# The impact of applying effort to reduce activity variability on the project time and cost performance

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## Abstract

During project execution, deviations from the baseline schedule are inevitable due to the presence of uncertainty and variability. To assure successful project completion, the project's progress should be monitored and corrective actions should be taken to get the project back on track. This paper presents an integrated project control procedure for measuring the project's progress and taking corrective actions when necessary. We apply corrective actions that reduce the activity variability to improve the project outcome. Therefore, we quantify the relation between the applied managerial effort and the reduction in activity variability. Moreover, we define three distinct control strategies to take corrective actions on activities, i.e. an interventive strategy, a preventive strategy and a hybrid strategy. A computational experiment is conducted to evaluate the performance of these strategies. The results of this experiment show that different strategies are preferred depending on the topological network structure of projects. More specifically, the interventive strategy and hybrid strategy are preferred for parallel projects, while the preventive strategy is preferred for serial projects.

*Keywords:* project management, schedule control, corrective actions, simulation

## 1. Introduction

Managing projects entails planning, executing and controlling projects in order to achieve the project objectives on time and within budget. Project control is, together with baseline scheduling and risk analysis, one of the three major aspects of Integrated Project Management

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and Control (Vanhoucke, 2014). The goal of project control is identifying potential problems and/or opportunities during the execution of the project, such that corrective actions to get the project back on track can be taken when necessary. Hence, two processes can be distinguished, namely project monitoring and corrective action taking. Project monitoring entails measuring the project progress and comparing this progress to the baseline schedule to assess whether it is acceptable. When the project progress is not acceptable, the project manager should take corrective actions to get the project back on track.

In order to implement these corrective actions, the project manager has to invest managerial effort in terms of time and/or money. Generally, the more effort is applied to implement corrective actions, the higher the impact of these actions. However, the amount of effort that can be spend by the project manager during the execution of projects is limited, and can be referred to as the *effort budget*. Since the available effort budget is limited, the effort should be carefully applied to maximise the impact of the corrective actions that are taken to get the project back on track. Consequently, several decisions should be made by the project manager to take effective corrective actions. First, he or she should determine which project activities are eligible to take corrective actions on. Subsequently, the activities on which corrective actions will be taken should be selected. Finally, depending on the selected activities and the available effort budget, the amount of effort that will be applied to the selected activities should be determined.

In this paper, an integrated project control study is performed to examine the impact of reducing activity uncertainty on the project outcome. Hence, when warning signals are generated during project execution, corrective actions are taken that reduce the expected variability of activity durations. Since the impact of corrective actions on the actual activity durations is not deterministic, we consider the stochastic nature of corrective actions in the computational experiment. Moreover, an interventive strategy, a preventive strategy and a hybrid strategy are introduced and reviewed in order to determine the activities that are eligible to take corrective actions on. Further, to select the activities on which corrective actions should be taken, risk analysis information is used. Finally, a flexible *effort-uncertainty reduction function* is defined to quantify the relation between the amount of applied effort and the reduced activity uncertainty. Using this function, the amount of effort that should be applied to implement the corrective actions can be determined.

## 2. Literature review

The project control process is an iterative process during project execution that consists of monitoring the project's progress and taking corrective actions when necessary. Project monitoring consists of periodically evaluating the actual progress and generating warning signals when the progress is not acceptable. For instance, when the schedule progress is monitored, warnings signals are generated when the deadline is expected to be exceeded. The generated warning signals act as a trigger for corrective action to get the project back on track. In section 2.1, the methods to generate warning signals for schedule control are discussed. Subsequently, section 2.2 reviews the literature on corrective action taking.

### *2.1. Tolerance limits for project control*

Tolerance limits for project control are a tool to evaluate the project's progress. These tolerance limits set threshold values for the schedule progress. When the actual progress is below these thresholds, a warning signal is generated indicating that the project is expected to exceed its deadline. Consequently, corrective actions are required to get the project back on track. Three types of tolerance limits for project control can be distinguished; static tolerance limits, statistical tolerance limits and analytical tolerance limits. First, static tolerance limits are constant throughout the entire project life cycle. They are determined using rules of thumb and have been introduced by Goldratt (1997) and Leach (2005). Second, statistical tolerance limits apply concepts of Statistical Process Control (SPC, Shewhart (1931)). These limits require historical data or Monte Carlo simulations to determine the desired state of the project's progress and can vary during the project life cycle. The statistical tolerance limits for project control introduced in literature have been validated using empirical data (Aliverdi et al., 2013; Bauch and Chung, 2001; Leu and Lin, 2008; Lipke and Vaughn, 2000; Wang et al., 2006) or artificial data (Colin et al., 2015; Colin and Vanhoucke, 2014, 2015). Finally, analytical tolerance limits have been introduced. These limits do not require historical data or Monte Carlo simulations, but use project-specific information to determine the thresholds for the project progress. Accordingly, they are easier to implement than statistical tolerance limits but more accurate than static tolerance limits. Analytical tolerance limits have been proposed and validated using simulation studies (Colin and Vanhoucke, 2015; Hu et al., 2016; Martens and Vanhoucke, 2017a,b) or empirical data (Martens and Vanhoucke, 2018).

### *2.2. Corrective actions*

When warning signals are generated, the project manager should act to get the project back on track. In literature, two distinct viewpoints to handle uncertainty during project execution are considered. First, proactive scheduling entails protecting the schedule as well as possible against anticipated disruptions. Second, reactive scheduling involves revising the baseline schedule when unexpected events occur. The process of taking corrective actions can be classified in the latter category.

Reactive scheduling approaches range from *schedule repair actions*, which are straightforward techniques to adapt the schedule with minimum changes, to more complex *full rescheduling* *approaches*. A common schedule repair action is activity right shifting, which entails that activities are moved forward to construct a new baseline schedule without re-sequencing the project activities. Moreover, several full rescheduling strategies with different objectives have been proposed. For instance, Calhoun et al. (2002) and Sakkout and Wallace (2000) aim to minimise the perturbation of the original schedule, while Zhu et al. (2005) focus on penalising changes in resource utilisation and in the selected modes for the multi-mode Resource Constrained Project Scheduling Problem (MRCPSP). For an overview of reactive scheduling procedures, the reader is referred to Deblaere et al. (2011); Hartmann and Briskorn (2010).

In section 2.2.1, we discuss three common types of corrective actions defined in literature. Subsequently, the concept of managerial effort, which is required to implement corrective actions, is introduced in section2.2.2. Finally, the corrective action decision making process is described in section 2.2.3.

### *2.2.1. Corrective action types*

Three corrective action approaches that can be defined as schedule repair actions can be distinguished, i.e. fast tracking, activity crashing and variability reducing. First, *fast tracking* entails that the original network structure of the project is overruled by executing precedence-related activities (partially) in parallel in order to reduce the total project duration. While it is often stated that fast tracking does not entail additional costs, the probability of rework increases considerably when activities are fast tracked. Hence, it is possible that fast tracking negatively affects the project outcome. In Krishnan et al. (1997), one of the first mathematical formulations for fast tracking are introduced and the difficulties for overlapping product development activities are discussed. Further, Vanhoucke and Debels (2008) examine the impact of fast tracking subparts of activities for the Resource Constrained Project Scheduling Problem (RCPSP). More recently, a stochastic model for schedule fast tracking has been proposed by Ballesteros-Pérez (2017). Further, *activity crashing* is a technique that aims to reduce the total planned duration by spending more money to reduce the duration of certain activities. In Vanhoucke (2010b), the impact of using activity sensitivity metrics to support the decision making process to improve the time performance has been reviewed using a simulation study. The implemented corrective actions have been modelled as an activity duration reduction of 50% of the planned duration. Hence, the activity crashing process was assumed to have a deterministic outcome. Further, Hu et al. (2016) and Vanhoucke (2011) implemented stochastic activity crashing processes that reduce the baseline activity duration between 0 and 50%. While the impact of an activity crashing action is thus not deterministic, it is assumed to be a positive impact. Finally, *variability reduction* entails that the activities' variability can be reduced by applying effort to control them. Contrarily to activity crashing, the impact of a variability reduction action is a reduction of the baseline standard deviation, rather than a reduction of the baseline duration. Reducing the variability can be achieved by taking corrective actions that mitigate certain risks associated with an activity, such as using more qualitative tools to avoid malfunctions. In Madadi and Iranmanesh (2012), the impact of variability reducing has been reviewed deterministically, i.e. by reducing the variability of the project activities once, before the start of the project. To the best of our knowledge, the impact of dynamically reducing the activities' variability, i.e. by applying effort to reduce the variability of certain activities during project execution, has not been examined yet.

Hence, while fast tracking partially overrules the original project network structure, activity crashing and variability reducing focus on changing the mean and standard deviation of an activity to reduce the mean and standard deviation of the project duration. Several studies have reviewed the impact of an activity's mean duration and variability on the project's expected duration and variability. The impact of an activity's standard deviation on the expected project duration and variability has been examined by Cho and Yum (1997) and Gutierrez and Paul (2000), respectively. Elmaghraby (2000) and Elmaghraby et al. (1999) evaluated the impact of an activity's mean on the expected project duration and variability respectively. First, Cho and Yum (1997) defined an uncertainty importance measure (UIM) for a single activity and for a pair of activities to evaluate the importance of the activity variability on the project variability. This metric has been developed using the Taguchi tolerance design technique (Taguchi, 1987) with modifications, assuming that the activity durations are independent and symmetrically distributed. The accuracy of Taguchi's method for approximating the mean and standard deviation of the project duration has been further examined by Elmaghraby et al. (1999) in order to evaluate the impact of changing an activity's mean duration on the project duration variability. Furthermore, Gutierrez and Paul (2000) investigated the impact of activity risk on the expected project duration to evaluate whether large projects dealing with subcontractors should focus on risk pooling or risk splitting. They found that, contrarily to the claim made by Schonberger (1981), increased activity variability does not necessarily lead to an increased mean project duration. Finally, in Elmaghraby (2000), the aforementioned issues are reviewed and the relation between changes in the activity mean and project mean are briefly discussed.

### *2.2.2. Managerial effort*

In this paper, we take variability reducing corrective actions to achieve timely project completion. Generally, the project manager has a limited availability of time and money for taking these corrective actions, referred to as the *effort budget*. In the computational experiment, the effort budget is expressed in monetary units since the time spent by the project manager to take corrective actions can also be expressed in monetary units based on his or her wage. Further, the amount of time and/or money that the project manager uses to implement corrective actions is referred to as *managerial effort*. For instance, the project manager can spend his or her time to improve the communication with subcontractors and suppliers, in order to avoid delays due to miscommunications. Further, he or she can assign more qualitative tools (which are more reliable than the initially assigned tools) to an activity in order to avoid delays due to malfunctions. These qualitative tools are typically more expensive than less qualitative tools (e.g. since they are from a premium brand, or more recent than the standard tools that are used). Accordingly, this type of corrective action comes at an additional cost.

In Vanhoucke (2011), the amount of effort required to control the project is compared to the impact of the corrective actions on the actual project duration, which is referred to as the *control efficiency*. The required amount of effort is reviewed by determining the amount of activities that are evaluated when a warning signal is generated to decide whether they require corrective action. Hence, the control efficiency focuses on the required effort to evaluate activities and does not consider the number of corrective actions that are taken and their required time and/or cost to be implemented. Further, in Madadi and Iranmanesh (2012), the authors have defined a function to describe the relation between the amount of effort that is applied by the project manager and the resulting level of activity uncertainty reduction. More precisely, the authors state that this relation decreases exponentially in real-life situations. Therefore, they specified equation (1) to describe the relation between the reduced uncertainty and the applied effort, with $\sigma^{'}$ the reduced uncertainty, $\sigma$ the original activity uncertainty, $\gamma$ the applied effort and $C$ a constant set to 3 based on experts' judgement.

$$\sigma^{'} = \sigma C^{-\gamma} \tag{1}$$

This formulation has two limitations. First, $\gamma$ is defined as the amount of effort applied to take a corrective action on an activity as a percentage of the project manager's effort. This implies that, for a same amount of applied effort, the rate of uncertainty reduction can change when the total effort budget changes. Further, equation (1) contains only one constant, namely $C$. However, the shape of equation (1) should reflect two aspects of the relation between applying effort and reduced activity variability. First of all, since activity duration variability is inevitable due to external risks that might occur, equation (1) should reflect the minimum variability that can be reached. Secondly, since the rate at which the minimum variability can be reached might differ for activities with different characteristics, equation (1) should include this rate. While the minimal variability can be defined as $\frac{\sigma}{C}$ for applying all available effort, it is not possible to describe different rates of variability reduction for activities with the same minimal variability. In order to deal with these limitations, we propose an adapted formulation in section 3.3.1. Further, to the best of our knowledge, we are the first to investigate the impact of corrective actions to reduce the activity variability on the project outcome within a limited effort budget. Moreover, contrarily to Madadi and

Iranmanesh (2012), our approach entails that corrective actions can be taken at multiple time periods during project progress when warning signals are generated.

### *2.2.3. Corrective action decision making process*

During project progress, several decisions concerning the corrective action taking process should be taken by the project manager. More precisely, he/she should decide (i) when corrective actions are required, (ii) which activities are eligible to take corrective actions on and (iii) which activities should actually be taken actions on.

In the literature, two prevalent project monitoring approaches are discussed, namely the top-down approach and the bottom-up approach. With respect to determining when corrective actions are required, the top-down approach generates a warning signal to the project manager when the aggregated project performance falls below a pre-defined threshold. The bottom-up approach, however, states that actions are required when the sensitivity of certain activities exceeds a pre-defined threshold. In order to decide which activities to take corrective actions on, given the limited available effort, the top-down and bottom-up approach focus on the critical and sensitive project activities, respectively.

Several studies have examined the impact of using a top-down or bottom-up approach on the project performance (Vanhoucke, 2010a, 2011). These studies found that the top-down approach is more effective for serial projects while the bottom-up approach is more effective for parallel projects. Recently, Hu et al. (2016) applied a combined top-down and bottom-up approach, in which they take corrective actions on the most sensitive activities when the aggregated project performance falls below the pre-defined threshold. However, the authors did not review how the performance of such an approach differs for serial and parallel projects.

None of these approaches (e.g. the top-down approach, bottom-up approach or combined approach) explicitly specify which activities are considered to be eligible to take corrective actions on, and different viewpoints are applied in literature. Vanhoucke (2010a) focus on taking corrective actions on ongoing and future (critical) activities, while Vanhoucke (2011) and Hu et al. (2016) focus only on ongoing critical or sensitive activities. Since this decision may affect the project control performance significantly, we define and compare three distinct strategies, i.e. an interventive strategy (which focuses on ongoing activities), a preventive strategy (which focuses on future activities) and a hybrid strategy (which focuses on ongoing and future activities). In order to review how these strategies affect the project control performance, we will review the performance of a combined top-down and bottom-up approach for the three distinct strategies.

## 3. Procedure

In this study, the impact of variability reducing to improve the schedule performance of projects will be reviewed using Monte Carlo simulation. Therefore, we define a quantitative relation between the amount of effort applied by the project manager and the amount of activity variability reduction. Further, three strategies are considered to select the activities that are suitable to apply effort on. The impact of applying effort to reduce activity variability will be evaluated in terms of expected delay and delay variability.

In figure 1, the general flow of the procedure followed in the computational experiment is depicted. Three phases can be distinguished, namely the static phase, the monitoring phase and the action phase. The *static phase* is the phase before the project execution is started and consists of constructing the baseline schedule, determining the project deadline and setting the tolerance limits. Further, the *monitoring phase* consists of monitoring the project progress at each tracking period. This progress is measured and compared to the threshold value of the tolerance limit at the time of the tracking period. When the schedule performance is below the threshold value, the project manager should proceed to the *action phase*. During this phase, the project manager applies effort to reduce the uncertainty of one or more selected activities. First, he or she should determine which activities are eligible to take corrective actions on. Subsequently, when there are eligible activities, the activities on which corrective actions will be taken should be selected. Finally, the project manager should determine how much effort should be applied to implement the corrective actions on each of the selected activities. Hence, the monitoring and action phase are consecutive and iterative phases.

In the computational experiment described in section 4, this procedure is applied on a dataset of 900 projects generated by the project network generator RanGen (Demeulemeester et al., 2003). This dataset has been extensively used in previous computational studies (e.g. in (Colin et al., 2015; Martens and Vanhoucke, 2017a)) and consists of project networks with varying topological network structures, ranging from close to completely parallel networks to almost completely serial networks. The topological network structure of the project networks is expressed by the SP-indicator (Vanhoucke et al., 2008). More specifically, low (high) SP-values correspond to project networks that are close to completely parallel (serial) networks. The dataset contains 100 project networks for each SP-value in $\{0.1, 0.2, \ldots, 0.9\}$. Further, each project network in the dataset consists of 30 activities. For each activity, a fixed cost between €10 and €90 and a variable cost between €100 and €900 are uniformly sampled.

The procedure described in figure 1 has been implemented using the project scheduling and control tool P2 Engine (Vanhoucke, 2014). In the remainder of this section, each of the three phases is discussed in more detail. Further, the computational settings are described for each phase of the procedure.

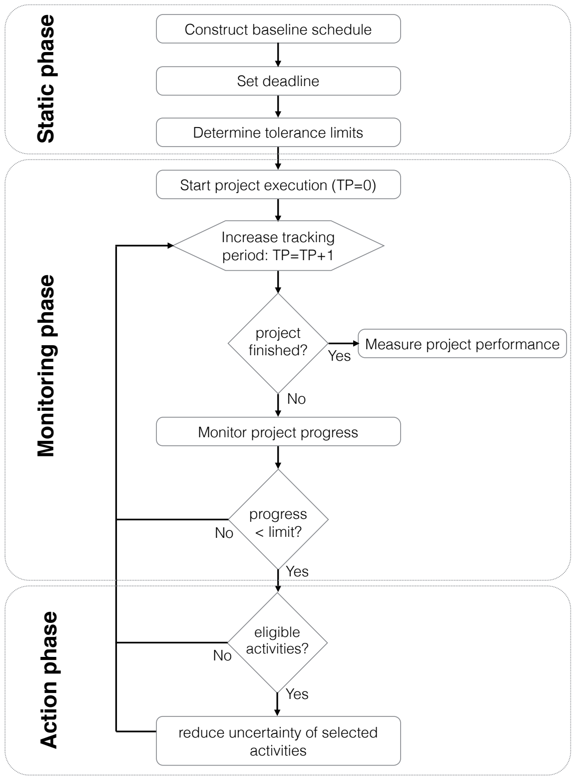


Figure 1: Shape for different parameters.

### *3.1. Static phase*

For each of the 900 projects in the dataset, an earliest start schedule is constructed. In this paper, we do not explicitly consider the presence of renewable resources. However, the procedure presented in this paper can be used for projects with limited renewable resources. During the monitoring phase, this baseline schedule will act as a point of reference to evaluate the project progress. Further, the project deadline at which the project should be completed is set by adding a project buffer of 10% of the planned duration to the project's planned duration. Finally, tolerance limits are set such that warning signals will be generated when the project is expected to exceed its deadline during the monitoring phase. These tolerance limits are set by assuming that the project buffer can be consumed proportionally with the value accrue of the project, as proposed by Martens and Vanhoucke (2017a). For instance, when the project is 25% completed in terms of value accrue, 25% of the project buffer is allowed to be consumed. The value accrue is measured and monitored using the well-known monitoring methodology Earned Value Management/Earned Schedule (EVM/ES). For an overview of EVM/ES, the reader is referred to Fleming and Koppelman (2010); Vanhoucke (2010a). Further, for a detailed discussion on how these tolerance limits are established, the reader is referred to Martens and Vanhoucke (2017a).

### 3.2. Monitoring phase

For each project in the dataset, a large number of project executions is simulated ($n = 1000$). Uncertainty and variation are added to the project by simulating real activity durations that follow a right-skewed probability distribution. The deployed probability distribution and its parameter settings are discussed in section 3.2.1. Further, the schedule progress of the simulated executions is measured and reviewed by comparing the actual progress to the tolerance limit set during the static phase. This process is discussed in more detail in section 3.2.2.

#### 3.2.1. Activity duration distribution

Since we suppose that the activity duration distributions are skewed to the right, a lognormal distribution is used to model the activity real durations. This distribution can be easily implemented and has been used to model activity durations in several studies (Bie et al. (2012); Hu et al. (2016)). In this section, we first discuss the properties of the lognormal distribution. Subsequently, the process of adding uncertainty to the activity duration is described. Finally, the parameter settings for the activity duration distributions without applied effort are specified. The parameters for the activity duration distribution with applied effort and reduced variability are discussed in section 3.3.2.

*Lognormal distribution.* The lognormal distribution can be parametrised using two parameters. Moreover, two different sets of parameters can be used: the arithmetic mean and standard deviation of the log-normally distributed variable (denoted by $m$ and $s$), or the arithmetic mean and standard deviation of the normally distributed natural logarithms of the variable (denoted by $\mu$ and $\sigma$). The relation between these parameter sets is described in equations (2) and (3).

$$\begin{cases} \mu = \ln(\frac{m}{\sqrt{1+\frac{s}{m^2}}}) \\ \sigma = \sqrt{\ln{(1+\frac{s}{m^2})}} \end{cases} \tag{2}$$

$$\begin{cases} m = e^{\mu+\frac{1}{2}\sigma^2} \\ s = e^{\mu+\frac{1}{2}\sigma^2}\sqrt{e^{\sigma^2-1}} \end{cases} \tag{3}$$

While the arithmetic mean $m$ and standard deviation $s$ can be used to characterise the log-normal distribution, they are not robust summary statistics for skewed distributions such as the lognormal distribution. More specifically, the arithmetic mean $m$ is positively affected by the high values of the right tail of the lognormal distribution and does hence not reflect the true central tendency of the distribution. As a result, the arithmetic standard deviation $s$, which is a measure of spread around the mean $m$, is affected as well. The geometric mean and standard deviation, however, are robust summary statistics for skewed data. For lognormal distributions, the geometric mean can be expressed as the exponentiated value of the arithmetic mean of the logarithms ($\mathrm{GM}[X] = e^{\mu}$). Moreover, the geometric mean of the lognormal distribution is equal to its arithmetic median. Similarly, the geometric standard deviation reflects the exponential of the arithmetic standard deviation of the logarithms ($\mathrm{GSD}[X]=e^{\sigma}$) (Kirkwood, 1979).

*Adding uncertainty.* The project management literature considers two separate causes of uncertainty, namely variation and risk (Loch et al., 2006). The variation component reflects the deviation of real activity durations from the baseline estimates. Further, the risk component reflects the project-wide impact of risky events. This component assumes that activity durations are not statistically independent. Both components are modelled using separate lognormal probability distribution functions. First, the risk component is modelled using the concept of linear association (Trietsch et al., 2012). This entails that a positive random variable $B$ is sampled from the lognormal distribution of the risk component which acts as a bias term representing the project-wide impact of risky events. This bias term can be seen as a consistent over ($B < 1$) or underestimation ($B > 1$) of the baseline estimates. Thus, by adding the risk component, each project activity $i$ has a biased baseline estimate $B\hat{d}_i$. Subsequently, the variation component is added by multiplying $B\hat{d}_i$ with a sample $G$ from the lognormal distribution of the variation component. Since the product of two independent lognormal random variables is log-normally distributed, the real activity duration distributions containing both the risk and variation component is lognormal as well.

*Parameter settings.* Since the arithmetic mean $m$ and standard deviation $s$ are easy to interpret and widely used to define activity duration distributions, the original distribution of activity durations without applied effort is represented by $m$ and $s$. These parameter setting are specified for the relative real durations $\frac{d_i}{\hat{d}_i}$, with $d_i$ the real duration and $\hat{d}_i$ the estimated duration of activity $i$. First, the arithmetic mean $m$ and standard deviation $s$ of the risk component and variance component without applied effort are set to 1.1 and 0.3, respectively. Subsequently, the parameters $\mu$, $\sigma$, $e^{\mu}$ and $e^{\sigma}$ of the risk component and variance component are derived using equations (2) and depicted in figure 1. The final distribution of the real activity durations is log normally distributed with $\mu$ and $\sigma^2$ equal to the sum of the $\mu$ and $\sigma^2$ of both components, respectively.

When effort is applied to reduce the activity uncertainty, the distribution parameters change.

More precisely, while the bias term remains, the variability of the variance component decreases. Since $m$ and $s$ are not robust for skewed distributions, we define the new distribution of the variance component of activities with reduced uncertainty by modifying the geometric standard deviation $\sigma$. In section 3.3.2, we elaborate on how the new parameters for these distributions are set.

### *3.2.2. Progress monitoring*

During project execution, the schedule progress is monitored periodically using EVM/ES and compared to the threshold values of the tolerance limits proposed in Martens and Vanhoucke (2017a). For a fair evaluation, an equal number of tracking periods at which the project progress is evaluated and at which action can be taken by the project manager is determined for all executions. More specifically, 4 tracking periods are considered in this experiment. Accordingly, the project progress of all simulated executions is evaluated at 20, 40, 60 and 80% completion. At each of these tracking periods, the schedule progress is compared to the tolerance limits to determine whether corrective actions are required. Finally, when the project is completed, the project performance is measured in terms of actual duration and actual cost.

## *3.3. Action phase*

During the action phase, the project manager has to decide how he or she will apply his or her available effort budget in order to control the project by reducing the uncertainty level of project activities. In section 3.3.1 we define a function to describe the relation between the amount of effort that is applied to take a corrective action on an activity and the resulting reduced uncertainty of the activity. Subsequently, in section 3.3.2, we describe which levels of uncertainty reduction are considered and how the parameters for the distribution of activity durations with reduced uncertainty are set. Finally, in section 3.3.3 we describe how the activities that should be controlled by the project manager are determined in the computational experiment.

### *3.3.1. Relation between applied effort and uncertainty reduction*

To measure the impact of corrective actions to reduce the activity uncertainty, the relation between the applied effort and the uncertainty reduction should be defined analytically. As mentioned in section 2.2.1, Madadi and Iranmanesh (2012) defined an exponential function to describe this relation (equation (1)). In order to deal with the limitations associated with this formulation, we propose equation (4) to define the relation between applied effort and reduced uncertainty, with $\sigma^{'}$ the reduced uncertainty, $\sigma$ the original activity uncertainty, $\gamma$ the percentage applied effort and $a$, $b$ and $C$ constants that define the shape of the function.

In the remainder of this section, the interpretation of constants $a$, $b$ and $C$ will be derived.

$$\frac{\sigma^{'}}{\sigma} = aC^{-\gamma} + b \tag{4}$$

The actual applied effort is measured in monetary units. In equation (4), contrarily to the definition of Madadi and Iranmanesh (2012), $\gamma$ reflects the applied effort as a percentage of the planned activity cost. Hence, while $\gamma$ cannot be negative, the applied effort can be higher than 100% (i.e. when the applied effort is higher than the original activity cost).

The shape of equation (4) can be determined using two characteristics, namely $\epsilon$ and $\tau$. First, $\epsilon$ reflects the theoretical minimal activity uncertainty as a percentage of the original variability ($\epsilon \in ]0,1[$). Consequently, in equation (4), constant $b$ reflects the value of $\epsilon$. Second, we define $\tau$ as the distance from the theoretical minimum $\epsilon$ as a percentage point when 100% effort is applied ($\tau \in ]0, 1-\epsilon[$). Accordingly, $\tau$ reflects how difficult it is (e.g. how much effort is required) to reduce the activity variability. With this information, the value of constants $a$ and $C$ can be determined. In order to determine the value of constant $a$, we consider the scenario in which no effort is applied (equation (5)). Since $\gamma$ is equal to 0 in this case, constant $a$ can be defined as $1-\epsilon$. Further, with the value of constants $a$ and $b$ are known, the value of constant $C$ can be determined by considering the scenario in which 100% effort is applied (equation (6)). Since in this scenario $\frac{\sigma^{'}}{\sigma}$ is equal to $\epsilon + \tau$, $C$ can be defined as $\frac{1-\epsilon}{\tau}$.

$$\begin{aligned} aC^{-0\%} + \epsilon &= 1 \qquad (5)\\ a &= 1-\epsilon \end{aligned}$$

$$\begin{aligned} (1-\epsilon)C^{-100\%} + \epsilon &= \epsilon + \tau \qquad (6)\\ \frac{(1-\epsilon)}{C} + \epsilon &= \epsilon + \tau\\ C &= \frac{1-\epsilon}{\tau} \end{aligned}$$

Consequently, the relation between applied effort and uncertainty reduction using parameters $\epsilon$ and $\tau$ can be expressed as follows:

$$\frac{\sigma^{'}}{\sigma} = (1-\epsilon) \times (\frac{1-\epsilon}{\tau})^{-\gamma} + \epsilon \tag{7}$$

In figure 2, the shape of equation (7) is displayed for different values of $\epsilon$ and $\tau$. These parameters can be interpret as follows. Since $\epsilon$ reflects the theoretical minimal activity uncertainty that can be reached, $\epsilon$ indicates the capability to reduce activity uncertainty. Hence, the higher $\epsilon$, the lower the capability to reduce uncertainty by applying managerial effort. Further, $\tau$ reflects the distance from $\epsilon$ when 100% effort is applied. Therefore, $\tau$ is a measure that indicates the cost of reducing activity uncertainty. Accordingly, with $\epsilon$ constant, a higher $\tau$ reflects a higher cost to reduce uncertainty.

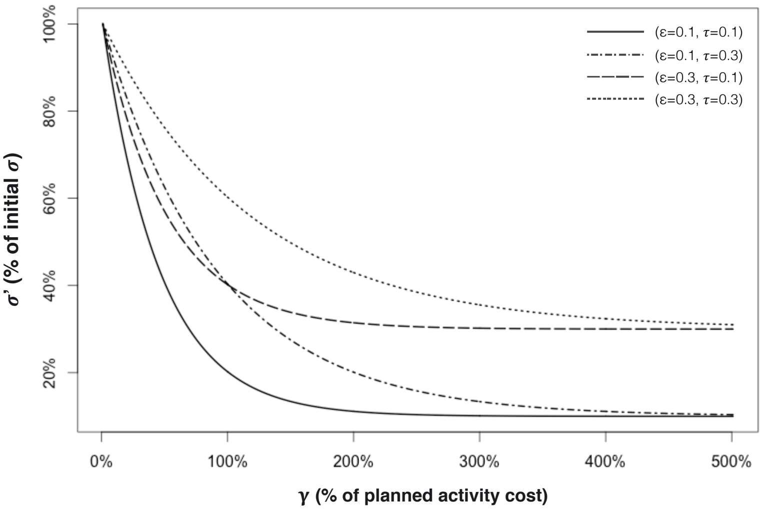


Figure 2: Shape for different parameters.

In the computational experiment, $\epsilon$ and $\tau$ will be set to 0.15 and 0.30, respectively. In other words, we assume that the minimal variability that can be reached by applying an infinite amount of effort is relatively low (i.e. 15% of the original variability), but that reducing the variability comes at a considerable cost (i.e., investing an amount of effort that is worth the planned activity cost, the variability can be reduced to 45% of the original variability). In order to review the impact of the values for $\epsilon$ and $\tau$ on the performance of the different strategies, a sensitivity experiment will be conducted.

### *3.3.2. Activity uncertainty reduction*

In theory, the activity uncertainty of each project activity can be reduced continuously, i.e. each $\frac{\sigma'}{\sigma}$ higher than $\epsilon$ and lower than 1 can be reached by applying effort. In the computational experiment, we will thus assume that the uncertainty of all activities can be reduced. In practice, however, it is possible that the variability of certain activities cannot be reduced. Moreover, in real-life situations, only a limited amount of corrective actions will be possible to be applied on an activity. As a result, the variability cannot be reduced continuously, but can be reduced to a certain number of discrete variability levels. Therefore, we decided to consider only a fixed number of predefined levels of uncertainty in the computational experiment. Further, in practice, it is likely that the number of corrective actions that can be taken (and the effort required for these actions) differs for different activity types. However, for the sake of a fair comparison, we assume that the available corrective actions are identical for all activities. More precisely, we consider three reduced levels of uncertainty (RLU) for each activity, namely RLUs of 75, 50 and 25% of the original variability. For instance, RLU 0.75 indicates that $\frac{\sigma'}{\sigma} = 0.75$.

In table 1, the arithmetic and geometric moments for the relative activity durations of the different levels of uncertainty reduction (RLU = 0.75, 0.50 and 0.25) are displayed for the risk component ($\boldsymbol{\omega_R}$), variance component ($\boldsymbol{\omega_V}$) and the final activity duration distribution ($\boldsymbol{\omega_R} \times \boldsymbol{\omega_V}$). As discussed in section 3.2.1, the arithmetic mean $m$ and standard deviation $s$ are not robust statistics to specify skewed distributions. While we used these statistics to define the activity duration probability distributions in case no effort is applied, we argue that adapting the variation of this original distribution by changing the standard deviation $s$ for a fixed mean $m$ would not be appropriate. More specifically, the arithmetic mean of a right-skewed distribution is positively affected by the high values of the right tail. When the project manager applies effort to reduce the activity uncertainty, the probability that these high values occur decreases. Consequently, both the arithmetic standard deviation and mean of the distribution for activities with reduced uncertainty should decrease. However, no linear relation between the amount of mean reduction and standard deviation reduction can be derived. Accordingly, we decided to reduce the standard deviation $\sigma$ of the variance component for a fixed mean $\mu$. As a result, the geometric mean $e^{\mu}$ remains constant for each RLU, while the geometric standard deviation $e^{\sigma}$ reduces with a factor $e^{-(1-\text{RLU})\sigma}$. Since the geometric mean of the lognormal distribution is equal to its arithmetic median, the probability distributions for the different RLUs have an identical median and different standard deviations. As shown in table 1, this approach results in lower arithmetic means for lower RLUs, for both the variance component and final activity duration distribution.

| | **Arithmetic moments** | | | | **Geometric moments** | |
|---|---|---|---|---|---|---|
| | **activity durations** | | **ln(activity durations)** | | **activity durations** | |
| | $\boldsymbol{m}$ | $\boldsymbol{s}$ | $\boldsymbol{\mu}$ | $\boldsymbol{\sigma}$ | $\boldsymbol{e^{\mu}}$ | $\boldsymbol{e^{\sigma}}$ |
| $\boldsymbol{\omega_R}$ | *1.0488* | *0.2004* | 0.0297 | 0.1894 | 1.030 | 1.2085 |
| $\boldsymbol{\omega_V}$ | | | | | | |
| **No effort** | *1.0488* | *0.2004* | 0.0297 | 0.1894 | 1.030 | 1.2085 |
| **RLU 0.75** | 1.0406 | 0.1486 | 0.0297 | *0.1420* | 1.030 | 1.1526 |
| **RLU 0.50** | 1.0348 | 0.0982 | 0.0297 | *0.0947* | 1.030 | 1.0993 |
| **RLU 0.25** | 1.0313 | 0.0489 | 0.0297 | *0.0473* | 1.030 | 1.0485 |
| $\boldsymbol{\omega_R \times \omega_V}$ | | | | | | |
| **No effort** | 1.1000 | 0.3000 | *0.0594* | *0.2679* | 1.0612 | 1.3072 |
| **RLU 0.75** | 1.0914 | 0.2621 | 0.0594 | 0.2367 | 1.0612 | 1.2671 |
| **RLU 0.50** | 1.0853 | 0.2324 | 0.0594 | 0.2118 | 1.0612 | 1.2358 |
| **RLU 0.25** | 1.0817 | 0.2132 | 0.0594 | 0.1952 | 1.0612 | 1.2156 |

Table 1: Parameter settings

*3.3.3. Selecting the activities to control*

When a warning signal is generated and effort is available to be applied, the project manager should decide which activities he or she will take corrective actions on, and which level of RLU can be attained given a limited effort availability. First, the project manager should determine which activities are eligible to take corrective actions on. Second, he or she should decide on which activities corrective actions will be taken and how much effort will be applied to reach a specific RLU.

***Determine eligible activities.*** In order to determine the eligible activities, different strategies can be deployed. First, an *interventive strategy* entails that only activities that are being executed can be controlled. Accordingly, when corrective actions are taken on an activity, the remaining duration of the activity will be affected. Hence, this strategy deploys a traditional view on corrective action taking for project control (Vanhoucke (2010b, 2011)). Further, a *preventive strategy* can be deployed. Using this strategy, the project manager decides to take corrective actions to reduce the activity uncertainty of activities that are not started yet. Consequently, the entire activity duration is affected by the action. Finally, the project manager can decide to focus on both active and future activities. This strategy is referred to as a *hybrid strategy.*

***Determine activities to control and amount of effort to apply.*** When the activities that are eligible to take corrective actions on are determined according to one of these strategies, the project manager should decide on which activities corrective actions should be taken. Madadi and Iranmanesh (2012) propose to apply the available effort budget on all project activities proportionally with their normalised activity sensitivity. However, they do not relate this proportionally applied effort to an absolute amount of available effort. Moreover, we consider a fixed number of predefined uncertainty levels that can be reached, rather than assuming that the activity uncertainty level can be reduced continuously. Therefore, while we adopt the viewpoint of Madadi and Iranmanesh (2012) that the available effort should be focused on the most sensitive activities, we adapted the uncertainty level reduction process as follows.

First, the sensitivity of the eligible activities is reviewed by performing an SRA analysis (Schedule Risk Analysis, Hulett (1996)). Since the Schedule Sensitivity Index (SSI) measures the relative importance of an activity by taking the Criticality Index (CI) and the relation between the activity's standard deviation and project's standard deviation into account, we employed the SSI to evaluate and rank the sensitivity of the activities. At each tracking period at which action is required, a Monte Carlo simulation is performed in which the actual duration of finished activities is assumed to be fixed, and the remaining duration of active activities and the actual duration of future activities follow a probability distribution according to their current RLU. Subsequently, the eligible activities are ranked from highest to lowest sensitivity according to their SSI value. Second, since the project manager has a limited amount of effort that can be applied and several RLUs can be reached for the eligible activities, the activities that will be controlled and their resulting RLU should be determined. We used the SSI-ranking of the eligible activities to determine the order in which the project manager should take corrective actions on the eligible activities. Moreover, we decided to maximally reduce the RLU of the activities (i.e., reduce the activities' variability to the lowest possible RLU), given the remaining available effort budget. Since the available effort budget is limited, it is possible that the available budget to take corrective actions is not sufficient to control all eligible activities.

In the computational experiment discussed in section 4, we assume that the project manager has an effort budget with a monetary value of 5% of the BAC. Moreover, this effort is equally divided over the tracking periods. Accordingly, since 4 tracking periods are considered, during each tracking period an amount of effort can be applied with a value of 1.25% of the BAC.

## 4. Computational experiment

In this section, we discuss the performance metrics used to evaluate the applied procedure (section 4.1) and describe the computational experiments that have been conducted (section 4.2). The results of this computational experiment are discussed in section 5.

### *4.1. Performance evaluation*

Applying effort to reduce activity uncertainty affects the total duration and cost of the project. Therefore, two performance metrics will be used to evaluate the time and cost performance of the different strategies. In terms of time, the goal of applying managerial effort is reducing the activity uncertainty to decrease the project duration and to minimise delays. Accordingly, we will use the delay reduction after corrective actions to evaluate the time performance of the different strategies. In terms of cost, the project is affected in two ways. First, applying managerial effort entails an additional cost. Second, by applying effort, the activity durations, and hence the variable activity costs, are affected as well. Thus, the total cost impact might be positive (i.e., the total project cost is lower after corrective actions) or negative (i.e., the total project cost is higher after corrective actions). We will compare the total cost impact to the available amount of effort to evaluate how effective the different control strategies used this effort.

More precisely, the *time effectiveness* and the *cost effectiveness* will be measured to evaluate the time and cost performance, respectively. The *time effectiveness* indicates the relative average delay reduction that can be achieved by applying effort and is described in equation (8), with $\overline{\text{Delay}}_{\text{No}}$ the average delay when no effort is applied and $\overline{\text{Delay}}_{\text{Yes}}$ the average delay when effort is applied, given a limited amount of available effort. As can be seen from equation (8), the time effectiveness is equal to 1 when the average delay with applied effort is equal to 0. Moreover, the time effectiveness will be equal to 0 when the average delay with and without applied effort is the same.

$$\text{time effectiveness} = \frac{\overline{\text{Delay}}_{\text{No}} - \overline{\text{Delay}}_{\text{Yes}}}{\overline{\text{Delay}}_{\text{No}}} \tag{8}$$

The *cost effectiveness* indicates the impact of applying effort on the total project cost for a limited availability of effort. The cost effectiveness is presented in equation (9), with $\overline{\text{Cost}}_{\text{No}}$ the average project cost without applying effort, $\overline{\text{Cost}}_{\text{Yes}}$ the average project cost with applied effort and $\text{Effort}_{€}$ the available amount of effort in monetary value. Consequently, the cost effectiveness of the procedure is equal to 0 when applying effort does not reduce the total project cost. A positive cost effectiveness indicates that the total cost with applied effort is lower than the total project cost without applied effort. In other words, a control strategy with a higher cost effectiveness for the same amount of available effort implies that this strategy uses the available budget more effectively, resulting in a lower total project cost. Finally, a negative cost effectiveness implies that the total project cost with applied effort is higher than without applied effort.

$$\text{cost effectiveness} = \frac{\overline{\text{Cost}}_{\text{No}} - \text{Cost}_{\text{Yes}}}{\text{Effort}_{€}} \tag{9}$$

### *4.2. Design of experiments*

In the computational experiment, the time and cost effectiveness of applying managerial effort is examined for the interventive, preventive and hybrid strategy. For each of the 900 projects in the dataset, 1000 executions have been simulated. In order to calculate the performance metrics discussed in section 4.1, two versions of each execution are required, namely a version in which no effort is applied, and a version in which the limited amount of available effort is applied to reduce the activity variability.

For the version in which no effort is applied, 1000 actual activity durations are generated for each project activity according to the original activity duration distribution. Subsequently, for the version in which effort is applied, 1000 actual activity durations are generated for the activities using the parameters of each RLU level. Consequently, these executions start with the same actual activity durations as the execution without applied effort. When effort is applied to activity $i$ during execution $j$ to reach RLU $k$, the original actual activity duration will be replaced by the generated duration for activity $i$ in execution $j$ according to RLU $k$. For future activities on which corrective actions are taken, this implies that the entire original activity duration is replaced. For active activities on which corrective actions are taken, the expected remaining part of the duration is replaced proportionally.

The time and cost effectiveness of the applied procedure is evaluated as follows. First, the overall time and cost effectiveness of the different strategies are examined for all 900 projects in the dataset. The results of this experiment are discussed in section 5.1. Further, we examine whether the topology of the project network affects the time and cost effectiveness of the different strategies in section 5.2. More specifically, the effectiveness is evaluated for 100 projects with an SP of $0.1, 0.2, \ldots, 0.9$. Finally, the impact of the shape of the relation between applied effort and uncertainty reduction in terms of reduction capability ($\epsilon$) and reduction cost ($\tau$) is reviewed in section 5.3.

## 5. Results and discussion

In this section, the results of the computational experiment are discussed. This section is structured as follows. In section 5.1, the overall performance of the three distinct control strategies (i.e. the interventive strategy, preventive strategy and hybrid strategy) is summarised using the two performance measures introduced in section 4, namely the time effectiveness and the cost effectiveness. In section 5.2, the performance of the control strategies is evaluated for different levels of the SP-indicator (i.e for projects with an SP of 0.1, 0.2, ..., 0.9). Finally, section 5.3 examines how changes in the effort-uncertainty reduction function affect the performance of the control strategies. Both changes in $\epsilon$ (i.e. changes in the minimal activity duration variability) and changes in $\tau$ (i.e. changes in the amount of effort that is required to reduce the activity duration variability to a certain level) are investigated.

### *5.1. Overall performance of the different strategies*

In figure 3, the overall results of the computational experiment are depicted. Box plots are used to indicate the distribution of the results. Further, the mean is denoted by the dot in the box plots and the median of the different strategies is depicted next to each box plot.

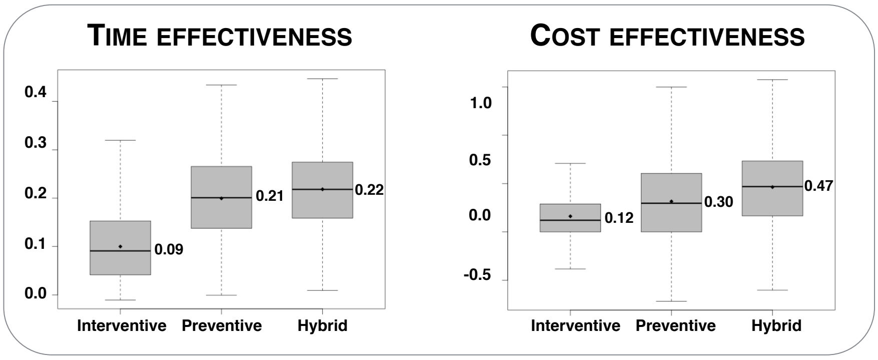


Figure 3: General results.

In terms of time, the interventive strategy is considerably less effective than the preventive and hybrid strategy, which have a comparable time effectiveness (0.21 and 0.22, respectively). The intervention strategy has the lowest cost effectiveness as well, while the hybrid strategy outperforms the preventive strategy in terms of cost effectiveness. While the cost effectiveness is on average positive, the results show that the cost effectiveness can be negative as well for all strategies.

Hence, the intervention strategy is the least performing strategy for both the time and cost effectiveness. Since the cost effectiveness of the hybrid strategy (0.47) is substantially higher than the cost effectiveness of the preventive strategy (0.30), the hybrid strategy can be considered to be the best performing strategy in general. However, from figure 4 can be seen that the range of the results is rather wide for both the time and cost effectiveness. Therefore, the impact of the network topology on the time and cost effectiveness of the different strategies is reviewed in the next section.

### *5.2. Impact of SP*

Figure 4 depicts the performance of each control strategy for different levels of SP-indicator. As mentioned earlier, project networks with a low SP-value are close to a completely parallel network, while high SP-values indicate project networks close to a completely serial network. From figure 4 it is clear that each of the control strategies performs differently for projects with different topological network structures.

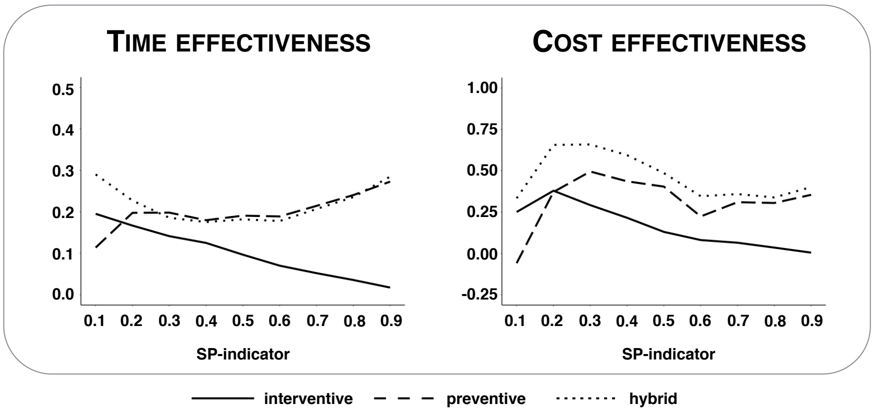


Figure 4: Impact of SP indicator.

*Time perspective.* For very parallel projects (SP=0.1), the difference between the different strategies is the most pronounced. While the time effectiveness of the hybrid strategy is the highest (0.29), the time effectiveness of the preventive strategy is the lowest (0.11). The low time effectiveness of the preventive strategy can be explained by the fact that, as the project progresses, there are future activities to take corrective actions on. Further, while of all SP-values the interventive strategy has the highest time effectiveness for projects with SP = 0.1, it is still outperformed by the hybrid strategy for these very parallel projects. This might indicate that, although there are many ongoing activities to take corrective actions on, the impact of corrective actions on ongoing activities is lower than on activities that still have to start. Finally, for increasing SP-values, the time effectiveness of the interventive strategy gradually decreases, while the preventive and hybrid strategy are comparably effective in these cases.

*Cost perspective.* In terms of cost, the preventive strategy is the least effective strategy for very parallel projects as well. For increasing SP-values, the interventive strategy decreases gradually and is consistently the least effective.The hybrid strategy, on the other hand, has the highest cost effectiveness for all SP-values.

Based on these results, using a hybrid strategy is the most effective in terms of delay reduction (i.e. time effectiveness) and total cost impact (i.e. cost effectiveness). For very parallel projects, the difference between the three strategies is the most pronounced. In this case, the effectiveness of the preventive strategy is the lowest in terms of both time and cost.

### *5.3. Impact of the effort-uncertainty reduction function*

In this section, the impact of changes in the shape of the effort-uncertainty reduction function on the performance of the control strategies is examined. In figure 5, the impact of changes in $\epsilon$ (i.e., the minimum variability of activity durations) and $\tau$ (i.e., the amount of effort that is required to reduct the activity duration variability to a certain level) is reviewed. More specifically, for a fixed $\tau$ (=0.30), $\epsilon$ is reduced to 0.10 and increased to 0.20. Similarly, for a fixed $\epsilon$ (=0.15), $\tau$ is reduced to 0.1 and increased to 0.50.

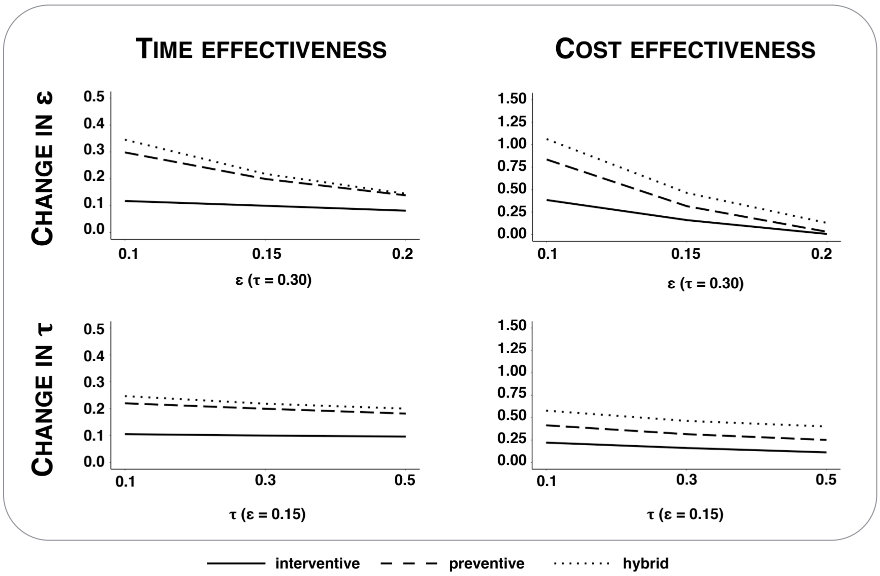


Figure 5: Impact of changes in $\epsilon$ and $\tau$

*Changes in $\epsilon$.* The upper part of figure 5 illustrates the impact of changes in the minimal variability that can be reached. As can be seen from this figure, both the time effectiveness and cost effectiveness decrease when the minimal variability becomes higher. However, the cost effectiveness is affected more significantly by a change in $\epsilon$. Further, while the interventive strategy is affected the least by changes in $\epsilon$, it remains the least effective in terms of time and cost. Thus, the general results remain when $\epsilon$ is changed.

*Changes in $\tau$.* The lower part of figure 5 shows the impact of changes in the amount of effort that is required to reduce the activity variability to a certain level, given a fixed minimal variability ($\epsilon = 0.15$). For increasing values of $\tau$, the time and cost effectiveness of the three strategies decreases. Similar as for changes in $\epsilon$, the impact on the cost effectiveness is higher than the impact on the time effectiveness. Further, this figure shows that the general results remain when $\tau$ is changed. Finally, figure 5 shows that changes in $\epsilon$ have a higher impact on the time and cost effectiveness of the different strategies than changes in $\tau$.

## 6. Conclusion

In this paper, we introduced an integrated project control procedure to measure the project progress and take corrective actions, assuming that a limited effort budget is available to implement these corrective actions during project execution. First, in order to monitor the progress and generate early warning systems when the project deadline is expected to be exceeded, the tolerance limits introduced by Martens and Vanhoucke (2017a) have been used. Subsequently, when warning signals are generated, corrective action have been taken. As proposed in Madadi and Iranmanesh (2012), variability reduction actions have been taken to reduce the activity duration variability. Further, since a limited effort budget to take corrective actions is assumed to be available, we defined a flexible effort-uncertainty reduction function to quantify the relation between the applied effort and the reduced uncertainty using two parameters, i.e. $\epsilon$ and $\tau$. While $\epsilon$ represents the minimal activity variability of the activity durations, $\tau$ indicates the variability level that can be reached when 100% effort is applied to control an activity. Finally, three control strategies have been considered to take corrective actions. The *interventive strategy* focuses on controlling activities that are being executed when a warning signal is generated. The *preventive strategy* on the other hand only considers future activities that have not been started yet. Finally, the *hybrid strategy*, focuses on both ongoing and future activities.

In order to evaluate the performance of the three control strategies, a large computational experiment has been conducted. Each control strategy has been applied on a dataset containing 900 project networks generated by the project network generator RanGen. First, the overall performance over all project networks has been examined. Subsequently, in order to determine the impact of the topological network structure, the performance has been reviewed for SP-values ranging from 0.1 to 0.9. Finally, the parameters of the effort-uncertainty reduction function have been modified to evaluate their impact on the performance of the different control strategies.

The main results of this experiment can be summarised as follows. When the overall performance of the three strategies are compared, the preventive and hybrid strategy have a time effectiveness that is twice as high as that of the interventive strategy. In terms of cost effectiveness, the hybrid strategy has the highest performance (0.47 compared to 0.30 and 0.12 for the preventive and interventive strategies respectively). However, by evaluating the performance for the different SP-values separately, the experiment has shown that substantial differences exist over the different SP-values. More precisely, the three control strategies differ the most for very parallel projects with an SP of 0.1. For these projects, the preventive strategy performs considerably less than the interventive and hybrid strategies. Further, since for all SP-values the cost effectiveness of the hybrid strategy is the highest and the time effectiveness is higher or comparable compared to the interventive and preventive strategies, the hybrid strategy is the overall preferred strategy. Finally, the sensitivity experiment on the parameters $\epsilon$ and $\tau$ has shown that the cost effectiveness is affected more that the time effectiveness by changes in these parameters. Further, changes in $\epsilon$ (i.e., the minimal variability that can be reached) have a higher impact on the effectiveness of the three strategies than changes in $\tau$.

Consequently, rather than narrowing the focus to the ongoing or future activities, the project manager can take the most time and cost effective variability reducing corrective actions by focusing on the most sensitive project activities that are not completed yet. Especially for very parallel projects, this hybrid strategy outperforms the interventive and preventive strategies.

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