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AN EARNED-VALUE-ANALYSIS (EVA)-BASED PROJECT CONTROL FRAMEWORK IN LARGE-SCALE SCAFFOLDING PROJECTS USING LINEAR REGRESSION MODELING

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SUMMARY: *In large-scale industrial construction projects, scaffolding activities account for a large amount of the construction budget, and overlooking the scaffolding management can lead to budget overruns and schedule delays. The scaffolding activities can be categorized by classifications and types based on the nature of the scaffold builds. To ensure the project progress on track, it is critical to measure project performance based on project progress data. However, given the nature of scaffolding activities, it has been challenging to track and utilize the scaffolding data for analytical purposes. Therefore, this paper proposes a project control framework based on Earned-value analysis (EVA), in which linear regression models are used for productivity prediction. Three scenarios of productivity based on historical data (i.e., low, medium, and high productivity) are introduced. The proposed framework is implemented in a real construction project for validation. The results have shown that the proposed framework can efficiently evaluate the project progresses integrated with the EVA. The construction companies, such as general contractors and scaffolding sub-contractors, can use this method for site progress tracking. For future work, the EVA can be integrated with other non-linear predictive models (e.g., neural network) for productivity prediction. The EVA results can be integrated with data visualization to create situational awareness for construction practitioners.*

KEYWORDS: *scaffolding management; regression models; project control; earned-value analysis*

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1. INTRODUCTION

In large-scale construction projects, such as heavy industrial projects, often encounters work to be performed at specific locations where access is not available in the first place, and scaffolding, as an indirect work, is often used to provide access to these locations. Due to the size and complex nature of these large-scale construction projects, scaffolding can account for quite substantial onsite work (e.g., scaffolding work can make up to 30% - 40% of the total manhour (Zolfagharian and Irizarry, 2014)). Mismanagement of scaffolding work can lead to budget overruns and schedule delays. Particularly, scaffolding work, as a type of temporary work, is challenging to track and manage. For example, the quantities and measurements of productivities are challenging to manage and track (see Fig. 1 for a complex scaffolding tower at an industrial construction site), which results from three reasons: (1) scaffolding data is difficult to acquire given that a large amount of material consumed onsite and low traceability of each material piece; (2) a lack of data-driven project control framework that can be used for industry practitioners for scaffolding management; and (3) efficient and reliable planning systems that can be applied to large-scale complex construction projects.

In the past, research efforts have been made to improve the scaffolding management from the above-mentioned three aspects. One type of effort focuses on using technologies to increase the traceability of scaffolding material. For example, a radio-frequency identification aided system was introduced for scaffolding tracking to improve stock management (Moon et al., 2018). Recently, scaffolding planning has benefited by incorporating Building Information Modeling (BIM) technologies to achieve automated design and plan generation: a rule-based computational algorithm was proposed to automatically generate scaffolding plans (Kim and Teizer, 2014); A feature lexicon was introduced to formalize representation of factors essential to scaffolding planning (Kim et al., 2015). To improve the efficiency of scaffolding planning and scheduling, mathematical algorithms have been developed, such as the discrete firefly algorithm-based scaffolding scheduling approach (Hou et al., 2017). Researchers have also considered safety (e.g., prevention from collapse) as part of the scaffolding planning and management (Cho et al., 2018; Kim et al., 2016). Also, past research has emphasized using data-driven decision support systems to aid scaffolding management. The basis for these systems is the productivity analysis, which is used for quantifying the output of scaffolding work (e.g., scaffolding material weight and volumes) completed over given inputs (e.g., manhours) (Moon et al., 2016).

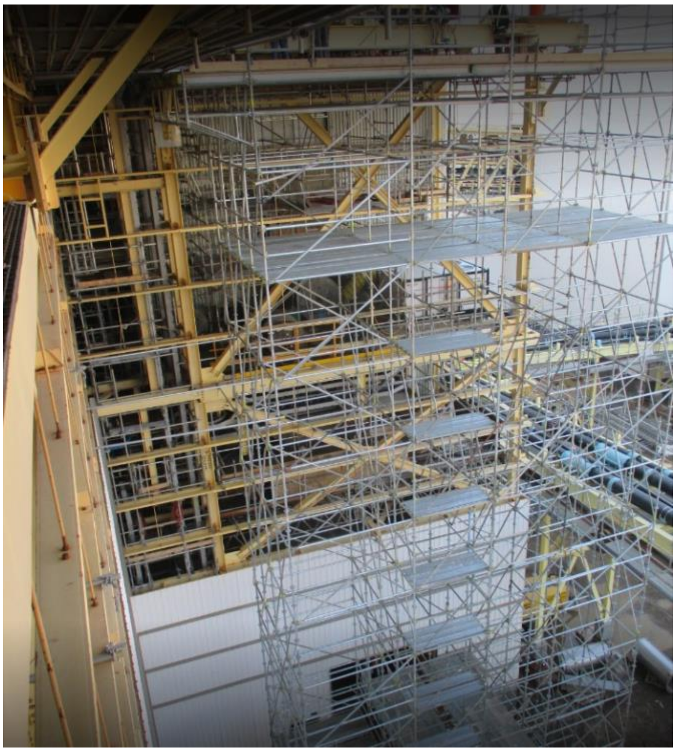

FIG. 1: Scaffolding tower at an industrial construction site.

In construction engineering and management (CEM), data analytics has gained attention in both academia and industry, as data has become accessible through emerging data collection technologies. Examples of such data collection mechanisms include Internet-of-things (e.g., mobile applications) and digital platforms, and image-based acquisition systems (Cheng et al., 2020; Soltani et al., 2016). Based on collected data, decision support insights can be generated through algorithm-based analytics. Machine learning (ML) and artificial intelligence (AI) have been utilized to achieve such predictions (Cho et al., 2018; Liu et al., 2018). For instance, analytical methods have been applied to analyze construction equipment costs (Liu, AbouRizk, et al., 2020; Liu, Lei, et al., 2020). Also, simulation techniques were applied to increase predictability in CEM (e.g., discrete-event simulation, system dynamics, etc.) (Alanjari et al., 2014; Ji and AbouRizk, 2018; Taghaddos et al., 2011). All these efforts contribute to the transformation of CEM towards a more digitized, automated, and autonomous state. However, past research has focused on scaffolding data collection and analysis, and not addressed how to use scaffolding data for project progress tracking; Also, there is a lack of research in the area of using machine learning techniques to construct productivity models to be used for EVA. This research thus proposes using a machine learning technique (i.e., linear regression modelling) to construct productivity models for scaffolding data in order to conduct EVA for project progress status analysis. The research contributions of this work include: (1) providing a generic data collection and classification approach for scaffolding data that result in productivity analysis; (2) dynamically incorporating EVA in scaffolding progress control using historical data; and (3) regression-based productivity modeling based on user-defined productivity categories. The industry contributions include: (1) providing a scaffolding management framework for large-scale construction projects; and (2) algorithms developed through this study can be implemented by industry companies to achieve near real-time project control for scaffolding work.

2. METHODOLOGY

The overall research framework is presented in Fig. 2 to show the steps taken throughout the implementation of the research. The research inputs include the scaffolding expertise and practice as provided by the industry practitioners. For example, the classification of the scaffolding types (the inputs will be elaborated in the section 2.1 “Data Structure Definition and Acquisition). This know-how is used to define the data structure and develop the data acquisition tools. Also, the users define the categorization of the productivity types based on their experience, which helps generate regression models. The research framework consists of three main components: (1) the data acquisition: IoT mobile app is developed to acquire field data, which can be deployed using Platform-as-a-Service (e.g., Microsoft PowerApps); (2) the Cloud-based SQL database: for data storage collected from the IoT apps; this can be deployed using Microsoft Azure SQL database, or Amazon Web Services (AWS); and (3) the analytical modeling system: using RStudio as the engine to perform data wrangling, productivity regression modeling, and EVA. Lastly, the research outputs allow the users to conduct project reviews based on collected data and predictive modeling, and review the project performance through the EVA. The proposed research framework is generic and can be applied to similar project contexts to analyze scaffolding data and project progress status. The research framework will be elaborated on in the following sections in detail.

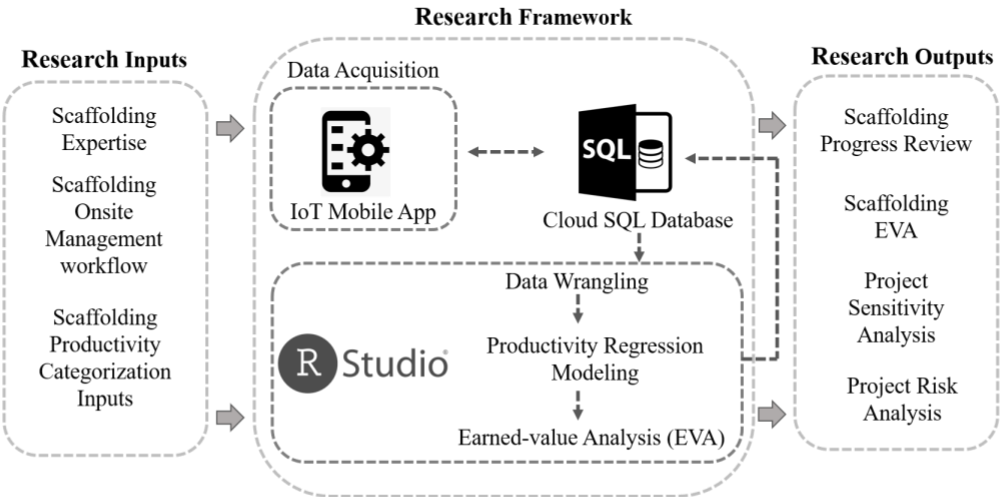

FIG. 2: Overall research framework.

2.1 Data structure definition and acquisition

Data acquisition is the first component of the research framework. In this research, IoT apps using the PowerApps platform were developed to collect field data. The data structure was defined together with the industry partner. After discussing with the industry partner, the research team has identified two main functions of scaffolding data acquisition systems: (1) material handling system: which deals with the material tracking of the scaffolding activities; the material master list is provided by the scaffolding component manufacturer, which is used as the basis for the data structure, including material ID, material name, and weight. For each completed scaffolding task, the field scaffolder reports what material has been used through the app; and (2) task requisition system: which handles the requisition of scaffolding tasks as requested by the field foremen and/or scaffolder. As shown in Fig. 3 as a typical scaffolding management workflow, the process starts with identifying the needs of scaffolding in the field. There are three types of needs: erection of new scaffolding structures, modification and dismantling of existing structures. After the need is identified, a scaffolding request is created with a request ID, which is later associated with multiple tasks (e.g., one request can consist of multiple tasks, 1: n relationship). The tasks are then sent back to the field crew for completion and report back with task progress and material consumption. Following this workflow, corresponding data structures were developed using an entity-relationship diagram (ERD) and further deployed in the Microsoft Azure SQL database (see section "Case Study" for an example of deployed data structure). Once data is collected from the field, it is processed to remove system outliers due to errors in entry (e.g., using database integrity checks, user-defined rules, etc.).

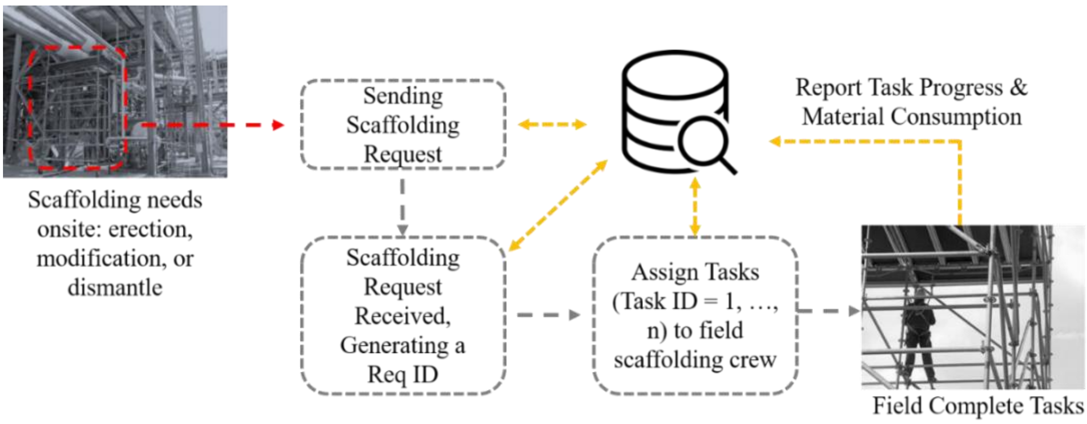

FIG. 3: Scaffold management workflow.

2.2 Productivity regression modelling

Regression modeling is a form of predictive modeling that investigates the relationship between the dependent and variables. In construction engineering and management, regression modeling has been used to provide decision support insights for construction operations (Bowen et al., 2014; Son et al., 2019). In this research, regression modeling is used to model the scaffolding productivity from onsite operations. The productivity, by its definition, can be measured as the outputs over the given inputs for any system, and in this case, is the amount of scaffolding work completed (i.e., outputs) over the manhours that are put into work (i.e., inputs). The measurement of scaffolding work completed can be defined by various metrics (e.g., weight and/or volume) (Moon et al., 2016). In this research, regression models were developed based on the total weight of scaffolding components and manhours involved in given tasks and manhours. Other variables (e.g., elevation of the work, etc.) can be used to develop regression models, however, due to the availability of data, weight is used as the sole variable for this analysis. Given this, the regression modeling is to seek the best fit line of the predicted value (manhours) for a given variable (scaffolding weight), by minimizing the cost function as shown below:

$$Min. \frac{1}{n}\sum_{i=1}^{n}(Mhr_p - Mhr_a) \tag{1}$$

Where: Mhr_p = predicted scaffolding manhour using the regression model; and Mhr_a = actual scaffolding manhours observed from field.

Considering the fact that the nature of different scaffolding work varies, categorizations are adopted to subset the entire scaffolding dataset for regression modeling for the purpose of improving model accuracy. There are four categorization criteria for the scaffolding data: (1) scaffolding work classification (e.g., erection, modification, and dismantle); (2) scaffolding types (e.g., tower, platform, etc.); (3) work discipline (e.g., piping, civil, etc.); and (4) productivity level (e.g., low, medium, and high productivity). Fig. 4 shows the process of regression modeling based on the categorization, which generates three types of productivity regression models: low, medium, and high productivity (see "Implementation" for results). The determining factor for these three productivity categories is defined by user (i.e., industry partner) based on past experience, and in this case, is 0.3 deviation from the overall dataset average, in both positive and negative directions.

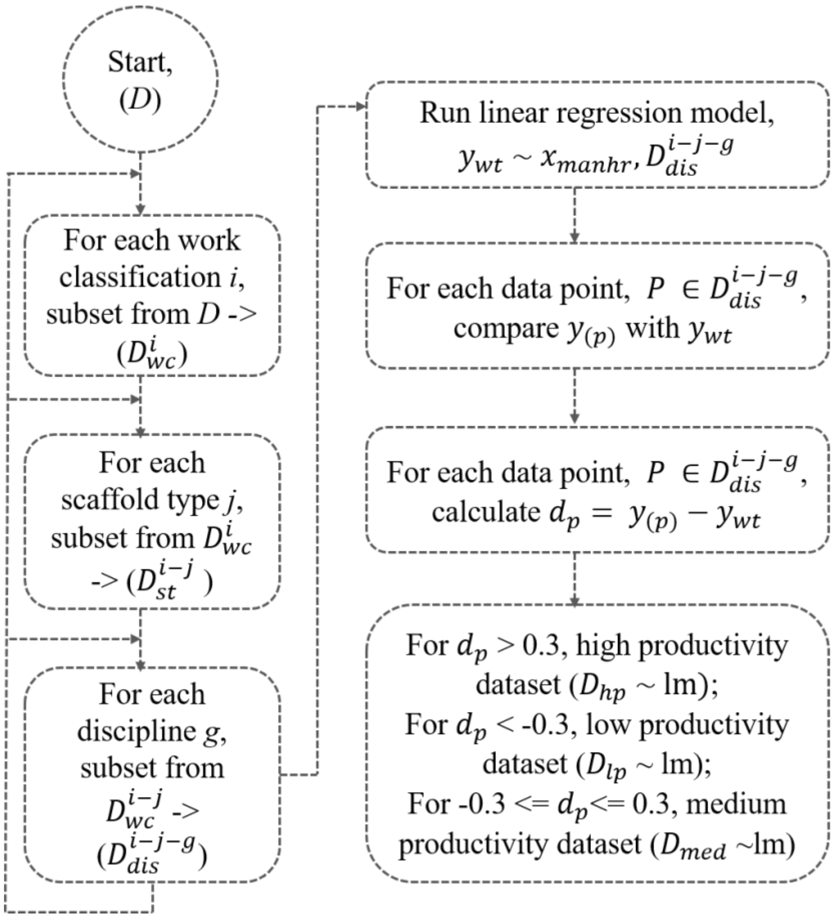

FIG. 4: Regression modelling flowchart.

2.3 Productivity regression modelling

Earned-value analysis (EVA) is a widely adopted project control technique in project management (Howes, 2000; Waris et al., 2012). It is based on the calculations of four main parameters to obtain the overall performance of project progress: (1) budgeted cost of work performed (BCWP); (2) budgeted cost of work scheduled (BCWS); (3) actual cost of work performed (ACWP); and (4) actual cost of work scheduled) (ACWS). Their definitions are self-reflected from their calculation formulas as shown as Eq. (2) – (4). The ACWP consists of commitments and payments due and made for a given project time period. Based on these four parameters, other project metrics can be calculated: (1) cost variance (CV); (2) schedule variance (SV); and (3) performance (productivity) factor (PF) (Eq. (5) – (7)). In this research, due to the regression modeling provides three categorized productivity predictions, it yields corresponding BCWP and BCWS with high, medium, and low planned productivity, along with its own probability, which will be elaborated with example in the "Implementation" section.

$$BCWP = Qt_{planned} \times P_{actual} \quad (2)$$
$$BCWS = Qt_{planned} \times P_{planned} \quad (3)$$
$$ACWS = Qt_{planned} \times P_{actual} \quad (4)$$
PF = Earned value manhours/Actual manhours (5)
$$CV = BCWP - ACWP \quad (6)$$
$$SV = BCWP - BCWS \quad (7)$$
$$CPI = \frac{BCWP}{ACWP} \quad (8)$$
$$SPI = \frac{BCWP}{ACWP} \quad (9)$$

Where: *BCWP* = budgeted cost of work performed (i.e., earned value); *BCWS* = budgeted cost of work scheduled; *ACWS* = actual cost of work scheduled; *ACWP* = actual cost of work performed; *CV* = cost variance; *SV* = schedule variance; *CPI* = cost performance index; *SPI* = schedule performance index.

3. IMPLEMENTATION

In this research, a heavy industrial project located in Alberta, Canada, is selected to implement and validate the proposed framework. The scaffolding data is collected through mobile applications that are designed following the workflow of Fig. 3. A proposed ER diagram is proposed and implemented in a Microsoft Azure SQL database (Fig. 5). The PowerApps (a suite of apps, services, connectors and data platform that provides a rapid application development environment to build custom apps for business needs) was then used to connect to the Azure SQL database for field data collection. For the test case, there are around 16,000 scaffolding task records collected with an approximate total scaffolding weight of 60 million lbs. From the collected data, there are a total of 6 scaffolding work classifications: (1) extension erection; (2) unplanned modifications; (3) partial dismantle; (4) planned modification; (5) new erection; and (6) full dismantle. There are 16 scaffolding types, such as stair towers, large platform access, and so on; a total of 24 disciplines were defined for the scaffolding tasks: e.g., piping, structural, electrical, etc. With these three classifications, the subset (i.e., the D_{dis}^{i-j-g} in Fig. 4) is populated and regression models were developed as classified as high, medium, and low productivities (i.e., based on 0.3 deviation threshold). Fig. 6 shows an example of scatterplot with regression models based on the classification criteria: “full dismantle – tower (typical) – piping”. The green line (representing green points) is medium productivity regression, while the brown refers to as the low productivity and violet as the high productivity. Following this method, each regression model is populated, and the R2 value is calculated using Eq. (8) – (10) to show how close the data is to the fitted regression line. An example of exported summarized productivity regression model is given as Table 1.

$$R^2 = 1 - \frac{RSS}{TSS} \quad (8)$$
$$RSS = \sum_{i=1}^{n} (y_i - f(x_i))^2 \quad (9)$$
$$TSS = \sum_{i=1}^{n} (y_i - \bar{y})^2 \quad (10)$$

Where: *RSS* = sum of squares of residuals; *TSS* = total sum of squares; y_i= given data point *y* value (i.e., actual manhours); $f(x_i)$ = predicted value using data point *x* value for the given regression model; $\bar{y}$ = mean value of the manhours of the sample.

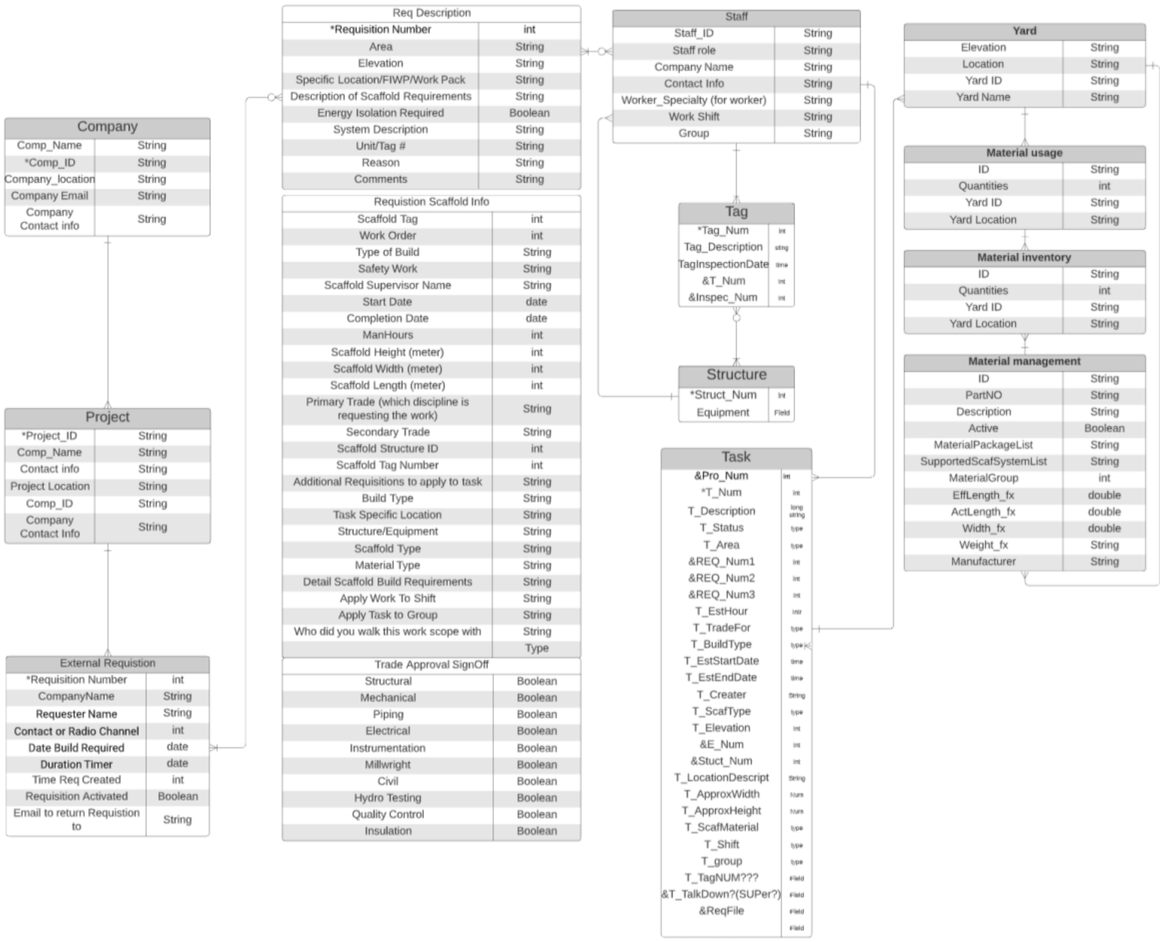

FIG. 5: Sample proposed entity relationship diagram of scaffolding management system.

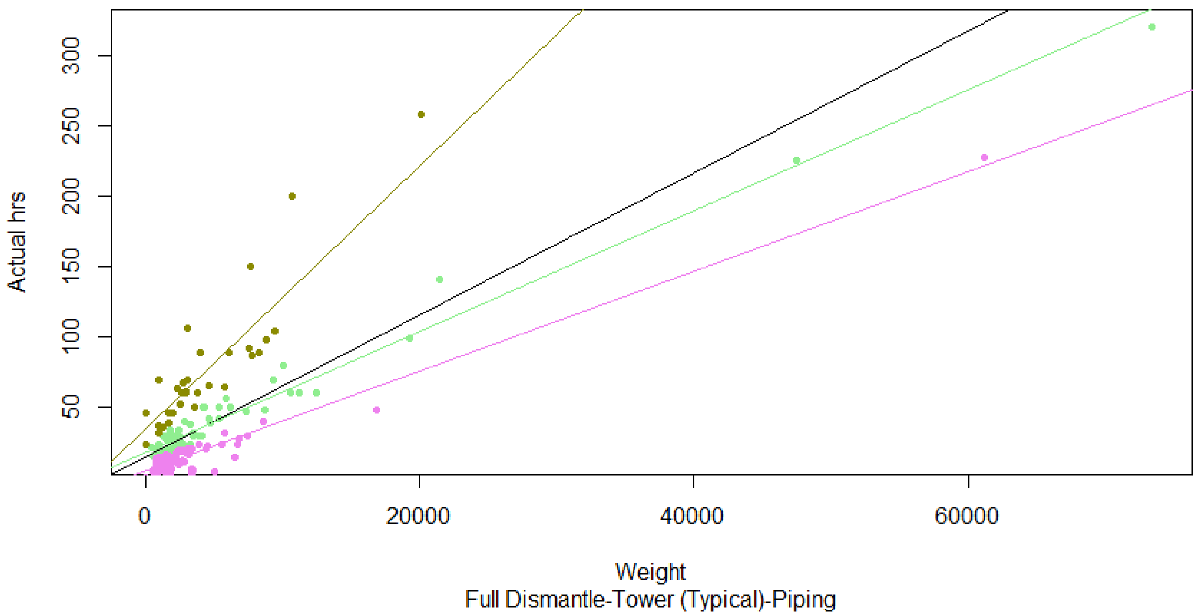

FIG. 6: Example of productivity regression models.

Once the regression models are developed, then the EVA can be performed using Eq. (2) – (7). In practice, the project management team can run the EVA based on the built regression models at different time points of the project and provide project control metrics. For example, Fig. 7 shows the overall Budgeted Cost of Work Scheduled (BCWS) at the 30% project progress. The red curve shows the BCWS calculated based on the high productivity regression models (BCWS_HP); the black as the medium productivity regression models (BCWS_MP); the orange as the low productivity models (BCWS_LP). In practice, the end-user can conduct EVA based on field-collected data as the project progresses. Table 2 shows an example of the results of the EVA based on project progress (i.e., 30%, 50%, 70%). Based on the EVA results, the CV, SV, CPI, and SPI can be calculated to demonstrate the project progress performances using Eq. (6) – (9). For example, for the 30% project progress, the CV for high productivity regression models = 41 – 18 = 23 million lbs (corresponding CPI = 41/18 = 2.3); the SV for high productivity regression models = 41 – 12 = 29 million lbs (corresponding SPI = 41/12 = 3.4). With CPI and SPI both bigger than 1, which indicates the project has a cost underrun and ahead of schedule. From the calculated CPI and SPI, the project management team can obtain insights if the project is on track. Similar calculations can be performed at different project progress statuses (e.g., 50%, 70%). However, in industry practice, the scaffolding estimation still relies solely on a percentage base (e.g., a certain percentage of the total direct work manhours), and scaffolding activities often occur on an ad-hoc basis. It is challenging to have an exact cap (i.e., total expected scaffolding expenses) and duration as a comparison. Also, the duration of scaffolding work often extends beyond the completion of the main construction structures, e.g., dismantling, etc. This will add complexity to the EVA analysis.

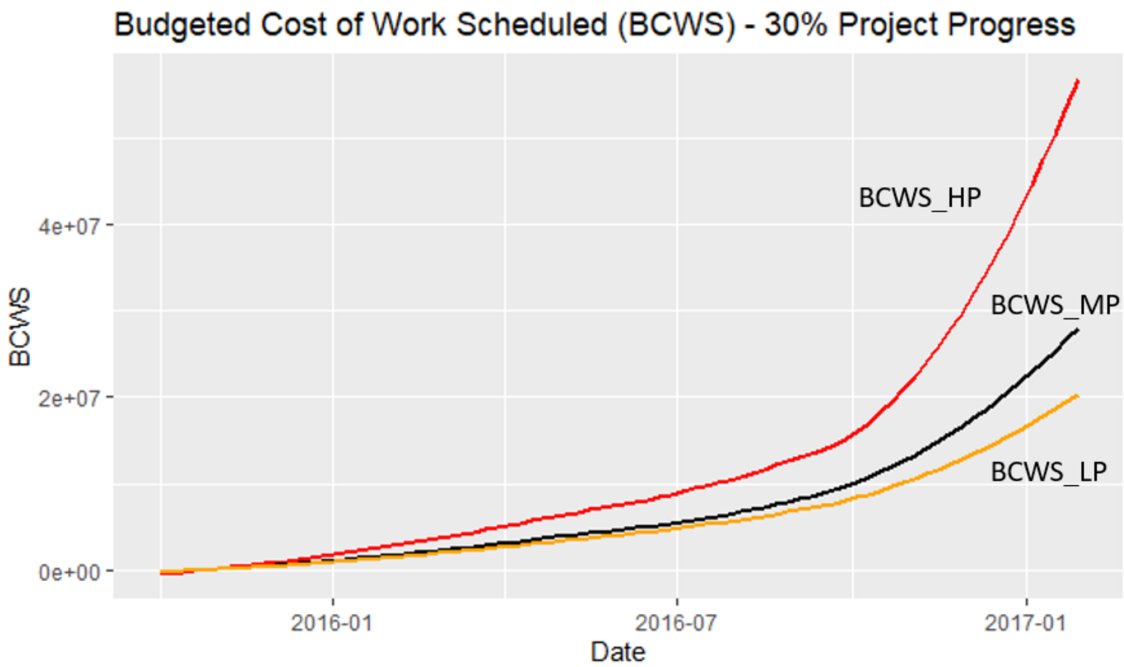

FIG. 7: Budgeted cost of work scheduled (BCWS) based on 30% project progress.

Table 1. Example of Results of Regression Models by Classifications

Work Classification	Scaffolding Type	Discipline	Medium Productivity (Slope)	Medium Productivity (Intercept)	Medium Productivity (R^2)	Low Productivity (Slope)	Low Productivity (Intercept)	Low Productivity (R^2)	High Productivity (Slope)	High Productivity (Intercept)	High Productivity (R^2)	General Productivity (Slope)	General Productivity (Intercept)	General Productivity (R^2)
Extension Erection	Stairtower	Structural	0.015751838	54.06825896	0.94545191	NA	NA	NA	NA	NA	NA	0.014684	45.70579	0.834591
Extension Erection	Large Platform Access	Piping	0.017126879	75.83303896	0.956036861	0.029651297	133.6736358	0.946808	0.01161	21.09507	0.96197	0.016838	68.98776	0.833505
Extension Erection	Large Platform Access	Structural	NA	NA	NA	NA	NA	NA	0.006732	13.96215	0.914807	0.008901	53.01735	0.495265
Extension Erection	Large Platform Access	Electrical	0.027741504	55.66820058	0.922106958	NA	NA	NA	0.012372	29.96179	0.778971	0.028143	39.03827	0.652922
Extension Erection	Tower (Typical)	Piping	0.021175533	18.88385485	0.958188537	0.036499711	40.45652459	0.931652	0.013083	4.479517	0.940725	0.020519	18.02973	0.76844
Extension Erection	Tower (Typical)	Structural	0.014467461	89.93131727	0.923624256	0.025444104	243.2006917	0.801508	0.005132	34.19858	0.69785	0.014006	72.07202	0.512412
Extension Erection	Tower (Typical)	Civil	0.015914588	22.09145986	0.978130573	NA	NA	NA	0.010756	6.5221	0.860197	0.015141	26.46719	0.675077
Extension Erection	Tower (Typical)	Electrical	0.018426138	37.36682836	0.960604073	0.02959803	80.12015961	0.916025	0.010511	14.36787	0.845679	0.017935	32.82119	0.775811
Extension Erection	Tower (Typical)	Mechanical	0.020863532	4.837116804	0.952295031	0.036075711	37.46063881	0.759188	0.014534	-0.70402	0.947908	0.019671	13.22373	0.822364
Extension Erection	Tower (Typical)	Instrumentation	0.017891243	22.51714911	0.871295455	0.026078415	53.33726413	0.85994	0.012684	6.004106	0.937134	0.017529	21.57142	0.623626
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New Erection	Barricade	Piping	0.019088989	7.990251563	0.947650966	0.030144536	21.6057935	0.778805	0.010995	3.122084	0.85659	0.018174	7.589283	0.611964
New Erection	Barricade	Structural	0.030150283	11.71301805	0.962188353	0.047853271	22.0203893	0.917292	0.011735	6.969111	0.789906	0.025355	12.34769	0.454869
Full Dismantle	Tower (Typical)	Piping	0.004293835	17.64618797	0.972425341	0.009349757	35.02214769	0.910456	0.003549	4.765679	0.948886	0.005037	14.69169	0.696866
Full Dismantle	Tower (Typical)	Structural	0.004974796	18.6737539	0.977482977	0.00991369	36.1483911	0.973161	0.004007	4.172978	0.997004	0.005211	16.1226	0.772929
Full Dismantle	Tower (Typical)	Civil	0.005487184	-0.358878467	0.971335215	NA	NA	NA	NA	NA	NA	0.00515	1.03364	0.816508
Full Dismantle	Tower (Typical)	Electrical	0.006154531	14.65520259	0.944864811	0.012931713	25.40447223	0.708281	0.004066	3.633553	0.88096	0.006282	10.72175	0.877742
Full Dismantle	Tower (Typical)	Mechanical	0.009975957	13.34296266	0.953320298	NA	NA	NA	0.006704	-3.04806	0.997422	0.009837	6.18502	0.894399
Full Dismantle	Tower (Typical)	General Management	0.011052301	-2.853072778	0.934649085	0.014784182	12.56001074	0.981537	0.004899	-0.47966	0.83743	0.009848	-1.29529	0.767511
Full Dismantle	Tower (Typical)	Sub Contractors	0.008556148	8.155295929	0.950410503	0.019842231	11.69468762	0.949157	0.004564	0.294077	0.953661	0.008355	6.844572	0.543199

*Note: (1) a total of 98 classifications based on work classification, scaffolding type, and discipline; and (2) "NA" refer to data sample that does not have enough data points to develop the model (i.e., 10 data points, etc.)

Table 2. EVA parameter calculation results at 30%, 50%, 70% project progress

Project %	BCWP_HP	BCWP_LP	BCWP_MP	BCWS_HP	BCWS_LP	BCWS_MP	ACWP	ACWS
30	41	18	24	12	32	46	18	36
50	69	28	40	14	41	60	30	48
70	95	37	55	17	49	74	42	63

*Note: unit in Table 2 is in lbs rounded to the nearest millions.

4. DISCUSSION AND CONCLUSIONS

In this paper, an earned-value-analysis (EVA)-based project control framework has been proposed for onsite scaffolding activities at heavy industrial projects. Regression models have been developed to model the productivity of scaffolding activities with classification criteria. In this paper, the authors have used work classification, scaffolding type, and discipline. Similar approaches can be adopted to handle similar datasets. Then the regression models are used to model the EVA parameters based on project progresses. The case study demonstrates the implementation of the proposed framework. The contributions of this research include: (1) proposing using classification criteria for categorizing scaffolding data for productivity prediction; (2) incorporating regression modeling with EVA based on different productivity performance ranges (i.e., low, medium, and high); and (3) providing a modified EVA method for practitioners to conduct near real-time project control. For future research, other than the regression modeling approaches, statistical methods can be introduced as an alternative approach to estimate productivity. For example, random variables can be sampled from historical distributions to construct the productivity metrics (e.g., Monte-Carlo simulation approach). In addition, Bayesian statistics can be introduced to incorporate the real-time data from the field to update the productivity distributions (Liu, et al., 2020). Another area of improvement of the current approach is to increase the quality of the collected data by incorporating integrity checks for scaffolding data requisition submissions. However, the proposed research approach requires historical data to construct the regression models for prediction. For the scenarios where historical data does not exist, the user needs to rely on experience-based productivity metrics to continue the analysis. However, the randomness of the productivity, considered as risks in the construction projects, can still be introduced from the experience-based approach (e.g., a triangular distribution representing the low, medium, and high productivity), which can be addressed and incorporated in the future work. A comparison between regression and statistical approaches can be conducted for further system validation.

Another aspect of the discussion that can be raised from this research is the suitability of EVA in scaffolding management, as compared to the percentage-based estimation. This has been mentioned earlier that due to the fact that the scaffolding activities often occurred on an ad-hoc basis on-site and at large construction sites where scaffolding work is often under reimbursable contracts, it is challenging to obtain the total expected expenses at the early stage of the project; instead, a percentage of the direct work is often used to estimate the total scaffolding expenses, based on which a S-curve can be used to monitor the project progress. Thus, the proposed EVA can fit into the S-curve approach for tracking the project progress. The proposed methodology can be used by general contractors and/or scaffolding sub-contractors to analyse scaffolding project progress. Other machine learning techniques can be applied to improve productivity modeling, e.g., non-linear models. This research also relies on reliable data collection from the field, without which the EVA analysis can be challenging. Another limitation is that companies with limited historical data may need to collect enough project data in order to start using this method.

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