Integrating Building Information Modelling (BIM) and System Dynamics Approaches to Decrease Cost Overrun in Mass Housing Projects

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Abstract

Cost is one of the most important criteria for evaluating the success of a construction project. Estimating construction costs is an increasing necessity for accurate budgeting and effective allocation of funding since the lack of accuracy in cost estimation could increase the risk of cost overrun. One of the major difficulties in estimating the project cost accurately is the changes occurred in materials price during the project completion period. The aim of this study was to develop a systematic multi-objective knowledge-based approach for estimating the project cost with more accuracy and decrease the risk of cost overrun at the conceptual stage. System development methodology comprises a framework to deploy a system that automatically generates conceptual cost estimates by integrating System Dynamics (SD) with Building Information Modelling (BIM) through an external data interchange protocol in synchrony with interoperability standards. The SD module is used to predict the material price during the project completion period whilst using BIM helps enter detailed properties of the materials as well as the quantity take offs. Deployment of the proposed system will minimise the subjectivity whilst making investment decisions related to building projects and assisting designers and cost engineers to obtain results in an integrated quantitative, qualitative, and dynamic manner. The results show that the model can predict the price of the material with a reliable accuracy and they are anticipated to be of major significance to owners, designers, and construction managers. An application of an actual mass construction project is presented in order to illustrate the usefulness and capabilities of the developed approaches.

Keywords: Building Information Modelling, System Dynamics, Cost Overruns, Multi-objective Optimisation, Expert System

1. Background of the study

The performance of every construction project is evaluated by three criteria, namely time, cost and quality (Khanzadi et al., 2018). It is an aim to complete construction projects at the estimated budget. However, cost estimation should be precise enough to meet the assumed budget. Cost estimation is one of the most important phases of the project planning (Hwang et al., 2012). The estimated cost is generally computed based on the cost of project determinants including construction materials, labour, equipment, and method (Myers, 2016). Yet, numerous other factors can affect construction cost such as the project locality, type, construction duration, scheduling (Rafiei & Adeli, 2018). Furthermore, the fluctuation of economic variables and indexes, can also cause variation in costs, especially in an unstable economic environment (Jafarzadeh et al., 2013; Rafiei & Adeli, 2015). As the material cost accounts for a significant portion of the construction cost, an accurate prediction of raw materials price is important for an accurate prediction of the total cost (Alvanchi *et al.*, 2011). Identifying cost factors has always been of the interest of construction researchers (Alvanchi *et al.*, 2011; Issa, 2000). However, there are limited studies, which concentrated on predicting the materials cost and applying it in a real construction project. Marzouk and Amin (2013) presented a system that utilises fuzzy logic to identify construction materials that are most sensitive to the price changes. This approach is used to modify the contract price with an attempt to predict the amount of future change in the price of materials by using neural networks technique. OuYang *et al.* (2013) proposed a back propagation neural network method to predict the value of the material price in construction projects. Hassan *et al.* (2013) measured the historical volatility of the prices of three key construction materials, namely steel, cement, and lumber. They assessed the degree of risk involving construction cost caused by material price fluctuation. Due to the dynamic changes on the value of the materials' price during the construction project, as well as the assignment of the budget to the work packages according to the initial cost estimation, cost overrun would be considered as a common challenge in the construction projects (Doloi, 2012).

There are many factors that influence material cost in the construction industry. Some studies introduced factors, taking into account the condition of the market or seasonal condition on the material price. However, identifying the quantitative relationship between these factors as well as collecting data by considering these factors are not easily possible. According to estimators in construction companies, the material price trends to be forecasted have the following characteristics: 1) no seasonal variations can be found in most material price time-series data; 2) material prices tend to remain steady even if they increase once in a recessionary period; and 3) extensive data collection is required to make a single prediction (Hwang *et al.*, 2012; Williams, 1994). Therefore, factors that consider the general conditions of the market are needed as primary indicators to study material price. Issa (2000) introduced seven factors which have impact on construction material price: number of privately-owned single-family housing which starts from the Bureau of the Census of the US Department of Commerce; prime interest rate from the US Federal Reserve Board; 30 years home mortgage interest rate from the Federal Home Mortgage Loan Corporation; US Consumer Price Index from the US Department of Labour; 30 years US Treasury Bond from the US Federal Reserve Board; the Dow Jones Industrial Average; and past price for that material.

In the recent years, Building Information Modelling (BIM) has emerged as a comprehensive concept of process and tools which integrates all projects required data and information (Eastman *et al.*, 2011). BIM offers the capability to generate take-offs, counts, and measurements directly from a model. The major application of applying BIM based tools to estimate project costs occurs during the quantity take off stage (Eastman *et al.*, 2011). BIM has been utilised in cost estimation, with research revealing that it is more efficient than the manual cost estimation and leads to project cost reduction (Azhar, 2011). Ma *et al.* (2010) proposed a prototype for BIM based construction cost estimating (CCE) software that used the Chinese standards. Hartmann *et al.* (2012) described the implementation of BIM-based tools to support the activities of the estimating department of a construction company on a large infrastructure project. Ok *et al.* (2009) established the methodology of property information modelling that could support the quantity take-off of a structural element for reflecting the cost estimate feature of a public building.

System Dynamics (SD) is a method, which is originally introduced by Forrester (1958), and concentrates on dynamic complexity (Lättilä *et al.*, 2010). SD represents the resources and dynamics within a system as a set of stocks and the flows between them. SD is useful for understanding the behaviour of complex systems and the effects of causal factors over time (Mostafavi *et al.*, 2012). There, are few studies utilising SD model and BIM to improve the performance of their systems. Bank *et al.* (2011) developed a decision-making framework for the sustainable design of buildings with a BIM tool. They integrated an SD model into BIM design process as a decision-making tool to improve measurement, prediction, and optimisation of sustainable building material performance.

This research proposes a new approach to the integration of SD and BIM for material cost estimation in construction projects. The solution is to develop a dynamic system, which can predict the value of the materials' price during the project running period and insert this value into the cost estimation system to provide more precise and dynamic cost estimation. Therefore, in this study, a BIM-SD method for calculating the accurate estimate of material cost is proposed to address the problems of budgetary inaccuracy, the lack of comprehensive, and the existence of serious waste of auxiliary materials during the main construction phase of mass housing construction. The successful implementation of such a methodology represents a tool, which helps project managers to predict the materials' cost more precisely and enclose the cost estimation more accurate and close to reality.

2. Methodology

The proposed model simplifies the process of building costs estimation and evaluates numerous factors, which have direct impacts on the cost of building materials. Because the material price changes in different areas, generating a general model to predict the material price as well as collecting data from different areas is not easy. However, the Producer Price Index (PPI) can be used as a criterion to consider the past price of the construction material. By predicting PPI from the provided data and by using the PPI formula, the material price can be obtained. According to USA Department of Labour/ Bureau of Labour Statistics: "Producer price index measures the average change in prices received by domestic producers for their output and it measures price changes that are received by mining, manufacturing, services, and construction providers. PPIs are based on a monthly sample of over 100,000 prices." PPI has a baseline starting from 1986. Bureau of Labour Statistics releases the PPI periodically to help industries to adjust the prices in their contracts.

The required data for the SD model are obtained from the specified sources after the names of the factors and the quantitative model created using a regression model. Because of the dynamics exists in the economics and the market, the value of the factors, which are affecting the material price change during the project period. The value of the factors changes during the construction process as well. Thus, assuming the constant values for the factors may decrease the accuracy of the output. Prediction of these factors requires economical calculation as well as an expertise in the economic and market condition. This study uses the predictions presented in the reliable economical websites to obtain more accurate results from the SD model. The predicted values for the introduced factors affecting the material price are provided from the website (www.forecasts.org) as an expert website in the prediction of economic factors. This website uses Time Delay Neural Network (TDNN) and Singular Spectrum Analysis (SSA) to predict the economic factors. Time Delay Neural Network is a certain type of neural network which works with time series data. SSA is a spectral estimation method used to decompose a time series into subcomponents such as trend, cyclical components, and noise. The value of material price can be calculated from the PPI. The current PPI, base material price and base PPI are needed to obtain the current value of material price. The base material price and base PPI are the material price and PPI at a base time. These values can be obtained from the historical data. Equation 1 represents the method on how the material price can be calculated.

$$Material\ Price = \text{Base material price} \times \left(\frac{Current\ PPI}{Base\ PPI}\right) \tag{1}$$

The SD-BIM integration model consists of four main phases: the SD, BIM, Database and the Dynamo modules. Each of the main phases has a significant role in the information exchange through the integrated model. Following are the explanations on the role of each section in the integration process making with their connections, which create the integration model. Figure 2 shows the main parts of the integrated model and their connections.

2.1 Phase 1. Developing SD Model

The aim of the SD model is to predict the value of the material price during the project duration. The prediction would be based on the regression model, which is provided by the historical data as well as the value of the factors that influences material price in the project duration, which is provided from the reliable economic prediction websites. The SD model has been developed based on seven factors that extract from (Issa, 2000) in the AnyLogic© simulation tool. Figure 1 shows the SD qualitative model of the material price.

2.1 Phase 2. Developing BIM Model

The second phase is focus on developing a BIM model for selected case study. The first step is to design and implement a 3D modelling and their associated keynotes for components commonly used in building projects. The BIM model where project cost estimation takes place and the initial value of the material cost and project duration would be inserted into the model. Also, the BIM model is the host for the average material price, which is taken from the database. This estimated price is calculated for the project duration, as shown in Figure 2. The quantity take-off and cost estimation for the whole project would be extracted from the BIM tool. Then the BIM model estimates the total cost based on the quantity take-off as well as the new material price in the BIM model.

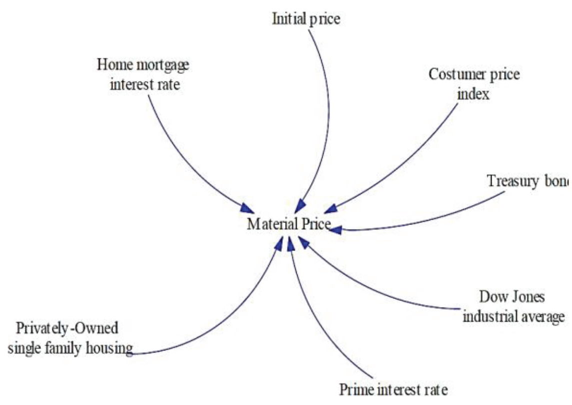

Figure 1: SD qualitative model

2.2 Phase 3. Developing Database

Due to major role that information play in BIM works, every BIM project needs a comprehensive database, which encompasses all materials' details. Hence, the materials used in each design should be identified physically and practically (Jalaei & Jrade, 2014). The integrated proposed model needs a database to interfere between the SD and BIM models since the tools that are used to develop the SD and BIM models cannot be connected directly. The data, which is going to be transferred between the models would be recorded in an Excel-based environment as the database. The models will use the information saved in the database when needed.

2.3 Phase 4: Using Dynamo

The automation process for information transfer between the Excel as the database and the BIM model is done by using Dynamo, which is the platform linked to the BIM tool (i.e. Autodesk Revit©) as an add-in. The developed algorithm in dynamo is used to enact as a bridge between Excel environment as the database and Revit as the BIM tool, which is illustrated in Figure 2. Dynamo uses visual programming to link finished code blocks in the way that they form a logical unit and perform certain tasks. The initial price of the material and project duration, which has been saved in the BIM environment would be sent out from the Revit to the Dynamo. Dynamo passes out the value of initial cost and project duration to the excel file, which stores these data in the database. The SD model reads the value of initial cost from the database and inserts it as a factor, which is used to predict the value of the material price in future months. At this stage, the SD model starts to simulate the value of material price in future months and generates the material price for every month. The monthly value of the material price that has been predicted by the SD model is inserted into the database. This monthly material price should be converted into one value since Revit cannot accept several values for the price of a specific material. Thus, the number of the months, which the project will take as the project duration will be sent out from the project duration section of the BIM tool (Revit) to the Database. In the Database, the average of the material price through the project duration would be calculated and the average price would be released to the Dynamo. The Dynamo then would change the value of the material price in the material properties box in the Revit. The BIM model will use this value as the value for cost estimation prices. Figure 2 shows the architecture of integration of SD and BIM model.

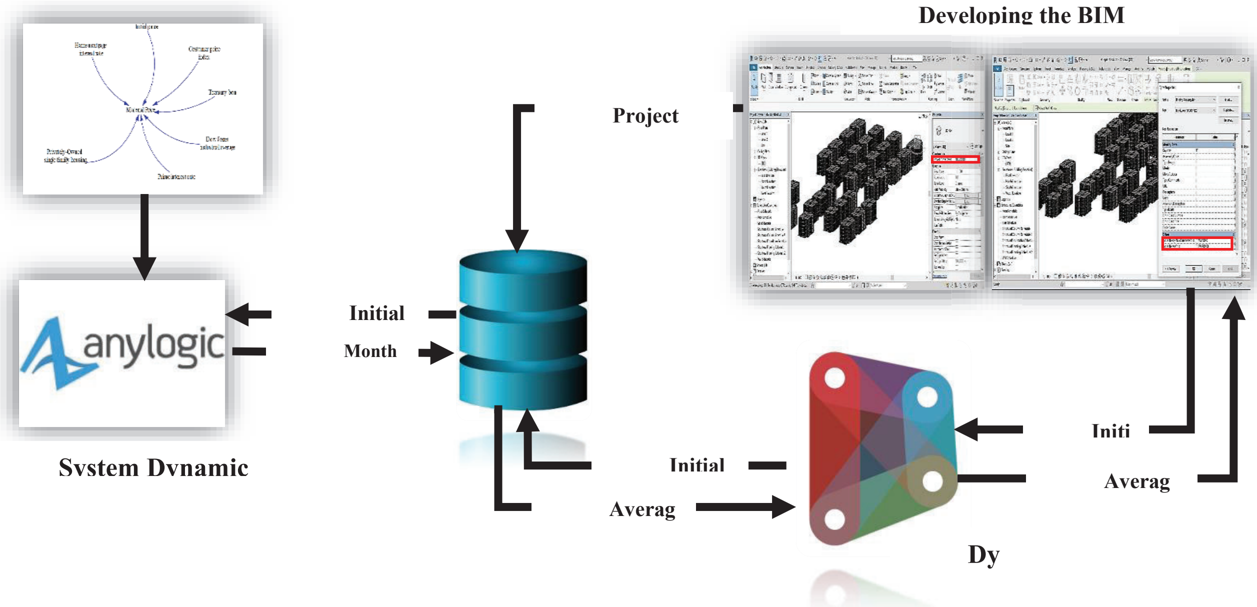

Figure 2: The structure of integration of SD and BIM

3. Model Implementation

This section describes the process of implementing the proposed integration of SD and BIM using data of a real construction project. The case study is a mass housing construction of a residential complex, located at British Columbia (BC), Canada. The residential complex consists of 35 stories blocks. There are many materials, which have been used for the construction project due to the limitations of the research, the cost for two major structural elements of this building project (i.e. freshly mixed concrete (28 MPa) and steel rebar [#8 to #18]) have been studied. However, implementation of the proposed model for these materials shows the ability and capability of the proposed model to be applied to all the materials that are used in the construction process. According to quantity take off from the BIM model of the case study, it would be needed 905.12 m^3 of freshly mixed concrete (28 MPa) as well as the 84.16 tons of steel rebar [#8 to #18] to complete each block of the project. Because the PPI value for every material is different, the quantitative model in the SD is different for every material as well. Thus, according to the historical data for the PPI for freshly mixed concrete and the steel rebar, a unique SD quantitative model is developed for each material. The BIM model of the mass housing construction has been developed and the initial cost of every material used in the construction process has been applied to the BIM model by the user. Figure 3 shows the snapshot of the case study, which is taken from the BIM model.

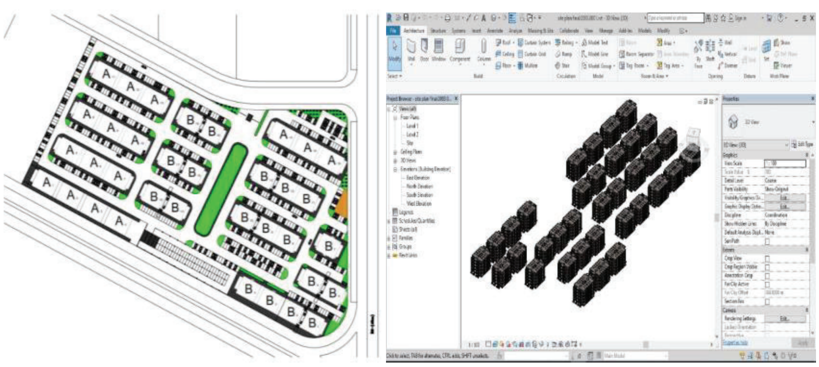

Figure 3: BIM model for the case study

The initial price for fresh mixed concrete and steel rebar is inserted into the Revit model. These values are transferred into the database using Dynamo, which is shown in Figure 4. Then, the SD model reads the initial cost of every material and insert it into the SD model associated with that material. The SD model simulates the price for every material and predicts the price for fresh mixed concrete and steel rebar on a monthly basis. The results of the SD model will be transferred to the Database. Figure 5 shows the linking between SD model and the database with Java programming interface code.

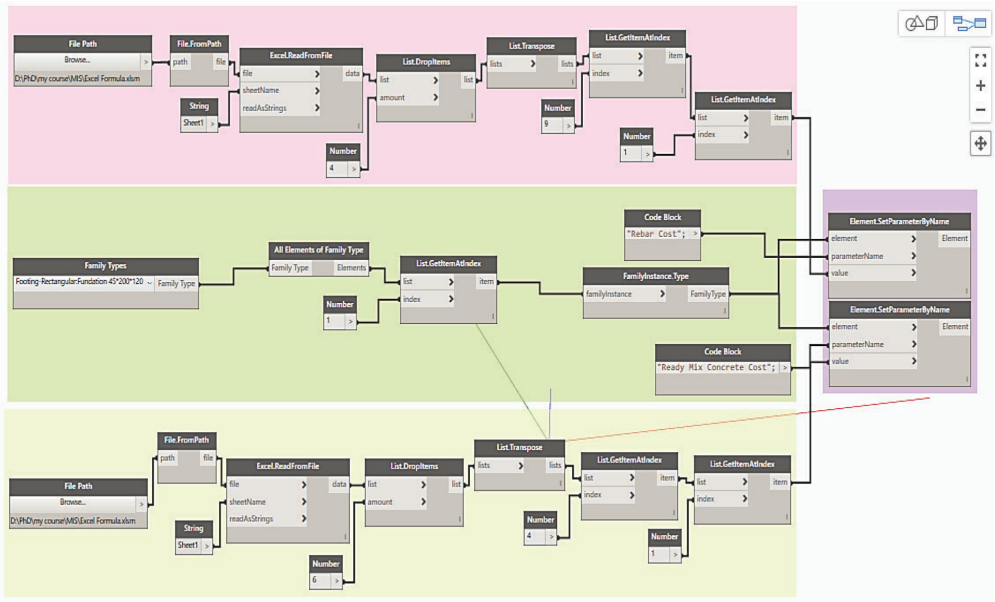

Figure 4: a Mutual connection between the BIM model and the Database using Dynamo

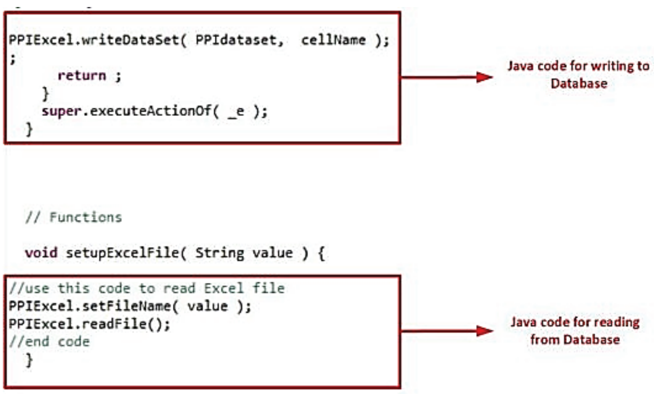

Figure 5: Programmed information flow between SD and Database

The construction programme is also transferred from Revit to the Database. Then, the average of quantities for the fresh mixed concrete and steel rebar in the project duration is calculated in the Database, which is illustrated in Figure 6. The average material price is transferred from the database into Revit by Dynamo, as previously shown in Figure 4. The value of the material price for each material is changed in the material parameter toolbox in Revit according to the new material price values as shown in Figure 8. The new material prices are used by BIM to estimate the project cost. The results of the model show the effectiveness of the model in the process of cost estimation. In this section, first, the reliability of the SD model is illustrated, then the effectiveness of integrating SD as a simulation tool into BIM is depicted in the represented case study

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Time	Ready Mix Concrete Cost	Project Time (Month)	Ready Mix Concrete Cost in Project Time	Project Time (day)
1	164.0258609	1	164.0258609	480
2	164.0258609	2	164.0258609	Project Time (Month)
3	164.6636019	3	164.6636019	16
4	165.325195	4	165.325195	Initial Ready Mix Concrete Cost
5	167.0600292	5	167.0600292	162.67
6	167.4894565	6	167.4894565	Average Ready Mix Concrete Cost in Project time
7	169.3125071	7	169.3125071	168.7642534
8	169.012527	8	169.012527	
9	170.0539897	9	170.0539897	
10	170.1698386	10	170.1698386	
11	170.4003581	11	170.4003581	
12	170.837728	12	170.837728	
13	170.6327751	13	170.6327751	
14	171.781694	14	171.781694	
15	172.1172306	15	172.1172306	
16	173.3194025	16	173.3194025	
17	173.3374376	17	0	
18	173.5515855	18	0	
19	173.8349593	19	0	
20	174.7300404	20	0	
21	175.2184299	21	0	

Time	Rebar Cost	Project Time (Month)	Rebar Cost in Project time	Project Time (Month)
1	1178.518176	1	1178.518176	16
2	1173.93232	2	1173.93232	Initial Rebar Cost
3	1159.010583	3	1159.010583	1158.82
4	1151.253731	4	1151.253731	Average Rebar Cost in Project time
5	1174.913064	5	1174.913064	1134.988781
6	1138.168006	6	1138.168006	
7	1139.674143	7	1139.674143	
8	1131.104142	8	1131.104142	
9	1127.381306	9	1127.381306	
10	1123.506412	10	1123.506412	
11	1120.247668	11	1120.247668	
12	1131.969694	12	1131.969694	
13	1112.11572	13	1112.11572	
14	1111.232051	14	1111.232051	
15	1090.136072	15	1090.136072	
16	1096.657406	16	1096.657406	
17	1151.253731	17	0	
18	1174.913064	18	0	
19	1138.168006	19	0	
20	1139.674143	20	0	
21	1131.104142	21	0	

Figure 6. The outputs of the SD model exported into database and calculation of average cost for ready mixed concrete and Rebar steel

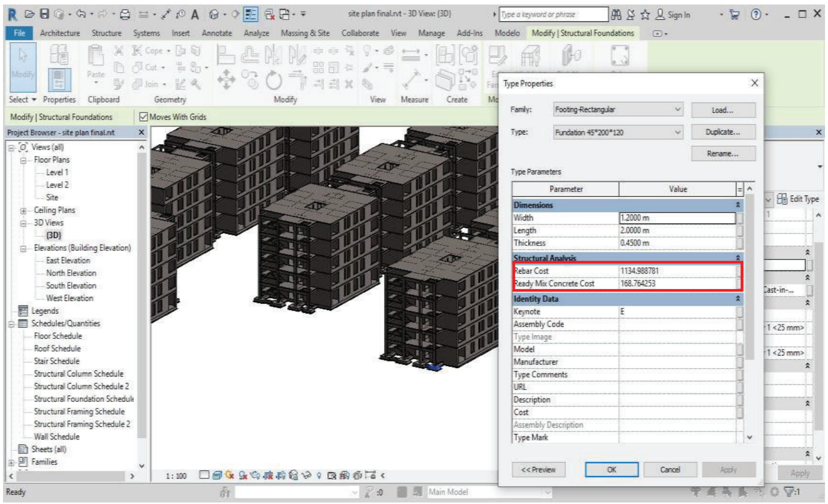

Figure 8: Ready-mixed concrete and rebar cost in the BIM

4. Validation of the SD model

This study uses the RSMeans as the main source for validation of the outputs of the SD model. RSMeans is a database that provides accurate and up to date cost for different materials and operations in North America to help contractors, owners, architects, engineers, and others in estimating projects cost more accurately. The reason for selecting RSMeans as a validation source is that the factors, which affect the value of material cost in this study convey the information about the North America market condition. Material price in RSMeans is presented based on every quarter of the year and the SD model in this study predicts the material price monthly. The average of the material price in three months, which is obtained from SD model would be used as the quarterly material price value to be compared to the output of the RSMeans. Table 1 show the values of the material price from the SD model and RSMeans for last quarter of 2017 as well as the first quarter of 2018. Several dollars difference for every ton or cubic meter of the material between the output of the SD model and the RSMeans depicts the reliable performance of the SD model. This reliability will be shown at the cost estimation in the next section.

Table 1: Predicted Ready-mixed concrete price and steel rebar price by RSMeans and the SD model

Ready mixed concrete (28 MPa) price			steel bar (#8-#18) price	
Data Source	**2017 Quarter 4**	**2018 Quarter 1**	**2017 Quarter 4**	**2018 Quarter 1**
RSMeans	163.33 $	162.83 $	1082.88 $	1065.02 $
SD model	164.238 $	166.625 $	1083.353 $	1069.303 $

Table 3 provides the simulated material price by the SD model for the rest of the project duration to be considered into cost estimation. According to the values that are provided from the forecasting website for the involved factors in the SD model, the SD model is adjusted to predict the material price for the duration of the project selected as the case study. Therefore, the maximum reliable output of the SD model to predict the material price is the first month of 2019.

Table 3: Predicted material price by the SD model for the future months

Month of the project	**4.2018**	**5.2018**	**6.2018**	**7.2018**	**8.2018**	**9.2018**	**10.2018**	**11.2018**	**12.2018**	**01.2019**
Mixed concrete price ($/m3)	169.3	169	170	170.17	170.4	170.8	170.6	171.78	172.1	173.32
Steel rebar price ($/ ton)	1139.67	1131.1	1127.38	1123.5	1120.2	1132	1112.1	1111.2	1090.1	1096.7

According to the conducted quantity take-off from the BIM model of the case study, it would be estimated about 905.12 m^3 fresh mixed concrete (28 MPa) and 84.16 tons steel rebar (#8 to #18) to complete each block of the project. Furthermore, the quantity of the material, which will be used for the whole of the project are 31,679.2 m^3 and 2,945.6 tons of freshly mixed concrete (28 MPa) and Steel rebar (#8 to #18) respectively. According to the Table 4, the initial cost for freshly mixed concrete (28 MPa) is 162.67 $/m^3$ as well as 1139.43 $/ton for the steel rebar (#8 to #18). While the SD-BIM model proposes 168.8$ m^3 and 1134.99 $/ton for freshly mixed concrete (28MPa) and steel rebar (#8 to #18) respectively. It can be seen that the material price for freshly mixed concrete is increasing, but the material price for steel rebar is decreasing. This trend has been shown in Tables 1, 2 and 3, which show a variation of the material cost at different quarters for the studied materials obtained from RSMeans and the proposed model.

Table 4. Quantity and cost of the materials

Material	**Quantity of the material**	**Initial unit cost**	**Unit cost by the proposed model**
Fresh mixed Concrete(28MPa)	31,679.2 m^3	162.67 $	168.8 $
Steel Rebar (#8-#18)	2,945.6 tons	1158.82 $	1134.99 $

Variations in the material price show their influence on the project cost during project completion time. Conventional cost estimation cannot track these variations accurately. Based on the conventional method for the project cost estimation, the cost value for one material equals the quantity of the material multiplied by the unit cost of that material. Therefore, according to the table 5, the estimated cost for the required fresh mixed concrete and steel rebar are 5,153,255.464 $ and 3,413,420.192 $ respectively. On the other hand, the cost estimation based on the material cost obtained from the proposed model are 5,347,448.96 $ and 3,343,226.54 $ for the needed fresh mixed concrete and steel rebar in turn. These results show that initial estimated cost of the concrete is lower than the actual cost, which the project will experience. Thus, the managers should consider 195,000 $ additional financial resources for providing enough freshly mixed concrete. Meanwhile, the initial steel rebar estimated cost is more than what the project will experience during the project completion duration. The reason is that the reduction in the cost of the steel rebar has not been considered in the conventional cost estimation while the proposed model could track the reduction and consider its impact on the cost estimation perfectly. Therefore, managers can save more than 70,000$ of their financial resources and reduce the estimated budget for the steel rebar.

Table 5. Conventional cost estimation versus cost estimation by the proposed model

Material	Initial cost estimation	Cost estimation by the proposed model
Fresh mixed Concrete(28MPa)	5,153,255.464 $	5,347,448.96 $
Steel Rebar (#8-#18)	3,413,420.192 $	3,343,226.54 $

5. Summary and Conclusions

Due to the changes on the value of the materials' price during the construction project as well as the assignment of the budget to the work packages according to the initial cost estimation, cost overrun would be considered as a common challenge in the construction projects. In addition, as became evident in the reviewed literature, despite the wide application of new technologies have utilized in the AEC industry, there are still inaccuracy cost estimation issues that causes project cost overruns. To address these issues, this paper has developed a workflow for the linking of data within a BIM to a SD model as an automated and integrated model that allows to a realistic predict of the material price and estimate the project cost. In view of this line, BIM is used to collect the material price for every item as well as the quantity take-off and cost estimation for the whole project. SD model is used to predict the value of the material price in the market. The material price is affected by numerous factors, which are included in the SD model as well as the predicted values for each factor that are used to increase the accuracy of the predicted material price. Information will be transferred between BIM and SD model mutually to develop an automated system to estimate the project cost. The model was verified using the construction cost data in RSMeans platform. Cost estimation variation of the proposed model were Several dollars difference with RSMean data base, thus demonstrating the effectiveness of the strategies employed in this research and the superiority of the proposed model.

The results show that the proposed method increases the estimation accuracy considerably. This accuracy assists construction managers to assess the proper budget for the projects and prevent the projects from cost overrun.

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