" demonstrates how $L_{eff\text{BIM}}$ can be used in real-life construction tasks. "Conclusions and Future Development" draws conclusions and proposes directions for further research.

Learning Curve

Learning effects tend to follow a learning curve. The learning curve was originally developed from a 1936 empirical study in airplane firms by Wright (Wright 1936; Adler and Clark 1991) and is still popular. The basic theory behind the learning curve is that, as a worker or project team learns by doing, the more often the worker or team repeats an operation, the more efficient the worker or team becomes (Couto and Teixeira 2005). This phenomenon is clear in many repetitive production activities and is known as the learning experience or learning effect. The learning curve can help identify the learning effects or, in other words, the relationship between performance improvement and the accumulative experience through learning. In this paper, the performance is often measured using productivity in several terms, such as staff-hours/cycle, cost/cycle, and time/cycle (e.g., Thomas 1986; Adler and Clark 1991; Farghal and Everett 1997; Couto and Teixeira 2005).

However, the learning curve is not only a curve reflecting the net direct labor productivity attributable to the laborer's own effort and skill (Lieberman 1987). Learning behind the learning curve results from an integrated effort of many factors, such as direct labor, indirect labor, technical personnel, and managerial or engineering action to change the technology, equipment, processes, or human capital (Oglesby et al. 1989; Lutz 1994). It should be pointed out that previous studies focus on individual workers in repetitive labor tasks, and the learning effects in managerial tasks such as project plan, jobsite management, and innovation have not been fully addressed. Nevertheless, the advantage of the learning curve is that it can describe the integrated effort of all these factors. Adler and Clark (1991) called this learning curve a catch-all model with one explanatory variable: experience.

The classical learning curve model is a power function, which can be further represented as straight lines in the logarithmic coordinate as shown in Fig. 1. The learning effects can be analyzed through the three stages shown in Fig. 1. The learning curve theory states that whenever the production quantity of a new or changed product doubles, the unit or cumulative average cost (e.g., hours, staff-hours, or dollars) will decline by a certain percentage of the previous unit or cumulative average rate (Thomas et al. 1986).

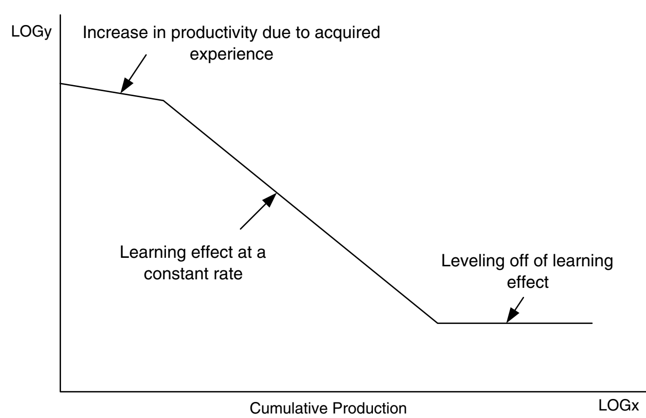

Fig. 1. Three stages in a theoretical learning curve

Table 1. Summary of Learning Curve Models

Type	Formula	Derivative	Remarks	References
Linear	$\log y = a + b \log x$	Linear x, y; linear x, $\log y$; linear $\log x$, y	Simplest, constant learning rate	Everett and Farghal (1997)
Quadratic	$\log y = a + b(\log x) + c(\log x)^2$	Quadratic x, y; quadratic x, $\log y$; quadratic $\log x$, y	Learning rate not a constant	Everett and Farghal (1994)
Cubic	$\log y = a + b(\log x) + c(\log x)^2 + d(\log x)^3$	Cubic x, y; cubic x, $\log y$; cubic $\log x$, y	Learning rate not a constant	Thomas et al. (1986)
DeJong's formula	$y = a[M + (1 - M)x^{-b}]$		Proportion of manual work in person-machine work incorporated	DeJong (1957)
S-curve	$y = a[M + (1 - M)(x + p)^b]$		Start of learning process more gradual than linear model suggests	Nembhard and Uzumeri (2000)
Stanford B	$y = a(x + p)^b$		Acquired experience before learning assumed	Yelle (1979)
Exponential	$y = k(1 - e^{-x/r})$	$y = k(1 - e^{-(x+p)/r})$	Learning by individuals for both manual an conceptual skills	Uzumeri and Nembhard (1998)
Hyperbolic	$y = k[x/(x + r)]$	$y = k[(x + p)/(x + p + r)]$	Learning by individuals for both manual an conceptual skills	Wong et al. (2007)

Note: Symbol definitions are listed in "Notation."

This percentage is called the learning rate and identifies the learning achieved. It also establishes the slope of the learning curve, as is shown in Fig. 1. Because a satisfactory industry-wide learning curve model for all products or activities does not exist, many other learning curve forms have been developed shown in Table 1.

The learning curve has been widely used to investigate learning in the AEC sector because of its strengths in facilitating cost control, forecasting, and strategic planning. For example, research has been conducted to find a best-fit mathematical learning curve model to describe the learning effects in a set of repetitive construction activities through historical data (e.g., Thomas et al. 1986; Everett and Farghal 1994; Lutz et al. 1994; Couto and Teixeira 2005). Studies have also been conducted to predict future performance through learning curves (Everett and Farghal 1997; Farghal and Everett 1997; Wong et al. 2007). One may argue that a multiple regression (MR) model or artificial neural network (ANN) can reflect this, too. Why does it have to be the learning curve? Wong et al. (2007) and Ling and Liu (2004) suggested that the MR approach assumes a linear relationship between learning and performance, thus leading to unsatisfactory results. In addition, the MR approach might not be feasible, particularly when there are many causal factors while the data used for regression are insufficient (Nembhard and Uzumeri 2000). The ANN might generate satisfactory results, but because of its black-box computation process, it is difficult to interpret the implications of the models (Dikmen et al. 2005). Therefore, the learning curve is recognized as a feasible tool to model the learning effects contributed by BIM in real-life construction tasks.

Methodology and Learning Effects Model of BIM

After a detailed review of literature on the learning curve, a methodology for present research becomes clear. To measure the learning effects contributed by BIM, learning curves of two situations are identified: construction tasks with and without BIM assisting in learning. If the two situations are identical except for one factor (BIM), the learning effects contributed by BIM can be modeled by comparing the two learning curves. Although the rationale underlying the methodology is straightforward, the learning effects must be identified by following a series of analytical processes (Fig. 2).

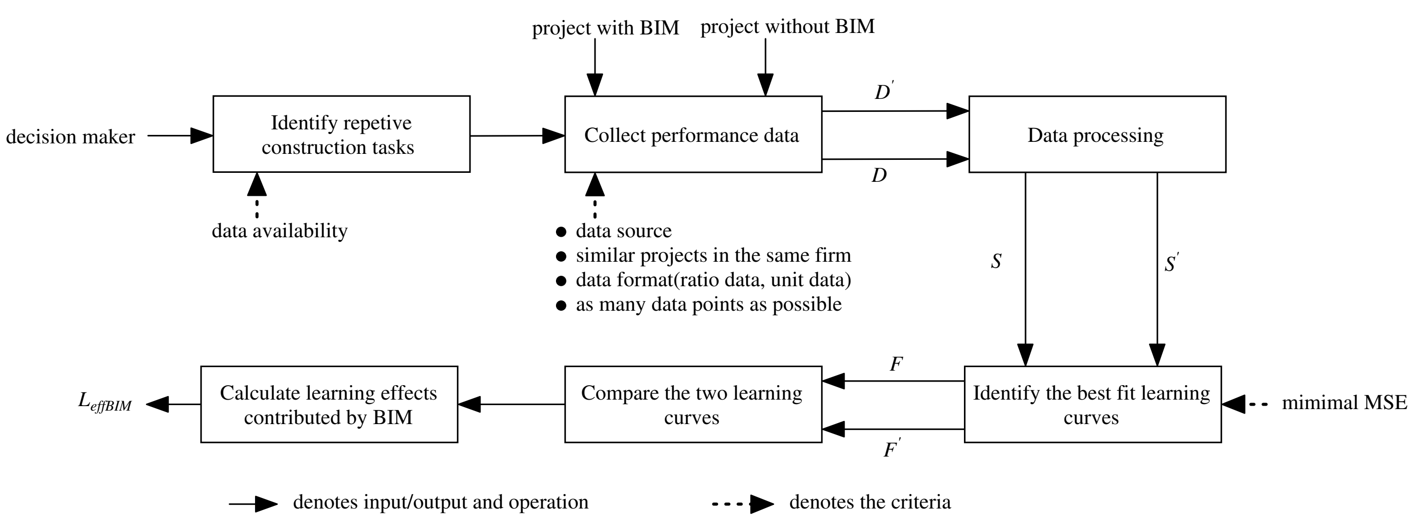

Fig. 2. Flowchart of modeling BIM's learning effects in construction works

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Step 1. Identify Repetitive Construction Tasks to Study

In this step, the decision makers will identify the concerned repetitive construction task. As discussed, the learning effects reside in repetitive construction activities. However, the scale of these repetitive construction tasks varies. The tasks can be small-scale activities such as assembling and dismantling formwork, concreting, erection of plasterboard partitions, precast plant, stonecutting, match casting, steel erection, and sewer-line installation (Everett and Farghal 1994; Lutz et al. 1994). They can also be large-scale repetitive works such as construction of multistory residential structures and road construction (Thomas et al. 1986; Lutz et al. 1994). Notably, Couto and Teixeira (2005) integrated the construction tasks required for the erection of a building-floor level into a single repetitive construction activity and investigated its learning effects in the development of a set of seven identical housing buildings. In addition to the physical execution of a project, some project-management activities, such as project planning and site coordination, could also be investigated with regard to their potential learning effects.

Step 2. Collect Performance Data

In this step, performance data of the repetitive construction tasks will be collected from projects. Ideally, two identical projects with only one factor (BIM) being different should be found so as to conduct the designed comparison. Yet, in real construction practice it is hardly possible to find two such projects. In real situations, there are many other variables, such as the site logistic plan, the project manager's leadership, and workers' craftsmanship, making any site unique.

In view of this, good research efforts have been made to reduce the uniqueness and make the two sets of data comparable, if not entirely identical. First, for example, one can select similar projects (in terms of gross floor areas, completion duration, or investment) from the same company, which will have the same organizational culture, working capability, and so on. Secondly, as introduced subsequently, data format is pondered iteratively to reduce the effect of factors such as floor areas or number of workers. Thirdly, the data sets will go through the data processing described in step 3 to reduce noise or scatter of data collected from turbulent construction sites.

Appropriate data format for measuring project performance is essential in this study. In line with previous references (e.g., Thomas et al. 1986; Adler and Clark 1991; Farghal and Everett 1997; Couto and Teixeira 2005), the performance of the construction work can be measured by using varying terms such as staff-hours/cycle, cost/cycle, and time/cycle. In this paper, the cycle stands for the piece of the repetitive construction task. Ratio data, such as productivity in staff-hours/m^2, can be adopted to reduce the effect of factors, such as floor areas and number of workers, that differentiate the two projects. Furthermore, Thomas et al. (1986) suggested that a researcher generally has the choice of using unit data or cumulative average data in applying the learning curve theory. Unit data are the time, cost, staff-hours, or productivity for completing a given cycle. Cumulative average data are the average time, cost, staff-hours, or productivity to complete all cycles. Everett and Farghal (1997) discussed the strengths and weaknesses of the two types of data, and found that an exponentially weighted average processing of unit data provides a better basis for modeling the learning curve. To this end, a decision was made in this paper to collect unit form of productivity in staff-hours/m^2 and process it using the exponentially weighted average, which will be elaborated in step 3 ("Data Processing").

In addition, the number of data points is a critical issue for learning curve fitting. Although one can find a curve fitting into any number of data points anyway, the curve may not be able to describe a real situation. This echoes Everett and Farghal (1994), whose critique noted that previous research used only four data points, and hence most of the learning curves identified are unconvincing. It is thus suggested that as many data points as possible be collected in such a measurement exercise.

The data source for the performance data is also critical. The research by Thomas et al. (1986), Everett and Farghal (1994), and Wong et al. (2007) accessed data from public resources such as the United Nations Committee on Housing, Building, and Planning or the Hong Kong Housing Authority (HKHA) Performance Assessment Scoring System (PASS) (HKHA 2012). To model learning effects contributed by BIM, more precise and tailor-made data are needed. One can derive the data (e.g., staff-hours/cycle, time/cycle, cost/cycle) from documents such as site logs, time sheets filled by employees, progress reports, inventory records, or suppliers' material/labor forms. The process of distilling the performance data is more convenient today because many project-management tasks are facilitated by software, such as *Microsoft Project* (Microsoft 2010) or *Primavera P6* (Oracle 2012). It is even more feasible with increasing application of integrating construction process documentation into BIM (Goedert and Meadati 2008).

As a result of step 2, two sets of performance data will be collected. They can be defined in mathematical language as shown in Eqs. (1) and (2)

$$D = \{D_1, D_2, D_3, \ldots, D_m\} \tag{1}$$

$$D' = \{D'_1, D'_2, D'_3, \ldots, D'_n\} \tag{2}$$

where D = set of performance data for a repetitive construction task without BIM support; D' = set of performance data of a repetitive construction task with BIM support; and m and n = cycle numbers of each task.

Step 3. Data Processing

This step aims to smooth the data. Because of the complex and turbulent environment in a construction site, the data usually contain a great deal of noise or scatter. Measures should be found to smooth out the noise of the data before the best-fit learning curve is modeled. As discussed previously, Everett and Farghal (1997) suggested that the exponentially weighted average of unit data offers a better basis for modeling the learning curve. The rationale behind the exponentially weighted average equation is that the previous average, which contains information about all prior cycles, should be counted more importantly than a single new observation. The exponentially weighted average equation is

$$S_i = \alpha D_i + (1 - \alpha) S_{i-1}$$

where i = cycle; S_i = smoothed performance data for cycle i; D_i = original performance data collected from cycle i; S_{i-1} = smoothed performance data for cycle $i - 1$; and α = weighting factor or smoothing parameter decided by the modeler.

By applying the equation to the data sets of D and D', two sets of smoothed performance data can be derived in this step as shown in Eqs. (3) and (4)

$$S = \{S_1, S_2, S_3, \ldots, S_m\} \tag{3}$$

where S = set of smoothed performance data of a construction task without BIM support; and $S_m = \alpha D_m + (1 - \alpha) S_{m-1}$

$$S' = \{S'_1, S'_2, S'_3, \ldots, S'_n\} \tag{4}$$

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where S' = set of smoothed performance data of a construction task with BIM support; and $S'_n = \alpha D'_n + (1-\alpha)S'_{n-1}$.

Step 4. Identify Best-Fit Learning Curves

This step involves the identification of a learning curve model that could best describe the performance data as shown in Eqs. (3) and (4). Numerous models exist for measuring the learning effects. Unlike previous studies to preset a learning curve model this research will explore all the learning curves to find the ones that best fit the two sets of performance data, respectively. Programs can be designed in *MATLAB* (MathWorks 2012) to conduct curve fitting to select the best-fit learning curves from those listed in Table 1. The authors have tried these in *MATLAB* (MathWorks 2012) on their own PCs. and each process cost less than 1 s; encouragingly, fast modern computers and software make full trials of all the learning curves possible.

A method called the least-squares curve fitting analysis (LSCFA) was used to evaluate the fitness of a learning curve model that describes the data trend (Everett and Farghal 1994; Wong et al. 2007). Means-square error (MSE) as shown subsequently is usually the specific indicator for the LSCFA

$$\mathrm{MSE} = \frac{\sum_{j=1}^{N}(x_j - y_j)^2}{N}$$

where N = number of performance data; x_j = performance data at the jth cycle after processing; and y_j = performance data agreeing with the learning curve model at the jth cycle (Wong et al. 2007). Test of fitness is conducted by comparing the MSE; the lower the MSE, the better the fitness of the learning model in describing the performance data. By following this LSCFA, a best-fit learning curve for each data set can be identified in this step, and its corresponding MSE is shown in Eqs. (5) and (6)

$$F = f(m) \quad \text{when } \mathrm{MSE} = \frac{\sum_{j=1}^{m}[S_j - f(j)]^2}{m} \text{ is minimal} \tag{5}$$

where F = best-fit learning curve for a repetitive task without BIM support; and

$$F' = f'(n) \quad \text{when } \mathrm{MSE}' = \frac{\sum_{j=1}^{n}[S'_j - f'(j)]^2}{n} \text{ is minimal} \tag{6}$$

where F' = best-fit learning curve for a repetitive task with BIM support.

The two learning curves identified through the analytical processes can also be illustrated in graphics (Fig. 3). The learning curves were derived on the basis of smoothed performance data. The learning curves as shown in Fig. 3 could be in an arc (i.e., an exponential model); however, they are in straight lines for demonstration purposes in this figure.

Further analysis will be on the basis of the two learning curve models in Eqs. (5) and (6) rather than the data sets as shown in Eqs. (3) and (4). Learning is a continuous process, as reflected by the continuous learning curves, whereas discrete data are collected for the purpose of identifying the continuous curves. Furthermore, the learning curves identified through the analytical processes help to reduce the noise in the discrete performance data, and thus are better in terms of reflecting the learning effects.

Step 5. Compare the Two Learning Curves

Two learning curves were identified as a result of previous analytical processes. The subtraction of the two learning curve models

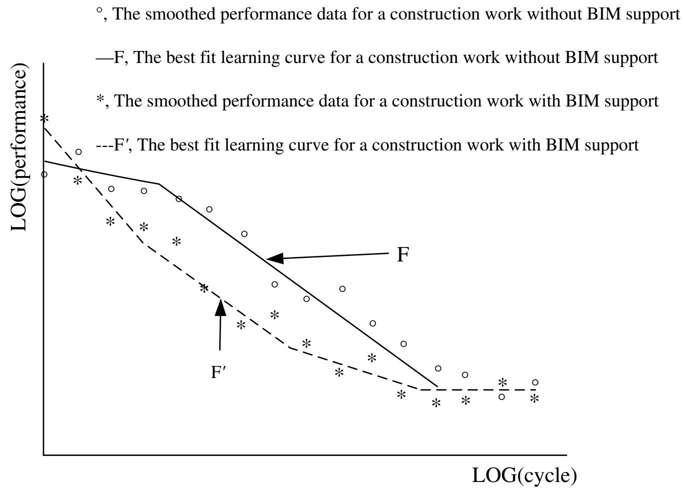

Fig. 3. Illustration of best-fit learning curves for construction works with and without BIM support

yields the learning effects contributed by BIM. This is shown in Eq. (7)

$$L_{eff\mathrm{BIM}}(T) = F - F' = f(T) - f'(T) \tag{7}$$

where $L_{eff\mathrm{BIM}}(T)$ = learning effects contributed by BIM in a given cycle T.

Step 6. Calculate Learning Effects Contributed by BIM

The aggregate learning effects contributed by BIM in the whole construction work are shown in the integration Eq. (8)

$$L_{eff\mathrm{BIM}} = \int L_{eff\mathrm{BIM}}(T) = \int [f(T) - f'(T)] \tag{8}$$

where $L_{eff\mathrm{BIM}}$ = aggregate learning effects contributed by BIM. It is represented in graphic form by the shaded area in Fig. 4.

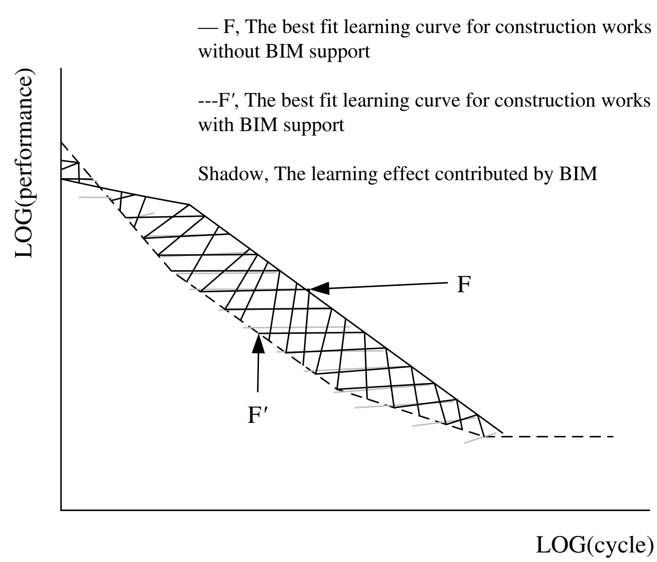

Fig. 4. Illustration of learning effects contributed by BIM

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Case Study for Illustrating $L_{eff\text{BIM}}$ Application

The analytic processes noted in the preceding section lead to a model, $L_{eff\text{BIM}}$, that enables BIM users to calculate the learning effects contributed by BIM in construction tasks. For simplicity of discussion without loss of generality, a case study is employed to demonstrate how this model can be applied in real-life construction tasks. The case is a synthesis of several real-life projects in which BIM has been implemented. The reasons for this are threefold. First, owing to the difficulties of deriving all data sets for this case study, some missing data are hypothesized; therefore, this case should not be claimed as a single real-life project. Nonetheless, the data collection and processing are described in this section so that potential users of the $L_{eff\text{BIM}}$ model can understand how to distill their own data sets when data accessibility is better. Second, it is necessary to ensure that data used in this section will not lead to identification of the projects according to the terms of the data-policy agreement. Third, the primary purpose of this case study is to demonstrate how the generic model and analytic processes are applied; identifying specific learning effects in a certain project is beyond the scope of this paper.

The project is a 66-floor high-rise building in a very compact metropolitan area. The gross floor area (GFA) of the standard floor is 3,200 m^2. The project adopts a typical structure for high-rise buildings, which is called central core, plus mega-columns and outrigger system. The main tasks for erecting the building include construction of the central core, mega-columns, and slabs, and the installation of the outriggers. The project also adopts the traditional cast in situ concrete building technology with all the materials, including steels, mixed concrete, formworks, and falseworks, being transported from outside the site. From the fifth to 45th floors is typical floor construction. In this study, we focus on the construction of floor slabs. During construction, a floor is often divided into four bays, each containing repetitive construction activities as listed in the first row of Table 2. The table gives the quantity information about these construction activities in the region.

Normally, a floor will take N days to complete depending on floor areas, site conditions, construction plan, and configuration of available resources (e.g., project teams, equipment, logistic, and supply chain). By repeating construction activities, a building escalates like a spiral. The contractor has successfully constructed other high-rise buildings previously and the experience has been helpful in winning this contract. But this new project is unique in two main aspects: The site conditions are different and the time scale for this project is tight. The contractor decided to adopt BIM to rehearse and optimize the construction plan for a typical floor. It is expected that, through such rehearsal, optimization, and learning, the project team can construct a floor more quickly while meeting the quality standard and cost requirement. Previous projects similar in terms of floor areas, completion duration, and investment in the company were selected for comparison.

Step 1. Identify Repetitive Construction Tasks to Study

In this case study, the sequential set of works—raising safety screen, setting up table form, erecting column formwork, fixing precast edge beam, hoisting rebar, lifting up placing boom, concrete (slab/beam/column), and raising Holland hoist—for a bay on each standard floor is treated as a single and repetitive construction activity (or, using a previous term, a cycle). As a meaningful representation of construction tasks in high-rise buildings, this integral activity has been investigated by several other studies (e.g., Tam et al. 2002; Li et al. 2008b).

Step 2. Collect Performance Data

Performance data in staff-hours/cycle were collected for two situations: previous works by the contractor and current works with BIM support in the new project. Apparently, the floor areas of the bays make a big difference; the larger the bay area is, the more staff-hours are needed for constructing such a bay/cycle. Therefore, the unit staff-hours/m^2 associated with each bay is adopted for performance data. As suggested in step 2 of "Methodology and Learning Effects Model of BIM," ratio data such as productivity in staff-hours/m^2 can be adopted to reduce the effect of factors such as floor areas or number of workers. In so doing, the two sets of works can be considered identical except for one differing factor (BIM).

From the project report, it is found that the performance of the previous project (without BIM) was approximately 6.32 staff-hours/m^2 and gradually reached 4.81 staff-hours/m^2. In contrast, performance of the current project (with BIM) was approximately 6.27 staff-hours/m^2 and gradually reached 4.83 staff-hours/m^2. It should be articulated again that the beginning set of data is calculated from real cases whereas the later sets are hypothesized on the basis of research with the contractor. The reason for this is that a project manager in real construction practice rarely slavishly follows the plan as shown in Table 2; when there are spare working areas and resources, a project manager often makes a quick decision, commanding the project team to move ahead. Nonetheless, this real data set can be distilled from on-site records, e.g., site logs, employee time sheets, progress reports, and inventory records, although it is difficult for us to obtain all such past records. The data set is shown in columns "Staff-hours/m^2 (previous project)" and "Staff-hours/m^2 (current project)" in Table 3. The productivity key performance indicator of the St. George Wharf development in South London, United Kingdom, may draw reader attention. In the St. George Wharf development project, productivity ranged from approximately 3.8–5.1 staff-hours/m^2.

Step 3. Data Processing

By using Eqs. (3) and (4) in *MATLAB* (MathWorks 2012), the smoothed performance data can be derived as shown in columns "Staff-hours/m^2, smoothed (previous project)" and

Table 2. Characteristic Activities of Typical Bay

Activities	Raising safety screen (RS)	Setting up table form (SF)	Erection of column formwork (EF)	Fixing precast edge beam (FE)	Hoisting rebar (HR)	Lifting up placing boom (LB)	Concrete (slab/beam/column) (CSBC)	Raising Holland hoist (RH)
Quantity	39	81	4	27	30.7	2	418	2
Unit	Numbers	Numbers	Numbers	Numbers	Tons	Numbers	m^3	Numbers

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Table 3. Performance Data for Constructing Standard Bay in Two Different Situations

Floor	Bay or cycle	Staff-hours/m^2 (previous project)	Staff-hours/m^2 (current project)	Staff-hours/m^2, smoothed (previous project)	Staff-hours/m^2, smoothed (current project)
5	1	6.32	6.27	6.32	6.27
	2	6.12	6.25	6.22	6.26
	3	6.24	6.2	6.23	6.23
	4	6.33	5.93	6.28	6.08
6	5	6.38	5.81	6.33	5.95
	6	6.37	5.73	6.35	5.84
	7	6.34	5.65	6.35	5.74
	8	6.27	5.55	6.31	5.65
7	9	6.18	5.47	6.24	5.56
	10	6.08	5.4	6.16	5.48
	11	5.97	5.34	6.07	5.41
	12	5.85	5.29	5.96	5.35
8	13	5.72	5.24	5.84	5.29
	14	5.59	5.2	5.71	5.25
	15	5.46	5.16	5.59	5.2
	16	5.33	5.12	5.46	5.16
9	17	5.2	5.09	5.33	5.13
	18	5.07	5.06	5.2	5.09
	19	4.94	4.95	5.07	5.02
	20	4.81	4.83	4.94	4.93

"Staff-hours/m^2, smoothed (current project)" in Table 3 ($\alpha = 0.5$). Everett and Farghal (1997) discussed the effects of different smoothing parameters and found that $\alpha = 0.5$ is better than $\alpha = 0.3$ in fitting performance data. Therefore, this research adopts $\alpha = 0.5$.

Step 4. Identify Best-Fit Learning Curves

By programming the fitting process in *MATLAB* again, the two learning curves that best fit the smoothed performance data are identified as shown in Eqs. (9) and (10) and Fig. 5

$$F(T) = 10^{\{0.8004-0.1268lg(T)+0.3715[lg(T)]^2-0.2576[lg(T)]^3\}} \quad \text{or}$$
$$lgF(T) = 0.8004 - 0.1268lg(T) + 0.3715[lg(T)]^2 - 0.2576[lg(T)]^3 \text{ when MSE} = 0.0011 \tag{9}$$

$$F'(T) = 10^{\{0.7991-0.0147lg(T)-0.0727[lg(T)]^2\}} \quad \text{or}$$
$$lgF'(T) = 0.7991 - 0.0147lg(T) - 0.0727[lg(T)]^2 \text{ when MSE}' = 0.0008 \tag{10}$$

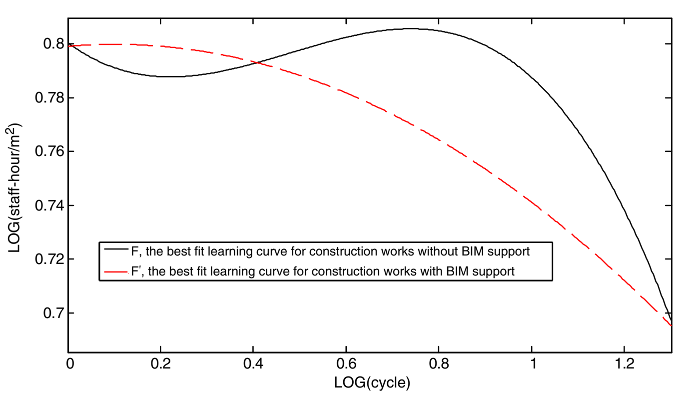

Fig. 5. Comparison of two learning curves for hypothetical case study

Steps 5 and 6. Compare the Two Learning Curves and Calculate Learning Effects Contributed by BIM

The aggregated learning effects in the 20 cycles can be calculated as Eq. (11)

$$L_{eff\text{BIM}} = \int_1^{20} 10^{\{0.8004-0.1268\,\text{lg}(T)+0.3715[\text{lg}(T)]^2-0.2576[\text{lg}(T)]^3\}} - 10^{\{0.7991-0.0147\,\text{lg}(T)-0.0727[\text{lg}(T)]^2\}} = 6.99 \text{ staff-hours/m}^2 \tag{11}$$

Aggregated learning effects indicate the cumulative productivity improvement in the concerned cycles. Saved money can be derived on the basis of the staff-hour rate and floor area. Assuming that the floor area of a cycle (one-quarter of the entire floor) is 800 m^2 and the staff-hour rate is 10/h, the aggregate learning effects within the 20 cycles (five floors) are $55,920 in monetary terms. This tangible benefit is useful to justify the investment of time and budget on BIM, particularly by comparing it with the cost of BIM.

Conclusions and Future Development

Identifying and measuring the benefits of BIM as a learning tool offer both academic and practical values, including improving people's understanding of BIM and helping to justify their investment in it. This paper envisages that BIM provides a less-expensive virtual environment for learning by doing, not only for physically repetitive construction tasks but also for project-management activities. Moreover, this paper empirically models the learning effects empowered by BIM through utilizing the classic learning curve theory. By following a series of six analytical processes, a model, $L_{eff\text{BIM}}$, is developed to recognize the learning effects in construction tasks. The applicability and understanding of this model are further enhanced by using mathematical language and graphic tools. Rather than focusing on identification of the learning effects in a given project, it is better to treat $L_{eff\text{BIM}}$ as a generic model that allows different BIM users to assess the learning effects in monetary terms by inputting their own project data.

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A model makes sense only when users are willing to use it. Future research will be conducted to encapsulate the generic model in a software package and invite BIM users to test the model using their own project data. In considering users that are geographically dispersed, we intend to make software an online solution by engaging Internet technologies. Particular consideration will be given to guidance for collecting data from various construction tasks. It is believed that raw data exist in one way or another but need to be distilled and tailored before the data can be fed into $L_{eff\mathrm{BIM}}$. Further research will also be conducted to help interpret test results with the hope of achieving more benefits through wider implementation of BIM as a valuable tool in construction tasks.

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Notation

The following symbols are used in this paper:

a = cost required for first unit or cycle;
b = slope of first segment;
c = additional slope of second segment;
d = additional slope of third segment;
J_1 = 1 when $x > x_{p1}$, otherwise 0;
J_2 = 1 when $x > x_{p2}$, otherwise 0;
k = upper bound or lowest cost an organization can achieve;
M = proportion of machine work in a person-machine task;
p = acquired experience factor before learning;
r = cumulative units or cycles required to attain $k/2$;
x = unit, cycle, or production volume;
x_{p1} = first point at which slope changes, usually end of acquired-experience phase;
x_{p2} = second point at which slope changes, end of learning effect; and
y = unit cost or cumulative average cost.

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