Study on complexity and uncertainty perception and solution strategies for the time/cost trade-off problem

Abstract

In this paper, the Discrete Time/Cost Tradeoff Problem (DTCTP) is revisited in light of a student experiment. Two solution strategies are distilled from data of 444 participants and are structured by means of five building blocks, namely focus, activity criticality, ranking, intensity and action. The impact of complexity and uncertainty on the cost objective is quantified in a large computational experiment. Specific attention is allocated to the influence of the actual and perceived complexity and uncertainty and the cost repercussions when reality and perception do not coincide.

Keywords: Project Scheduling Game, Simulation, Complexity, Uncertainty

1. Introduction

Time/cost trade-offs in project scheduling find their roots in the Critical Path Method (CPM), developed at the duPont company and at Remington Rand Univac (Kelley and Walker (1959), Walker and Sawyer (1959) and Kelley (1961)). CPM is a project scheduling technique to analyze and represent the tasks involved in completing a given project. Although this method does not explicitly take resource requirements into account, it assumes that the cost of an activity is a function of its duration. As the duration of an activity is decreased, its associated costs will rise, since more resources need to be allocated to that activity. Initial research efforts on the time/cost trade-off problem focused on the continuous case and can be found in standard texts such as Elmaghraby (1977) and Moder et al. (1983). Several techniques were used to solve this type of problem (Robinson (1975), Hindelang and Muth (1979), Phillips and Dessouky (1977) and Meyer and Shaffer (1965)). An overview of the literature until the mid nineties is given by De et al. (1995). We will cover the contributions related to the time/cost trade-off problem from the mid nineties onwards. The Discrete Time/Cost Trade-off Problem (DTCTP), shown to be NP-hard by De et al. (1997), was solved exactly by Demeulemeester et al. (1996). In this paper, the authors present two approaches based on dynamic programming for reaching the optimal solution of the three objective functions of the DTCTP. Three possible variants of the time/cost trade-off problem can be identified. Scheduling project activities with the goal of minimizing the total project costs while meeting an

imposed deadline is known as the deadline problem (DTCTP-D). The budget problem specifies a limit on the budget (DTCTP-B). The objective is then to minimize the duration of the project. Finally, the third objective deals with generating a complete and efficient time/cost profile. Demeulemeester et al. (1998) improved the computational results for solving the DTCTP optimally. This is done using a branch-and-bound procedure that calculates lower bounds by convex piecewise linear underestimations of the time/cost trade-off curves of the activities. This contribution is of special relevance to this paper since it will be used to provide an optimal solution for the data instances of the computational experiment.

The last decade, two new research avenues on the time/cost trade-off problem were examined. The first new direction is the extension of the (D)TCTP, while the second direction focuses on the inclusion of stochastic characteristics to the (D)TCTP. A brief overview of the key publications belonging to each avenue, along with their contribution, is provided in Table 1.

INSERT TABLE I HERE

The contribution of this paper to the existing body of literature is threefold. First of all, two solution strategies of students participating in a project management business game, the Project Scheduling Game (PSG), are distilled. These solution strategies are a combination of five building blocks, namely focus, activity criticality, ranking, intensity and action. Secondly, we take two contextual factors, namely complexity and uncertainty, into account. While the first contribution makes use of real-life data, experiments are constrained by the fact that classroom sessions need to be held in order to gather additional data. The final contribution overcomes this problem by testing the derived solution strategies on computer-generated project networks. In the remainder of this section, we will elaborate on these contributions from a literature point of view.

Business games Business games have a long history within an educational context. Early research focused on the internal validity through assessing advantages and disadvantages of simulations versus other pedagogies (Schumann et al. (1997)). Later on, the validity of top management games was confirmed by Wolfe (1997). The most-cited advantages of the use of business games are their high degree of realism, a broader learning environment, competition between players, as well as soft skills such as communication skills, group behaviour and organization skills (Saunders (1997) and Faria (2001)). On top of this, business games craft personal experiences by challenging participants on an intellectual and behavioural level and hence fall within the nominator experiential learning (Kolb (1984)). Parente et al. (2012) argue in favour of business games by stating that real-life experience imposes limitations since there is no opportunity to experience the full range of

possibilities and skill development. Business games have been applied to simulate business and operations management in the electronics industry (Haapasalo and Hyvönen (2001)), to teach business ethics (Schumann et al. (1997)), to develop entrepreneurial skills (Stumpf et al. (1991)) and to enhance systems thinking and business process redesign (Van Ackere et al. (1993)).

Complexity and uncertainty The papers of Table 1 all focus on what Pollack (2007) describes as the hard paradigm, which is commonly associated with quantitative techniques and deductive reasoning. However, the author identifies research streams that suggest an increasing acceptance of the soft paradigm, which focuses on qualitative techniques that emphasize contextual factors and relevance. Examples of soft paradigm publications can be found in Turner and Müller (2005), Ojiako et al. (2014), Green (2004) and Yang et al. (2011) and the reader is referred to the relationship school and behavioural school of Söderlund (2011) for a literature review on soft paradigm aspects. More and more, researchers are calling for a broader view of project management (Hanisch and Wald (2011)), an increased alignment of research and practice (Hall (2012)) or the inclusion of contextual factors (Crawford et al. (2006)). With regard to the latter point, Maylor et al. (2008) argue that one-size-fits-all approaches are inconsistent with the contextual diversity managers are confronted with. In this paper, we take two contextual factors, namely complexity and uncertainty, into account by means of data from students participating in a business game.

The choice for complexity and uncertainty is inspired by two reasons. Firstly, Howell et al. (2010) noted that uncertainty was easily the most dominant theme, with complexity ranking second. This confirmed the findings of Shenhar (2001) who discovered an emergence of uncertainty and complexity based on a review of the classical as well as the more recent literature. It is worth noting that the works dealing with stochastic characteristics in Table 1 revolve around uncertainty. Additionally, the works of Thomas and Mengel (2008) and Hanisch and Wald (2011) explicitly recognize complexity and uncertainty as crucial (contextual) factors. Secondly, integrating contextual factors can be regarded as a response to areas for future research. Hanisch and Wald (2011) argued that the influence of complexity on the project outcome needs to be studied, while Maylor et al. (2008) wondered whether a quantification of complexity was feasible. While research on uncertainty has witnessed a spike in interest from academics, it is still among the top challenges for future research (Hall (2012)).

Simulation Complexity can be defined from a hard paradigm perspective (see the complexity measures of Pascoe (1966), Mastor (1970), Bein et al. (1992) and De Reyck and Herroelen (1996)) or include soft paradigm aspects (such as organizational complexity (Wolfe (1996)) or socio-political complexity (Geraldi et al. (2011)).

In this work, we focus on structural complexity and more specifically on system size (Sommer and Loch (2004)). Apart from a large body of work that supports this stance (Dvir et al. (2006), Geraldi and Adlbrecht (2007), Müller and Turner (2007)), the main rationale for focusing on system size can be found in the final contribution this paper makes. Once the student files are analyzed and turned into solution strategies, these strategies are applied to computer-generated project networks, for which multiple settings are changed. In order to do this, a more technical definition of complexity (and uncertainty) is required. Specific attention will be allocated to the discrepancy between the actual complexity and uncertainty and how these contextual factors are perceived. Individuals perceive reality in their own way (Jaafari (2003)), implying that complexity and uncertainty are also in the eye of the beholder (Nutt (1998), Vidal and Marle (2008), Osman (2010), Ojiako et al. (2014)). Simulations aid decision makers in anticipating and quantifying the effects of actions and events (Fang and Marle (2012)) and allow us to generate a wide spectrum of outcomes.

The outline of the paper is as follows. In section 2, a general overview of the Project Scheduling Game is given. Section 3 focuses on the data collection phase. The building blocks of the solution strategies, the link to the student data of section 2 and how the solutions are evaluated are discussed in section 4. An illustrative example is provided to demonstrate the 5 components that make up a solution strategy. Section 5 introduces the general framework that forms the foundation for the solution strategies and introduces the time-based and cost-based solution strategy. Section 6 includes details about the test design. Parameter settings are divided depending on whether they are project-specific or whether they relate to the complexity and uncertainty dimension. The results of the solution strategies are discussed in section 6.2, where a distinction is made between the general performance, the performance in case of judgement errors and an investigation of a varying degree of level of effort. Finally, a discussion of the results and general conclusions can be found in section 7.

2. Game description

Crowston and Thompson (1967) were among the first authors to stress the importance of the interaction between the planning, scheduling and control phase of a project. The focus of the Project Scheduling Game, presented by Vanhoucke et al. (2005), lies in the scheduling and control phases of the project life cycle. More precisely, it is the aim of the player to follow an iterative approach, known as reactive scheduling, that compares the project baseline schedule with the current project performance (simulated during the execution phase) in order to control the project and take corrective actions in case the project objective is in danger. The game consists of several phases which require periodic input from the game player. An overview of the game process is given in figure 1.

First of all, the project network, along with a baseline schedule and other input data for the game such as the trade-off details are proposed by the course teacher. The baseline schedule ends at time T . In order to acquaint students with uncertainty, unexpected events occur. A new deadline, δ_n <T, is imposed by the client along with a penalty cost for every day the deadline is exceeded. Therefore, the PSG imposes a soft deadline that need not be met. However, late project delivery is discouraged by means of a penalty that is incurred for every day the project finishes after δ_n. These changes require an update of the baseline schedule which is the task of the player of the game. The update process of the baseline schedule boils down to a new trade-off selection for a number of activities. New trade-offs lead to a shortened or prolonged duration of an activity and lie at the heart of the CPM. Second, the project is divided into multiple decision moments. The game then simulates periodic project progress in which uncertain events might occur. Changes to the original activity durations lead to deviations from the initial baseline schedule and endanger the project objective. For every decision moment, the player has to evaluate periodic review reports and rebaseline the unfinished activities of the project schedule in order to bring the project back on track. This process of rescheduling, taking a decision and assessing the new information is repeated until the final decision moment is reached. Third, after a predefined number of decision moments, the game reports the final project status in terms of the total project duration and cost. At this point, feedback is given by the course teacher regarding the main learning objectives of the PSG.

3. Data collection

The PSG is taught to management and engineering students at 2 universities (Ghent University (UGent, Belgium) and University College of London (UCL, United Kingdom)) and 2 business schools (Vlerick Business School (VBS, Belgium) and the EDHEC business school (France). 444 data points were collected, among which 176 business engineering students (UGent), 203 civil engineering students (UGent), 36 civil engineering students (UCL), 5 management science students (UCL) and 24 MBA students at the VBS and EDHEC school. Most of these students do not have previous working knowledge. It is worth remarking that the students business engineering and most of the civil engineering students hail from the same university (UGent).

A distinction can be made between data captured during game progress and final results. All the data captured during game progress is saved in a log file. For every student playing the PSG, a log file is available. These log files store commands students execute. The most important commands are the change of an activity's trade-off option and taking a decision, implying a move to the next decision moment. Taking a decision executes the new trade-off settings for the activities and simulates project progress for the next decision moment. Examination of

the commands leading to intermediate and final solutions permits an identification and classification of solution strategies taken by the students. For instance, by executing the commands stored in the log files chronologically, it is possible to know whether a student made a change to a critical or non-critical activity and what that change consisted of. The final time and cost solution for every student is only available at the end of the game. Table II summarizes the results of the different student groups. The average deviation compared to the global minimum cost point is less than 2% for all student groups. The best solution of the student groups displays only a very small deviation from the best solution possible (less than 1%). The best overall solution was found by a business engineering student, whereas on average, the management science students of UCL report the best average score. They also achieve the smallest standard deviation in cost and the lowest maximum cost deviation. It is worth remarking that the group of management science students at UCL only comprises 5 people. Welch's t-test was applied to find out whether the cost deviations between the groups differ significantly. The only statistically significant difference ($p < 0.05$) is found for the students Civil Engineering at UGent and the students Civil Engineering at UCL.

INSERT TABLE II HERE

4. Data structuring

Based on the aggregated data, the log files and time/cost deviations, it is necessary to transform the data into information by finding a certain structure according to which students play the PSG. This is accomplished by looking for recurring data patterns. A data pattern that corresponds with a certain class of behaviour, exhibited by many students will be called a solution strategy. Section 4.1 expands on the 5 building blocks that form one solution strategy. The following section explains the link between the solution strategy components and the student data of section 3. Section 4.3 presents details about the performance measures that will be used to evaluate the strategies. Section 4.4 provides an illustrative example and shows the different steps going from activity selection to applying a trade-off change.

4.1 Solution strategy components

From the data collection phase and through many discussions with the students at the educational institutions, we learned that very few students approach the PSG without any underlying logic. It is possible to discern 5 building blocks that are in line with when and how students select a new mode for the different activities. The 5 components that characterize a solution strategy are focus, activity criticality, ranking, intensity and action. It is worth noting that the first 4 elements are related to selecting a set of activities whereas the final element, action, determines how the trade-offs of the set of activities will be altered. This corresponds with the three general building blocks of heuristics (Gigerenzer and Gaissmaier (2011)). Search rules specify the direction of the

search space and are accounted for by focus, activity criticality, ranking and intensity. Stopping rules determine when the search process ends and is governed by the time limit of the PSG. Decision rules elaborate on how the final decision is reached. This is done by the fifth component, namely action.

At the start of a decision moment, every activity that has not started is subject to a possible change. Out of this group of activities, focus, activity criticality, ranking and intensity perform a stepwise selection of a subset of activities. The process of stepwise selection can be described as follows:

- Focus: specifies the length of the time window during which actions will be taken. All activities that start or are still in progress during this time window are selected. The focus is expressed as a percentage of the number of decision periods that are taken into account. The focus can vary from a local to a global orientation. A local orientation is characterized by a narrow time window because the number of decision periods taken into account is small. At the other end of the spectrum is a global orientation, which uses a wide time window. In this case, many activities will be subject to a possible trade-off change.

- Activity criticality: the subset of activities that start or are in progress during the time window specified by the focus can be further refined based on whether these activities are critical or non-critical at the current decision moment. If both critical and non-critical activities are taken into consideration, the subset of activities before this phase equals the subset at the end of the phase.

- Ranking: the elements of the subset of activities are ranked based on the value of a priority rule. Within the context of human decision-making, priority rules are easy to apply and in line with techniques that are used to give priority to certain activities. A tight match could be witnessed between the followed solution strategy and the selected priority rule. For instance, students who thought that the minimum cost solution would lie in the neighbourhood of the deadline would adopt a more time-based strategy and select a priority rule that takes into account activity durations. This selection step does not reduce the subset of activities but accords a ranking to the activities. These rankings serve as input for the intensity phase. The priority rules used by the solution strategies are the Greatest Rank Positional Weight (GRPW), Maximum Slack (MAXSLK) and Average Most Expensive Activity (the activity cost divided by its duration) rules.

- Intensity: given the fact that students have a limited amount of time to take decisions, it is crucial to focus on the most important activities. Intensity further selects activities by determining a cut-off point for the ranked subset that resulted from the previous phase. A percentage between 0% and 100% of the number of remaining activities of the ranked subset is used as a value for the intensity. This percentage is multiplied by the number of elements that are present in the ranked subset.

This subset then serves as input for the action phase, where the trade-offs of activities that are elements of the

subset may be changed.

- Action: an action is defined as a move on the trade-offs of an activity that may potentially change an activity's cost and associated duration. This need not be the case since a lot of students check whether the action leads to an immediate cost decrease or not. If there is no improvement, it is possible that the activity's cost and duration is reverted. Actions can go from simple to more advanced operations. An overview of the type of actions and an accompanying description is given in Table III.

INSERT TABLE III HERE

The rationale for the different refinement phases leads back to the nature of the PSG, where students only have a limited amount of time to make changes and advance to the next decision moment. Hence, it is necessary to focus on the activities that are most important. In order to clarify the building blocks of the solution strategies, the stepwise selection and action will be illustrated using a straightforward example.

4.2 Link to the student data

The previous section outlined the different building blocks of a solution strategy. The aim of this section is to connect the 5 components (focus, activity criticality, ranking, intensity and action) to the student data of section 3. The link between these two sections results from two aspects, namely data analysis and the feedback sessions with the participants of the Project Scheduling Game. Most of the time, these aspects go hand in hand. For instance, many of the conversations revealed that students first select a number of activities to which a trade-off change can be made. Further questioning led to the formalization of this selection and to the inception of focus and intensity.

Focus The values for the focus and intensity could be retrieved from the log files of the students. We witnessed that a wide focus range is used by the students, which explains why low and high numbers for the focus are used by the solution strategies.

Activity criticality Activity criticality is the second of the five building blocks that make up a solution strategy. It is logical that both critical and non-critical activities are changed.

Ranking Arguably, the student feedback proved most valuable in identifying the priority rules for the ranking phase that were used most often, especially since these are much harder to keep track of in the log files.

Intensity The process for translating intensity from the student data to the solution strategies was slightly different. Intensity, as defined in section 4.1, can reach any value in the interval [0,100]. A careful trade-off needs to be made between a sufficient data representation and having as few values for the intensity setting as possible. In theory, it would be possible to incorporate all possible values the intensity can achieve in the solution strategies. However, this entails that a huge number of branches need to be created to test which value

will be applied under which circumstances. Such a situation reflects the data in an extremely accurate fashion but is no longer feasible for the computational experiment. As a rule of thumb, the fewer different values that represent the data of the students' adopted intensity well, the better. Feedback from the students taught us that selection of a number of activities typically occurred through a rule-of-thumb, such as "1 out of 4 activities" will be retained. There are two principal reasons why a limited number of values for the intensity were embedded in the solution strategies. First of all, from a cognitive point of view, it is better if the different values are almost equally spaced in the interval that ranges from 0 to 100. Secondly, while there are only a limited number of different values, the data is represented in a sufficiently accurate way.

Action The final element, the actions, once again resulted from the feedback and the log files. For this dimension, it is easier to find in the data which actions were followed, with one notable exception. An enumeration of different trade-off options can easily be confused with sequential swaps. The data showed that participants of the game make frequent use of swapping trade-off options, which explains the frequent inclusion of this action in the solution strategies.

4.3 Evaluation

The solution strategy components of the previous section were derived using the data accessible from the log files. As mentioned in section 3, the second type of data, the results, are gathered at the end of the game. In order to rate the quality of the student solutions, represented by the derived solution strategies, it is necessary to define performance measures. The proposed measures capture 2 dimensions of a final solution, namely cost and level of effort. Every dimension can be measured using a specific metric, which is outlined below and depicted in figure II. The x-axis of figure II represents the deviation from the deadline in absolute numbers, whereas the y-axis displays the total costs. The curve shows the efficient time/cost profile. The time value of the minimum cost solution across the entire efficient time/cost profile is denoted by t^*. Finally, the dot stands for the solution of a student at the end of the game.

- Cost performance: the cost deviation is measured using the global cost deviation. This deviation compares the project cost of the solution strategy (the dot) to the solution that yields the minimum cost across all possible time points of the complete time/cost profile (the cost or y-value at time t^*). The global cost deviation is expressed as a percentage deviation:

$$\Delta cost_{global} = \frac{c^s - c_{t^*}^*}{c^s}$$

In this calculation, c^s stands for the cost of the solution strategy and $c_{t^*}^*$ denotes the cost of the efficient

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time/cost profile at time t^*. It is possible to break down the global cost deviation into 2 constituent parts, namely activity costs and penalty costs. If a project finishes later than the specified deadline, it incurs a penalty cost. Hence, by looking at the penalty cost, we implicitly derive some information as well.

• Level of effort: captures how much effort it takes to reach a solution, which results from one of the solution strategies. It is worth noting that the level of effort is a function of focus, activity criticality and intensity. As the focus increases, the amount of potential activities that are changed rises and consequently, the level of effort increases as well. This dimension aims to establish the link between solution quality and the amount of work that was performed to reach that solution. One unit of effort corresponds with one trade-off option that is considered for a change. For instance, in order to determine the minimum cost slope, a number of trade-off options are considered. Each of those trade-offs augments the level of effort by 1 unit.

INSERT FIGURE II HERE

4.4 Illustrative example

Figure III(a) represents the Activity on the Node (AoN) notation of an example network. We note that this example merely serves as an illustration: the networks of the computational study count more activities and different trade-off options. In this example, there are 7 activities in total. The possible durations of the trade-off options for every activity are indicated above each node. The associated costs of the trade-offs are listed under each node. The currently selected trade-off is bolded. For instance, for activity 2, the currently selected trade-off has a duration equal to 2 at a cost of €100. Figure III(b) depicts the earliest start Gantt-chart, taking into account the precedence relations between the activities. Critical activities (activities 1, 3, 4, 5 and 7) are highlighted in grey, whereas non-critical activities are indicated by the non-coloured bars (activities 2 and 6). There are also 3 different decision moments (DM). In this example, it is possible to make changes to a set of activities at time points 0, 5 and 10 respectively. The total duration of the project equals 16 days. We assume that a decision needs to be made at time point 0 and that a deadline of 13 days is present. If the project duration exceeds the deadline, a penalty cost of €100/day is incurred. Hence, we are at the beginning of the project. Let E denote the set of eligible activities. Eligible activities are defined as activities for which the currently selected trade-off will be changed. Hence, at the start of the project, the set E consists of every activity present in the network:

$$E = \{1, 2, 3, 4, 5, 6, 7\}$$

INSERT FIGURES III(a) AND III(b) HERE

The example settings for the 5 components (focus, activity criticality, ranking, intensity and action) are listed in Table IV. The focus is assumed to be equal to 2 decision moments (0.67 * 3, the total number of decision moments). From that set of activities, only the critical activities will be retained. These will then be sorted according to the Most Expensive Activity priority rule. From the ranked subset, only the first 67% will be withheld. Finally, those remaining activities will be crashed by applying a swap operator.

INSERT TABLE IV HERE

• Focus: in this example, a focus of 2 decision moments is used. Given the fact that the current decision moment is equal to 1, the time window for the activities that will be retained is equal to:

$$\text{Time window} = [1, 1 + 2[$$

Hence, activities that start later than decision moment 3 (after time point 10) will no longer be considered.

$$E = \{1, 2, 3, 4\}$$

• Activity criticality: only critical activities will be taken into consideration. This implies that activity 2 will be removed from E.

$$E = \{1, 3, 4\}$$

• Ranking: cost is the most important objective for this example network. Hence, the priority rule Most Expensive Activity will be used. Activity 1 has a cost of €50, activity 3 a cost of €60 and activity 4 costs €40. Consequently, the activities in E are reordered as follows:

$$E = \{3, 1, 4\}$$

• Intensity: further refinements can be made based on the intensity. In this example, an intensity value of 0.67 will be used. This means that only 2 (0.67 * 3 activities) activities will be left. Because of the ranking in the previous phase, the first two activities will be selected.

$$E = \{3, 1\}$$

The 5 building blocks have gone from a set where all activities could be changed to a situation where only 2 activities are left. In the final phase, an action will be applied to those activities to change their selected trade-off:

• Action: activities 3 and 1 will be crashed by selecting the neighbouring trade-off option. This implies that the duration of activity 3 will become 3 time units, with a cost of €120. Activity 1 will now take 4 days to complete at a cost of €80. This leads to the Gantt-chart in figure IV, which will be the initial situation for the next decision moment (decision moment 2). The Gantt-chart indicates that the critical path has changed and now consists of activities 1, 4, 6 and 7. The total duration of the project has decreased from 16 to 14 days. The project's total cost has decreased from €690 (€390 + 3 days * €100)

to €580 (€480 + 1 day * €100).

INSERT FIGURE IV HERE

In order to demonstrate the trade-off between solution quality and Level Of Effort, 4 solution strategies are applied to the toy example described in the paragraphs above. The first strategy consists of doing nothing, yielding a total cost of €690. Strategy 1 employs a focus and intensity of 0.33, strategy 2 assumes a focus and intensity of 0.66 and strategy 3 adopts a maximal focus and intensity (=1). The upper part of Table V shows which activities were changed or considered for a change. The lower part displays the project's final outcome and compares it to a scenario where no action is taken. While there is an improvement in cost between doing nothing and strategies 1 and strategies 1 and strategies 2, there is no advantage in increasing the focus and intensity beyond 0.66. Hence, it is shown how an increasing focus and intensity improves the cost objective until a point is reached where further increases lead to a dramatic increase in Level Of Effort, to the same cost solution or both.

INSERT TABLE V HERE

5. Strategic Framework

The strategic framework contains information about the conditions in which the derived solution strategies operate. Two defining criteria are determined, namely complexity and uncertainty. The general framework of the solution strategies, as well as complexity and uncertainty appraisal, are the subject of section 5.1, in which the interplay of these dimensions with the solution strategies will be clarified. Section 5.2 lists the 2 proposed solution strategies. One of these strategies will concentrate on time while the other strategy adopts a cost-based point of view.

5.1 General framework

Section 4 described the 5 building blocks of a solution strategy: focus, activity criticality, ranking, intensity and applying an action. These elements will be used to construct the strategies that were derived based on the data collected in the log files and based on the discussions with the students after finishing the game. However, the proposed strategies take 2 important criteria into account, namely complexity and uncertainty. A crucial element throughout this paper is the difference between the *real* and the *perceived* complexity or uncertainty. People make decisions based on the perceived complexity or uncertainty without knowing their real value. Hence, it is possible that judgement errors, in which the threshold value differs from the real value, occur. If the uncertainty or complexity estimate exceeds a threshold value, the outcome for that dimension will be judged high. Otherwise, that dimension will be judged low. Details on these thresholds will be provided in section 6.1. The

outcome of the judgement of the complexity and uncertainty will steer the logic of the solution strategies into a different direction. This implies that different settings for the stepwise activity selection (focus, activity criticality, ranking and intensity) and action phases may be applied. Complexity is measured by the average number of trade-offs of the different activities and is calculated as follows:

$$C = \frac{\sum_{i=1}^{n} nrto_i}{n}$$

with n denoting the total number of activities and $nrto_i$ the number of trade-off options for activity i. Students often use the proportion of activities that were subject to a delay in previous decision periods as an indicator for future uncertainty. The outcome of the complexity and uncertainty criteria is a binary value: either a project is highly complex (or very uncertain) or not. The values for complexity and uncertainty are taken into account by all the solution strategies. The actual complexity and uncertainty is imposed by the decision maker. Individuals differ on how they judge complexity and uncertainty (Mintzberg et al. (1976), Bourgeois (1985)), which will be imitated in the computational experiment by incorporating different threshold values, leading to a different judgement of complexity and uncertainty.

The general framework of the solution strategies is given in figure V. At the start of the project, the complexity is analyzed. If the complexity is low and the project is about to start (the decision moment equals 0), a group of settings and actions labeled **A** is triggered. If some activities are finished already, a new estimate of the uncertainty is made. If uncertainty has shifted from low to high or high to low, the focus and intensity are adapted (**B**). If uncertainty is smaller than the threshold value (U<), it is checked whether the activity is critical. If this is the case, **C** will be triggered. In the alternative case, the settings and actions encompassed in **D** are executed. Finally, if uncertainty is high, a similar check with regard to the (non-)critical nature of an activity is performed. If the activity is critical and has only 1 predecessor, the procedure moves to the branch labeled **E**. If the activity is non-critical, the actions and settings comprised in **F** will be activated. A similar but slightly more intricate pattern is executed in case the project's complexity exceeds the threshold value. When the project has just started, a couple of additional branches (**G-I**) are present. Furthermore, if a critical activity has more than 1 predecessor, a set of settings and actions will be applied as well. After applying a set of actions from one of the possible groups, a check is performed in order to determine whether the project has ended. If this is not the case, the project moves to the next decision moment. Otherwise, the output measures are calculated and the solution strategy has come to an end. This framework and its different branches will be used in the next section to structure the proposed solution strategies.

INSERT FIGURE V HERE

5.2 Proposed strategies

Armed with the student data and the structure explained in section 5.1, it was possible to derive 2 solution strategies. The first strategy, treated in section 5.2.1, focuses on time and more specifically on reaching the imposed deadline δ_n. The second strategy employs cost-saving measures at the expense of increased risk and is discussed in section 5.2.2. The level of effort was controlled using the focus and intensity parameters, which differ based on the level of complexity and uncertainty. This was necessary to ensure that the level of effort was equal across all settings for the computer experiment.

5.2.1 Time strategy

The goal of the time strategy is to approach the deadline as closely as possible. This solution strategy, abbreviated SS_1, uses three specific mechanisms that employ a time-based focus. First of all, the Greatest Rank Positional Weight (GRPW) rule is invoked in several branches. This rule takes the duration of the activity under study and the durations of its immediate successors into account, thus capturing a small portion of the network structure. Secondly, a buffer mechanism is employed. The buffer is based on the Slack Duration Ratio (SDR) by Hazir et al. (2010) and implies that a minimum value for the ratio of an activity's slack to its duration should be maintained. Consequently, non-critical activities are protected against delays that could turn them into critical activities and delay the entire project. The buffer mechanism is invoked when the uncertainty is judged to be high. Finally, the protect deadline action is used to ensure that the project duration does not deviate too much from the imposed deadline. Protection of the deadline is done when the project is in progress (DM≠0). It ensures that the deadline does not exceed student-specified bounds. If the project is slightly uncertain, the project duration should lie between 98% and 101% of the deadline. For highly uncertain projects, the lower bound on the deadline becomes 96%. Because of the increased uncertainty, the delays will push the duration closer to the deadline, which explains why a smaller lower bound is chosen. The downward protection of 98% and 96% is not applied when the complexity is judged high. In this case, more effort is put into the examination of different trade-off options. However, the protection of 101% of the deadline is still in place in order to minimize penalty costs.

5.2.2 Cost strategy

The cost strategy, SS_2, aims to minimize the sum of activity costs and the penalty cost. Contrary to the time strategy, taking risk will be an integral part of this solution strategy. This is done using 3 different mechanisms. First and foremost, the average most expensive activity rule is used a lot more compared to the time strategy, implying that the importance of costs versus the duration of an activity becomes more important. Secondly, the elitism criterion is used frequently. Only accepting better solutions can be done for simple and complex actions,

for instance by selecting the best outcome of a minimum cost or maximum revenue slope. Third, consumption of slack plays a central role. Including this action has a double effect. On the one hand, costs will decrease because longer activity durations (at a lower cost) will be selected. On the other hand, because there is less slack in the project's schedule, the amount of risk increases. The logical result is that activity delays will have a larger impact on the schedule, thus increasing the penalty costs. Again, a distinction is made between judging projects to possess a low or high degree of complexity.

INSERT TABLE VI HERE

A summary of the principal differences between both solution strategies is given in Table VI. The reader is referred to Table VII for an exhaustive overview of the two proposed solution strategies. While this Table is mainly relevant for researchers who want to imitate our computational experiment with identical parameter settings, it can easily be skipped by the reader without losing the general overview of the theme of this paper. Table VII lists the settings of the solution strategy components for every branch. The letters of the respective branches correspond with those depicted in figure V. For focus and intensity, an additional distinction is made based on the actual complexity, which can be low (denoted C_L) or high (denoted C_H). For the ranking component, Avg MEA is the abbreviation for the average Most Expensive Activity priority rule, whereas Max SLK denotes the maximum slack priority rule. Finally, in the action column, MC represents the Minimum Cost while MR stands for the Maximum Revenue. The subscript elit refers to elitism, meaning that if an action leads to a cost deterioration, the action will be undone and the project reverts to the trade-offs before the action was applied. For a step-by-step procedure of the data generation phase and the settings of the solution strategies, the reader is referred to the Appendix.

INSERT TABLE VII HERE

6. Computational Experiment

The computer experiment aims to reproduce the behaviour exhibited by the students on a diverse set of generated projects. The goal of this section is not to compete with existing exact and (meta-)heuristic approaches but rather to discern the circumstances in which each solution strategy reaches the best results. In fact, large cost deviations illustrate the limitations of human decision makers and identify the need for more involved population-based optimization techniques. These more advanced techniques were discussed in the literature overview of section 1. The outline of this section is as follows. Section 6.1 provides details about the data generation process where a distinction is made between project-based parameter settings and settings related to the complexity and uncertainty. A baseline scenario is defined and will serve as the main vehicle to illustrate predominant relations for the different complexity and uncertainty combinations. Using this baseline

scenario, the impact of judgement errors on the cost performance is studied. Finally, the effect of a varying level of effort is discussed.

6.1 Data generation

A distinction can be made between project-based parameter settings and settings related to the complexity and uncertainty. First of all, the project-based parameters will be discussed and the baseline scenario will be established. Afterwards, the settings related to complexity and uncertainty are divulged. All of these settings are summarised in Table VIII and discussed in the following paragraphs. Table VIII is illustrated on a specific example and combined with the settings of one of the solution strategies in the Appendix.

Project-based settings 100 project networks with 30 activities were generated using the RanGen2 generation engine (Vanhoucke et al. (2008)) for 9 values of the Serial/Parallel (SP) indicator, ranging from 0.1 to 0.9 in steps of 0.1. Although the SP indicator is named the I2 indicator in the paper by Vanhoucke et al. (2008), it is commonly referred to as the SP indicator in several simulation studies (e.g. Vanhoucke (2010)). The SP indicator measures a network's degree of closeness to a completely serial or parallel network (Tavares (1999)). The following project-based parameter concerns the nature of the generated trade-offs. These can be random, linear, convex or concave. Convex trade-offs entail steeply increasing costs as an activity's duration is crashed. The opposite observation holds for concave trade-offs. We only consider random trade-offs. Robustness checks were performed for linear, convex and concave trade-offs without leading to different results.

Imposing a deadline for the project is done after the instance is solved in an exact way, using the procedure of Demeulemeester et al. (1998). The exact solution method returns an efficient time/cost profile. Let D_{min} denote the minimum project duration and D_{max} denote the maximum project duration. The deadline, δ_n, is determined using the parameter θ, as follows:

$$\delta_n = D_{min} + \theta * (D_{max} - D_{min})$$

3 levels for θ are suggested: 0.25, 0.5 and 0.75. Finally, the penalty parameter determines how extremely exceeding the deadline is discouraged. A low penalty setting (€350 per day) and high penalty setting (€3,500 per day) are taken into consideration. The height of the penalty has a direct influence on the global cost deviation. If a solution is reached with only a small time deviation but the penalty is set to a high number, the global cost deviation will be much higher than a situation with a low penalty setting. The combination of a certain value for the deadline and penalty determines the location of the optimal cost on the efficient time/cost profile. Finally, for every possible mode, a combination of durations and costs needs to be generated. The number of modes will be specified in the complexity and uncertainty settings paragraph. Activity costs range

from €500 to €2,500 with a maximum allowed interval of €1,000 between two modes of an activity. The minimum durations of an activity go from 10 to 20 with a maximum interval of 1 time unit.

INSERT TABLE VIII HERE

Baseline Scenario The baseline scenario is used as an instrument to identify the main effects of different combinations of the complexity and uncertainty parameter. The characteristics that closely resemble the PSG's properties were employed to construct this scenario. An exception is made for the penalty parameter, where both values were used.

Complexity and uncertainty settings Complexity refers to the average number of trade-offs of the different activities and was first introduced in section 5.1. There are two levels for the complexity of the generated projects. The activity modes of the projects are generated according to a triangular distribution with 1, 4 and 6 modes as the minimum, mode and maximum for projects with a low degree of complexity and 4, 7 and 9 modes for highly complex projects. There are two settings for the complexity threshold which determine if a project is judged to be complex or not. The first threshold setting is equal to 0, thus indicating that every project will be judged complex. The other parameter value equals 10 and implies that every project will be judged lowly complex.

The second dimension is uncertainty, which consists of 3 elements, namely the uncertainty type, proportion and size. The delay type denotes the amount of positive and negative delays. A proportion of 90% positive delays (10% negative delays) is put forward. Negative delays result in activities finishing earlier than planned and are included to reflect that uncertainty can also yield opportunities (Ward and Chapman (2003)). Consequently, the delay type penalizes or rewards risk takers who do not incorporate a lot of slack into their projects. Closely linked with the delay type is the percentage of activities subject to a delay. This is applied to move the project's execution closer to or further away from the baseline schedule. The percentage of activities subject to a delay is applied to all activities at the start of the project's execution. Hence, an activity can only be delayed once. If this percentage is low, few unanticipated delays will distort the decisions about the activity modes taken by the project manager. Two levels for the uncertainty proportion are proposed. A low degree of uncertainty proportion corresponds with values that are drawn randomly from an interval with values between 20% and 40%. A high degree of the uncertainty proportion originates from a random draw with 60% and 80% as its lower and upper bound, respectively. The third component of the delays is the size of the delays. This is drawn from a triangular distribution and varies from 1 to 9, with the mode equal to 4. The parameter values for the uncertainty threshold

are equal to 0 and 1.0. Hence, the project will be judged to be highly or only slightly uncertain, respectively. In the remainder of this manuscript, the term uncertainty will be used for the proportion of delays, unless noted otherwise.

6.2 Results

In the previous section, the settings for the baseline scenario were discussed. This scenario will now be used to analyze the different links between complexity, uncertainty and how these dimensions are judged. The results for the baseline scenario are divided into 3 paragraphs. The first paragraph deals with the performance of both solution strategies when complexity and uncertainty are assessed correctly. Two situations may occur, namely when the complexity or uncertainty is low and when the complexity or uncertainty is high. The second paragraph takes a look at the two possible judgement errors. One of the dimensions, complexity or uncertainty, may be low *in reality* but can be judged high. Alternatively, the real complexity or uncertainty may be high but *judged* to be low. The significance results of a correct assessment and the judgement errors can be found in Tables IX and X. Table IX deals with the significance results of the main experiment, whereas the judgement error results can be found in Table X. The third paragraph looks at how a higher level of effort impacts the cost performance of both solution strategies.

Performance In this paragraph, we limit ourselves to situations in which the decision maker judged the complexity and uncertainty correctly. The following five observations with regard to the performance of both solution strategies can be made:

1. The penalty costs for the time-based strategy (SS_1) are lower compared to those of the cost-based strategy (SS_2) across all complexity, uncertainty and penalty levels.

This implies that the project duration attained by SS_1 lies closer to the deadline than it is for SS_2, resulting in a lower amount of incurred penalty costs.

2. For a high penalty setting, a larger deadline deviation leads to a steep cost deterioration.

It is no surprise that due to this increased importance of the timing aspect, SS_1 thrives in a high penalty setting.

3. Even though SS_1 has a smaller share of penalty costs, the activity costs of SS_2 are much lower, indicating that a better trade-off selection takes place.

The timing aspect does not have a substantial impact when the penalty is low. Hence, SS_2 almost always returns better results than SS_1. The difference between both strategies is more pronounced for a high degree of complexity.

4. The complex search process for better trade-offs proves advantageous for a cost-based approach (SS_2).

When the complexity is high, SS_2 is slightly but not significantly better even when the penalty is high. In that case, the proportion of penalty costs is larger than for SS_1 but the activity costs are much lower.

5. When there is little uncertainty, SS_2 performs better or there is only a small difference compared to SS_1. Clearly, a low degree of uncertainty only has a minor impact on a project's duration.

INSERT TABLE IX HERE

Judgement Error A central topic in this paper is the discrepancy between the *real* complexity or uncertainty and how it is *judged*. Hence, judgement errors can be made in which a dimension is low but judged to be high or vice versa. The results of these judgement errors lead to the following three conclusions:

1. A general conclusion for both strategies is that safety is the best policy.

It is better to prepare for the worst and judge the complexity dimension to be worse (highly complex) than it may be in reality (low complexity).

2. For a high penalty setting, the time-based approach (SS_1) performs well compared to the cost-based approach (SS_2).

The preferred solution strategy depends on the (actual and perceived) **complexity** of the judgement error. Even though the time-based strategy (SS_1) performs slightly better than the cost-based strategy (SS_2) when the complexity is high but judged to be low, the difference was found to be statistically insignificant. When the complexity is low but judged to be high, the cost-based strategy comes out on top.

When it comes to the **uncertainty** dimension, SS_1 performs slightly better than SS_2 for both judgement error positions. Interestingly, the activity costs are lower for SS_2 but the higher penalty costs push the global cost deviation of SS_2 higher than that of SS_1.

3. For a low penalty setting, the cost-based strategy (SS_2) clearly outperforms the time-based strategy (SS_1).

INSERT TABLE X HERE

Influence of the Level Of Effort In order to ensure that no large differences in the level of effort materialize for the generated projects, the level of effort was controlled using focus and intensity. The focus and intensity settings for the baseline scenario were described in section 5.2. In this section, the effect of an increased level of effort is studied. Three separate experiments were conducted to study the effect of an increased level of effort on the performance of the solution strategies. The global cost deviations of the three experiments can be found in Table A7 of the Appendix. The main findings for each experiment can be summarized as follows:

1. Experiment 1 adopted a focus of 100% in absence of any uncertainty (U = 0).

The intensity was varied from 0.6 to 1.0 in steps of 0.1. The results indicate that an increased intensity leads to better cost deviations.

2. Experiment 2 adopted an intensity of 100% in absence of any uncertainty (U = 0).

The focus was varied from 0.6 to 1.0 in steps of 0.1. Similar to the first experiment, the global cost deviation decreased as the focus was increased, but the decrease was less steep compared to the findings of the first experiment.

3. Experiment 3 reintroduced the uncertainty settings of the baseline scenario, while the focus was kept at 100% and the intensity was varied again from 0.6 to 1.0.

Hence, compared to the first experiment, these settings allowed us to explore the influence of the uncertainty. As the intensity (and thus the level of effort) increased, the global cost deviation decreased. However, the cost deviations are higher than those of the first experiment, which can be attributed to uncertainty affecting the activity durations.

Finally, we have also tested the influence of the deadline and the SP level. The deadline parameter was varied by selecting the 25th and 75th percentile. Both solution strategies share a decreasing deadline deviation trend as the deadline increases, without leading to different conclusions for the overall performance. The SP factor was varied from 0.1 to 0.9 with steps of 0.1. No consistent trend for the solution strategies across the complexity and uncertainty dimensions could be established.

7. Discussion and conclusion

In this paper, three contributions were made. First, the decisions of students throughout the Project Scheduling Game were translated into two major solution strategies. These are comprised of five building blocks, namely focus, activity criticality, ranking, intensity and action. The first solution strategy focuses on time and employs three mechanisms to approach the deadline. The Greatest Rank Positional weight priority rule is used, as well as a buffer based on the slack duration ratio of Hazir et al. (2010) and a final check to protect the deadline is performed. The second solution strategy heavily focuses on costs, at the expense of an increased exposure to risk. The average most expensive priority rule is used to rank activities. Elitism is applied to only accept cost improvements and non-critical activities' slack is consumed to a larger degree.

Second, complexity and uncertainty were included as contextual factors. The literature overview of section 1 indicated that these are dominant themes and that a link between complexity and project outcome (Hanisch and Wald (2011)) and a continued study of uncertainty (Hall (2012)) were among the challenges for future research. To that end, we have conducted a large computational experiment that allows us to quantify the impact of

complexity (Maylor et al. (2008)) and uncertainty. The following five conclusions can be drawn from the experiment:

1. A high degree of complexity has a negative effect on the cost deviation.

Since heuristics are designed to make a trade-off between effort and accuracy (Gigerenzer and Gaissmaier (2011)), complex situations call for either more advanced solution methods or for an increase in additional resources and managerial attention, as established by Shenhar (2001).

2. The effect of uncertainty greatly depends on its impact.

Uncertainty was defined as a variation in the duration of an activity. Since most variations led to activity delays, a higher degree of uncertainty generally leads to a longer project duration. Hence, a high degree of uncertainty combined with a severe penalty for deadline overruns led to steep cost increases.

3. Individuals vary in how they assess complexity and uncertainty.

This variation can be partly due to the experience or capability of the project managers in assessing those contextual factors. In the experiment, this was addressed by means of a threshold function, in which the actual and perceived level of complexity and uncertainty were varied. A discrepancy between the actual and perceived level of complexity or uncertainty led to a judgment error. We came to the conclusion that the direction of judgement errors is crucial. Perceiving a project as highly complex and uncertain while this is not true in reality yields significant advantages compared to the opposite scenario. Hence, we recommend project managers who are incapable of correctly assessing a project's complexity and/or uncertainty (e.g. through limited information) to err on the safe side.

4. We identified the conditions in which each solution strategy thrives.

The time-based solution strategy performs particularly well when deadline overruns are heavily penalized and in highly uncertain environments. The cost-based solution strategy yields better results in low penalty and highly complex environments.

5. Increasing the level of effort exhibits a positive effect on the capability of the strategies.

In this paper, we focused on quantifying the effect of complexity and uncertainty on cost outcomes. Hence, the limitation of this paper is that little attention was paid to the behavioural and psychological aspects of complexity and uncertainty. For instance, one can wonder what the effect of tight deadlines on team motivation is and how this relates to previous research on this topic (Chang et al. (2003), Engwall and Westling (2004)). Additionally, demographic variables such as age, background and project role (cf. Ojiako et al. (2014)) could be included, especially when dealing with complexity and uncertainty judgements.

From a data analysis and model perspective, two future research avenues can be identified. First of all, while we

provided an initial analysis to discern between two major solution strategies, it would be interesting to find out if participants of the PSG switch between strategies throughout the game and by which circumstances this switch is prompted. A similar question arises for niche strategies. Secondly, additional mechanisms can be put in place that further complicate the decision-making process. For instance, increasing or decreasing the time participants have to make decisions throughout the PSG, as well as the presence of a contingency budget may well lead to different choices. A new round of data collection and modeling should be undertaken to bring this meritorious extension to fruition.

Acknowledgements

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Yang, L.-R., Huang, C.-F., and Wu, K.-S. (2011). The association among project man- ager's leadership style, teamwork and project success. International Journal of Project Management, 29:258–267.

Figures

```
┌─────────────────────────────────┐
│           Game input            │
│         Project network         │
│ Project schedule with completion time T │
└─────────────────────────────────┘
                 │
                 ▼
┌─────────────────────────────────┐
│         Unexpected events       │
│ Client stipulates new deadline δₙ < T │
│  Penalty cost per day of exceedance  │
└─────────────────────────────────┘
                 │
                 ▼
┌─────────────────────────────────┐
│           User input            │
│        Reschedule project       │
└─────────────────────────────────┘
                 │
                 ▼
┌─────────────────────────────────┐
│           User input            │
│          Take decision          │
└─────────────────────────────────┘
                 │
                 ▼
┌──────────────────────────┐   ┌──────────────────────────┐
│      Game output         │◄──│       Game input         │
│ Simulate partial project │   │ Activity duration uncertainty │
│        progress          │   │                          │
└──────────────────────────┘   └──────────────────────────┘
                 │
                 ▼
┌─────────────────────────────────┐
│          Game output            │
│     Project progress reports    │
└─────────────────────────────────┘
                 │
                 ▼
            ◇ Project finished? ◇
                 │
                 ▼
┌─────────────────────────────────┐
│           Game over             │
│    Evaluate total project cost  │
│     Feedback and discussion     │
└─────────────────────────────────┘
```

Figure I: The process of the Project Scheduling Game (source: PM Knowledge Center (www.pmknowledgecenter.com))
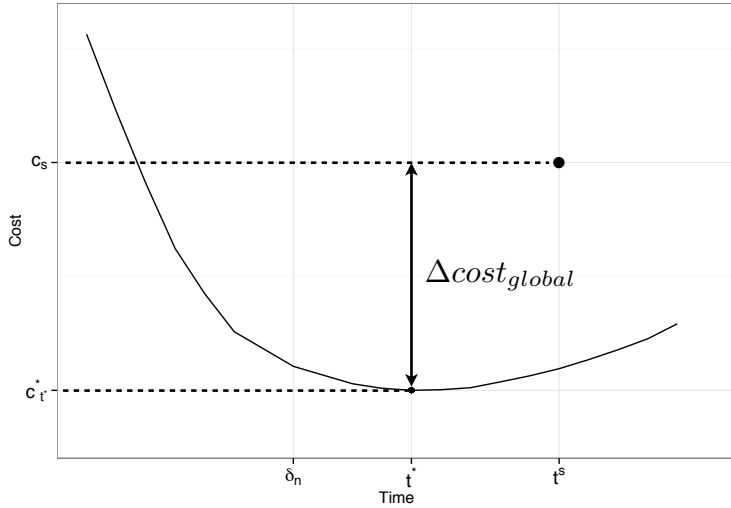
Figure II Visualization of the global cost deviation

Figure IIIa Activity on the Node (AoN) notation of the illustrative example

Figure IIIb Gantt-chart of the illustrative example

Figure IV New Gantt-chart after actions on activities 3 and 1

Figure V: Overview of the framework of the solution strategies

Tables

Table I: Overview of current literature on the Discrete Time/Cost Trade-off Problem

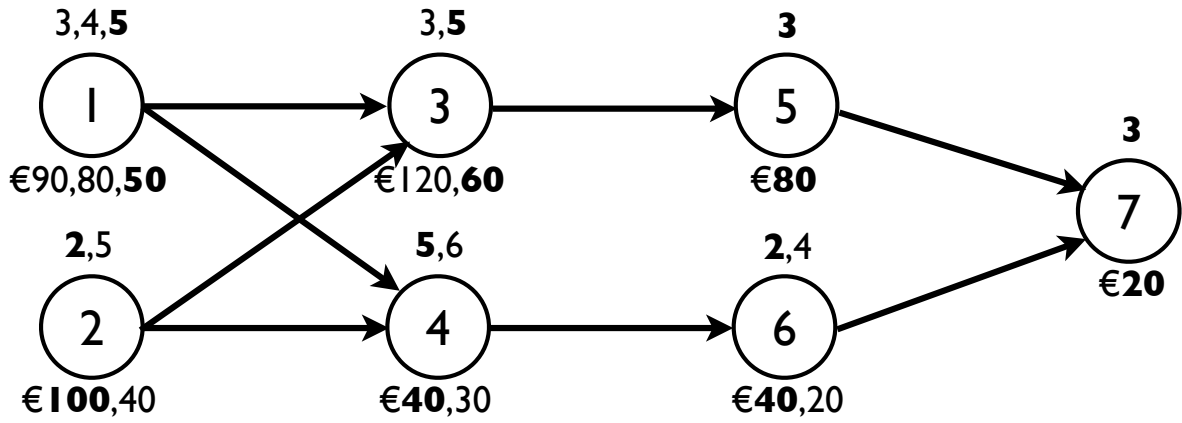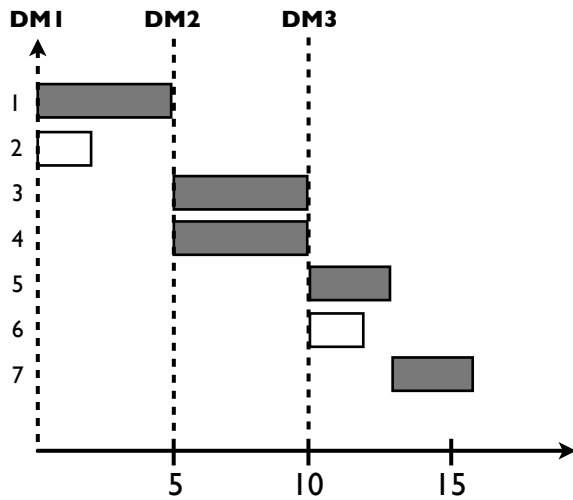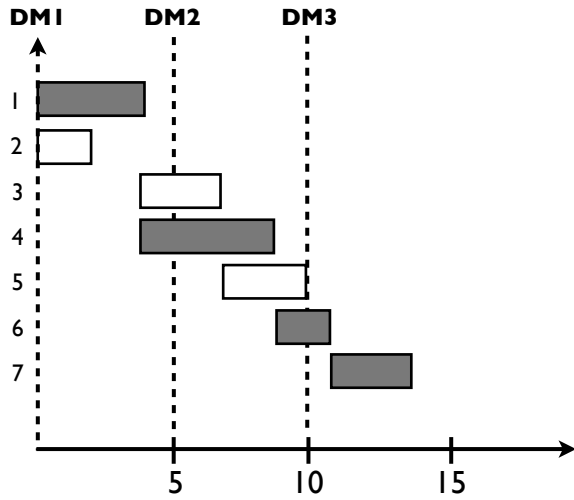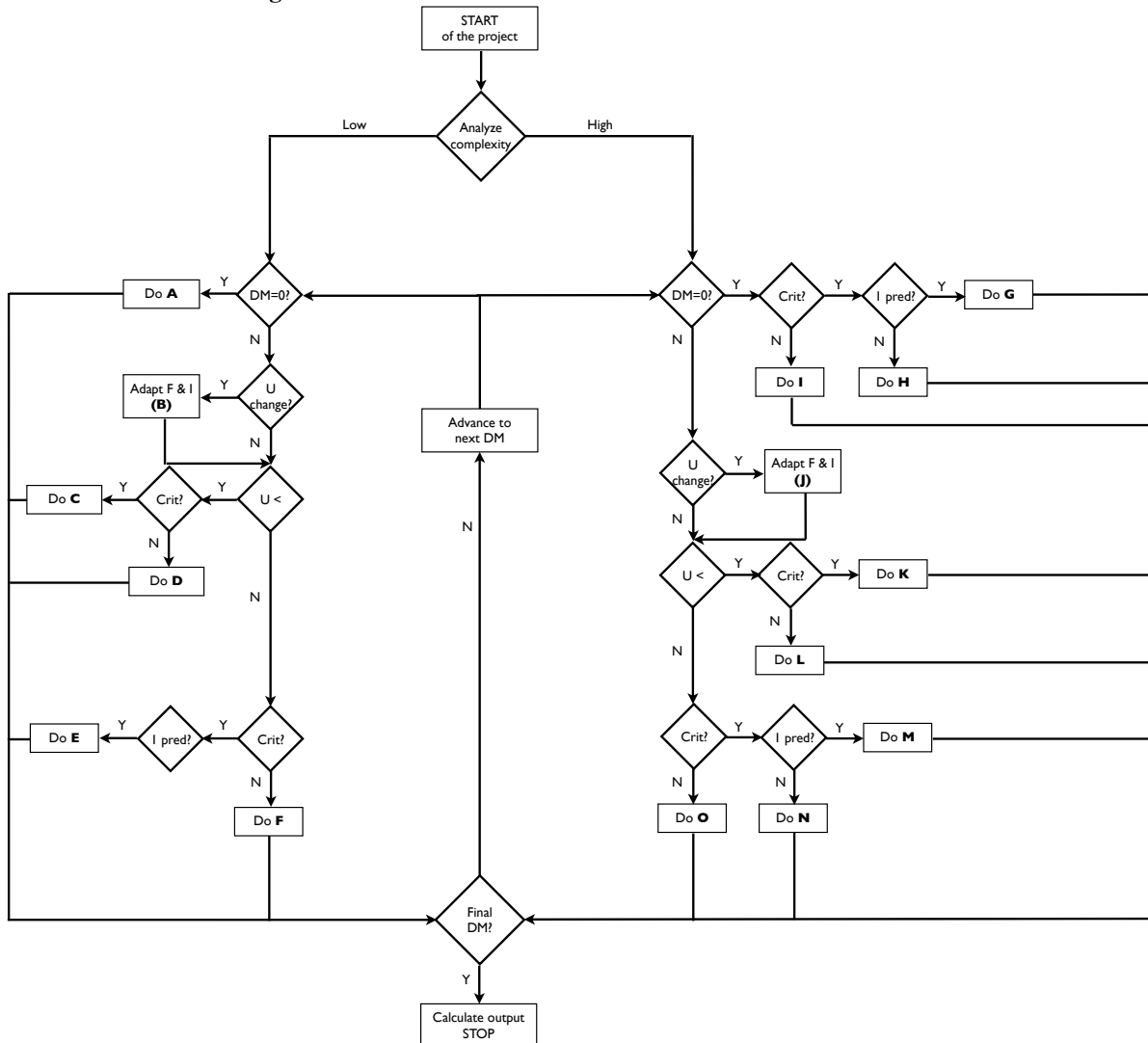| Research stream	Paper	Contribution
Problem extensions	Vanhoucke (2005)	DTCTP with time-switch constraints. Outperforms Vanhoucke et al. (2002).
	Vanhoucke and Debels (2007)	Metaheuristic for time/switch constraints, work continuity and net present value maximization.
	Sonmez and Bettemir (2012)	Hybrid genetic algorithm for the DTCTP.
	Tareghian and Taheri (2006)	Three integer programming models for the time/cost/quality trade-off problem.
	Tareghian and Taheri (2007)	Scatter search with electromagnetic properties for the time/cost/quality trade-off problem.
	Pour et al. (2010)	Genetic algorithm: hill-climbing and decreasing mutation rate for the time/cost/quality trade-off problem.
Stochastic characteristics	Azaron et al. (2005)	Genetic algorithm for multi-objective TCTP with activity durations $\sim$ Erlang.
	Azaron and Tavakkoli-Moghaddam (2007)	PERT network as queuing system, spawning of new project and activity durations $\sim$ Exponential.
	Cohen et al. (2007)	Robust optimization for the stochastic TCTP.
	Ke et al. (2009)	Genetic algorithm-based algorithm for the stochastic TCTP.
	Hazir et al. (2010)	Robust scheduling and robustness measures based on slack.
	Klerides and Hadjiconstantinou (2010)	Two-stage stochastic integer programming approach.
	Hazir et al. (2011)	Schedule robustness with unknown interval-based cost parameters.
	Mokhtari et al. (2011)	Ant system approach for the stochastic TCTP.
	Chen and Tsai (2011)	TCTP using fuzzy numbers.
	Ke et al. (2012)	Formulation of three stochastic TCTP models using chance-constrained & dependent-chance programming.
	Ghoddousi et al. (2013)	Non-domination based genetic algorithm for multi-objective TCTP.

Table II: Overview of the student results

Student group	#students	Cost deviation (%)			
		Minimum	Maximum	Average	σ
Business Engineering (UGent)	176	0.19	12.46	1.52	1.76
Civil Engineering (UGent)	203	0.24	12.76	1.29	1.44
Civil Engineering (UCL)	36	0.38	4.52	1.75	0.82
Managmeent Science (UCL)	5	0.50	1.79	1.10	0.54
Management (VBS & EDHEC)	24	0.38	4.60	1.72	1.34

Table III: Overview of the type of actions

Type of action	Description
Swap	Select neighbouring trade-off.
Slack consumption	increase duration until no slack is left.
Minimum cost slope	Select trade-off with maximum duration decrease at minimum cost.
Maximum revenue slope	Select trade-off with minimum duration increase at maximum savings.
Enumeration	Enumerate all trade-off for set of activities.
Protect deadline	Decrease/increase project duration until acceptable deviation from δ_n.

Table IV: Overview of the 5 components for the illustrative example

Component	Setting
Focus	0.67
Activity criticality	Critical
Ranking	Most Expensive Activity
Intensity	0.67
Action	Crash with swap move

Parameter	Value
Deadline	13 days
Penalty	€100

Table V: overview of the actions for the 3 alternative strategies and their outcome (NA indicates an activity cannot be crashed any more)

Strategy	Decision Moment	Activity	Old trade-off Time	Old trade-off Cost	New trade-off Time	New trade-off Cost
Strategy 1	1	1	5	50	4	80
	2	5	3	80		NA
	3	5	3	80		NA
Strategy 2	1	3	5	60	3	120
		1	5	50	4	80
	2	6	2	40		NA
	3	6	2	40		NA
		7	3	20		NA
Strategy 3	1	5	3	80		NA
		3	5	60	3	120
		1	5	50	4	80
		6	2	40		NA
		4	5	40		NA
		7	3	20		NA
	2	4	5	40		NA
		6	2	40		NA
		7	3	20		NA
	3	6	2	40		NA
		7	3	20		NA

Strategy	Project duration	Project cost	Level Of Effort
Do nothing	16	690	0
Strategy 1	15	620	1
Strategy 2	14	580	3
Strategy 3	14	580	3

Table VI: Principal differences between the solution strategies

Solution strategies	
SS_1	SS_2
GRPW priority rule	Avg MEA priority rule
Buffer (SDR of 30%)	Elitism (only accept cost improvement)
Protect deadline	Slack consumption

Table VII: Overview of the solution strategies and their components

Solution Strategy	Perception		Branch	Solution Strategy Component			
	Complexity	Uncertainty		Focus	Intensity	Ranking	Action
Time (SS$_1$)	Judged L	NA	A	C_L=0.3 | C_H=0.3	C_L=1 | C_H=0.5	GRPW	Crash/prolong Swap$_{elit}$
		Judged L	B & C	C_L=0.4 | C_H=0.3	C_L=0.5 | C_H=0.5	GRPW	Crash MC Slope
			B & D				Prolong MR Slope
		Judged H	B & E	C_L=0.4 | C_H=0.3	C_L=1.0 | C_H=0.5	Avg MEA	Crash MC Slope
			B & F				Prolong Swap
	Judged H	NA	G				Crash/prolong Swap$_{elit}$
			H	C_L=1.0 | C_H=0.7	C_L=1.0 | C_H=1.0	GRPW	Crash Swap
			I				Prolong Swap
		Judged L	J & K	C_L=0.9 | C_H=0.5	C_L=1.0 | C_H=0.7	GRPW	Crash Swap$_{elit}$
			J & L			Max SLK	Prolong Swap$_{elit}$
		Judged H	J & M	C_L=0.2 | C_H=0.1	C_L=0.5 | C_H=0.7	GRPW	Crash Swap$_{elit}$
			J &N				Enumerate
			J & O			Max SLK	Prolong Swap$_{elit}$
Cost (SS$_2$)	Judged L	NA	A	C_L=1 | C_H=1	C_L=1 | C_H=0.7	Avg MEA	Crash/prolong Swap$_{elit}$
		Judged L	B & C	C_L=0.9 | C_H=1.0	C_L=0.2 | C_H=0.7	Avg MEA	Crash Swap$_{elit}$
			B & D				Prolong MR Slope
		Judged H	B & E	C_L=1.0 | C_H=1.0	C_L=1.0 | C_H=0.7	Avg MEA	Crash MC Slope | Prolong MR Slope
			B & F				Prolong Swap
	Judged H	NA	G				Crash MC Slope | Prolong MR Slope
			H	C_L=0.1 | C_H=0.2	C_L=0.3 | C_H=0.2	Avg MEA	Crash/prolong Swap$_{elit}$
			I				Prolong MR Slope
		Judged L	J & K	C_L=0.5 | C_H=0.4	C_L=0.5 | C_H=0.6	Avg MEA	Crash/prolong Swap$_{elit}$
			J & L				Consume slack
		Judged H	J & M	C_L=0.6 | C_H=0.2	C_L=0.2 | C_H=0.2	Avg MEA	Crash MC Slope | Prolong MR Slope
			J &N				Enumerate
			J & O			Avg MEA	Consume slack

Table VIII: Overview of the data generation parameters

Description		Settings
Project parameters	SP-factor	0.1-0.9, Δ=0.1
	#Projects	100
	Trade-offs	Random
	θ	0.25-0.75, Δ=0.25
	Penalty	€350-€3,500
	Activity Costs	$\sim$R(500-2,500)
	Activity Durations	$\sim$R(10-20)
Baseline scenario	SP-factor	0.5
	θ	0.5
	Penalty	Low: €350
		High: €3,500
Complexity & Uncertainty	Complexity Low	$\sim$Tri(1,4,6)
	Complexity High	$\sim$Tri(4,7,9)
	Complexity Thresholds	0-10
	Uncertainty Low	$\sim$R(0.2-0.4)
	Uncertainty High	$\sim$R(0.6-0.8)
	Uncertainty Thresholds	0-1.0

Table IX: results of the main experiment (correct judgement). An asterisk denotes a significant difference: p < 0.05

Dimension	Actual & Perceived	Penalty	Global cost deviation			Penalty share		
			SS_1	SS_2	Sign.	SS_1	SS_2	Sign.
Complexity	Low	Low	11.65%	5.90%	*	2.10%	5.06%	*
		High	20.14%	27.32%	*	11.47%	25.21%	*
	High	Low	25.42%	13.13%	*	1.04%	6.30%	*
		High	25.61%	25.30%		4.82%	15.18%	*
Uncertainty	Low	Low	20.61%	13.08%	*	0.97%	3.84%	*
		High	21.67%	22.55%	*	4.56%	11.42%	*
	High	Low	17.97%	11.27%	*	1.94%	5.08%	*
		High	25.75%	28.12%	*	12.88%	21.57%	*

Table X: results of the main experiment (judgement error). An asterisk denotes a significant difference: p < 0.05

| Dimension	Actual	Perceived	Penalty	Global cost deviation			Penalty share		
				SS_1	SS_2	Sign.	SS_1	SS_2	Sign.
Complexity	Low	High	Low	13.48%	7.79%	*	1.88%	3.34%	*
			High	20.96%	18.84%	*	12.41%	13.04%	
	High	Low	Low	27.10%	21.52%	*	1.26%	3.41%	*
			High	28.84%	29.13%		6.53%	11.92%	*
Uncertainty	Low	High	Low	19.07%	11.25%	*	1.03%	4.27%	*
			High	21.04%	21.13%		5.47%	12.30%	*
	High	Low	Low	20.01%	12.74%	*	2.33%	4.93%	*
			High	27.09%	28.79%	*	12.33%	20.06%	*

A. Appendix

This appendix contains results or clarifications that were either too expansive to add to the main text of the manuscript or did not alter the main insights of the paper. It provides an example of the data generation process (section 6.1) and the link with Table 3 of the main text.

A1. Data Generation example

In this section, the data generation of the computational experiment, found in section 6.1, is illustrated by means of an example of the dataset. The different steps are outlined below:

- Network Generation: generate a network with 32 activities and a value of the SP indicator equal to 0.8

  The Activity-on-the-Node (AoN) representation is given in figure A1.
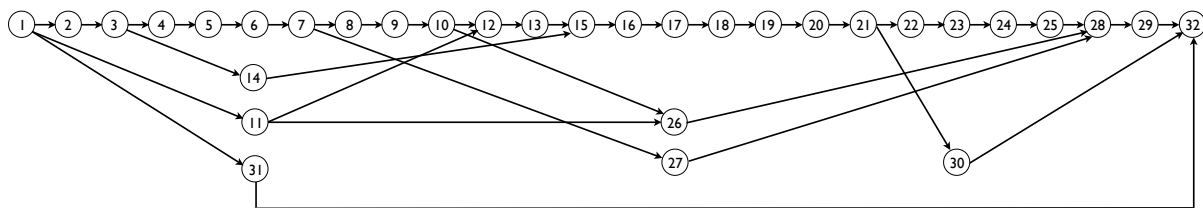
Figure A1: AoN representation of the generated network

- Generate time/cost trade-offs: in this example, a low complexity will be maintained. For each activity, the number of trade-offs is drawn from a triangular distribution with 1, 4 and 6 as the minimum, mode and maximum respectively. Each trade-off has a duration between 10 and 20 time units and a cost between 500 and 2,500 monetary units. A full overview of the generated time/cost trade-offs for all activities can be found in Table A1.

Activity 1		Activity 13		19	1663
15	1485	17	1410	20	872
16	1400	18	516	Activity 27	
17	929	Activity 14		11	2485
18	543	18	2377	12	2393
Activity 2		19	1440	13	2389
15	2421	20	1026	14	1637
16	1431	Activity 15		Activity 28	
17	1194	10	2921	10	2240
18	593	11	2912	11	2011
Activity 3		12	1990	12	1258
10	4367	13	1344	13	1119
11	3443	Activity 16		Activity 29	
12	2527	17	732	15	3524
13	1949	Activity 17		16	2784
Activity 4		17	3794	17	2508
16	2935	18	3516	18	1769
17	2848	19	2869	Activity 30	
18	2078	20	1897	15	2025
19	1986	Activity 18		16	1116
Activity 5		17	3298	Activity 31	
17	3489	18	3092	13	4820
18	3095	19	2176	14	4164
19	2100	Activity 19		15	3279
20	1241	16	3375	16	2429
Activity 6		17	2769	Activity 32	
19	2899	18	2616	14	560
20	2588	19	1923		
21	2444	Activity 20			
22	1961	14	2209		
Activity 7		15	1786		
15	3897	16	1491		
16	3029	Activity 21			
17	2190	17	1553		
18	1494	18	1549		
Activity 8		19	1517		
17	1310	20	1271		
18	777	Activity 22			
Activity 9		18	1453		
14	2324	19	1258		
15	1925	20	1160		
16	1739	21	619		
17	906	Activity 23			
Activity 10		18	762		
14	1894	Activity 24			
15	1331	12	3138		
16	623	13	2320		
Activity 11		14	1817		
17	949	15	885		
18	615	Activity 25			
19	587	13	3441		
Activity 12		14	2965		
18	1691	15	2104		
19	1428	Activity 26			
20	1093	17	2657		
21	726	18	2246		

- Generate delays: the uncertainty proportion determines the amount of activities that will be subject to a delay. In this instance, a value of 0.2 is generated, implying that 0.2 * 32 ≈ 6 activities will be delayed. The size of the delays is drawn from a triangular distribution with 1 and 9 as the minimum and maximum and a mode equal to 4. An overview of the activities that are delayed is shown in Table A2.

Table A2: Overview of the generated delays

Activity	Delay
6	6
8	5
10	4
13	6
15	3
25	5

- Generate deadline and penalty: the example is solved exactly, resulting into an efficient time/cost profile. Since no penalty is imposed yet, lengthening the project leads to cost reductions. The deadline is set to 0.5 in this example, which corresponds with the time value of the 20th (0.5 * 40 timepoints) point of the efficient time/cost profile. For every day the deadline is exceeded, a penalty cost of 350 monetary units is incurred. Figure A2 shows how the penalty negatively affects the efficient time/cost profile.
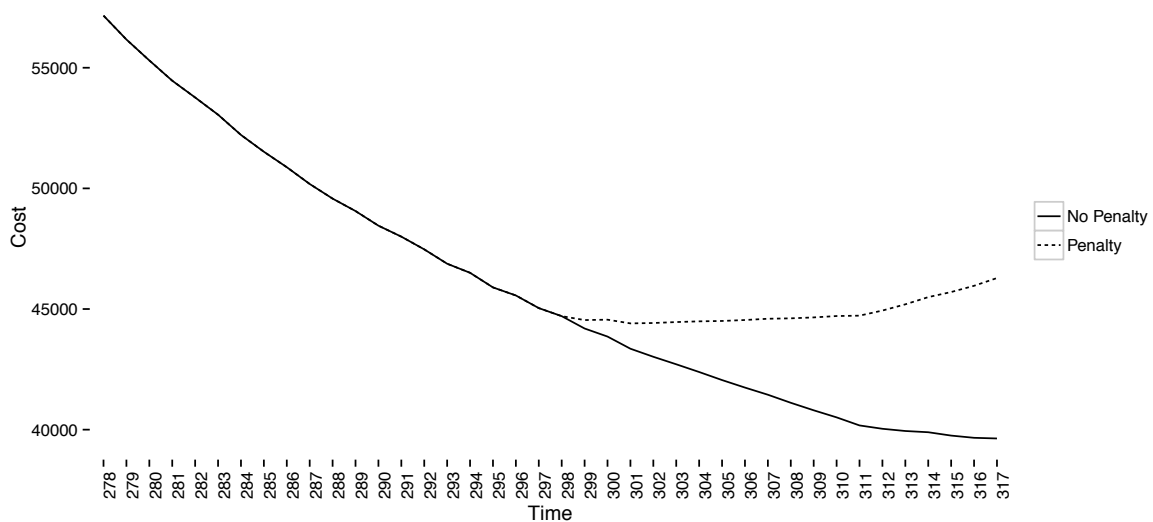
Figure A2: efficient time/cost profile with and without the penalty of 350 monetary units

- Apply one of the solution strategies to the problem at hand. In this example, the actual complexity is low. Assume that the thresholds for complexity and uncertainty are equal to 0. In that case, complexity and uncertainty will be judged low. This implies that for the time-based strategy, the focus will be equal to 0.4 and the intensity will be 0.5. The GRPW priority rule will be invoked. Critical activities will be crashed according to the minimum cost slope, whereas non-critical activities will be prolonged

following the maximum revenue slope. These settings can all be found in Table 3 of the manuscript. The global cost deviation of the time-based solution strategy for this example is equal to 16.12%, with the activity cost making up 100% of the global cost deviation. Hence, the time-based solution strategy manages to finish before the project's deadline.