PRODUCTIVITY MODELING FOR QUANTIFYING CUMULATIVE IMPACT OF CHANGE ORDERS

Golnaraghi, Sasan[1] , Zangenehmadar, Zahra[2, 3], Yeganeh Bakhtiary, Abbas[2] and Arabpour, Mohammad Javad[1]

[1] Concordia University, Montreal, Canada
[2] Iran University of Science and Technology, Tehran, Iran
[3] z_zange@encs.concordia.ca

Abstract: In labor-intensive construction projects, labor costs are a substantial percentage of the total budget for construction projects. Thus, understanding labor productivity is essential to project success. If productivity is impacted by any reasons such as the extensive number of changes or poor managerial policies, project labor costs will increase over and above the overall project total costs. Changes are considered as the integral part of construction projects by researchers and industry practitioners and their cumulative impact should not be overlooked since it can be detrimental to a project success. Although the measured mile method is well known and widely accepted for quantifying the cumulative impact of changes on labor productivity, it is not easily applicable to many cases. It is difficult to identify and measure this impact on the mentioned productivity. Hence, modeling labor productivity using different techniques are becoming more desirable. It is a challenging task as it requires identification and quantification of the influencing factors on labor productivity and considering the interdependencies among those factors. In this paper, three regression methods of Best Subset, Stepwise, and Evolutionary Polynomial Regression (EPR) are used to model the labor productivity. The dataset used in modeling the labor productivity in this research has been gathered by Khan (2005) from formwork installation of two high-rise buildings in the downtown of Montreal. The best model will be selected based on statistical performance indicators. The model has a potential to be used for quantifying unimpacted productivity which later can be used for implementing measured mile method. Results show that the developed model through EPR has the best performance, however, expert's judgment and preprocessing are necessary to modify the model and prepare it for construction practices in evaluating the cumulative impact of changes on labor productivity.

1   Introduction

According to Statistics Canada, $404 billion was invested in construction, machinery, and equipment in 2014; this was a slight increase of 1.4% from 2013. The total contribution of public and private investments were $89 and $315 billion dollars, respectively (Statistics Canada, 2014). Construction projects are interesting because they are the combination of design technicality, soft and interpersonal skills for managing the workforce, business knowledge, and unique organizational structure representing the way people interact within a project (Ibbs and Vaughan, 2013). As a project progresses, its scope may change due to many obvious and clear causes. Change unquestionably takes place during the course of a project regardless of its size or complexity. The Construction Industry Institute (CII) defines change as "any event which results in a modification of the original scope, execution time, or cost of work being inevitable on most construction projects due to the uniqueness of each project and the limited resources of time and money available for planning" (CII, 2000).

This paper estimates the expected productivity considering the effect of environmental and operational variables for formwork installation in a construction project. These variables are selected because they are causing variations in productivity on daily basis (Khan, 2005). The variables are weather (temperature, humidity, wind speed and precipitation), crew (gang size and labor percentage) and project (work type, floor level, and work method). Three different regression analysis methods of Best Subsets Regression (BSR), Stepwise Regression (STR) and Evolutionary Polynomial Regression (EPR) are used to model construction labor productivity based on the collected data. The main purpose of regression analysis is to forecast and explain the causal relationship between input and output variables. The output variable is named as the response variable and input variables are known as predictor variables. The response variable is expressed as a function of the predictor variable(s). Their results have been compared to find the best method for estimating the expected productivity as the baseline productivity.

2   Background

The Association for the Advancement of Cost Engineering (AACE) defines productivity as "a relative measure of labor efficiency, either good or bad when compared to an established base or norm…" (AACE, 2004a). Productivity is a delicate aspect of any construction projects. The Oxford Dictionary defines productivity as "the state or quality of being productive" or "The effectiveness of productive effort, especially in industry, as measured in terms of the rate of output per unit of input" (Oxford Dictionary, 2015). Three key elements of the concept of productivity are indicated in the following definitions (Yi and Chan, 2014):

- The state or quality of being productive is the strength of construction;
- Effectiveness is the degree to which productive effort is utilized efficiently in constructing a preferred result; and
- The rate is a measure of output against input over a finite time interval.

Unquestionably, productivity definition in construction can cause some confusion because of the various different ways to define it. Strictly speaking, productivity is a component of cost and not a tool for measuring cost. It is not a method for estimating the cost of resources but is instead a quantitative assessment of the correlation between the number of resources used and the amount of output made (Khan, 2005). Consequently, productivity in construction is considered as a measure of output that is achieved by a combination of inputs. By considering this perspective, the concepts total and partial factor productivity can be explained (Yin and Chan, 2014). Total Factor Productivity is the most common measurement technique of construction productivity. The output is measured against all the inputs (Goodrum and Haas, 2002). Total Factor productivity is an economic model and is very advantageous for developing strategy and assessing the state of the economy, however, it is not beneficial to contractors (Thomas et. al., 1990). Partial Factor Productivity is also referred to as a single factor productivity, in which output is measured against a single input or selected inputs.

In most construction projects, the labor cost is 30 to 50% of the total project cost (Gupta, 2014). In other words, construction is regarded as a labor-intensive industry, and so it can be assumed that labor is the governing productive resource, hence, productivity is chiefly contingent on labor productivity (Yin and Chan, 2014).

3   Best Subsets Regression Modeling

The Best subset is the first technique employed in regression analysis and is a linear regression modeling technique. Best Subset is an exploratory modeling technique that compares all possible models that can be created based upon an available dataset of predictors. In other words, it searches for all possible models and finally introduces the best candidates (Minitab17, 2018). The best result will be identified based on performance criteria of R-squared, Adjusted R-squared, Predicted R-squared, Mallows Cp, and S (Mean Square Error). It should be noted that Best Subset regression is not suitable for modeling cases with a large number of variables due to finding the best combination of predictor variables will take more computational time. In this study, 9 predictor variables are used to predict the labor productivity and 41 models are developed using Minitab 17. Symbolic expressions of T, H, P, WT, GS, LP, WS, and FL represent temperature, humidity, precipitation, work type, gang size, labor percentage, wind speed and floor level respectively. The best model is selected based on the smallest S (Mean Square Error), highest R2, and

adjusted R2. It is recommended to use the adjusted R2 over R2 for comparing models with different numbers of terms. Table 1 shows the model that Subsets picked based on the criteria above.

Table 1: Selected Best Subsets Model

Performance Indicators	Value
No. of Predictors	8 (T, P, WS, GS, LP, WT, FL, WM)
R-Squared	46.80
Adjusted R-Squared	44.1
Mallows Cp.	8.1
S (Mean Square Error)	0.2587

Subsequently, the following linear regression equation is obtained:

[1] $Productivity = 2.17368 + 0.0163662T - 0.0559208P - 0.00772945WS - 0.0106864GS - 0.00810366LP - 0.0160492WT + 0.0037892\,FL + 0.0792147WM$

4   Stepwise Regression Modeling

Stepwise regression modeling technique eliminates predictor variables in order to find a useful subset which should be included in the regression model. Establishing this subset is called the variable selection problem. Two contradictory ideas are behind the step selection approaches; i) the first idea is to include every predictor variables that even slightly connected to relate variable in order to have a realistic and complete model. ii) The model should include as fewer predictor variables as possible because including irrelevant variables will decrease the accuracy of the model. Thus, the aim of variable selection is to attain an equilibrium among simplicity and best fit model (NCSS, 2018).

Stepwise regression analysis is performed using Minitab 17. The first step for developing stepwise in Minitab is to set a significance level (Alpha) for adding or deleting a predictor variable. Alpha-to-Enter and Alpha-to-Remove represent significance level which is set to 0.15 by default in Minitab. The effect of significance level (Alpha) on performance indicators to find the optimum value for Alpha-to-Enter and Alpha-to-Remove is quantified by trial and error approach. Alpha-to-Enter is the value that determines if any of the predictor variables not currently in the model should be added to the model. Alpha-to-Remove is the value that determines if any of the predictor variables in the model should be removed from the model. Figure 1 shows that model with best statistical performance will be reached when significance level is set to 0.15.
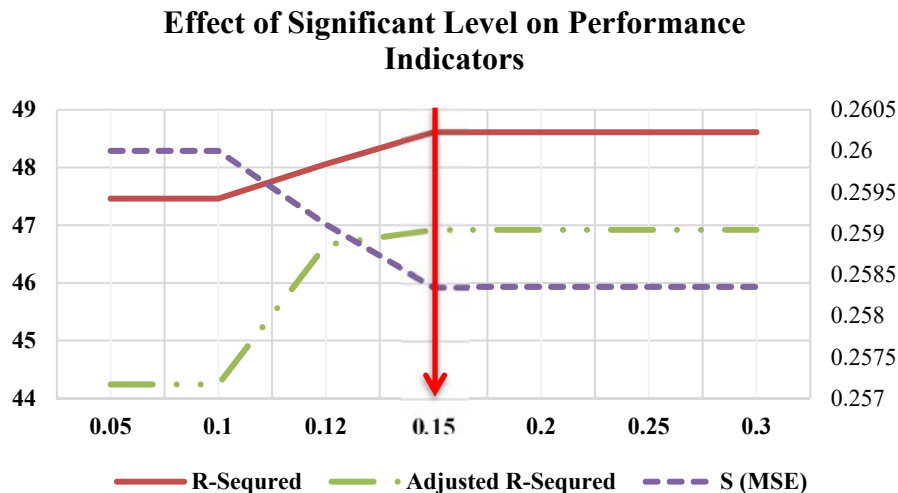

Figure 1: Effect of Significance Level on Performance Indicators

After the significance level is specified, one predictor variable is added to the regression equation only p-value is less than 0.15. In other words, the first predictor should have the smallest the smallest p-value among other predictor variables. The next predictor will be added only if it has the smallest p-value less

than Alpha-to-Enter. After adding the second predictor, the significance level of the first predictor will be reassessed if entering the second predictor has impacted on the significance level of the first predictor variable. The first predictor will be removed if significance level of the first predictor is greater than 0.15. The similar step will be repeated for adding other predictor variables. It should be noted that the process will be stopped if no predictor has a t-test P-value less than 0.15. The following linear regression model is made subsequent to the predictor variables selection step:

[2] $Productivity = 2.221 + 0.01700T - 0.0606P - 0.00755WS - 0.01203GS - 0.00806LP - 0.1585WT + 0.0850WM$

Two variables of humidity and floor level are removed for regression equation due to having p-value greater than 0.15. The performance parameters of the regression model are shown in Table 2.

Table 2: Stepwise Regression Model

Performance Indicators	Value
No. of Predictors	7 (T, P, WS, GS, LP, WT, WM)
R-Squared	48.61
Adjusted R-Squared	46.92
S (Mean Square Error)	0.2584

5   Evolutionary Polynomial Regression

The mathematical modeling is classified into three groups of white, gray and black based on the understanding of the mathematical structure and the level of prior information required (Giustolisi and Savic, 2006). Evolutionary Polynomial Regression (EPR) is non-linear stepwise regression method, and it is classified as a grey box method based on designed model expressions for a given set of data. Grey box models are conceptual models whose mathematical structure is built based on conceptualization or physical insight, however, parameter assessment is needed by using data. Unlike Artificial Intelligence modeling, EPR does not need large datasets for developing the model and EPR provides expression for a model to define the relationship between predictor variables and output. Like other modeling techniques, expert knowledge should be accompanied with EPR technique to validate if the produced mathematical model and correlations between utilized inputs and output are practical. The EPR was developed by Giustolisi and it was mainly applied to environmental cases modeling (Giustolisi and Savic 2006, Giustolisi et al. 2008). In a nutshell, the theory behind the EPR can be explained in two stages; an evolutionary procedure based on Genetic Algorithm for exploring model structure, and linear regression step based on least squares (LS) method for calculating model coefficients.

In this research, the EPR creates several symbolic expressions that can forecast the labor productivity based on data gathered by Khan for two high rise buildings. The best expression of labor productivity will be selected based on the observed fitness and parsimonious of the equation. The fitness to the observed data is measured by the value of R-Squared and MSE. Furthermore, the number of terms and factors in each expression should be minimum to fulfill the requirement for the parsimonious equation and computational time for generating the best expression (Berardi et al. 2008).

The value of CoD and SSE are shown in Figure 2. The blue graph shows actual data for productivity and the red line represents predicted value by using the model.

Model_1

Actual Productivity = $+0.60084\{T\}^{0.5}$

Data ID	Actual Productivity	Predicted Productivity
1	1.85	1.795765644
2	1.68	1.695119717
3	1.54	1.695119717
4	2.5	1.718460338
5	1.76	1.729906155
6	2.35	1.633844806
7	1.09	1.455307398
8	1.45	1.413186239
9	1.25	1.358307741
10	1.36	1.48709216
11	1.37	1.546501804
12	1.88	1.806314768
13	1.45	1.827081567
14	1.15	1.581282107
15	1.78	1.74120977
16	1.55	1.806314768
17	2.33	1.806314768
18	1.7	1.646463307
19	1.21	1.48709216
20	1.36	1.621027551
21	1.34	1.479289644
22	1.23	1.539343976
23	1.47	1.44710954
24	1.3	1.509970504
25	1.52	1.594757173
26	1.27	1.430383604
27	1.27	1.307882822

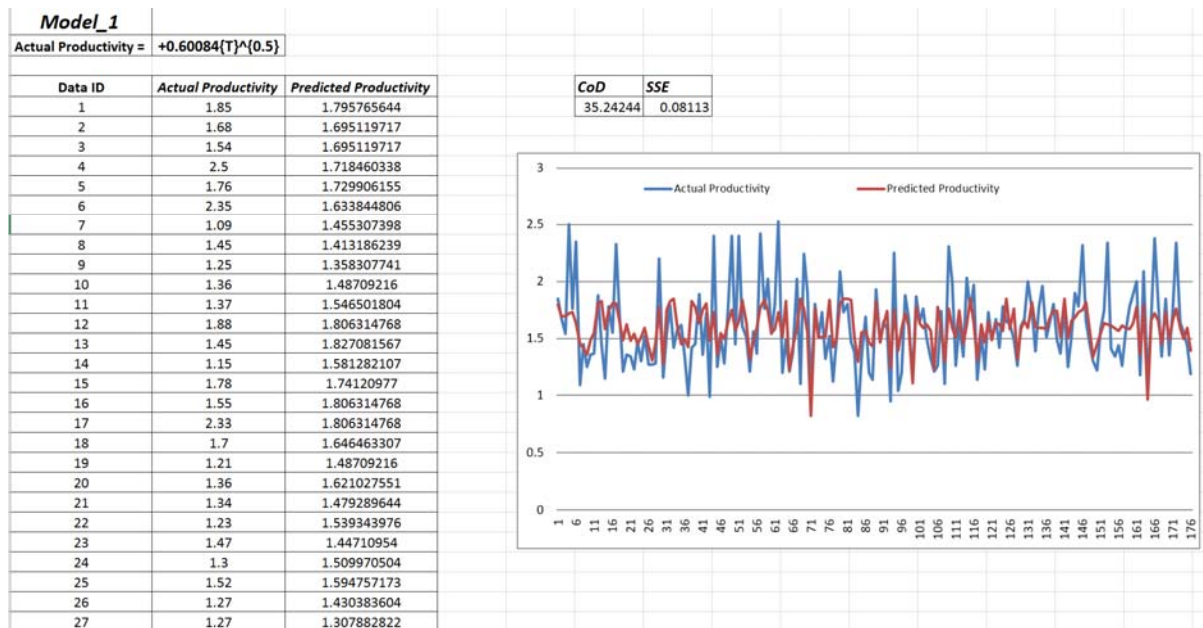| CoD	SSE
35.24244	0.08113

Figure 2: Graphical Representation of Actual and Predicted Productivity

The EPR produce models for predicting the output, based on either one or several predictor variables. In other words, the EPR can develop Multi Input Single Output (MISO) and/or Single Input Single Output (SISO) models. It is noteworthy that the model can be developed with an incomplete historical dataset by using linear interpolation for finding missing data points. However, the accuracy of linear interpolation is subject to question for reconstructing data points.

5.1 Evolutionary Polynomial Regression Optimal Structure

The EPR methodology was mainly used for hydrological modeling by its developers at the early years and more recently it was used for modeling the sewer pipe failures, deterioration models for water distribution networks (Giustolisi and Savic 2006, Giustolisi et al. 2008, Doglioni et al. 2008, Berardi et. al. 2008, Rezania et al. 2008, Xu et al. 2011). The capability and outstanding performance of EPR in different disciplines of civil engineering making this novel approach a viable candidate for labor productivity modeling. Because this model has not been used for modeling construction labor productivity, the setting of the software should be done through trial and error approach.

The EPR setting has been changed to identify the optimal setting for datasets available for modeling labor productivity. A specific combination of structure and function are carefully chosen at each setting during EPR process. The level of accuracy for the output EPR models at each setting is evaluated based on the fitness function. Table 3 shows the results of different settings including CoD and SSE of training dataset values for each setting.

For simplicity, in all the analyses the number of terms is set to 3 and the range of potential exponents was selected as values between -2 and 2 with 0.5 incremental step. As mentioned before, it is recommended to include the value zero for discarding those variables which are not beneficial for the model.

Table 3: Different Scenario EPR Setting

Setting Options	Setting 1	Setting 2	Setting 3	Setting 4	Setting 5
CoD - Training	70.34%	72.94%	56.51%	61.07%	77.15%
SSE - Training	0.037	0.034	0.054	0.049	0.029

Table 3 reveals that the setting 5 produces more accurate results than other four other setting scenarios. Thus, the setting 5 is foundation block for analyzing the effect of number terms on EPR models for predicting labor productivity. Accordingly, nine scenarios are planned based on the number of terms in the EPR models. The number of terms increased from one to nine for identifying a parsimonious model with an

acceptable accuracy based on the setting 5 as well as less computational time.
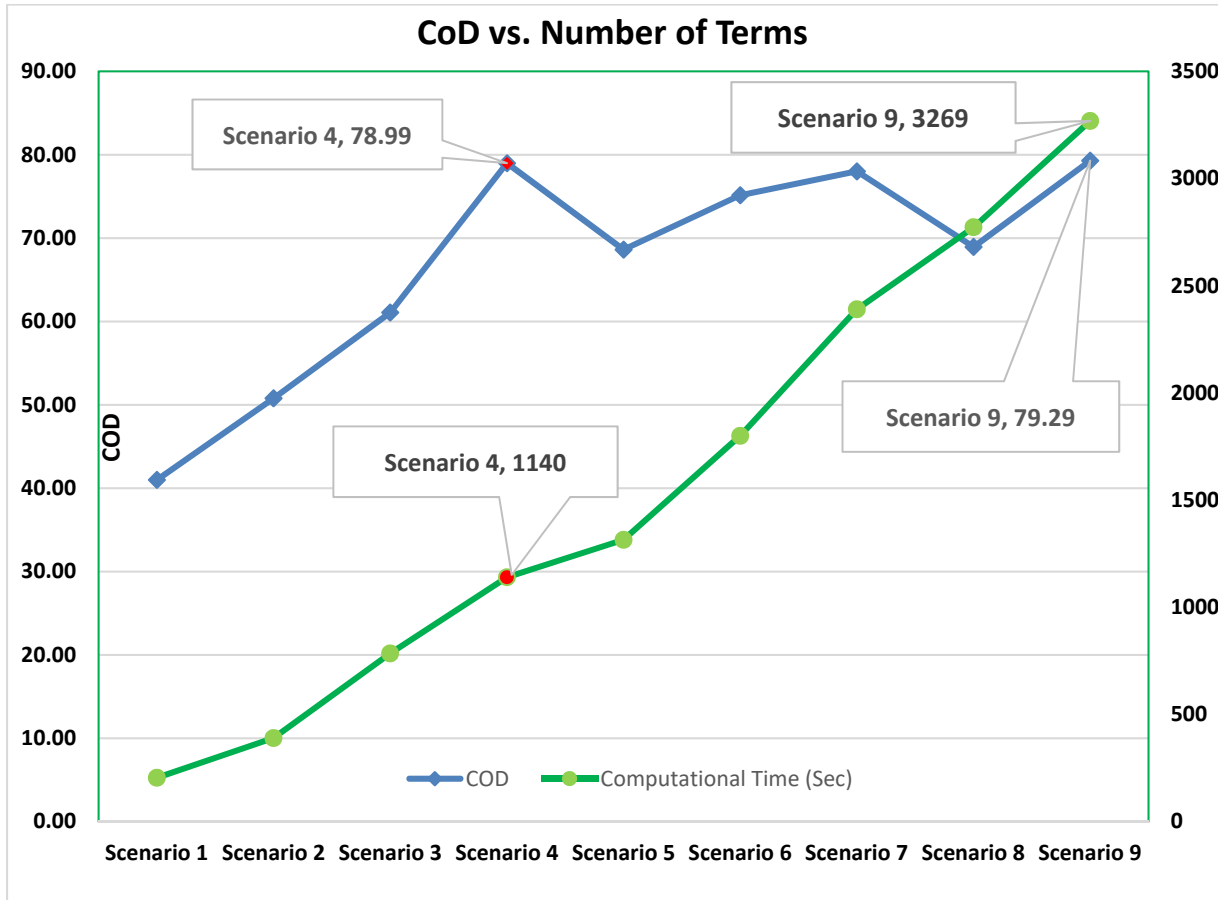

Figure 3: Number of Terms, Accuracy, and Computational Time of EPR Models

Figure 3 shows that the accuracy of models based on the number of terms (blue line) and computational times (green line) for each developed model. It can be seen that increasing the number of terms in EPR, increases the computational time while it does not necessarily increase the accuracy of the predictions. It should be noted that the application of these terms also leads to more convoluted relationships for mathematical modeling. Scenario 4 and 9 show better results than other scenarios. Scenario 4 has COD of 78.99% with a computational time of 1140 seconds and scenario 9 shows the accuracy 79.29% with computational time 3269 seconds. Although scenario 9 seems to be a bit more accurate, the computational time and complexity model lead us to select scenario 4.

5.2 Modeling Labor Productivity Using EPR

In the dataset of two high-rise buildings and based on scenario 4, seventeen symbolic expressions were generated to predict the construction labor productivity for formwork activity. As discussed earlier, the best model should be selected between all expressions based on the model fitness and parsimony. Model 17 was selected as the best one with the highest value for R-Squared, even though nine models have acceptable R-Squared scores. Accuracy indexes such as SSE, BIC, MSE, FPE, AIC, and GCV are exposed in Table 4. Also, by observing the results shown in this table, model number 17 has the minimum values in all indexes. This observation confirms that this model is the most promising one in predicting the output.

Table 4: Performance Indexes for Two High-Rise Buildings Downtown Montreal Dataset

Model	SSE	AVG	Model	SSE	AVG	Model	SSE	AVG
Model_1	0.0811	13.9252	Model_7	0.0435	10.5903	Model_13	0.0280	8.7077
Model_2	0.0692	13.0164	Model_8	0.0379	9.9132	Model_14	0.0272	8.6894
Model_3	0.0639	12.8015	Model_9	0.0342	9.3314	Model_15	0.0271	8.5980

Model_4	0.0624	12.7083	Model_10	0.0311	8.9783	Model_16	0.0267	8.7010
Model_5	0.0594	12.1327	Model_11	0.0300	9.0113	Model_17	0.0263	8.5511
Model_6	0.0472	11.0896	Model_12	0.0292	9.0154			

The dataset randomly was divided into training and testing datasets. A number of 177 (80%) samples were selected for training purpose and 44 samples were considered as the testing dataset. It is worthy to mention that testing samples were not included into the model during its development. Figure 4 shows actual productivity based on the dataset and predicted value using Model 17 which is represented by the following mathematical equation as follows:

[3] $Productivity = -0.0042494H0.5T0.5\ln(P0.5WT/GS) - 1.0983THWS0.5FL2\,LP0.5 + 1.281T1.5 + 6.1584T2GS2FL0.5\ln(GS0.5FL0.5/T0.5)$
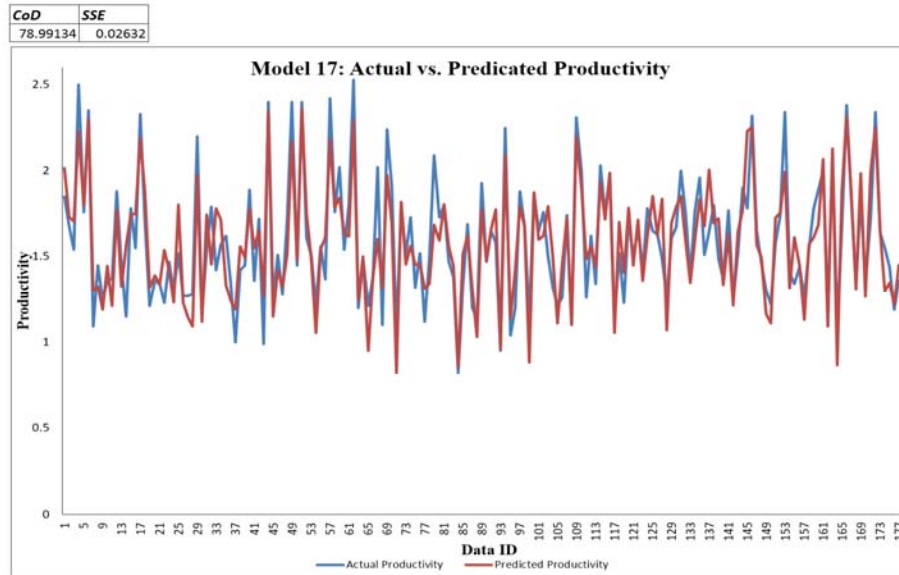
CoD	SSE
78.99134	0.02632

Figure 4: Actual vs. Predicted Productivity for Training Dataset Using Model 17

The blue line shows the actual productivity values against those predicted values for productivity (red line) by the EPR using Equation 3. An acceptable predication pattern was attained between the experimentally gathered values and the EPR predicted values.

After training is done, the performance of the trained EPR model is validated using the testing dataset which has not been utilized as a part of the model development process. The purpose of this step is to study the abilities of the trained model to generalize the training to situations that have not been appeared throughout the training step. In order to validate the capability of trained EPR models over the testing dataset, Equation 15 was used to predict the labor productivity curves and the results shown that predicting model using testing dataset does not show a strong prediction pattern between actual and predicted data developed by the EPR.

It should be noted that the EPR process is required some subjective judgment by the analyst's experience instead of being purely based on mathematical criteria (Rezania et al. 2008). The EPR is used for the first time in this research for labor productivity modeling. It is possible some subjective judgments may lead to more improvement the result of the EPR. Thus, more experimentations are needed by other researchers using the EPR for productivity modeling. Since EPR shows better performance than other techniques a sensitivity analysis will be performed in the next section.

5.3 EPR Sensitivity Analysis

Sensitivity analysis was performed to identify the effect of variables on the predicted productivity. The value of factor under analysis will change while the rest of variables will maintain the initial value. Figure 5 shows the effect of changing of all input variables on the productivity. In this Figure, the vertical axis is productivity value and the horizontal axis shows a normalized value of variables. Since each variable has its own unit,

the horizontal axis was plotted by means of the normalized value from 0.01 to 1. This graph was made for since it is important to understand the interdependencies between productivity and its input variables. Moreover, it helps to identify what the most sensitive independent variables are.
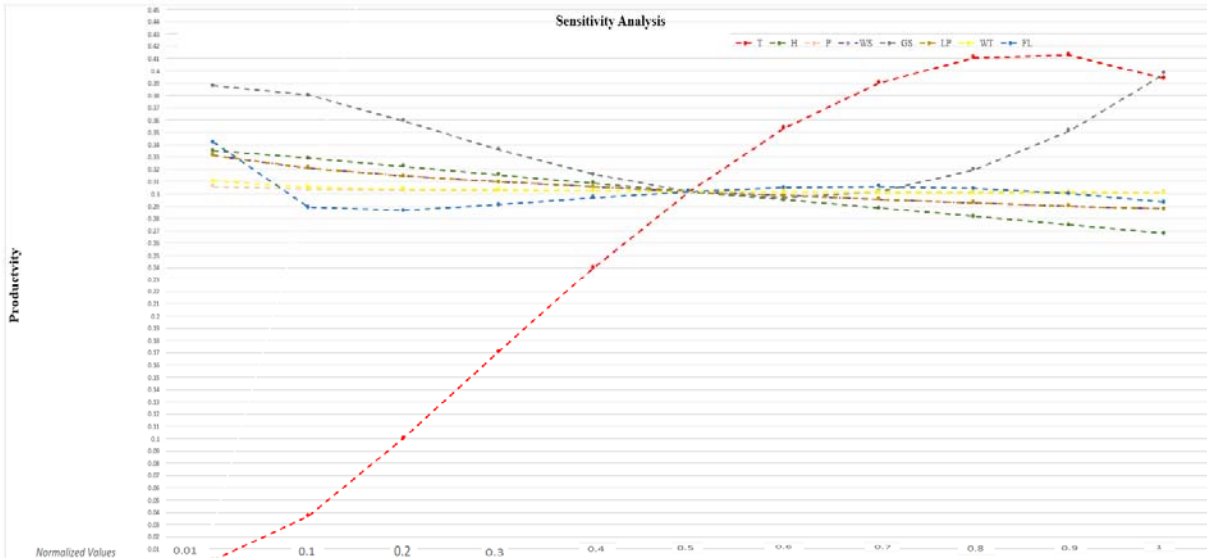

Figure 5: EPR Sensitivity Analysis for Two High-rise Buildings Dataset

For a better picturing of the effect each variable, the actual values of each variable are tabulated below the normalized values. The results show the strong relationship between temperature and gang size as inputs and labor productivity as the output. The effect temperature on the productivity is well known as a considerable amount of research carried out by academia and industry (Abele, 1986; Thomas and Yiakoumis, 1987; Moselhi, 1998; Moselhi et al, 2005; Lee and Peña-Mora, 2007). The gang size trend shows overmanning issues which is increasing the number of workers within the same trade can lead to productivity loss. Although it is possible to gain some better rates of production without having the overtime problems such as fatigue, it is a good chance to lower productivity due to congestion and less direct supervision.

It should be noted that there is an improvement in productivity at the last 30% of variations in the gang size, but the amount of improvement is not substantial compares to the number of workforces.

Floor level trend in Figure 5 shows interesting behavior. There is an obvious inverse relation between floor level and productivity for the first 50% of variations in floor level which can be caused by the learning curve factor. As Khan (2005) mentioned, the floor level variable is the only variable which is synchronized with the project start. Therefore, it is the only variable can gradually incorporate the effects of learning. The productivity shows improvements after workers pass the learning curve phase.

Humidity and labor percentage trends are very similar and they have an inverse relationship with productivity, i.e. increase in humidity or labor percentage cause decrease in productivity. The low percentage of humidity have a positive impact on the productivity; however, passing beyond a certain level of humidity will impact labor productivity negatively. Labor percentage can contribute to the labor productivity negatively if the ratio of labor to the skilled worker is higher than the norms of the industry for a task.

In other words, there should be specified optimal labor percentage in the crew for supporting skilled worker otherwise the overall productivity is adversely impacted. For example, in a hydropower dam is under construction in Northeast of Canada, the optimum value for labor percentage is between 25 to 30% for the formwork activities. Less these numbers or above this is proven to impact the productivity of formwork negatively.

In spite of the overall trend of changes in productivity against changes in work type and precipitation, values show an inverse relationship, this change can be ignored due to the low amount of changes.

6 Conclusions

Having applied the different regression techniques on the given dataset and quantified their basic performance indicators, it is beneficial to recapitulate the results and present some assessment of performances. In this research, the application of each three techniques explained and tested against datasets of two high-rise buildings related to formwork operation. A summary of the best-achieved results for all three techniques is presented in Table 5.

Table 5. Performance Results Comparison

Technique	R-Squared	MSE	Time (Sec)	Number of Variables
Best Subset	46.8	0.2587	~2	8
Stepwise	48.61	0.2584	~2	7
EPR	52.697	0.057	1140	8

From this comparison, the following remarks can be concluded:

- EPR regression produces higher accuracy and lower MSE than Best Subset and Stepwise techniques. However, the R-squared is not close to 100%. Therefore, the dataset needs an expert review to be prepared for model implementation.
- Best Subset and Stepwise regression techniques have shown very close performance in predicting the productivity comparing their R-squared and MSE.
- EPR has the highest computational time compares to two other techniques. It is due to the fact that in EPR, datasets are divided into training and testing datasets for modeling; however, Best Subset and Stepwise regression were applied on the whole dataset. The number of variables used in the productivity model is seven and eight variables, which are approximately the same.
- Preprocessing of the dataset and studying the characteristics of the given data, before applying these techniques result in more accurate models.

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