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Schedule Risk Analysis for Defence Acquisition Projects (DRDC-RDDC-2016-P049)

Abstract

Project scheduling is an important component of project management. In the defence acquisition context, projects usually have extended and complicated schedules that can be affected by various sources of uncertainty. Examples of risks for project schedules include technology readiness, contracting delivery, learning curve estimation, decision delay, etc. Handling this uncertainty has been an ongoing challenge for military decision makers for many decades. Schedule risk affects not only the completion time but also the cost and the overall performance of the acquisition project.

In this paper, a comprehensive review of theoretical methods for analyzing schedule risk of defence acquisition projects is discussed and presented. A novel schedule risk analysis approach integrating Monte Carlo simulation, decision analysis and optimization techniques is proposed to determine the expected critical path and completion time of an acquisition project. The approach determines a ranking probability matrix for the different critical paths of the project schedule. The condition that defines a particular critical path ranking as most probable is described in the context of an assignment problem. The most probable critical path is then found by solving the assignment problem using the path ranking probability matrix.

Once the expected critical path is determined, an "S" curve is used to portray the schedule risk and to estimate the project schedule buffer for different confidence levels. A case study using a military aircraft replacement project for the Canadian Armed Forces is presented to illustrate the approach. Future work would include the development of a similar approach for cost risk analysis as well as an integrated cost and schedule risk analysis approach for future defence acquisition programs.

Keywords: Schedule risk; Schedule buffer; military; aircraft

In this paper we:

- explore uncertainty in defence acquisition project scheduling;
- present the state-of-the-art for schedule risk analysis;
- propose a novel schedule risk analysis approach;
- illustrate the approach using a case study;

1.1 Introduction

Defence acquisitions are often complex and large-scale projects with long durations and interrelated activities. Handling uncertainty in these complex projects is a key factor to their success or failure. Project scheduling is an important source of this uncertainty. Schedule overrun (or schedule delay) refers to a situation where a project does not come to completion within the planned period. Cost overrun (or cost escalation) occurs when actual costs exceed previously estimated values (Kaliba et al., 2009). The ability to accurately define a project schedule is challenged by uncertainties similar to those encountered in building an estimate of the project cost, namely the impact of technological change, resource constraints, and programmatic obstacles. Schedule risk analysis is the process of associating a degree of confidence with the schedule duration estimate. The combination of defining probability distributions for various task durations and establishing network relationships among the tasks allows one to forecast the probability of meeting the targeted dates of key milestone events.

Uncertainty in project scheduling can occur due to three categories of complications (Kaliba et al., 2009; Khodakarami et al. 2007): ambiguity (i.e., lack or incompleteness of data), variability (i.e., trade-off between available and required resources), and occurrence of uncertain causal events. Schedule risk has been a persistent concern for defence project managers. Schedule risk would not only affect the completion time but also the cost and the overall performance of the acquisition project. A significant schedule overrun results in detrimental consequences and may lead to project failure. It could hamper the funding profile, generate additional costs, and result in further slippage in schedule. Understanding the key factors of this risk and quantifying its probability and impact could ease these problems and mitigate these costs.

This paper explores challenging issues of handling uncertainty in defence acquisition project scheduling. A state-of-the-art of the best-known techniques and tools for schedule risk analysis is provided. A schedule risk analysis model, combining Monte Carlo simulation and optimization techniques to determine the expected completion time of an acquisition project, is proposed. The model uses an S-curve to portray the schedule risk and to estimate the project schedule buffer for different confidence levels. A case study using a military aircraft replacement project for the Canadian Armed Forces is presented to illustrate the approach. The proposed model would provide decision makers with useful indicators about the expected schedule buffer and potential critical activities. It would also enable them to better handle common causal risks and minimize the consequences of adverse events.

This paper is organized into five sections. Following the introduction, Section 2 provides a comprehensive review of literature on analytical methods for project schedule risk analysis. Section 3 presents the formulation and the underlying assumptions of the proposed schedule risk analysis model. An illustrative example of schedule risk analysis using a defence acquisition project is provided in Section 4. A summary of contributions as well as future research directions are indicated in Section 5.

1.2 Schedule Risk Analysis Methods

This section discusses schedule risk analysis methods for defence acquisition projects. In general, there are two main approaches for conducting schedule risk analysis, depending on data availability for the project: Phase driven approach and event driven approach.

1.2.1 Phase driven approach

The phase driven approach provides a high level assessment of schedule risk using phase level data of historical projects. Using this approach, the project schedule is divided into a number of phases with different distributions of completion times. A confidence interval around the project schedule probability estimate can be built by combining the probability distributions of the phase completion times. Phase completion times can be derived from historical dates marking the beginning and end of project phases. The beginning and end of a phase are associated with the occurrence of some type of events such as a major project milestone. Before a phase completion time distribution can be generated, an appropriate dataset must be selected for use in generating the distribution. This requires the condition that the underlying factors, which contributed to the phase completion times of the historical projects, are similar to those that would be experienced by the project phase under consideration.

The phase driven approach applies econometric techniques to historical data to identify the major schedule drivers of historical projects (Fabrycky and Blanchard, 1990). The schedule drivers are then used in the schedule estimating relationships of the analyzed project. Historical projects that are considered similar enough to be used for comparison are termed analogous. Identification of analogous projects focuses on similarities between the different phases of historical projects and the phases of the project under consideration. Similarities are evaluated in terms of project characteristics that affected the project phase schedules. Examples of project characteristics would include type of equipment, acquisition strategy, system capabilities, and critical technologies. Statistical analysis may be used in order to assist in identifying the project characteristics which are most strongly associated with differences or trends in schedule duration. Additionally, subject matter expertise may also be utilized to identify historical project phases that would be appropriate to use for modeling a given phase of a project. Once a set of phase duration times has been determined, the project schedule distribution can be generated.

A growing body of literature recognizes that a parametric method (e.g., phase driven method) is an effective schedule risk analysis approach. Younossi et al. (2002), for example, explored the parameters that affect the development phase duration of military jet engine. These authors employed least-squares regression methods to develop a series of parametric relationships for forecasting the engine development time.

1.2.2 Event driven approach

In contrast with the phase driven approach, the event driven approach provides a detailed assessment of the project schedule risk using stochastic simulation methods. The most common method used in stochastic simulation is Monte Carlo simulation. The approach uses the Critical Path Method (CPM) schedule to determine the project duration. A CPM schedule is a collection of all the activities needed in order to complete a project, where each activity has a predecessor to its start date and a successor from its finish date (Hulett, 2012). The activity duration is determined either based on historical standards or from the advice of subject matter expertise if there is little or no historical data. The largest sum of these durations that form a single continuous path from start to finish defines the minimum time required for the project to be complete and is known as the critical path. It is imperative that the CPM schedule is constantly scrutinized and reviewed to ensure the data used in the analyses is relevant and accurate. Two event driven methods can be used for schedule risk analysis: Activity driver method and risk driver method.

a. Activity driver method

The activity driver method is the traditional bottom up analysis of estimating scheduling risk. It places uncertainty on each activity in the schedule, changing the static values to a range of values. This range of possible values or probability distribution, can take on many forms, most typically uniform or triangular distributions. Many tools can be used to establish a probability distribution for the schedule as a whole. There is a growing body of techniques that the activity driver method can use to handle risk and uncertainty. These techniques can be divided into four main categories: (1) Project Evaluation and Review Technique (PERT), (2) Critical chain methods, (3) Bayesian networks, and (4) Simulation models (Purnusa and Bodea, 2013).

Instead of using a single deterministic duration as in CPM, PERT incorporates uncertainty by using three-point estimates (optimistic, most likely, and pessimistic) for each activity. Many researchers have contributed to the extension of PERT. Pritsker (1966) developed the Graphical Evaluation and Review Technique (GERT) for NASA's Apollo program (Cates, 2004). In this technique, activity durations are represented by continuous or discrete variables. Each branch of the project network may be assigned a probability of not being performed during the project (Morris, 1997; Galway, 2004; Cates, 2004). GERT was later enhanced with the ability to integrate cost and resource constraints. Development in GERT also includes Q-GERT that can consider queuing within the analyzed system (Arisawa and Elmaghraby, 1972; Hebert 1975; Pritsker, 1979). Moeller (1972) introduced the Venture Evaluation and Review Technique (VERT). This time and cost oriented technique provides a more integrated risk analysis. VERT is logically guided by the principle that that there is a connection between time, cost, and performance.

Critical Chain Project Management (CCPM) was proposed by Goldratt (1997) as a new project management method. Goldratt (1997) noticed that safety time is spread over the activities rather than being where it is needed the most. This situation would make the planning dynamic ineffective in keeping projects on time and within budget. CCPM strategically removes safety time from individual activities and places it in project buffer (at the end of the project) and feeding buffers (at nodes where non-critical activities feed into the critical chain). It is mainly a mix of the theory of constraints, and Total Quality Management (Leach, 2000). In contrast to CPM and PERT, CCPM does not put emphasis on activity order and scheduling. It focuses on the resources required to execute project activities (Galdratt, 1997; Cates, 2004). The critical path may change and become the critical chain, if the resources required are considered. This method has been used by many top organisations such as NASA in the United States (Hagemann, 2001; Cates, 2004).

A typical weakness of Goldratt's method is its inability to determine the appropriate size for the project buffers. This approach was interpreted as setting the buffers at 50 percent of the unpadded critical chain duration. Many ways of sizing the buffers were suggested in the literature to address this issue. Assuming a standard normal distribution, Newbold (1998), for example, suggested sizing the buffer at two standard deviations of protection (or 90th percentile). This point corresponds to the difference between the worst case and the average duration for each activity. Shou and Yeo (2000) suggested a two-step process to estimate a buffer size. In their process, activities are first divided into four categories according to their level of uncertainty. In the second step, risk attitude of the decision maker is divided into three levels (low, median, and high). The buffers sizes are organized in a double entry table composed of two axes: a vertical axis listing the activity categories; and a horizontal axis comprised of a range of risk attitude levels.

A Bayesian Network (BN) is a directed graph of nodes and arcs with an associated set of probability tables. In this network, each node represents an uncertain variable with a set of states. Each arc represents a causal relationship between variables (Heckerman et al, 1995). Each state has its own probability of occurrence. Two categories of variables are used: (1) marginal probabilities for prior nodes and (2) conditional probabilities for nodes with parents. A marginal probability or prior distribution represents the state of knowledge or prior belief about a given variable. A conditional probability represents the probability of a state given the states of its parent. BN is used in project scheduling by adapting and incorporating the CPM parameters. In contrast to the other techniques, this approach integrates the source of uncertainty and the causal relations between project parameters to inform project scheduling. It can also analyze the trade-off between time and the level of required resources in project activities.

Simulation models use computer representations to investigate the behavior of a dynamic system and forecast the effect of potential changes to it. As a project management method, simulation can virtually mimic a real-world project. The project assessment by simulation technique allows one to repeatedly generate different scenarios (Schyler, 2001) and use different "what-if" analyses. It can provide numerous critical paths and use diverse probability distributions of the project duration (Purnusa and Bodea, 2013).

b. Risk driver method

The risk driver method is a top-down approach for analyzing risk using stochastic simulations. It is an examination of the most prioritized risks from the risk register (list of risks that have historically had a large impact on projects similar to the current one). This method utilizes known risks to the entire schedule to drive the simulations, rather than placing uncertainty on each activity. The risks drawn from the risk register have two main characteristics: the probability that the risk will occur and the impact in case it does occur. The probability of a risk is often given as a percentage, and the impact as a range of multiplicative factor. The risk driver then applies these risks to the CPM schedule and runs it through a Monte Carlo simulation. This generates a probability distribution and an associated S-curve, which is used to determine the total schedule time.

1.3 The Model

Two major questions are generally asked about any project (Chinneck, 2009): The first is about the shortest time in which the project can be completed. The second is about the activities that must be finished on time to complete the project in the shortest possible duration. These activities form the critical path (Chinneck, 2009). This section suggests a stochastic approach to objectively identify the most likely critical path and the corresponding completion time. It combines Monte Carlo simulation and optimization techniques to solve a scheduling problem. This approach can be summarized by the following six-step algorithm:

Step 1 - List all activities required to complete the project. In this step, the causal dependencies between the activities are summarized within a work breakdown structure and potential critical paths are identified. A schedule may have a series of concurrent critical paths with varying probabilities of occurrence. A list of near-critical paths may be used to reduce the computation effort.

Step 2 - Apply a probability distribution for the duration of each activity. A three-point estimate (minimum, most likely, and maximum) approach may be used to assess the likely fluctuation of activity durations. Two typical distributions are particularly suitable at this stage: Triangular and PERT distributions.

Step 3 - Run Monte Carlo simulation. Use Monte Carlo simulation to generate multiple schedules. For each iteration of the simulation, the potential critical paths are ranked according to their total durations. At the end of the simulation, the distribution of each output variable is derived by consolidating the number of possible combinations from all iterations.

Step 4 - Estimate the critical path ranking probabilities: Let p_{ij} be the probability that path i ranks at position j. This probability is generated by dividing the number of times path i is ranked at a position j by the total number of simulation runs. A ranking probability matrix can be used to organize the potential critical path rankings from Monte Carlo simulation.

Step 5 - Derive the risk-adjusted critical path. To derive the risk-adjusted critical path and its probability, let k be the number of potential critical paths and define the variable x_{ij} (

The most probable rankings of potential paths and the corresponding ranking probabilities can therefore be determined by maximizing the following objective function ever, to avoid issues with sensitive information, we used illustrative data for the schedule risk analysis in this paper.

1.4.1 Input Data

The dataset for this example contains a set of 26 tasks of the project schedule. Typical tasks include, for example, the preparation of the procurement documents, requirement foundation documents, release of the request for proposal, in-service support contract documents, etc. Tasks are divided into two categories: (1) Standard tasks that require resources and execution time (T1 – T22), and (2) Delays or waiting times associated with some tasks (D1 – D4). Delay tasks involve, for example, waiting time for a senior leadership approval. For each task, Table 1.1 provides the predecessor and successor tasks as well as the minimum, most likely, and maximum durations (illustrative).

We applied the schedule risk analysis method to the aircraft replacement project dataset and identified three potential critical paths (CP1, CP2, and CP3) in the schedule. A critical path should be ruled out if it is clearly dominated by another one in a pair-wise comparison. A critical path is said to be dominated if its maximal completion time is smaller than the minimal duration of another one (Alvarez-Benitez et al., 2005).Table 1.2 presents the critical path ranking probability matrix (in which probabilities are expressed as percentages) obtained using the schedule risk analysis method for 10,000 simulation runs. The probability matrix can be interpreted as follows: Critical path CP1 (for example) ranked first for 60.12% of the simulation runs, second for 32.49%, and third for 7.52%. The same rationale applies for the remaining paths.

Table 1.1 Task, Durations, and Dependencies

Task	Description	Duration (months)			Successors
		Minimum	Most Likely	Maximum	
T1	Start	0	0.5	1	T2
T2		1	1.5	2	T3,T5
T3		2.5	3	3.5	T4
T4		0.5	1	1.5	T6

T5		18	20	22	T10
T6		6	7	8	T7
T7		6	7	8	D1,D2,T10
T8		0.5	1	1.5	T10
T9		1	2	3	T10
T10		0	0.5	1	T11
T11		0.5	1	2	T12,T13
T12		1	3	5	T14
T13		33	35	37	T22
T14		2	4	6	T15,T20
T15		3	4	5	D3,T18
T16		1	3	5	D4,T18
T17		2	3.5	5	T18
T18		1	2	3	T19
T19		1	2	3	T22
T20		4	6	10	T21
T21		0.5	2	3.5	T22
T22	Finish	1	2	2.5	T23
D1	Delay 1	0.5	1	1.5	T8
D2	Delay 2	0.5	0.5	0.5	T9
D3	Delay 3	1	1	1	T16
D4	Delay 4	1	1	1	T17

The examination of the ranking probability matrix indicates that the expected order of the potential critical paths and their respective ranking probabilities (highlighted in Table 1.2) are: CP1 (60.12%), CP2 (47.23%), and CP3 (47.80%). Given that CP1 has a high ranking probability (i.e., greater than 60%), its position would unlikely be sensitive to minor changes in the task durations. However, as CP2 and CP3 have comparable ranking probabilities (i.e., 47.23% and 47.80%), their positions will likely be more sensitive to changes in the task durations. As such, the project manager should primarily focus on path CP1 for schedule risk mitigation but need to pay close attention to critical tasks in paths CP2 and CP3.

Table 1.2 Critical Path Ranking Probability Matrix

Path	**Tasks**	**Rank Position**

		1	2	3
CP1	T1, T2, T3, T4, T6, T7, D2, T9, T10, T11, T13, T22	60.12%	32.49%	7.52%
CP2	T1, T2, T3, T4, T6, T7, D1, T8, T10, T11, T13, T22	8.86%	47.23%	44.68%
CP3	T1, T2, T5, T10, T11, T13, T22	31.02%	20.28%	47.80%

1.4.2 Schedule risk profile

The project schedule risk analysis was conducted using stochastic simulation. Activity durations are represented by a PERT distribution function. The total project duration is calculated using the Critical Path Method. Figure 1.1 presents the project schedule risk profile. This graph depicts the CDF of the most likely critical path duration. It shows the probability for the project to be completed in less than a given time. For example, the median of the project duration distribution is approximately 61 months. This means that the probability that the project will be completed in less than 61 months would be 50%. The minimum and maximum durations for this project would be 56.86 months and 64.60 months, respectively. The 95% confidence interval for this duration would be [58.70, 63.19].

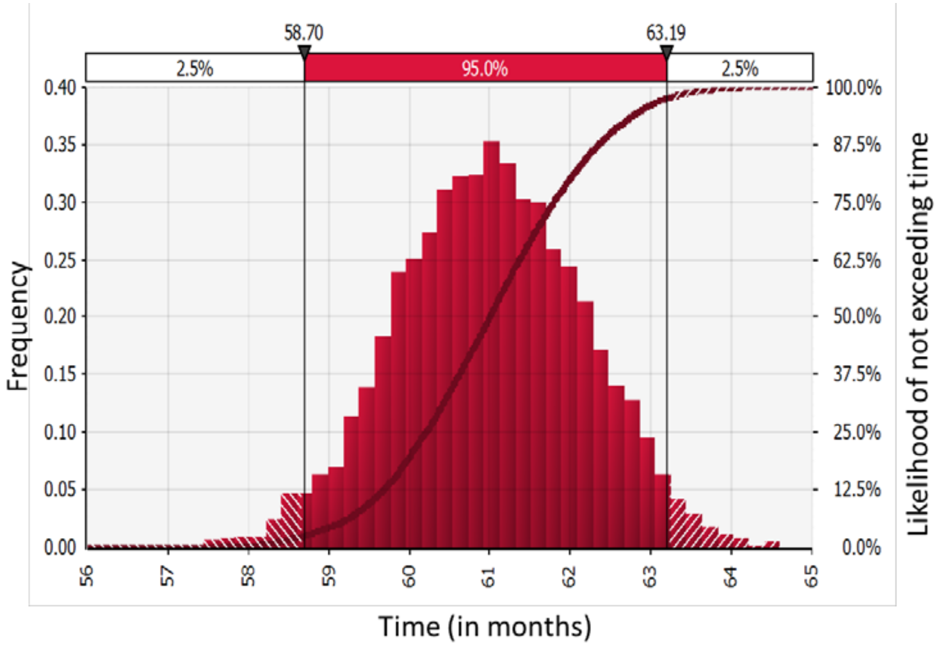

Figure 1.1 CDF of the total project duration

To evaluate the robustness of the schedule risk profile, a sensitivity analysis was carried out to assess the impact of some key activities on the results. As shown in Figure 1.2, the most critical variable in terms of schedule risk is T13. This activity has the highest impact on the project duration mean. A pairwise association between the project duration and this simulated predictor shows the relative significance of this activity. The correlation coefficient between these two variables is approximately 0.67. Any increase in the activity T13 would expectedly push the project schedule upward. The decision makers should define a strategy to mitigate variability in this activity.

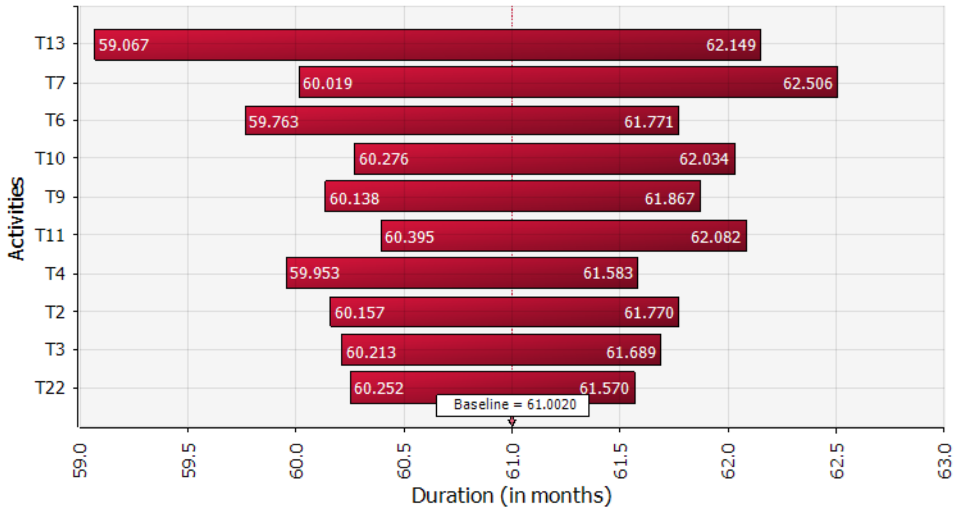

Figure 1.2 Effects of the the main activities on the project schedule

1.5 Conclusion

Handling uncertainty in defence acquisition projects has been an ongoing challenge for military forces. The ability to accurately define a schedule for these projects is challenged by their large scale and uncertainties in their interrelated activities.

This paper provided a comprehensive literature review of the best-known techniques and tools for schedule risk analysis. It also suggested a six-step schedule risk analysis approach to analyze the expected completion time of an acquisition project. This new approach combines simulation and optimization. It starts by listing all activities required to complete the project and ends by deriving a schedule risk profile using the CDF of the most likely critical path duration. An illustrative example using a military aircraft replacement project for the Canadian Armed Forces is also presented and discussed.

Further efforts are being undertaken to handle risk and uncertainty in military projects. These efforts include, for example, the ability to integrate time and cost within the same stochastic framework.

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