Artificial Intelligence (AI) Based Tool to Estimate Contract Time

TASK 1 REPORT

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1. Introduction

Getting a construction project done on time is a major performance goal that many DOTs including Montana DOT (MDT) constantly monitor. However, most DOTs continue to struggle to meet the schedule performance target of their highway projects. For example, in 2017, approximately $144.5 millions of road projects in Montana experienced schedule delay (Fraser, 2017). Estimating and tracking construction project duration is crucial in the project development process since it not only directly affects the agency's key performance indicator, but also affects the contractor selection, construction costs, construction quality, safety, and public satisfaction. Both unreasonably short or long construction contract times can result in negative consequences such as high bid prices, lack of qualified bidders, poor work quality, claims and disputes, prolonged inconvenience to the traveling public, lack of innovations, increased administration costs, and safety issues (FHWA, 2002; Hildreth, 2005; H. S. Jeong et al., 2009).

MDT is in the process of modernizing their contract time determination processes by developing user-friendly tools to facilitate the project duration estimation and contract time determination processes. MDT has successfully developed the Production Rate Estimation Tool (PRET) for controlling activities and visual construction sequence logic diagrams for common types of highway projects (Jeong et al., 2019; Jeong & Alikhani, 2020). These tools are bottom-up tools that can help support specific work tasks during the scheduling and contract time development processes. As continuation of this modernization effort, there is a need to develop a top-down tool that can estimate a project's duration when a limited amount of project information is available during the preconstruction stages. This tool can be used throughout the preconstruction phases to quickly determine a reasonable project duration for proper project planning and delivery, and it can also be used as a reality check tool along with the bottom-up tools during the procurement stage.

In recent years, artificial intelligence (AI) technologies have improved their technical capabilities for pattern recognition and prediction. Promising AI techniques such as Artificial Neural Networks (ANNs) are capable of processing various types of data and learning complex patterns to make a prediction with reliable accuracy. An AI-based data-driven model can leverage historical project characteristics and performance data to estimate a reliable project duration for a new project. In this research, an AI-based model and its tool will be developed using historical highway project data. The model will identify the most influential factors that affect project duration such as project type, estimated cost, location, material type, starting season, major controlling work items and their quantities. It will use those factors as input variables to estimate the project duration with a certain level of confidence. This project will provide a robust support tool for a quick and reliable estimation of a project's duration.

2. Literature review

The FHWA requires State Transportation Agencies (STAs) to have adequate written procedures for the determination of contract time. Contract time is defined as the maximum time allowed in the contract for completion of all work contained in the contract documents (FHWA, 2002). Current practices of Contract Time Determination (CTD) identified by a recent survey indicated 68% of DOTs across the US participating in the survey had a formal procedure for CTD (Taylor et al., 2017). Fifty three percent of the DOTs have developed agency-specific production rates of controlling work items and 39% of the DOTs use a project-specific sequence logic to estimate contract time.

Two main approaches are mostly used for project duration estimation at the end of the design phase to estimate the contract time: the bottom-up and the top-down approach. The bottom-up approach develops a pre-construction schedule to compute the total project duration that includes a) estimating the durations of work items using the production rates and b) determining activity relationships using activity sequence logics (FHWA, 2002; Daradkah et al., 2018; DX, 2018; H. D. Jeong & Alikhani, 2020). DOTs have developed specific tools such as spreadsheet-based production rate estimation tools, production rate adjustment tools for weather and site factors, activity sequencing logic diagrams and contract time determination templates to help the scheduler develop a bar chart or a CPM-based schedule to determine the project duration.

For example, Virginia DOT categorizes their highway projects into six types and uses production rates and sequence logics for estimating project duration (Gondy & Hildreth, 2007). The Kentucky Transportation Cabinet and Texas DOT have developed a series of tools to support production rate estimation and construction activity sequencing using the critical path method concept (Connor, 2004). Montana DOT (MDT) developed an Excel-based tool to estimate production rates of major controlling activities considering factors affecting production rates such as work item quantity, working hours, work types, different seasons of work, districts, area types (urban/rural), and budget types (Jeong et al., 2019). The tool is used to determine a reliable duration of each controlling activity in project schedule. Also, MDT developed activity sequence logic templates that include major controlling activities for each common project type to help schedulers determine the sequence of activities in project schedules (Jeong & Alikhani, 2020). Although the bottom-up technique provides a reliable estimation of project duration before construction, it requires that the project is well-defined before commencement and the project information such as work items and their quantities is known with high certainty. However, such detailed information is not usually available in the early pre-construction stages.

A top-down approach for project duration estimation can be used in the pre-construction phases when the project's scope is not well defined. However, even at this early stage of project development, a DOT needs a reasonable project duration estimation for project planning and budgeting purposes. Therefore, a top-down project duration estimation is desirable during the pre-construction stages when a limited amount of project information is available, and the project design is not finalized. Also, this top-down tool will be handy to check the reasonableness of the project duration and the contract time calculated using the detailed bottom-up methods.

Some DOTs such as the Kentucky Transportation Cabinet, Indiana DOT, Ohio DOT, and Colorado DOT have developed a top-down project duration estimation tool based on the fact that there is strong correlation between project duration and key project characteristics such as project type, estimated cost, project location, and bid quantitates (Attal, 2010; KYTC, 2014; Taylor et al., 2017; Ohio DOT, 2020). Regression models were mostly used to establish the statistical relationship between key project parameters and project duration. In a survey, some DOTs reported that the regression method was more accurate and easier to use than their previous contract time estimation methods that are based upon production rates and generic precedence logic diagrams (Taylor et al., 2017). For example, Ohio DOT (2020) developed a regression model for each project type (in total, 19 types) using eight years of project data including project cost, project type, project location, and starting season to estimate project duration. Ohio DOT uses these models to estimate the duration of a project in early preconstruction stages by determining a mean duration with 90% and 95% confidence level. The agency uses such regression tools for preliminary estimation of contract time and use production rate charts and scheduling tools for final setting of contract time.

2.1 Current leading practices

The CTD system of Texas DOT (TxDOT) was initially developed by Hancher et al. (1992) and further improved by Connor (2004) who developed a production rate estimation system. TxDOT categorized its highway projects into 13 project types. The CDT system asks the user to input work item quantities and the program finds a default production rate for each work item. The default production rates of the system can be adjusted for a particular project by the user. The system takes factors such as the location, traffic condition, complexity, soil conditions, and weather that affects the production rates and duration of work items. The system allows the user to determine the relationship of activities to finally generate a bar chart presenting the activities, relationships, and their duration (Hancher et al., 1992; Texas DOT, 2018).

Kentucky Transportation Cabinet (KYTC) (2014) divided highway projects into small size (lower than $1,000,000) and large size (higher than $1,000,000) and developed unique regression models for ten project types of small size and five project types of large size. The small projects account for more than 90% of the KYTC highway projects. The regression models require project identification number, construction estimate, the letting date, and the selected design project type as input variables. The model returns an estimated lower, mean, and upper range of completion dates and working days with 95% of confidence level. For large projects, the input variables for the model include the construction estimate and key bid item quantities (KYTC, 2014). For example, the regression model for a large New Route Highway project is:

Project Duration = 39.289 + 6.894E-5* Construction Estimate – 0.001* Steel Reinf. (LB) – 0.018* DirtWork_Granular Emb (CU. YD.) – 0.010* Perforated Pipe (LF) – 4.51E-4* Striping (LF)

An MS Excel tool was developed to facilitate the estimation process as shown in Figure 1. Once the input variables are entered, the tool calculates and provides a mean, lower, and upper bound of the estimated project duration.

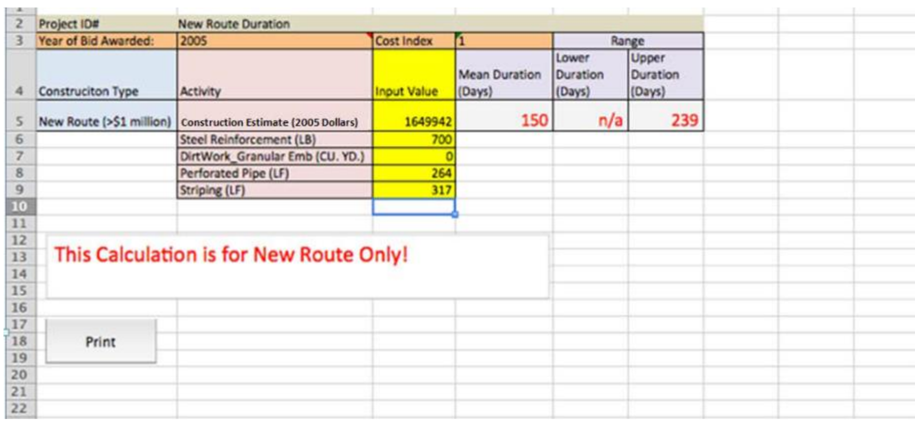

Figure 1. Screenshot of KYTC Excel tool (KyTC, 2014)

Ohio DOT (2020) developed a unique regression model for each project type (total of 19 types) using eight years of data. The regression models take multiple project variables such as project cost, project type, project location, and starting season to estimate project duration with 90% and 95% confidence interval. Ohio DOT applies such regression models for preliminary estimation of contract time and uses production rates and scheduling tools for final setting of contract time that is illustrated in Figure 2 (Taylor et al., 2017). The project duration estimation tool, shown in Figure 2, is an MS Excel tool that includes three steps. The first step is to input major work items for a new project then the tool automatically calculates the production rates and adjusts them with adjusting factors. The adjusting factors are determined based on factors such as the location of the project (rural/urban), the traffic, complexity, soil condition, and the size of the project. After production rates calculation, the user inserts the major work items in the Bar Chart and identifies the work item relationships. Step 2 computes the overall duration of the project. Step 3 captures the total duration and the starting month and considers the weekends, holidays, and weather to adjust the project duration and estimate the completion date of the project (Ohio DOT, 2020).

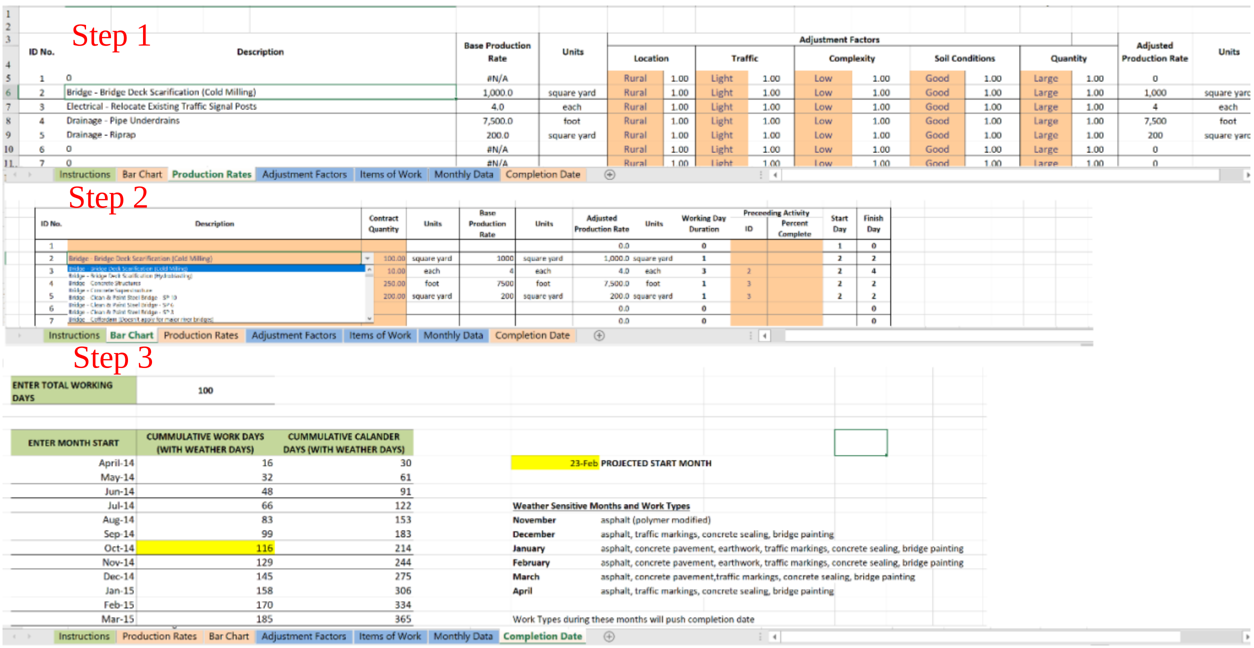

Figure 2. Screenshot of the Excel tool of Ohio DOT (Ohio DOT, 2020)

Virginia DOT (Gondy & Hildreth, 2007) categorizes its highway projects into six categories and uses production rates and sequence logics for CTD. As Figure 3 shows, for less complex projects, the sum of the duration for major work items account for the project duration. But, for more complex projects, after determining duration for major work items, a scheduling technique such as CPM or Bar Chart is used to develop a schedule for CTD.

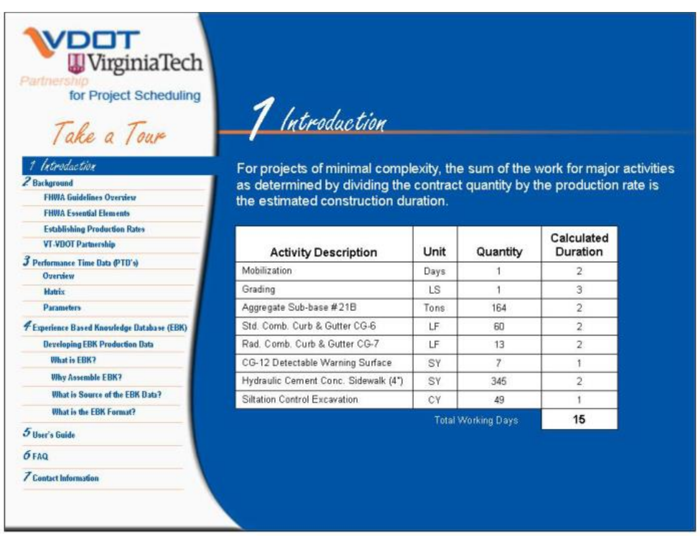

Figure 3. Screenshot of the Virginia DOT tool for CTD (Gondy & Hildreth, 2007)

Nevett et al. (2020) collected highway project data from Colorado DOT that included information about quantities of work items, item level costs, and durations of 15,000 projects. They analyzed 22 variables and developed a multi linear regression model that can receive ten project characteristics such as project type, cost, traffic condition, and work item quantities to predict project duration with 66% of accuracy.

Jeong et al. (2008) developed a comprehensive automated scheduling system for Oklahoma DOT (OKDOT). The research team categorized OKDOT highway projects into three tiers based on complexity (tier I has the highest complexity) and developed the scheduling system for Tier II and III that account for more than 90% of OKDOT highway projects. They developed a standalone computer application and linked Microsoft Projects to a database of project types and production rates in Microsoft Access. The application receives estimated quantities of controlling work items from the user and finds the associated production rates of the work items from the database and computes durations of activities that can be adjusted by the user (Figure 4). Then, the application exports the information to a Microsoft Project that includes the pre-established activity sequence logics for different project types to determine the relationship of activities using CPM and create a reliable schedule that can be used as a basis for contract time (Figure 5).

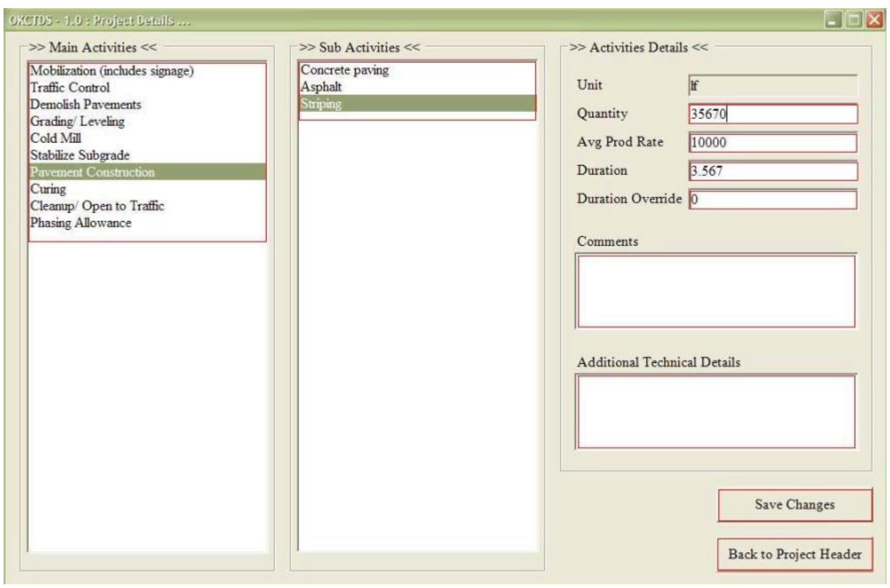

Figure 4. Screenshot of determining project information (Jeong et al., 2008)

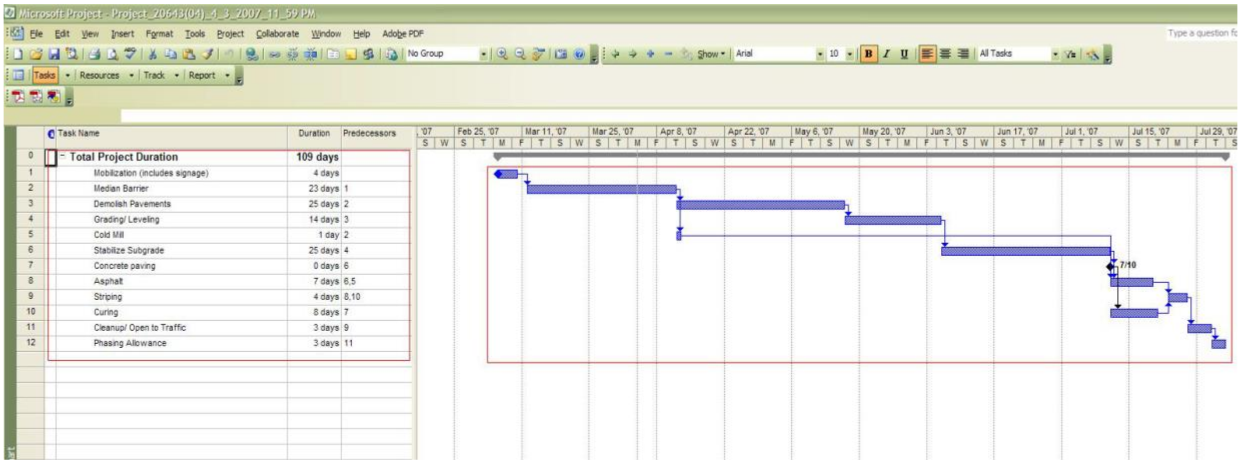

Figure 5. Total project duration and CPM diagram in Microsoft Project (Jeong et al., 2008)

2.2 Discussion on the leading practices

The top-down approach of project duration estimation is used as a quick and reliable approach in different DOTs for determining the contract time before the beginning of construction. DOTs developed different computer systems that take key project characteristics as the inputs and predict project duration as the output. To facilitate using the models, different software programs were developed. A summary on the tools, methods, and project attributes is provided in this section.

- **Project attributes:** key project characteristics such as project location, type, size, estimated cost, traffic condition, soil condition, weather, as well as work item quantities were considered as the input variables to predict the project duration.
- **Software program:** Microsoft Excel is widely used as the main tool (Ohio DOT, 2020; Taylor et al., 2013; Texas DOT, 2018). Researchers used Visual Basic as a programming of Excel to further improve the capability of MS Excel in project information analysis in DOTs (Jeong, Shane, et al., 2019). Other software programs such as Lotus, Flash-up, and Microsoft project were used to link the database to the main tool and present the bar chart schedule (Jeong et al., 2008; Texas DOT, 2018). Due to the simplicity, high capabilities, and availability of MS Excel in DOTs, MS Excel will be used in this research as the main tool.
- Stochastic and deterministic approach: Some DOTs used a stochastic approach to estimating a range of project durations within a certain confidence level (Ohio DOT, 2020; KYTC, 2014; Taylor et al., 2013). The stochastic approach can provide a more realistic insight of project duration since there are many uncertainties associated with project variables before the beginning of a project. Therefore, this research will use stochastic approach in order to consider such probabilities and uncertainties.

2.3 Influential factors on contract time

Recent studies identified key project characteristics as predictors of project duration estimation as shown in Table 1. Controlling work items are activities that are highly likely to be on the critical path of a project. Controlling work items and their quantities were identified as key influential factors by previous researchers. Project location is another contributing factor to project duration. For example, traffic congestion in urban areas may prolong the duration of an urban project. Also, difficulties of carrying materials to mountainous areas may also increase the project duration. Project work type is critical in project duration estimation since each project type has its specific activities and sequences. Project's estimated cost is another factor determining the size of the project that is influential in project duration, since larger projects tend to have more expenses, larger material procurement, and more equipment pieces. Weather condition is highly influential. Cold weather can slow down the construction process especially in districts where the winter is long and severe.

Table 1. Highway project attributes used for contract time estimation

No.	Parameters	References
1	Project location	Ohio DOT (2020), Abdel-Raheem et al. (2020), Taylor et al. (2013), Attal (2010), Hegazy and Ayed (1998), Hancher et al. (1992)
2	Project size	Nevett et al. (2020), KYTC (2014), Jeong et al. (2008)
3	Estimated cost	Nevett et al. (2020), Ohio DOT (2020), KYTC (2014), Wilmot and Mei (2005)
4	Controlling work item quantities	Ohio DOT (2020), Mensah et al. (2016), KYTC (2014), Williams and Heldreth (2009), Jeong et al. (2008), Hancher et al. (1992)
5	Scope of work	Attal (2010)
6	Contract execution date	Ohio DOT (2020), Attal (2010)
7	Design method	Hoffman et al. (2007)
8	Project type	Nevett et al. (2020), Ohio DOT (2020), Attal (2010), Jiang & Wu, (2004), Skitmore & Ng (2003)
9	Population of the area	Leu & Yang (1999)
10	Number of lanes	Mahmood et al. (2017), Williams & Heldreth (2009)
11	Traffic condition	Ohio DOT (2020), Nevett et al. (2020), Jiang & Wu, (2004), Hancher et al. (1992)
12	Production rates	Connor (2004), Jiang & Wu (2004)
13	Weather conditions	Ezeldin & Sharara (2006), Jiang & Wu (2004)

Use of project characteristics in a project duration estimation model is highly dependent on the availability of data. In general, applying more project features results in a higher accuracy and reliability of the estimated duration. In this project, the project information listed in Table 1 will be obtained from the MDT as many as possible to develop a statistical model that is capable of handling multiple variables. Other than variables used in literature and mentioned in Table 1, other project characteristics and attributes available in the MDT historical project databases will be carefully evaluated and analyzed to assess its importance and contribution to project duration.

2.4 Review of statistical methods

Project duration estimation using key project characteristics requires a statistical model that can estimate the relationship between multiple numerical and categorical independent variables (i.e., project characteristics) and one numerical dependent variable (i.e., the project duration). In statistics, regression analysis is primarily used for such purposes.

Regression models were mostly used to establish the statistical relationship between key project parameters and the project duration. Some DOTs reported that their regression method was more accurate and easier to use than their previous contract time estimation methods that were primarily based upon production rates and generic precedence logic (Taylor et al., 2017). Kentucky, Indiana, and Ohio recently developed single variate and multivariate regression models that use cost estimates and selected bid item quantities to estimate contract time (Jiang & Wu, 2004; Zhai et al., 2016). Nevett et al. (2020) collected highway project data from Colorado DOT that included information about construction quantities, cost, and contract time of 15,000 projects. They analyzed 22 variables and developed a multi linear regression model that uses ten influential variables and predicts project duration. Ohio DOT (2020) developed a regression model for each project type (in total, 19 types) using eight years of project data including project cost, project type, project location, and starting season to estimate project duration. Ohio DOT uses these models to estimate the duration of a project in early preconstruction stages by determining a mean duration with 90% and 95% confidence level. The agency uses such regression tools for preliminary estimation of contract time and use production rate charts and scheduling tools for the final setting of contract time. KYTC (2014) developed regression models for ten project types of small size and five project types of large size that receive project attributes such as work item quantities and project cost to predict project duration with a defined level of certainties. Ohio DOT uses these models to estimate an early construction duration with 90% and 95% confidence level (Taylor et al., 2017). Nevett et al. (2020) analyzed 22 variables in Colorado DOT and developed a multi linear regression model that can receive ten project characteristics to predict the project duration with 66% of accuracy.

Although regression analysis models have been used vastly in literature for project duration estimation, Artificial Neural Networks (ANNs) have been applied recently because of their capability of recognizing complex non-linear relationships between inputs and output (Attal 2010; Mensah et al., 2016; Petruseva et al., 2019; Cheng et al., 2019; Karaca et al., 2020; Alikhani et al., 2020). Attal (2010) identified six key project characteristics in highway projects of Virginia DOT and used them as input variables and applied ANNs to predict project duration. They achieved the accuracy of 91% for ANNs in predicting contract time. They compared the accuracy of ANNs with regression analysis, which was 91% and 89% respectively, and concluded that the ANNs had a better performance in prediction. Al-saadi et al. (2017) used ANNs for predicting contract time and achieved the accuracy of 90% and compared the method with other techniques and concluded that the ANN worked more accurate than other methods. Cheng et al. (2019) used ANN to obtain schedule to completion of construction projects and achieved 99% of accuracy. Gransberg et al. (2017) conducted a research study for the MDT and used ANNs for early cost estimation of highway projects. They proposed a top-down estimating approach and embedded the ANN model into an Excel Tool to facilitate usability of the model. They concluded that MDT could enhance the accuracy of cost estimation using the proposed ANN model comparing with their last practice. Due to the higher capability and accuracy of ANNs in comparison with other statistical techniques, this research will develop an ANN model and tune its hyper parameters to achieve a high accuracy of project duration estimation.

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