Uncertainty Management Associated With Project Scheduling in Mine Construction: A Coal Mining Case Study

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Uncertainty Management Associated with Project Scheduling in Mine Construction: A Coal Mining Case Study

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Abstract

Due to the cyclical nature of commodity prices, the profitability of mining projects relies on proper timing. To ensure optimal profits, mines should be brought online at the time, which maximizes the potential value of the asset. In this paper, a coking coal mine construction case is used to demonstrate the effectiveness of scheduling large-scale construction projects with uncertain durations under price cyclicality. Project parameters are obtained stochastically via Monte Carlo sampling, allowing for the influence of uncertainty to be quantified. The critical path method and linear programming are employed to analyze the results and to optimize the construction process, ensuring the maximum value of the mining project. The parameters are repeatedly sampled to obtain distributions of possible project outcomes, allowing for risk and sensitivity quantification. The optimal schedule for construction was determined to be 247 weeks, with a most likely value of $813 million.

Keywords: mine construction; Monte-Carlo sampling; coal mining; uncertainty management; risk quantification; linear programming

1. Introduction

Mining greenfield projects, due to their enormous size and complexity, have numerous factors affecting timing, cost, and value (Brahm & Tarziján, 2015). Constantly changing commodity prices, geological uncertainty, production delays, and even exchange rates can drastically alter the outcome of a mining venture. Of these risks, economic uncertainties affecting the profit margins for commodities pose the most significant threat to a mining project (Haque, Topal, & Lilford, 2016). Unfortunately, because these factors tend to be external in nature, it can be very difficult to effectively mitigate the resulting risks. Mining companies can adjust their practices to produce more cheaply or efficiently but cannot control market conditions and thus are very susceptible to significant changes (Trench & Sykes, 2014). Consequently, it is challenging to accurately value a mining project in the pre-production phase; mining projects that are incredibly profitable at current commodity prices may struggle to break even just years later. Nonetheless, the valuation of a potential project is of utmost importance, allowing for options to be considered and the optimization of investment to be achieved (Sabour & Wood, 2009).

A valuation can be completed on a broad spectrum of complexity with similarly varying success. The base case for a project valuation requires simple estimations that are treated as fixed parameters. These estimations can be adapted from previous experience, sample evaluation, expert consultation, or even pilot testing. However, these estimations hold no guarantee of truth, and provide no quantitative consideration of uncertainty, often leading to discrepancies between plans and outcomes and under-valuation of projects (Botin, Del Castillo, & Guzman, 2013) (Del Castillo & Dimitrakopoulos, 2014). To properly represent the value of a mining project, risks must be quantified. These risks can be categorized based on how they will affect the project outcome; risks can either be external (affecting the outcome of the project regardless of how it is handled) or internal (affecting the performance of the project itself) (Botin, Del Castillo, & Guzman, 2013). For mining projects, external risks include commodity prices, social/political climate, licensing, and regulation, whereas internal risks include geological, temporal, process, and cost uncertainties (Del Castillo & Dimitrakopoulos, 2014; Zhang, Nieto, & Kleit, 2015).

Thus, with so many uncertainties, it is evident how simple estimates fail to account for project risk adequately.

Typical risk mitigation efforts come in the form of stochastic price forecasting, but commodity prices are impossible to accurately and precisely predict. Trends for commodity prices (base metals in particular) tend to follow cyclical periods of highs and lows, but the periods are rarely uniform in length. While some methods exist to quantify volatility (Haque, Topal, & Lilford, 2016), commodity prices can often be expected to stray significantly from initial estimates (Sabour & Wood, 2009). Starting mine construction in down periods on the assumption of a coming price increase presents an unacceptable risk for resource companies and their investors. It is critical, thus, that mining projects are timed properly. Under ideal conditions, a mining project will start to produce on the upswing of a commodity price cycle. To achieve this, mine construction must be rigorously scheduled and monitored. Even if prices are expected to increase in the near future, delaying production could result in a lower present value of the project. This paper aims to evaluate a large-scale coal mining project for the optimization of decision making during the construction scheduling process. The effects of temporal uncertainty will be demonstrated to allow for optimization of activity scheduling and resource allocation using the critical path method and Monte Carlo sampling-based linear programming.

2. Literature Review

Past studies have explored a variety of risk factors for mining projects as well as ways to both mitigate and quantify the effects of uncertainty. Among the most common and perhaps the most critical uncertainties to be considered for mining production are uncertainties associated with commodity prices. Sauvageau & Kumral (2018), Sabour & Wood (2009), and Haque, Topal, & Lilford (2016) examined the effects of volatility for commodity prices and exchange rates using stochastic price simulation and real options valuation (ROV). Similarly, Dimitrikopoulos & Sabour (2007) used a simulation-based ROV method to evaluate fixed schedules for mine extraction to aid decision making under uncertainty. Zhang, Nieto, & Kleit (2015) applied mean-reverting processes to commodity pricing as well as ROV to

determine the value of flexibility and optimal extraction schedule of mineral commodities. Muniappen and Genc (2020) investigated the performance of a coal mining system through dynamic simulation to evaluate a mine life extension project. The majority of the literature for dealing with financial uncertainty in the mining industry is applied to commodity prices and how management can efficiently react to changes to future market conditions. As demonstrated by Zhang, Nieto, & Kleit (2015) and Trench & Sykes (2014), significant value can be achieved by timing mineral extraction properly. In the timing context, Ugurlu and Kumral (2019) quantified the relationship between cost and timing of drill bit replacement in a coal mining operation using Monte-Carlo simulation.

Similar to this paper, uncertainty management attracted significant attention because delay costs in the construction industries can reach massive amounts quickly. Unspecific to mining, construction scheduling research has been thoroughly explored in the past, with main focuses including duration uncertainty and scheduling under unpredictable circumstances (Zhou, Love, Wang, Teo, & Irani, 2013). Martens and Vanhoucke (2017) proposed a different approach to project management in the construction industry based on reacting and correcting unexpected events throughout the project management. Other studies have employed a variety of optimization models to construction scheduling problems such as simulated annealing (Azaron, Sakawa, Tavakkoli-Moghaddam, & Safaei, 2007, König & Beißert, 2009), ant colony optimization (Xiong & Kuang, 2008), particle swarm optimization (Guo, Zhu, Ding, & Li, 2010), neural networks (Adeli & Karim, 1997), and genetic algorithms (Guo, Zhu, Ding, & Li, 2010; Eldin & Senouci, 2004; and Calp & Akcayol, 2018). A comprehensive compilation of methods of scheduling optimization and their respective successes and failures can be further explored in (Zhou, Love, Wang, Teo, & Irani, 2013; Lau & NG, 2013). The projects described by these studies are all of the different types but are all similar in the sense that they represent engineering construction projects, and are all projects that can be broken down into individual activities related to each other by precedence constraints. As such, the proposed method could be applied to any of these projects in place of the methods used in the previous literature.

While these explored methods have been proven to improve the value of construction projects by optimizing various aspects such as cost, timing, and resource allocation (often at the same time), the methods can be difficult to implement and are often not well understood by both the general public and typical project management personnel. In 2008, the Chartered Institute of Building completed a comprehensive survey of over 2,000 construction projects, revealing some troubling shortfalls in the construction industry. Among other problems, fewer than 10% of projects surveyed indicated familiarity with complex scheduling software (with the most common method of scheduling, being a simple bar chart), while a further 10% reported no software used at all, and over 90% of respondents calling for increased education and training for project scheduling (Chartered Institute of Building, 2008). The study clearly displayed a lack of utilization for improvement methods that have been made available for decades, despite proven motivation in the form of increased value or efficiency. This suggests that the available methods are prohibitively complex and/or require resources that are not commonly available to construction firms.

The originality of this paper resides in the creation of a method which has the capacity to optimize the construction scheduling process for maximum value under the effects of temporal uncertainty, using tools and concepts with widespread availability and simplicity. The proposed method is based on a stochastic approach and will apply CPM and Monte-Carlo based-LP to mine construction planning to determine efficient resource allocation while optimizing project value in such a way as to take into account the effects of unexpected realizations of variables. Thus, mine management will have range possible outcomes regarding the project value and timing. If this range does not coincide with the risk perception of the management, a risk mitigation strategy can be implemented. This paper is an extension of our previous work (Renaud & Kumral, 2020) and takes a further step that incorporates uncertainties into the project planning procedure.

3. Methodology

3.1 Model Basis

The mine construction project is displayed by a network diagram (see Appendix 1.4) where nodes represent individual activities to be completed, and links (arrows) represent precedence relationships between activities. Activities are divided into certain and uncertain categories. Certain activities are those whose duration can be predicted with a reasonably high degree of accuracy, and it follows that uncertain activities are those whose duration cannot be accurately predicted. Uncertainty in activity duration is handled stochastically; each uncertain activity is given a random duration value from a PERT probability distribution, special case of the beta distribution, that takes three parameters: a minimum, maximum, and most likely (mode) . To obtain the distribution, which is a modified beta distribution, activities' optimistic (a), pessimistic (b), and most likely ($t_{mode} = s$) durations are estimated with the addition of a scale parameter λ (which decides the height of the distribution). The mean (μ) and the standard deviation (σ) is given by:

$$\mu = \frac{a+b+\lambda s}{\lambda+2} \tag{1}$$

$$\sigma = \frac{(b-a)}{6} \tag{2}$$

and the parameters v and w (which dictate the shape of the distribution curve) are calculated as:

$$v = \frac{(\mu-a)(2s-a-b)}{(s-\mu)(b-a)} \tag{3}$$

$$w = \frac{k(b-\mu)}{(\mu-a)} \tag{4}$$

The distribution gives the density function:

$$f(x) = \frac{x^{s-1}(1-x)^{t-1}}{B(v,w)}, 0 \leq x \leq 1 \tag{5}$$

Values for uncertain activity durations are sampled randomly from the probability distribution shown in equation (5). Sampling the distribution for each uncertain activity using their respective estimation parameters (a, b, and s), provides a simulation of the project representing one possible outcome. By simulating all activities many times, a life distribution of project outcomes is created. The distribution of outcomes allows for optimistic, pessimistic, and most likely estimates for the project schedule at a fixed cost, or project cost (and/or value) at a fixed duration (depending on the distribution created). The number of iterations simulated is flexible (any value can be input), so it is left to the discretion of the user (scheduler/project management team) to balance accuracy of results with calculation time.

The Critical Path Method (CPM) is used to evaluate the project network as well as scheduling risk for individual activities. The CPM algorithm (the intricacies of which are widely published) first calculates the earliest start (EST) and finish times (EFT) of each activity in a "forward pass" and then calculates the latest start (LST) and finish times (LFT) of each activity in a "backward pass". The slack time or "float" is given by the difference of LST and EST, which represents the allowance for the delay in completion for each activity. Activities with a float of zero are considered "critical activities" as any delays to these activities would also delay the completion of the project. After all iterations of the simulation are complete, the likelihood (percent chance) of any activity being critical (on the longest path through the network) can be calculated by counting the number of simulations where the activity in question has zero slack time available. As activity duration estimates change, different activities may dictate the earliest start time of others, changing the critical path. Critical activities carry the most risk, as their performance has a direct impact on the final outcome of the project; thus, it is an important consideration for project management.

One of the main benefits of the critical path method is the ability to use the relationship between time and cost for each activity. The idea behind this relationship is that an activity can be expedited by increasing the amount of resources (money) available. This action is known as “crashing” an activity. For

example, suppose a team of four people work eight hours per day to achieve a task in four weeks. Perhaps, if they were to work 12 hours per day, the task can be achieved in only three weeks, but, since workers are now working extra hours, they must be paid overtime for their efforts. Now, the labor cost has risen to 131% of the original scenario, but the duration has been reduced to 75% of the original. Next, consider the addition of three more workers working overtime to further reduce the duration by another week. The additional cost for extra workers per unit decrease in duration will be more expensive than the initial improvement due to overtime pay. These successive cost-time relationships are known as "crash levels". Each crash level is a linear relationship between the dependent and independent variables (cost and time, respectively) that exists on a finite domain (increasing resources at a specific incremental cost can only reduce duration so far before becoming more expensive). For a project with a fixed duration and uncertain base case activity durations, critical activities must be crashed in order to meet the specified deadline. The following section will describe how to handle crashing activities to maximize value.

3.2 Monte Carlo Sampling-Based Linear Programming Model

A Monte-Carlo sampling based Linear Programming model (MCS_LP) was implemented to optimize project simulations. The simulation can be conducted (estimating project outcomes) in two ways: fixed cost and fixed duration (cost or duration are the independent variables, respectively). For the fixed cost version, every activity is assigned a sampled duration (from the distribution described in the previous section) based on a base case fixed cost (estimated from various sources). In the fixed duration section, a distribution of possible costs is created by applying the linear programming model to the activity duration estimates. Since each activity's duration will be different in each iteration, critical activities need to be crashed (increased cost for the decreased duration) to satisfy the fixed project deadline, returning a unique cost outcome for each iteration. The linear programming model achieves this at the minimum possible cost. By repeating the process for a variety of fixed durations, an informed decision can be made by the project management team for both deadline selection and resource allocation. Similar to the previous section, the probability of criticality for each activity under crashed conditions is

still displayed, allowing for individual risk of activities to be monitored. The formulation of the LP model uses the following notation:

$i = activity\ number\ (i \in \mathbb{N})$.

$n = crash\ level\ \left(n \in (A, B, C)\right)$.

$m = total\ number\ of\ activities\ (m \in \mathbb{N})$.

$j_i = available\ crash\ levels\ for\ activity\ i\ \left(j \in (A, B, C)\right)$.

$T_i = base\ case\ duration\ for\ activity\ i$.

$t_{in} = crashed\ duration\ of\ activity\ i\ at\ crash\ level\ n$.

$C_{Ti} = base\ cost\ of\ activity\ i$.

$c_{tin} = cost\ of\ activity\ i\ crashed\ at\ level\ n$.

$x_{in} = time\ reduction\ for\ activity\ i\ at\ crash\ level\ n$.

$l_{i,i'} = lag\ time\ for\ link\ joining\ activity\ i\ and\ activity\ i'$.

As activities are crashed, the decrease in duration is a result of an increase in cost. The relationship between the two parameters for activity *i* at crash level *n* is given by:

$$\tilde{g}_{in} = \frac{C_{tin} - C_{Ti}}{T_i - t_{in}} \tag{6}$$

Cost *k* for each activity *i* is given as the base case cost combined with the sum of crash costs incurred:

$$k_i = C_{Ti} + \sum_{n=A}^{j_i} (g_{in} x_{in}) \tag{7}$$

Note that $\sum_{i=0}^{i} C_{Ti}$ is a constant, so to optimize the project cost, the objective function is simply:

$$Min\ Z = \sum_{i=1}^{m} \left(\sum_{n=A}^{j_i} \left(\tilde{g}_{in} x_{in}\right)\right) \tag{8}$$

Constraints for the LP model are implemented to preserve precedence relationships. The use of an auxiliary variable y_i (representing the EST for each activity i) helps to formulate the following constraint for each activity i and succeeding activity i':

$$y_i + \left(T_i - \sum_{n=A}^{j_i} x_{in}\right) + l_{(i,i')} \leq y_i' \tag{9}$$

Many activities have multiple predecessors with different finish times. It follows then that only one of the activities would dictate the earliest start time for the next activity. However, since activities' durations can be changed by employing CPM crashing, every link between preceding and succeeding activities must be represented with a constraint such as the one in *eq.* 9 to preserve the relationships in the LP model. Then, since each crash level exists over a finite domain, the reduction instances for each activity i and crash level n are restricted by:

$$x_{in} \leq t_{i(n-1)} - t_{in} \tag{10}$$

Finally, all variables are assigned a nonnegativity constraint as each activity cannot take longer than its base case and activities cannot have a start time before the start of the project:

$$y_i, x_{in} \geq 0 \tag{11}$$

Please note that this formulation was developed for a previous study written by the same authors of this paper. The previous study used a similar formulation to determine optimal scheduling of a mine construction under price cyclicality without considering uncertainty. This study can be considered as a continuation and/or an improvement to the previous study to expand the capabilities of the model and address issues that are more pertinent to the construction industry as a whole. Please refer to the previous study for further details and intricacies of the linear programming formulation (Renaud & Kumral, 2020).

Depending on which aspects of planning are fixed (i.e., project cost or duration), the next step is completed in different ways. First, for a fixed cost (using the base case cost estimates), multiple iterations of the CPM/ MCS_LP combination produce a distribution of project durations. Note that the number of

iterations is left up to the scheduler; without LP, the script runs almost instantaneously. With LP, the duration is significantly slowed, but should scale of the project cause the script to exceed time requirements of the scheduler, projects could easily be broken down into sub-problems for quicker optimization. This is achieved in the proposed model by employing a simple Visual Basic script to complete the following steps (see Appendix 1.2 for the employed script):

1. Clear data from previous simulations.
2. Sample the probability distribution for each uncertain activity to provide a duration estimate.
3. Enter duration simulation results for all 80 activities into the CPM algorithm sheet.
4. Determine project duration and criticality of activities (using the CPM algorithm).
5. Record activity slack times and project duration in a results table.
6. Repeat steps 2-5 for the specified number of iterations (2,000 by default, but more or less can be specified by the user).

To determine these numbers, we gradually increased the number of iterations until the results were stabilized.

Next, by fixing the project deadline, a life distribution of project cost and the present value is produced. As for fixed cost, the script completes many iterations according to the following steps:

1. Clear data from previous simulations
2. Sample the probability distribution for each uncertain activity.
3. Enter duration simulation results into the LP model.
4. Crash select activities (using the LP model) to ensure deadline compliance.
5. Enter crashed activity durations into the CPM algorithm.
6. Determine the criticality of crashed activities via CPM.
7. Record project cost, NPV, and activity slack times in a results table.

8. Repeat steps 2-7 for a specified number of iterations (500 by default as the LP model takes significantly more time than simply employing the CPM algorithm).

The code for the described script can be found in Appendix 1.2.

For both simulation options, some extra factors must be defined. While it is useful still to compare project costs between different outcomes, the project's present value provides a much better indicator of success. Due to the cyclical nature of commodity prices, the project option that takes much more time at a lower cost will not necessarily provide the best value. Thus, to examine project value during the simulations, some assumptions about the mine must be made. In practice, these assumptions would be legitimate parameters that are project-specific, but to prove effectiveness, the factors will be estimated, as explained in the following section.

4. Case Study

To demonstrate the proposed model and its benefits, it will be applied to the construction plan of a large-scale mountaintop metallurgical coal mine. Metallurgical coal mines could benefit significantly from the proposed scheduling method, as price trends for this commodity closely follow cyclical trends of supply and demand from emerging economies (Connolly & Orsmond, 2011). The network diagram of this case study is given in Appendix 1.4. At the start of the project, the land for the mine is owned by major resource company a Commodity Mining Corporation (CMC) and is located adjacent to currently operating successful coal mining operations also owned and operated by CMC. The new mine will be constructed in such a way to make use of the existing tailings facility of an adjacent project; thus, the construction costs of tailings management facility are not included in the construction plan. The land, while yet undeveloped, is in a stable political jurisdiction and CMC is on good standing with the surrounding communities after providing employment opportunities, sponsorships, and education to residents. Note that any project parameters included in this analysis do not represent any particular mine

currently or previously in existence. A more in-depth description of the project and its assumptions can be found in the preceding study (Renaud & Kumral, 2020).

The proposed model is built to accept a wide variety of inputs for various parameters, including commodity price, operating expenditure, capital expenditure, production rates, the life of mine, and the cost of capital. This is accomplished thanks to the simplicity of the excel model. Simply labelled input points allow for user-contributed parameters for use in the model. As such, the model allows for any input as needed by the user. It should be noted as well that the model can be used outside of the mining context. For this case study, the commodity price schedule represents the benefit to the project of adhering to a specific deadline or schedule, but for the general use of the model, this input can be replaced by another project-specific benefit for punctuality. Similarly, production rates and life of mine inputs allow for further quantification of the value of schedule compliance. Finally, operating and capital expenditures, as well as the cost of capital, are common and can be applied to any project.

In reality, these parameters will vary from project to project as a result of the sociopolitical and physical environments, and best practice would dictate the involvement of project stakeholders to develop initial estimates (such as production rates, the life of mine, and cost of capital). For this case study, however, assumptions will be made using a variety of sources to use the described method. Note that the proposed model could accept stochastic estimation methods for all the parameters described above; however, more iterations may be required, and, as more probability distributions are involved, each iteration of the simulation will take more time to complete. In practice, there would be sufficient time to run lengthy simulations for the benefit they provide, but, as a proof of concept, this paper will fix parameters deterministically as described in the following paragraph.

The mine to be constructed is fairly large, with 50 million tonnes of proven metallurgical coal reserves. The planned production rate is based on the maximum capacity of the railroad, producing five million tonnes per year (giving a mine life of ten years). The rate is assumed to be constant over each year's quarters (1.25Mt each quarter) and for all ten years of production for the sake of simplicity. Rather

than estimating a commodity price schedule, the historical price chart will be used. The construction project is slated to start in Q3 2005. Operating expenditures (mining/processing/transportation costs) are estimated to average at 75 USD/tonne, and both operating and capital costs are discounted at a 12% cost of capital. It is important to note that the case for a real mine would be different than many of the assumptions made in this paper. Proven reserves are often expanded as the mine ages. Stockpiling strategies are developed to weather low price periods. Operating costs may rise or fall as equipment ages, stripping ratios change, and haul profiles expand or contract. Especially, mounting and maintenance costs, and inspection intervals associated with mining assets have significant effects on project management (Golbasi and Demirel, 2017). These cases represent the sources of risk not addressed quantitatively by this paper.

The construction process is broken down into 80 individual activities (with the addition of two milestones or zero-duration "dummy" activities for the start and finish points). The 80-activity network covers all aspects of a mine construction project, including (but not limited to) permitting, planning, exploration, testing, equipment procurement, financing, facility construction, and even overburden removal. At the time construction process is considered complete (the finish milestone), productive mining (moving/processing/selling coal) can start. The goal of the proposed method is to determine either when mining can start or how much it would cost to start mining by a specific time (for this case study, the specific time is explored by fixing different quarters to the end period such that different scheduling options can be compared). Combining both with the price schedule, it is shown which plan holds the highest value, and which parts of the project carry the most risk. A full list of activities, their base-case durations (most likely PERT estimate), and their predecessors can be found in Appendix 1.1.

Often, megaprojects fail to properly consider resource availability when planning for activity costs or, worse still, they fail to consider individual activity cost all together (Chartered Institute of Building, 2008). For this case study, estimations of cost and duration are completed using various

sources[1] as well as some personal experience of the authors to mimic best practices. However, costs are aimed to be justified from a published source as much as possible. For example, activities whose costs result from equipment operation are estimated based on hourly costs applied to the activity duration. All equipment used in the construction/development process is assumed to be purchased new, and procurement and operating costs for equipment are based on the estimates provided by CostMine's Mine and Mill Equipment Cost Estimator's Guide (InfoMine USA, Inc., 2016). Also included in activity cost estimates are personnel costs for labor, planning, and management from various sources[3] as well as auxiliary costs such as software licenses and travel/delivery expenses. For CPM analyses, Weaver (2011) recommends an efficiency factor be added to cost estimates to help account for various biases; thus, base cost estimates for the case study are modified by a factor of 1.2. Causes and effects of these biases will be described in the Limitations section of this paper. A more in-depth description of the cost estimation process can be found in the previous study (Renaud & Kumral, 2020).

4.1.Results

[Insert Fig. 1 here]

The first application of the model to the case study involves fixing project cost to obtain a distribution of possible project durations for a base case cost (no crashing!). Cost is fixed at $987.99 million, and 2,000 simulations provide a distribution of outcomes, as shown in Fig. 1. The most likely result was given as 275 weeks, with an average and a median of 276 and 277 weeks, respectively. The most likely value for project duration (275 weeks) at the base case cost returns the present value of $659.75 million. With 95% confidence, the duration for the base case cost falls between 262 and 292 weeks. Critical activities carry the most risk, as their delays directly affect the project outcome, and similarly are the most sensitive to change.

[1] Activity cost/duration information adapted from: (Access Consulting Group, 2008) (Canadian Institute of Mining, 2011) (InfoMine USA, Inc., 2016) (Kenneth P. Green, 2017) (Kihn, 2015) (National Native Title Tribunal, 2009) (National Resources Canada, 2006) (PayScale, Inc., 2018) (Smith, 2014) (U.S. Securities and Exchange Commission, 2016)

[Insert Fig. 2 here]

Next, project durations are fixed on a quarterly basis. The lowest deadline option considered was determined to be 4.75 years (247 weeks), because, at this deadline, approximately 15% of simulations were deemed unfeasible (crashing every possible activity to its maximum could not reduce the simulated duration to 247 weeks). It should be noted that this is a limitation specific only to this case study. The formulation of the mine construction problem (namely the possible crash levels) forms the boundaries of the schedule outcomes. For general use, similar feasibility issues will be encountered based on the project-specific constraints of the project to which the method is applied. Similarly, the scalability of this method is of no particular concern, as the project being analyzed can be broken down and each part analyzed separately with no loss of optimality. The maximum considered was 5.5 years (286 weeks), as nearly all simulations set to 5.75 years provided a lower value than the 286-week deadline. The deadline that provided the highest value was found to be 4.75 years; the results (NPV) of 500 simulations for the 4.75-year (247-week) deadline are shown in Fig. 2. The most common simulation result for the 247-week project was $813 million, with a minimum value of $733 million and a maximum value of $913 million. The average value is approximately $794 million, with a median value of $790 million. The standard deviation of NPV is $5.14 million. The value of the project limited to 247 weeks can be predicted between $750 million and $850 million at 95% confidence. Note that while 247 weeks provided the highest average, median, and mode, it was shown to be unfeasible for a significant portion (15%) of time, even at the maximum possible cost (all activities at crash point). However, allowing the project deadline to extend another quarter (5-year/260-week deadline) not only reduces the average value by over $20 million, it also reduces the maximum possible value by nearly $100 million (although the minimum possible value is approximately equal to the 247-week option). Thus, it is determined that the project management should aim for project completion in 247 weeks and allocate resources to critical activities accordingly. The standard deviation of the project completion is 8.94 weeks. The activities with a 100% chance of criticality at 247 weeks (with the exception of activities "Mining Method Planning" and

"Production Rates & Targets" were critical in 97.4% of simulations). Activity 206 ("Mining Transport Planning") and Activity 10 ("Stripping 2") are critical in 58.6% and 11.8% of simulations, respectively. Activities with 100% criticality represent those most sensitive to delays, and those that carry the most risk. Note that in the case of criticality for activity 10, there exist two critical paths, as activity 10 and 11 will have the same duration and occur simultaneously.

Note as well that the distribution of project values for the 247-week deadline is unbalanced. This situation is due in part to the unfeasible results providing the lowest values (all activities fully crashed with a delayed revenue commencement) and in part to the activity crashing structure. Without the unfeasible results, the left side (lower values) would be more sparse, showing mainly outliers, similar to the high value-tail (this effect can be seen in the 5-year suboptimal result distribution shown in Appendix 1.3). As shown in the fixed cost section, a 247-week deadline is unlikely to be reached without activity crashing. This results in an imbalance in activity values where outliers without (or with minimal) crashing prove to be worth far more than those that require higher percentages of crashed activities. Furthermore, many activities whose crash costs are proportionally lower occur earlier in the construction process, meaning that their influence is more significant than similar crash costs later in the project (for example, speeding up site planning by one week is much cheaper than increasing the rate of overburden removal). This results in "bunching" of values, where many successive iterations of crashing only change the project value slightly, despite reducing the duration significantly. For these reasons, a larger concentration of results provides lower value, and there exists a natural drop-off where little to no crashing is employed. Results from sub-optimal deadlines can be found in Appendix 1.3.

4.2. Limitations

The proposed method is not without its flaws. Whenever estimations are used to determine project parameters, various biases will influence the results. Estimations for cost and time are nearly always optimistic (Weaver, 2011), and even though duration estimates are determined stochastically, the

initial estimates to create the PERT distribution carry their own biases. The most influential of these are optimism bias, expectation bias, and the human tendency to be self-serving. Optimism bias can be described simply as the tendency for humans to underestimate resources (time/cost) necessary to achieve a goal, even if that goal had proven itself to be more costly in the past. This is especially evident when recalling the personal experience, as people tend to block out or diminish negative memories and favor those where success was achieved, regardless of the circumstance (Taylor, 1991). Expectation bias refers to the propensity for a scheduler to choose or accept estimates that most closely resemble their goal. For example, if a manager expects an activity to take two weeks and cost $50,000, they are far more likely to accept a contractor who says they can complete the activity for $48,000 in 15 days than a contractor who says it is not possible to finish the activity in fewer than three weeks with fewer than 70,000$, even if the second contractor is correct. Any estimate that allows the goal to be attained more easily will be chosen over one that does not, even if both are equally likely (Shepperd, Malone, & Sweeny, 2008). Similarly, a scheduler is more likely to present a schedule or plan to his management that is cheaper and faster as it makes them look better to their superiors or appear more competent. This effect is very evident in contractor estimates, as the expectation bias described previously would dictate that the contractor with the cheapest bid would be the one to receive the job (Espinoza R. D., 2011). The cumulative effect of these biases often presents a plan rife with unwarranted optimism. While optimism is generally considered detrimental when an accurate and precise estimate is required, an optimistic schedule often has a motivating effect on the development teams. However, the increased risk presented by an unrealistic schedule is unlikely to be offset by the increased motivation (Weaver, 2011).

Once past the inputs, the model has some limitations of its own. When applying CPM to a project network, there exists “merge bias”, which can be described as the optimism incurred by ignoring paths that are not critical. Often, there will exist sub-critical paths with very little slack time, and any minor delays to these sub-critical activities could change the critical path and delay the project completion (Weaver, 2011). The CPM analysis assumes that sub-critical paths will always be completed prior to the

critical path, and the only risk quantification presented is the slack time for individual activities or paths. The proposed model gives some insight as to which paths or activities are more likely to be critical through the stochastic duration simulations by presenting a probability of criticality for each activity. A more thorough quantification of risk could be achieved by the use of the Program Evaluation and Review Technique, whose algorithm presents a likelihood of any path being completed in the given deadline (Hillier & Lieberman, 1986). Furthermore, simply examining the present value of certain decisions can lead to other problems. Ideally, the LP model should output a schedule that provides the maximum present value. To achieve this, however, activities should be scheduled as late as possible to delay spending (allowing for lower discounted costs). By doing this, however, every activity becomes "critical" as all the slack time has been consumed before the capital is employed. This situation is not an acceptable risk, clearly, as now any delay in any activity will directly affect project performance. Thus, the model accounts for this effect by assuming all costs are incurred at the EST. Unfortunately, this means the result is not truly optimized, as delaying the start of some activities by consuming slack time could provide slightly higher value with increased risk. The value/risk trade-off is a decision that must, therefore, be considered by management on a case-by-case basis. This model simply demonstrates the outcomes of various schedules, providing flexibility for increased resource efficiency.

The decision-making process for the proposed model uses a traditional discounted cash flow (DCF) method to compare the value of different scheduling scenarios. DCF valuation is widely used due to its ease of implementation and relatively low barrier to entry (Hall & Nicholls, 2007). However, it is becoming increasingly evident that DCF valuations fall somewhat short of reality; the value associated with the ability to react to changing parameters and change plans based on various options is not properly captured by the standard DCF method (Hall & Nicholls, 2007) (Sabour & Wood, 2009) (Botin, Del Castillo, & Guzman, 2013) (Samis, Martinez, Davis, & Whyte, 2012). A study by Samis, Martinez, Davis, & Whyte (2012) describes three main limitations of the DCF method as the ignorance of randomness for cash flow contributors, the ignorance of financial effects of flexibility, and the ignorance

of changes of risk over time. The first shortcoming can be mitigated somewhat through a Monte Carlo simulation, as completed in the proposed model. Since not every variable has been simulated, this criticism remains valid, but it should be noted that the model can accept simulated values for every input if the user wishes to do so. The second criticism of DCF is similarly valid for the proposed model. Changes to an initial plan are nearly inevitable, especially for large-scale complex projects such as mine construction. The ability to revise decisions based on changes in various parameters or other information not previously available (such as new technology) carries a significant value (Sabour & Wood, 2009) (Hall & Nicholls, 2007). The undervaluation associated with the DCF method should not be ignored, but it should be noted that its effects could be muted when combined with the optimism described in previous paragraphs. The third shortcoming of the DCF method is perhaps the most important but is one that can be incorporated into the proposed model. Changes to risk over time can be simulated by developing the risk profiles of each parameter used in the valuation. As the project continues, any deficiencies or proficiencies from the earlier stages can be included in the model, and their effects over time can be quantified. The proposed model, while simple, can be used at any point in the process to aid in making changes to initial plans or changing decisions. The strength of the model is its proficiency in providing a clear valuation of a wide range of possibilities moving forward from the present time; a task at which DCF excels (Espinoza & Morris, 2013). Note that a Real Options Valuation could be applied to this model by incorporating the value of the DCF shortcomings, but this may risk reducing the ease of access and simplicity of this method–one of the primary strengths and reasons for implementation. This sentiment was confirmed by Ampofo (2017), who surveyed mining professionals and concluded that a combination of lack of education, trust, and access to software had prevented implementation of such methods in the mining industry in the past.

5. Conclusions

To maximize the value of a potential mining project, commodity price cyclicality must be considered along with various uncertainties associated with project parameters. Mines must be brought

online at the right point in a price cycle to produce maximum profit. To achieve this, mine construction projects should be scheduled to take advantage of the positive swings in price cycles. The proposed model achieves this through the use of CPM and LP to determine the value of different plans or project outcomes. In the case study, a large-scale open-pit metallurgical coal mine is paired with a historical price schedule. At the base case cost, a life distribution of durations is produced, allowing management to explore the potential for success at a minimum cost. Next, various fixed deadlines are explored, and distributions of their value are produced. It is determined that the coal mine should have a set deadline of 4.75 years, providing an average value of $794 million and a most likely value of $813 million. At the base case cost, the most likely outcome for mine construction duration is found to be 275 weeks (giving a project value of $656 million).

Continuations to this study may include incorporation of more randomized variable estimation. While the method allows for a wide variety of parameters to be modeled stochastically, activity duration was the only non-deterministic variable. As more variables are calculated from probability distributions, a more accurate representation of the outcome of mine construction projects can be realized. It should be noted, however, that applying stochastic estimation to more aspects of the plan will require more simulations and more computation time. This improvement could help mitigate the effects of optimistic bias on parameter estimation to give a more realistic valuation. Similarly, a real option valuation (ROV) could be applied to supplement the DCF valuation used in this study. An ROV would help to quantify the value of flexibility and help further prove which schedule provides the maximum value. This would also improve the ability of a management team to mitigate possible risks in the construction process. It should be noted, however, that the option with the highest ROV is not necessarily the best design option (Dimitrakopoulos & Sabour, 2007). Finally, this model could be applied to fields other than mining, as it is designed to optimize the scheduling of long-term complex projects with multiple inputs. While a mine construction project is sufficiently complex and uncertain to demonstrate the effectiveness of the

proposed model, it is not limited to mining applications, but rather can be applied anywhere there exists multiple activities with complex precedence relationships.

6. Acknowledgement

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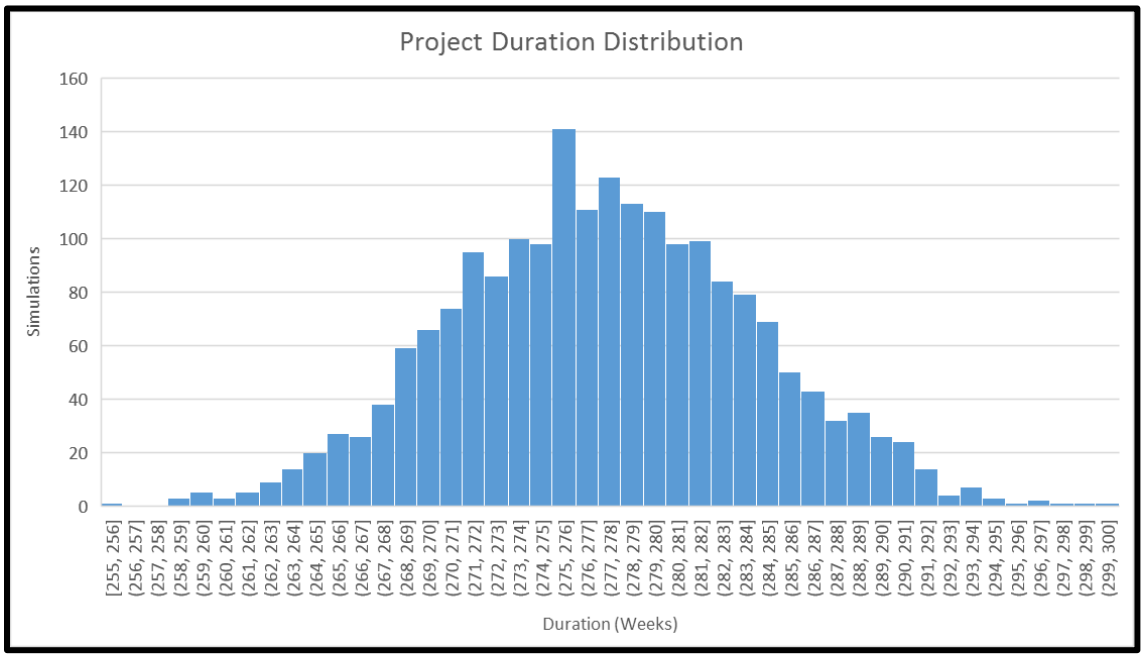


Fig. 1 Fixed Cost ($987.99) Simulation Results

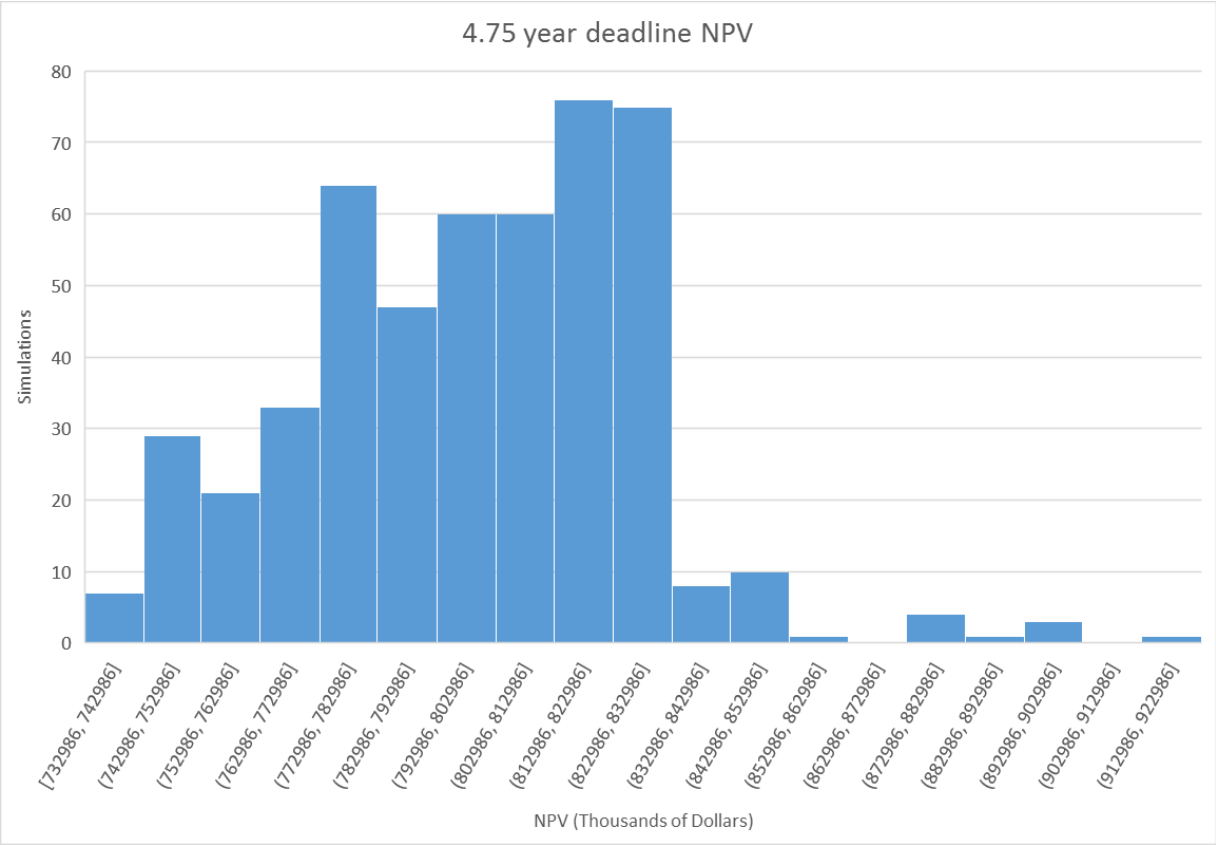


Fig. 2 Fixed duration (247-Week Deadline) Simulation Results

Appendix

1.1 Activity List (with predecessors and sample duration)

Act	Description	Dur	Predecessor	Act	Description	Dur	Predecessor
1	Regional research	5	-	1104	Road finishing	1	1102, 1103
2	Regional airborne recon	6	1	1111	Planning/prep	2	1054
3	Data analysis, area selection	4	2	1112	Foundation/structural construction	10	1111
4	Obtain exploration license	24	-	1113	Water/power/HVAC	10	1112, 1052
5	Ground recon, surveying	12	6	1114	Exterior construction	6	1112
6	Exp. equipment delivery	10	3, 4	1115	Interior construction	6	1114, 1113
7	Map design	4	5	1116	Admin finishing	2	1115
8	Surface sampling	6	6	1121	Foundation/structural construction	8	108
9	Stripping 1	2	7	1122	Exterior construction	6	1121
10	Stripping 2	8	9	1123	Water/HVAC systems	8	1122
11	Exploration drilling	12	9	1124	Power systems	8	1122
12	Pitting	8	9	1125	Mineral processing equipment installation	12	123, 1123, 1124
13	Mapping	4	12, 15	1126	Plant finishing	2	1125
14	Resource estimation	6	16	1131	Planning/staking/prep	2	1054
15	Detail drilling	16	10, 11	1132	Foundation	10	1131
16	Pilot testing	12	15, 17	1133	Structural construction	12	1132
17	Bulk sampling	6	12	1134	Water systems	8	1052, 1133
18	Financial analysis	6	14, 21	1135	Power systems	6	116, 1133
19	Feasibility study	12	13, 18	1136	Equipment installation	20	1135, 2001
21	Sample testing	12	8, 17	1137	Maintenance finishing	6	1136, 1134, 1139
202	Design scheduling	1	19	1138	Shop testing	4	1137
203	Mining method planning	7	202	1139	Exterior construction	8	1133
204	Production rates & targets	2	203	114	Ordering mining equipment	4	106
205	Mine service planning	8	202	115	Transportation/assembly of mining equipment	24	1104, 114
206	Mining transport planning	8	202	116	Energy supply	8	104
207	Mine sequencing	7	204, 206	117	Mineral labor recruitment	10	106
208	Production & economic model	5	205, 207	118	Ordering mineral processing equipment	4	106, 108
209	Plan optimization	2	208	119	Blasting material supply	4	109
104	Obtaining operating license	10	208	120	Testing the mine equipment	2	115, 116
1051	Clearing	2	209, 104	1211	Survey/staking	2	120
1052	Water management	4	107, 1053, 1000	1212	Drilling/loading first bench	6	1211, 119
1053	Secondary survey/staking	2	1051	122	Processing equipment supply and transportation	12	118, 1104
1054	Ground prep	4	1053, 1000	123	Assembly of mineral processing equipment	16	122
106	Obtaining financing	10	104	124	Training of the mineral processing workers	8	117, 125
107	Water supply to the site	10	104	125	Testing the mineral processing equipment	2	1126, 1123, 116
108	Processing plant planning	6	1052, 1054	126	Overburden removal	52	1001, 1212, 1138, 1116
109	Explosive storage construction	12	1054	1000	Construction equipment delivery	8	1104
1101	Clearing/prep	6	104	1001	Labor training	8	120, 117
1102	Ditching	3	1101	2000	Ordering maintenance equipment	4	106
1103	Surfacing	3	1101	2001	Delivery of maintenance equipment	8	2000, 1104

Adapted from (Renaud & Kumral, 2020)

1.2 VBA Code Samples

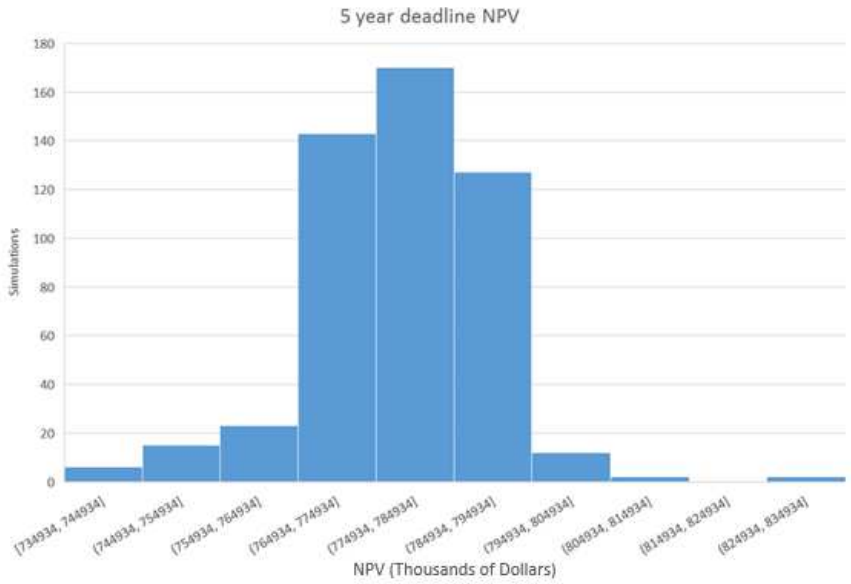
```
Sub RunExperiments()

With Application
  '  .Calculation = xlCalculationManual
    .EnableEvents = False
    .DisplayAlerts = False
    .ScreenUpdating = False
End With

Call GetMC

'"C2:ALN84"
Worksheets("Results").Activate
Sheets("Results").Range(Cells(2, 4), Cells(90, 2004)).Select
Selection.Clear
For i = 14 To 513
    UpdateMCcolumn (i)
    Worksheets("CPM Calc").Activate
    Call RunOpenSolver
    Call ResultsPaste


    Next i


    With Application
  '  .Calculation = xlCalculationAutomatic
    .EnableEvents = True
    .DisplayAlerts = True
    .ScreenUpdating = True
End With

End Sub
```

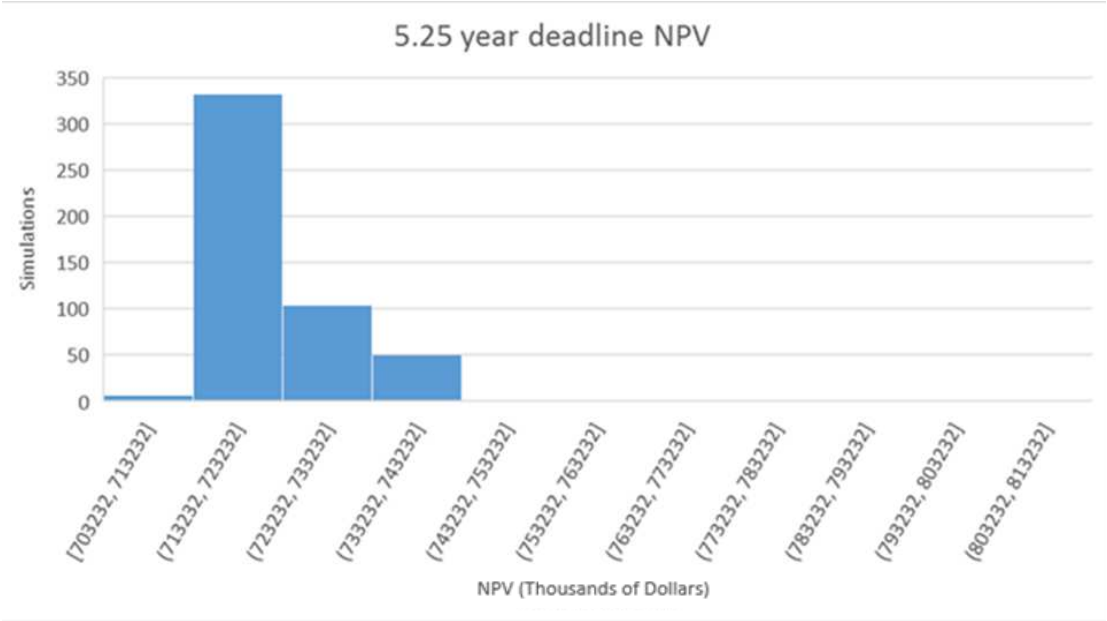
```
Sub UpdateMCcolumn(Column As Integer)
'
' UpdateMCcolumn Macro
'

'
'14 is for N ("N2:N81")
    Worksheets("MC").Activate
    Sheets("MC").Range(Cells(2, Column), Cells(81, Column)).Select
    Application.CutCopyMode = False
    Selection.Copy

    Sheets("MC").Range("B2").Select
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=False


End Sub
```

```
Sub GetMC()
'
' creates new MC values
'

'
Worksheets("MC").Activate
    Range("N2:N81").Select
    Application.CutCopyMode = False
   ' Selection.AutoFill Destination:=Range("N2:BYK81"), Type:=xlFillDefault
     Selection.AutoFill Destination:=Range("N2:DI81"), Type:=xlFillDefault
    'Range("BYK26:BYM27").Select
End Sub
```

```
Sub ResultsPaste()
Dim NextCol As Long

    If Sheets("Results").Range("B1").Value = "" Then
        NextCol = 1
    Else
        NextCol = Sheets("Results").Cells(2, Columns.Count).End(xlToLeft).Column + 1
    End If
    Worksheets("Complex Precedence").Activate
    Sheets("Complex Precedence").Range(Cells(4, 6), Cells(90, 6)).Select
    Application.CutCopyMode = False
    Selection.Copy

        Sheets("Results").Cells(2, NextCol).PasteSpecial Paste:=xlPasteValues
End Sub
```

1.3 Suboptimal Deadline Simulation Results




5.25 year deadline NPV
Simulations
350
300
250
200
150
100
50
0
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(713232, 723232]
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(733232, 743232]
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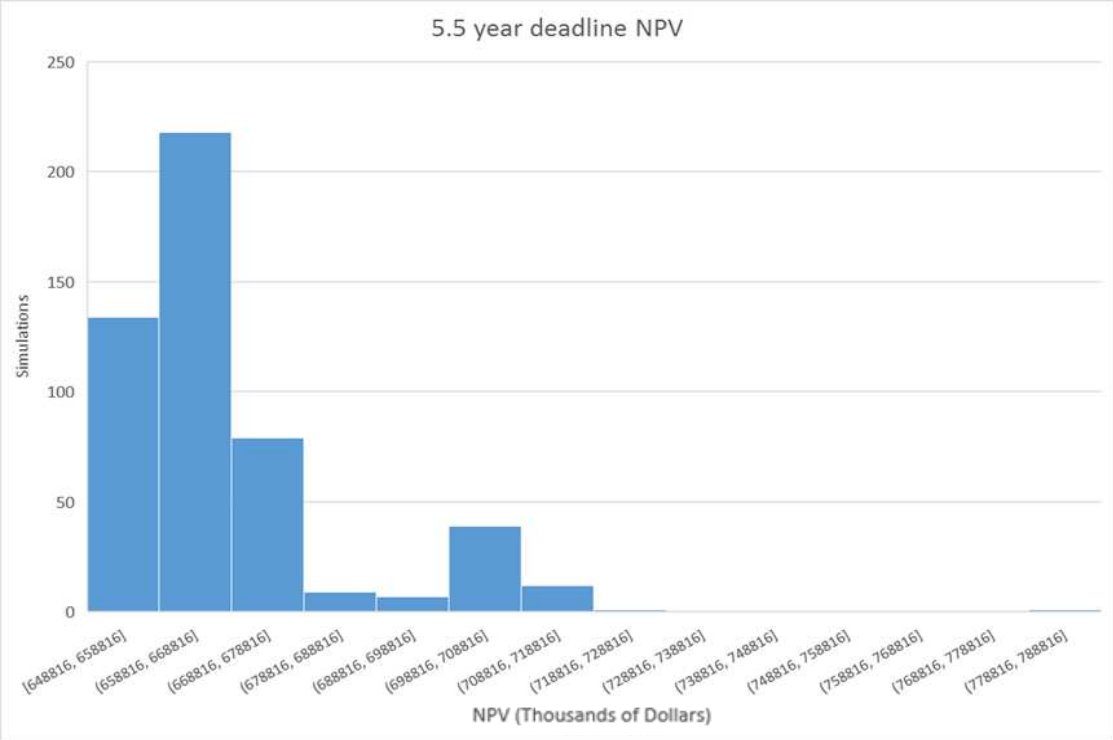
(803232, 813232]
NPV (Thousands of Dollars)


5.5 year deadline NPV
Simulations
250
200
150
100
50
0
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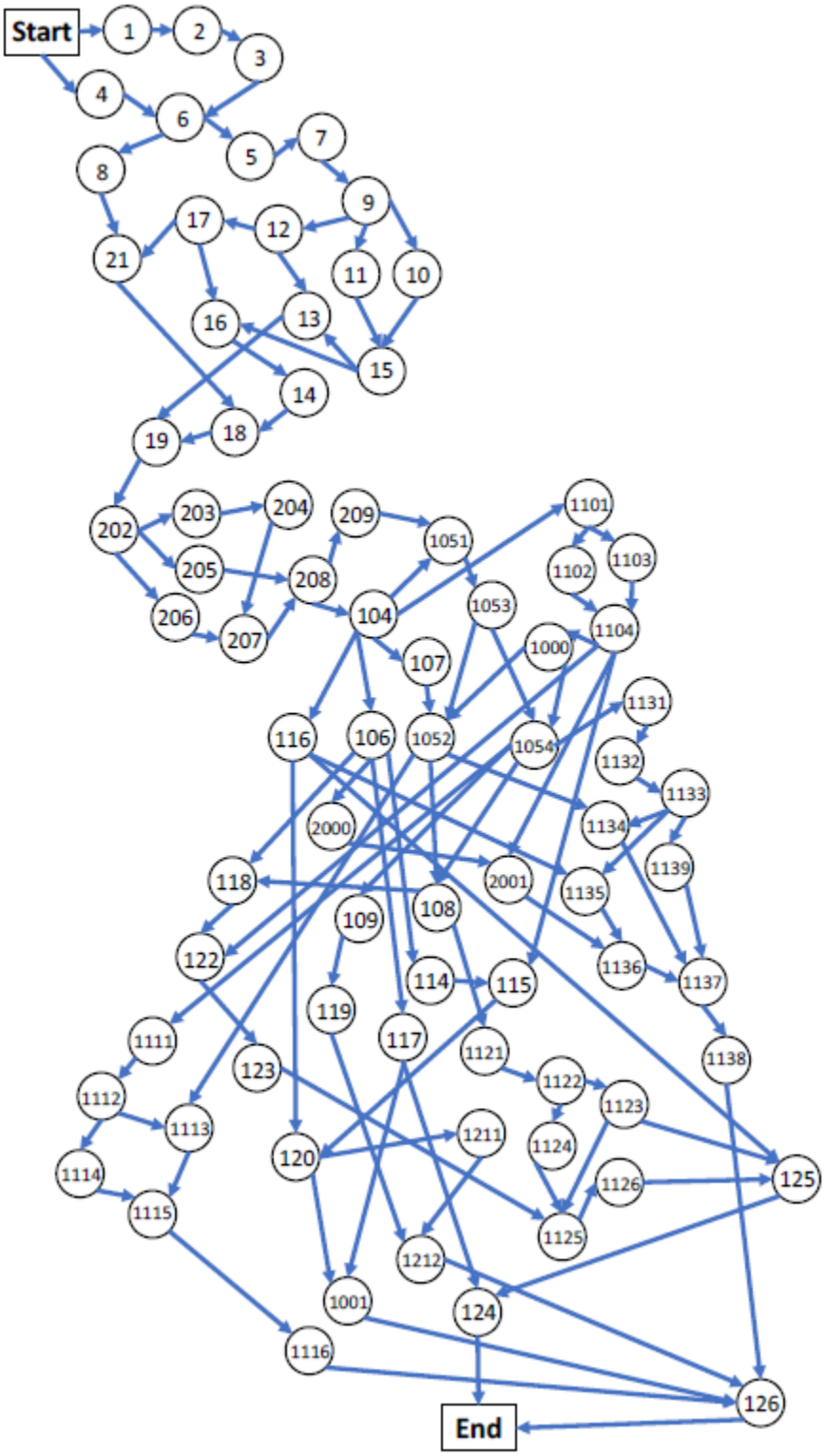
(778816, 788816]
NPV (Thousands of Dollars)

1.4 Activity Network Diagram



Figures

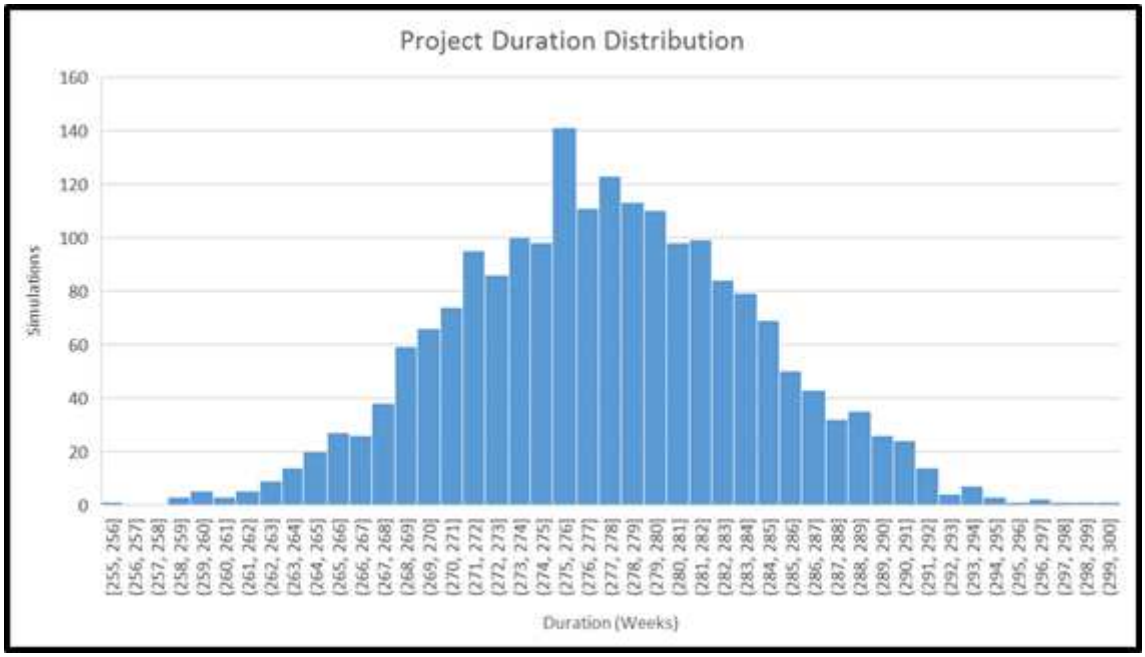


Figure 1

Fixed Cost ($987.99) Simulation Results

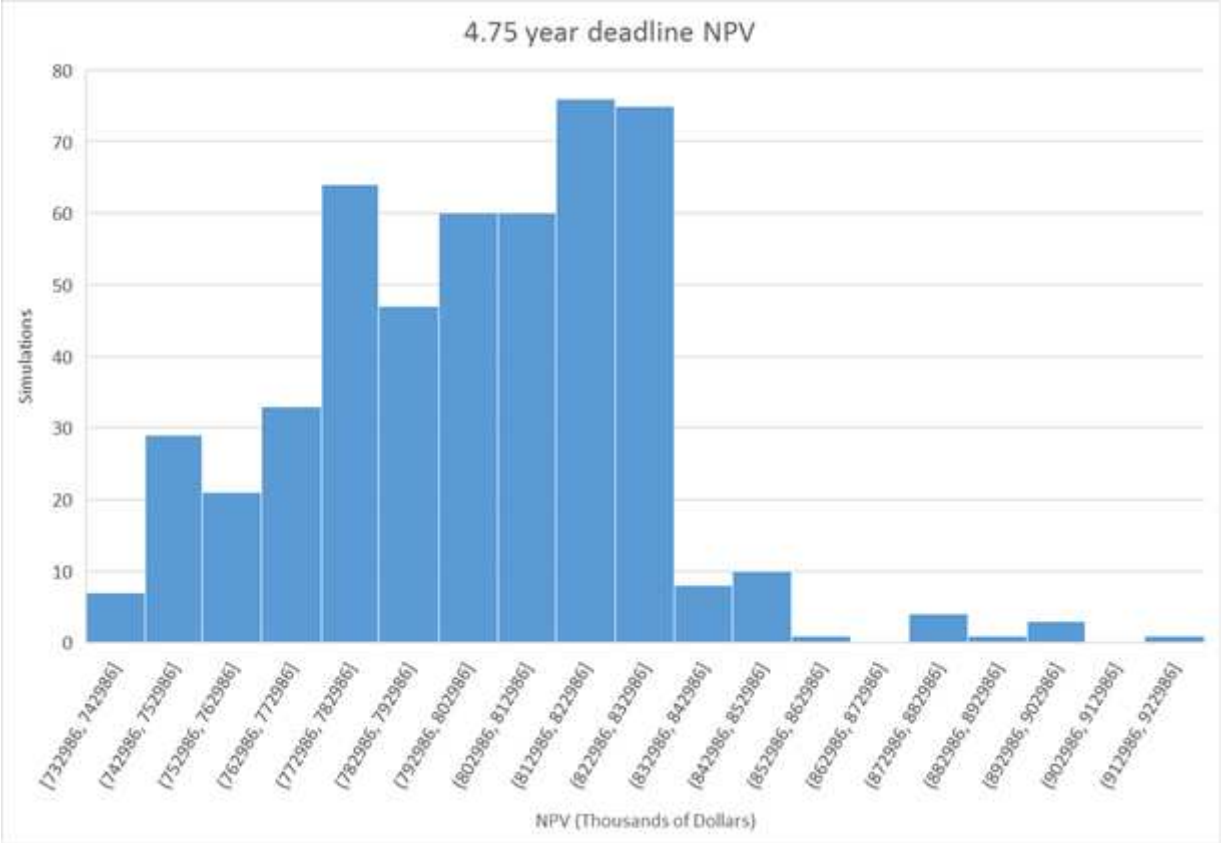


Figure 2

Fixed duration (247-Week Deadline) Simulation Results