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ESTIMATING CONTRACT TIMES FOR TRANSPORTATION PROJECTS: CREATING A STATISTICAL MODEL TO ESTIMATE TIMES USING BID QUANTITIES

Nevett, Guillermo [1,3], Goodrum, Paul M.[2]
[1, 2] Doctoral Student, Dept. of Civil, Environmental, and Architectural Engineering, Univ. of Colorado at Boulder, Boulder, CO, 80309-0428, U.S.A.
[3] Nicholas R. Petry Professor in Construction Engineering and Management, Dept. of Civil, Environmental, and Architectural Engineering, Univ. of Colorado at Boulder, Boulder, CO 80309-0428, U.S.A.
[3] guillermo.nevett@colorado.edu

Abstract: Developing the time requirements for highway transportation projects has always been a big challenge due to the differences in project scope, location, goals and size. It's not uncommon for state transportation agencies (STAs) to produce inaccurate estimates of project durations, which leads to contractors not investing their maximum effort in a project. Several previous attempts have been made to make more accurate estimations by using different methods. The objective of this research is to find a new method able to produce accurate estimates by using historical data. This paper describes the preliminary steps of developing a tool with sample data from Montana's Department of Transportation (MDT; DOT). The data provided by MDT consists of bid tabulations, budget estimates, and project type. This paper is part of an ongoing investigation so this model might not be the most accurate by the end of the project, mostly because of the details included in other databases recently received. Nevertheless, the paper will provide an overview of the approach used to conduct such investigation. The paper provides readers with an idea of which bid items are more significant on project durations and shows how a statistical model can estimate a project duration during the design phase of a project.

1 Introduction

Developing an accurate estimate of a project's duration, especially during planning and design, is challenging. There are several factors that influence a project's duration, such as change orders, materials shortages, changes in scope or drawings, poor planning, etc. (Kraiem 1987; Majoh and McCaffer 1998; Kalibe et al. 2009). One of the bigger challenges of developing accurate estimates is that these estimates are expected during the planning phase, before any of these challenges are encountered. As if this wasn't enough, every project is different across multiple dimensions, including size, scope, goals, nature, and creating a big challenge for STAs to produce their estimated durations, which is very important for contractors' commitment, life cycle cost analysis, project cost, and bid proposals, among others (Williams 2006; Ifran et al. 2011).

This research's objective is to help fulfill the niche of accurate schedule estimations by developing a statistical tool that uses historical bid data to predict projects' durations based on their characteristics. In this paper, the authors present how a stepwise regression model was built as a preliminary time estimation tool based of MDTs sample data. Although not definitive, the results of this process are very encouraging with very limited data, which suggests that a better model can be developed by incorporating more detailed data provided by different states involved in this study effort, which includes MDT.

2 Literature Review

The first scheduling models were based on linear relationships between cost and duration (Fulkerson, 1961). Cost-schedule relationships have evolved with time to more complex non-linear relationships, such as concave (Falk and Horowitz 1972), hybrid of both (Moder et al. 1995), quadratic (Deckro et al. 1995), and discrete formulations (Skutella 1998; Zheng et al. 2004). Recently, researchers have created piecewise discontinuous time-cost functions (Moussourakis and Haksever 2004, Yang 2005), and other variables have been added to create a more complex relationship with scheduling, such as contract type (Anastasopoulos 2007).

A concept that has been recently gaining popularity is parametric estimating modeling, which allows the use of multiple factors or parameters to produce more statistically significant estimates. The three justifications used by Zhai et al. (2016) to use parametric modeling for STAs are the following: 1) high correlation between durations and bid quantities; 2) highway construction projects are repetitive, linear in nature, and construction methods are similar across the US; and 3) historical databases are used to develop parametric models. Even though parametric methods have been widely used in cost estimating modelling, they have been almost ignored in time estimation for construction projects. Parametric modeling has been used in estimating scheduling for highway projects by different authors: Boussabaine and Elhag (1997) used a combination of fuzzy systems and artificial neural networks; Jiang and Wu (2007) created a regression model using data from projects of Indiana's DOT executed between 1995; Liu et al. (2011) estimated the influence of random factors using Monte Carlo simulation; and Zhai et al. (2016) created a multiple regression model using 2,503 projects.

Even when multivariate regression analysis was used by Zhai et al. (2016), this research uses it to develop a parametric model to estimate project duration for MDT. This paper's contribution to the body of knowledge is the testing multivariate regression analysis's applicability to MDT and future research will include data from other DOTs to develop a more complex model.

3 Current State-Of-The-Practice for Time Estimation Modeling

Currently, the construction industry uses a variety of cost and scheduling software that have been created by researchers and software developers though time. Some examples of these software are RSMeans® and WinEst, that use historical daily rates and wages, or Pertmaster and @Risk, add-ins to Primavera and excel respectively, which rely on probabilistic modelling of risk. Regarding STAs, 58% (29 out of 50) have contract time determination procedures available online (Taylor et al. 2012). Taylor et al. (2012) wrote that 28% of these 29 states' models are based purely on production rates, 17% use job logic without considering production rates, and 49% use a combination of production rates and job logic. Although most states have developed tools for time estimation, Taylor et al. (2012) found that they have very poor accuracy, ranging the 100% margin. Per the FHWA (2016), the most popular cost/schedule estimating software used by STAs are: AASHTOware Project © Estimator, HCSS HeavyBid, Cost Estimate Validation Process (CVEP), Long Range Estimate, and Estimate Bid Analysis Systems (EBASE).

Linear Regression

This research uses a multivariate linear regression analysis to develop the MDT models and it's described as follows:

$$\Upsilon = \beta_0 + \beta_1 X_1 + \cdots + \beta_1 X_n + \epsilon$$

$$\epsilon \sim \mathrm{NID}(0, {\sigma^2}_{\epsilon})$$

$$\beta_i \text{ (i = 1 to n)}$$

where:

Υ= dependent variable, Charge Days

β = regression coefficient (see first model),

X = observed value of independent variables,

ε = random error term or noise (accounts for all other factors that affect Y than X), and

NID= normally and independently distributed.

The regression model assumes the following are true about the error term (ε): 1) population mean of ε is zero, 2) ε_i have the same variance ${\sigma^2}_{\epsilon}$ for all values of X, and 3) ε is normally and independently distributed.

Stepwise regression was used to optimize this model as it minimizes impacts of multicollinearity, takes into consideration more relevant models during the iterations to obtain the best model, and limits the number of independent variables by including only those with high statistical significance (Zhai et al. 2016).

4 Data Collection

The data provided by MDT consisted of 259 sample projects executed between 2009 and 2015, and 43 different bids. The data provided for each project included: critical project dates (award, notice to proceed, completion, etc.), charged days, Engineer's Estimate (EE), and several bid item quantities, which had to be grouped within similar categories per daily rates, according to RSMeans®, due to the high ratio of independent variables (bid items) to sample size (number of projects). Independent variables were reduced from the original 43 bid items to 19, as shown in Table 1. Another adjustment that had to be made to the data that's worth mentioning, is the conversion of all the EEs to the same year (2015) to account for inflation. This was achieved by using the National Highway Construction Cost Index (NHCCI) (FHWA 2015).

Table 1. Grouped Bid Items Frequency

Position	Bid Item	Freq.	Position	Bid Item	Freq.
1	Crushed aggregate course	177	11	Commercial Asphalt mix 3_4	20
2	Plant mix 3 4	96	12	Plant mix 9mm	19
3	Excavation unclassified	92	13	Commercial mix 3 8	6
4	Gen. Asphalt commercial mix	82	14	Plant mix 1 2	4
5	Special borrow neat line	67	15	Plant mix 3 8	4
6	Embankment in place	57	16	Commercial mix mm	3
7	Steel	41	17	Concrete class structure	2
8	Excavation borrow	32	18	Concrete class deck	1
9	Concrete Class DD Bridge	31	19	Concrete class SD repair	1
10	Concrete General	31			

Table 2 shows the different project types, as provided by MDT. This factor was not modified to run the regression, since it is a nominal variable with twenty different values and not 20 different variables.

Table 2. Types of Projects

Project Type	Freq.	Project Type	Freq.
Overlays	87	Signals	3
Reconstruction, Grading	60	Miscellaneous	2
Bridge construction, rehab, and removal	28	Portland cement/concrete pavement	2
Safety	27	Bike and pedestrian	1
Slides or slope stabilization	14	Crack seal	1
Seal and cover	13	Fencing	1
Rehab (minor grade and overlay)	6	Micro-surfacing	1
Guardrail	4	Scour Projects	1
Drainage	3	Sidewalk	1
Environmental and Wetland	3	Signing	1

5 FINDINGS: MODEL DEVELOPMENT

The statistical method used in this model, as mentioned previously, is stepwise regression. In this method the regression runs an iterative process that removes not statistically significant variables until the optimal model is produced, and the output includes only those statistically significant factors when the model reaches the highest possible coefficient of determination (R^2). Since R^2 is no warranty of the predictive accuracy of the model, 20% of the data was set aside to use as validation while the model was created using the other 80%, known as train/test in machine learning. To validate the data, the predicted value of the independent variable – charge days – was compared to the actual – observed – duration of the projects used to validate and the percent error was determined by using the following formula (Zhai et al. 2016).

$$\text{Percent Error} = \frac{|\text{Predicted Value} - \text{Observed Value}|}{\text{Observed Value}} \times 100$$

Given the nature of the projects, and the fact that not all projects had the same number of predictors, extreme outliers were present, which skewed the data. Because the data was skewed, the median was used as a central tendency measure instead of the commonly used mean. Several iterations of the model are explained below, including different characteristics for each iteration.

5.1 First Model Iteration (General Model)

The first model developed by the team was a general model, including all project types and sizes, but still using only 80% of the data.

$$\text{Y} = 44.532 + 9.253\text{E} - 6 * \text{X}_1 + .008 * \text{X}_2 + .001\text{X}_3 + 5.421\text{E} - 5 * \text{X}_4 + .002 * \text{X}_5 + \varepsilon$$

Goodness of fit F=121.354, significance =.000, Adjusted R^2=.746, Mean Percent Error= 44.59%, Median Percent Error= 29.54%.

where:

X_1: EE (2015 USD)

X_2: CONCRETE_GENERAL (CY)

X_3: SPECIAL_BORROW_NEAT_LINE (CY)

X_4: EXCAVATION_UNCLASSIFIED (CY)

X_5: PLANT_MIX_1/2”(Ton)

After running the first model and analyzing the descriptive statistics of the Engineer’s Estimates (EEs), the most important predictor, the team split the data into three subgroups by budget size. The first group (second model) consisted of projects with budgets ranging between $0 and $1,000,000; the second (third model) one for projects that ranged between $1,000,001 and $3,000,000; and the third (fourth model) for projects with EEs greater than or equal to $3,000,001.

5.2 Second Model

The second model was developed based on only the projects within the range explained before ($0,$1,000,000], so the sample size was 91 projects. 73 were used to build the model and 18 were used for validation. The results of this analysis were the following:

Goodness of fit F=8.344, significance =.000, Adjusted R^2=.237, Mean Percent Error= 58.75%, Median Percent Error= 24.75%

5.3 Third Model

The third model's sample size was 76 projects. 60 were used to build the model and 16 were used for validation. The results of this model are as shown below:

Goodness of fit F=14.592, significance =.000, Adjusted R^2=.48, Mean Percent Error= 22.42%, Median Percent Error= 19.35%

5.4 Fourth Model

The fourth model had a sample size of 93 projects. 73 were used to build the model and 20 were used for validation. The results of this model are:

Goodness of fit F=27.641, significance =.000, Adjusted R^2=.649, Mean Percent Error= 42.28%, Median Percent Error= 19.59%

5.5 Model Summary

As seen in the models explained above, the first model delivers a larger R^2, but that doesn't mean it's better at predicting the outcome variable, as can be seen in the mean and the median percent error, which are computed during the validation process, are higher than in the other models (except for the mean error for the second model). A second remarkable observation is that the projects' size is proportional to R^2 – when one increases the other one does the same – and is inversely proportional to the median percent error – project size increases and median percent error decreases –, so the model becomes better at predicting the dependent variable, charge days. Lastly, it's worth mentioning that, even when all the variables were included in each model, the significant predictors were not always the same. For example, crushed aggregate was highly significant for the fourth model, but it did nothing at predicting charge days on the third model, meaning that different project sizes do require different models to use as estimating tools so they shouldn't be analyzed as equals.

6 Conclusions

Current DOT time estimation systems' accuracy is not suitable for such important agencies as STAs, affecting their construction practices. Poor estimation can negatively impact contractors' commitment, bid proposal pricing, project costs, and even life-cycle cost analyses (Williams 2006; Ifran et al. 2011). It also affects the end user. The duration estimating model presented exhibits significantly greater accuracy than the current STA schedule estimating practices.

Even though this model shows promise, there are several steps that are required before disseminating it to all STAs. Although the model is accurate, a richer dataset is available to strengthen the model and the team is already working towards developing better models by including more factors, such as other bid items, delivery methods, projects' locations (to control for topography and other factors influenced by location), projects' condition (new vs. old), project size, etc. Future research includes using the presented approach in DOTs throughout the US, determining its national, and even universal, applicability. Another goal is to develop a Microsoft Excel-based estimating tool and test the accuracy and applicability for easy use of the model on STA project level.

Future research goals include testing the model's applicability at a nationwide level and developing the mentioned Excel-based model to be used by STA planners. In order for this to happen, the existing model has to be strengthened and tested on multiple DOTs.

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