INTEGRATING CORRECTIVE ACTIONS IN PROJECT TIME FORECASTING USING EXPONENTIAL SMOOTHING

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ABSTRACT

Earned Value Management (EVM) and Earned Duration Management (EDM) are established methodologies to monitor the project performance during execution. These methods serve as a basis to forecast the final project duration and/or project cost. The aim of this paper is to improve the accuracy of project time forecasting by extending exponential smoothing for project time forecasting using EVM and EDM with the integration of corrective actions that are taken during project progress. In order to evaluate the forecasting accuracy of this approach, eight projects conducted in recent years have been followed up in real-time. Based on the nature of the observed corrective actions, six distinct categories of corrective actions are identified. The empirical experiment showed that explicitly integrating the occurrence of corrective actions into the forecasting process improves the forecasting accuracy of traditional forecasting methods and forecasting methods using standard exponential smoothing, especially for the middle and late phases of projects. Consequently, by including corrective actions in the forecasting process, project managers can predict the final project duration more accurately.

Keywords: Project forecasting, Empirical data, Exponential Smoothing, Corrective Actions

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INTRODUCTION

Due to uncertainty and risks during project execution, deviations from the project plan are inevitable. These deviations often result in late project delivery. Since timely project completion is an essential factor for project success, project time forecasting is an important aspect of project management.

The well-known project monitoring methodology Earned Value Management (EVM, Fleming and Koppelman (2010)) is often used to obtain accurate project duration forecasts (Vandevoorde and Vanhoucke 2006; Wauters and Vanhoucke 2017; Batselier and Vanhoucke 2017). EVM periodically monitors the project performance during execution by comparing the actual progress, i.e., the Earned Value (EV, in monetary units), to the planned progress, i.e. the Planned Value (PV, in monetary units). Since the EV and PV are both cost-based measures, the EVM time forecasts depend on the duration and cost of the project activities. To overcome this issue, Earned Duration Management (EDM, Khamooshi and Golafshani (2014)) has been introduced as a completely time-based adaptation of EVM. Recently, several studies have used EDM rather than EVM as a basis for project time forecasting (Khamooshi and Abdi 2016; de Andrade et al. 2019).

In literature, EVM/EDM forecasting methods have been proposed that make use of the past performance of the project itself or of the progress of similar historical projects. These historical projects should have a high degree of similarity with the project in order to achieve a high forecasting accuracy (Batselier and Vanhoucke 2017). Since historical data are not always readily available to the project manager and a robust methodology to define a *high degree of similarity* has not yet been clearly defined, these techniques cannot always be applied (Batselier and Vanhoucke 2016). This issue is avoided by using forecasting methods that use the past performance as an indicator for future project performance.

However, the past performance is not always a realistic indicator for future performance. More precisely, the current performance might be affected by natural improvements (e.g. due to learning and productivity improvements) or managerial interventions (i.e. corrective actions taken on a limited number of activities to get the project back on track) (Batselier and Vanhoucke 2017).

Therefore, Leon et al. (2018) developed a system dynamics model to simulate intervention scenarios by the project manager and forecast their impact on several project performance indicators. Further, exponential smoothing, a time series forecasting technique that assigns greater weights to recent observations, has been applied for project time forecasting by Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) to account for these effects.

When corrective actions have been taken in recent periods and large weights are assigned to these periods to apply exponential smoothing, too optimistic forecasts might be produced. In this paper, a project time forecasting method is introduced that accounts for the impact of managerial interventions in order to improve the forecasting accuracy by applying exponential smoothing with adaptive smoothing parameters. More specifically, adequate smoothing parameters will be selected to account for the impact of managerial interventions during project execution of the final project duration. In order to evaluate the performance of this approach, eight projects were monitored in real-time during recent years. The empirical experiment on these projects was executed to determine the most appropriate smoothing parameters during project progress and to assess the accuracy of the proposed approach compared to the standard project time forecasting formulas for EVM and EDM and to the forecasting formulas for EVM and EDM with exponential smoothing.

The contribution of this paper is thus twofold. First, the type and timing of corrective actions taken during project execution have been documented by following up eight projects in realtime. The observed corrective actions have been classified in six categories. To the best of our knowledge, this information has not been documented before, although it affects the project outcome (Leon et al. 2018). Accordingly, future research studies can include this enhanced project data information to empirically validate their project control methods. Second, the effect of these corrective actions has been integrated in the project time forecasting process by applying exponential smoothing with an adaptive smoothing parameter in order to obtain more accurate project duration forecasts. By including this information in the project forecasting process, project managers can thus obtain a more accurate prediction of the final project duration.

LITERATURE REVIEW

Since project time forecasting methods use the actual project progress during execution, the project performance should be monitored during execution. The moments at which the project performance is measured are referred to as *tracking periods*. When the project performance at a tracking period is unacceptable according to the project manager, they take corrective actions to get the project back on track. This process is referred to as *project monitoring and control*. Further, the final project duration can be forecasted using the project performance information. This process is referred to as *project time forecasting*. In the remainder of this section, these aspects, which are identified as critical factors to improve the reliability of project control metrics (Orgut et al. 2020), are discussed in greater detail.

Project monitoring and control

Project monitoring entails measuring the actual project progress periodically and comparing this progress to the project plan to detect potential problems in a timely manner. Two established project monitoring methods that are used for project time forecasting are discussed in this section, namely Earned Value Management/Earned Schedule (EVM/ES) and Earned Duration Management (EDM).

EVM is a project monitoring methodology that measures the actual progress of projects in monetary units and constructs performance metrics for the cost and schedule progress by comparing the actual progress to the baseline planned progress. For an extensive overview on the concepts of EVM, the reader is referred to Vanhoucke (2010a) and Fleming and Koppelman (2010).

Since the EVM key indicators are all expressed in monetary units, the EVM schedule performance metrics, the Schedule Variance (SV) and Schedule Performance Indicator (SPI), are known to behave unreliably towards the end of the project. (Lipke 2003b; Henderson 2003; Corovic 2006) To overcome this issue, Lipke (2003b) introduced the Earned Schedule (ES) concept to monitor the schedule progress in time units. The corresponding schedule performance metric, the SPI(t) ($= \frac{\text{ES}}{\text{AT}}$), measures the schedule performance of projects by comparing the ES to the actual time AT. However, while the ES translates the EV of a given time t into time units, it is still based on the cost-based EVM metrics. Therefore, EDM has been developed by Khamooshi and Golafshani (2014) as a time-based project monitoring methodology. They introduced the Earned Duration concept ED, which is the completely time-based equivalent of the ES. The EDM equivalent of the EVM/ES schedule performance indicators is the Duration Performance Indicator DPI ($= \frac{\text{ED}}{\text{AT}}$), which compares the ED to the actual time AT.

An overview of developments in and extensions to EVM/ES and EDM is provided in Willems and Vanhoucke (2015). Recent extensions aimed at integrating time and cost incentives (Kerkhove and Vanhoucke 2017) and controlling the environmental performance of projects (Abdi et al. 2018). Further research efforts focused on generating warning signals for delayed projects (Martens and Vanhoucke 2017; Colin et al. 2015).

When the project progress is not acceptable to meet the final project requirements, the project manager should take corrective actions to get the project back on track. In literature, three types of corrective actions are distinguished, namely fast tracking, activity crashing and variability reducing. First, fast tracking entails overruling the original network structure of the project to reduce the total project duration, by executing precedence-related activities partially in parallel (Krishnan et al. 1997; Vanhoucke and Debels 2008; Ballesteros-Pérez 2017). Further, activity crashing is a technique to reduce the project duration by spending more money to reduce the duration of certain activities (Vanhoucke 2010b; Vanhoucke 2011; Hu et al. 2016). Finally, variability reducing consists of reducing the variability of activity durations by applying effort to control them (Madadi and Iranmanesh 2012; Martens and Vanhoucke 2019).

Project time forecasting

Project time forecasting involves predicting the final project duration given the current project performance. EVM time forecasting is an established project time forecasting approach. Several formulas have been proposed to determine the Estimate at Completion for time or the EAC(t), namely the Planned Value Method (PVM, Anbari (2003)), the Earned Schedule Method (ESM, Lipke (2003a)) and the Earned Duration Method (EDM, Jacob and Kane (2004)). It should be noted that this Earned Duration Method is different from the Earned Duration Method proposed by Khamooshi and Golafshani (2014). In Vandevoorde and Vanhoucke (2006), these forecasting techniques are compared by means of an extensive simulation study. The results of this study showed that the ESM method is the only method that produces reliable results during the entire project duration. The ESM formula to calculate the EAC(t) is as follows:

$$\text{EAC}(t) = \text{AT} + \frac{\text{PD} - \text{ES}}{\text{PF}} \tag{1}$$

with AT the actual time, PD the planned duration of the project and PF the performance factor, which is an indicator for future performance. The equivalent EDM time forecasting formula, the Estimated Duration At Completion (EDAC, Khamooshi and Golafshani (2014)), is defined as follows:

$$\text{EDAC} = \text{AT} + \frac{\text{PD} - \text{ED}}{\text{PF}} \tag{2}$$

According to Vandevoorde and Vanhoucke (2006), the most common performance factors are 1 and SPI(t). A PF of 1 can be used when future performance is expected to follow the baseline schedule, while the SPI(t) is used when the future performance is expected to be in line with the current time performance of the project. Similarly, the DPI can be used as a PF for the EDAC when the future performance is expected to be in line with the current time performance of the project. (Khamooshi and Golafshani 2014)

In recent literature, several studies focused on project time forecasting. Wauters and Vanhoucke (2015) studied the stability and accuracy of EVM forecasts by conducting a simulation study and using historical data. De Marco et al. (2009) conducted an empirical study to review the practicality and predictability of traditional forecasting methods. Further, Elshaer (2013) used Monte Carlo simulations to incorporate the activity sensitivity measures in the project time forecasting process. In Kim and Kim (2014), the sensitivity of EVM forecasting methods to the characteristics of the planned value and earned value S-curves of projects is examined. The concept of stochastically S-curves has been applied by Barraza et al. (2004) to improve the forecasting accuracy. Artificial Intelligence methods for project time forecasting have been in Wauters and Vanhoucke (2016) and

Wauters and Vanhoucke (2017). Exponential smoothing for project time forecasting, a forecasting method based on weighted averages of past observations, has been applied by Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) to give greater weights to the project performance in recent periods. Both Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) use simple exponential smoothing to smooth the performance factors for the project time forecasting formulas in equations (1) and (2). While Batselier and Vanhoucke (2017) focus on the accuracy of EVM time forecasting with exponential smoothing, Khamooshi and Abdi (2016) compare the accuracy of EVM and EDM for project time forecasting with exponential smoothing. For the EVM methodology, the smoothed performance factors of Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) are represented by equations (3) and (4) respectively:

$$\mathrm{SPI}(t)'_{t,KA} = \alpha \mathrm{SPI}(t)_t + (1-\alpha)\mathrm{SPI}(t)'_{t-1} \tag{3}$$

$$\mathrm{SPI}(t)'_{t,BV} = \frac{T_{t,ES}}{T_{t,AT}} = \frac{\alpha(\mathrm{ES}_t - \mathrm{ES}_{t-1}) + (1-\alpha)T_{t-1,ES}}{\alpha(\mathrm{AT}_t - \mathrm{AT}_{t-1}) + (1-\alpha)T_{t-1,AT}} \tag{4}$$

with $\mathrm{SPI}(t)'_{t,KA}$ and $\mathrm{SPI}(t)'_{t,BV}$ the smoothed performance factors at tracking period t of Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017), α the smoothing parameter, $T_{t,ES}$ the trend of the ES per period and $T_{t,AT}$ the trend of the actual time AT per period.

Selecting an appropriate value for α is an important aspect to achieve accurate project time forecasts. Generally, the closer the smoothing parameter is set to 1, the more weight is assigned to recent observations. Batselier and Vanhoucke (2017) introduced two viewpoints to determine an appropriate value for the smoothing parameters α, namely a static viewpoint and a dynamic viewpoint. In the *static viewpoint*, the smoothing parameter is set to a constant value for each tracking period. The *dynamic viewpoint* implies that the smoothing parameter may vary for different tracking periods. Batselier and Vanhoucke (2017) defined a qualitative and a quantitative dynamic approach. The *qualitative dynamic approach* entails that the smoothing parameter might be adjusted by the project manager, based on human insight. A *quantitative dynamic approach* entails using a quantitative approach to determine the smoothing parameter for each tracking period.

Khamooshi and Abdi (2016) applied the static viewpoint and varied α between 0.1 and 0.9, in steps of 0.1. They found that low values for α (e.g., $\alpha = 0.2$) produced the most accurate results. Batselier and Vanhoucke (2017) investigated both the static viewpoint and the quantitative dynamic viewpoint. The authors determined the static smoothing parameter using Reference Class Forecasting (RCF, (Kahneman and Tversky 1979; Lovallo and Kahneman 2003), by ascertaining the optimal α for a set of similar historical projects. Further, Batselier and Vanhoucke (2017) applied a quantitative dynamic approach as well, by setting the smoothing parameter for a tracking period as the optimal α for the previous tracking periods. The qualitative dynamic approach for project forecasting using exponential smoothing has not been applied yet, since it requires the real-time follow up of projects. Finally, according to Leon et al. (2018), the inability to include the impact of managerial interventions on the future project performance is an important limitation of existing project forecasting approaches, which prevents these approaches to be used as decision-support tools for project managers. Therefore, Leon et al. (2018) developed a system dynamics model to simulate the behavior of the real project and to predict the impact of managerial interventions on the future project performance.

Although many approaches for project time forecasting have been proposed in literature, the inability to include the impact of corrective actions on the future project performance remains an important limitation (Leon et al. 2018). Therefore, the aim of this study is to tackle this limitation by integrating the occurrence of corrective actions in the project time forecasting process. Accordingly, the improved forecasts provide more accurate information to the project manager. Exponential smoothing is used since it allows to assign different weights to different tracking periods (Batselier and Vanhoucke 2017; Khamooshi and Abdi 2016). Further, a qualitative dynamic smoothing parameter is applied to distinguish between periods with or without corrective actions.

METHODOLOGY

In this section, the data collection and documentation process is discussed. Subsequently, the applied approach to integrate corrective actions into project time forecasting is described and the settings of the empirical experiment are outlined.

Data collection and documentation

Batselier and Vanhoucke (2015a) have constructed a large and diverse database of empirical project data that can be used to validate project control methodologies in a real-life setting. This database contains more than 100 projects for which the baseline schedule, risk analysis and project control information is documented and has been used in several studies on project control and project forecasting (Martens and Vanhoucke 2018; Batselier and Vanhoucke 2015b; Colin and Vanhoucke 2016; de Andrade et al. 2019). However, in order to evaluate the performance of the proposed EAC(t)-CA and EDAC-CA forecasting techniques, the corrective actions that are taken during progress should be registered. Since this data is not included in the database of (Batselier and Vanhoucke 2015a), this database is not suitable for our study. Accordingly, recent projects had to be followed up in real time to document the required information on the corrective actions taken during project progress. More precisely, eight recently executed projects have been followed up in real-time by Martens and Mareels (2018). The baseline schedule, project control and corrective actions data has been added to the database of Batselier and Vanhoucke (2015a), Which is publicly available at www.projectmanagement.ugent.be/research/data/realdata (project IDs C2019-01 until C2019-08) and can thus be used for future research studies.

The data collection process followed by Martens and Mareels (2018) is represented in figure 1. Initial meetings were set up with project managers working for companies in the construction and production industry. When the project managers agreed to collaborate in this study and to share their data, one of their projects was selected to be followed up in real time. In order to be suitable for this study, the selected projects should be a number of criteria. First, the project should be started recently or in the near future, such that it could be followed up in real time. Second, both the planning and control data should be available at the activity level. Finally, in order to calculate the EVM/ES and EDM key metrics, the activity cost data should be available. Alternatively, cost data that are available at a higher level could be used if they could be converted to activity cost data after consulting the project manager. If these criteria are met, the project was followed up at each tracking period, by means of collected datafiles, meetings and on site visits. For each suitable project, not only the baseline schedule information (i.e. the planned activity durations and costs) and project control information (i.e. the actual activity durations and costs) has been monitored and documented, but also the information on the timing and nature of the corrective actions taken during project execution.

Table 1 shows the main characteristics of these projects, i.e. the baseline start and end, the industry, the Budget at Completion (BAC),the number of activities (# acts) and the number of tracking periods (# TPs). An overview of the actual performance of the monitored projects is given in table 2. This table lists the planned and actual duration and cost of each of the monitored projects. As this table shows, none of these projects has been completed on time, with delays ranging from negligible (0.85% of the planned duration) to substantial (58.26% of the PD). Further, only one project has been completed within the budget (i.e. P4, with a total cost that is 2% lower than the BAC).

Finally, for each of the projects, the timing and nature of the corrective actions that occurred have been documented. Based on the nature of the observed corrective actions, six different categories of corrective actions can be identified (table 3). Further, these categories are reviewed to determine to which type of corrective action discussed in literature (i.e. fast tracking, activity crashing and variability reduction) they belong. Finally, it should be noted that these six categories are based on the observed corrective actions taken during the 8 projects, and are thus not an exhaustive enumeration of all possible categories of corrective actions.

Table 3 denotes the different corrective action categories, their description and the corrective action type each category belongs to. *Status update calls* are phone calls, e-mails, personal tasks and informal feedback moments to apply pressure towards employees or subcontractors. *Using a new resource/supplier* entails the selection of another subcontractor, engineer or designer when current collaborations are likely to fail. Before this rather drastic type of action is used, the project manager often uses the *compensation claims in contracts* to apply pressure to the subcontractor, engineer or designer. Further, to enforce authority, the project manager might *involve higher management*. Finally, *working overtime* might be considered to speed up the progress of the project.

In order to determine the type of corrective action for each category, the following approach has been considered. If an observed corrective action of a category was executed to start a certain activity before its predecessors were finished, the action is labelled as *fast tracking*. Further, if the action aimed at applying pressure and reducing miscommunications to avoid delays, the action is considered as a *variability reducing action*. Finally, actions taken to speed up the progress and reduce an activity's duration are defined as *activity crashing*. As table 3 shows, actions from a specific category might belong to different types of corrective actions. For instance, status update calls to employees or subcontractors can be made to avoid miscommunications resulting in a delay (variability reducing) or to speed up the progress of a specific activity (activity crashing). Finally, table 4 gives an overview of the timing and type of corrective actions that have been taken during the execution of the eight projects. The most occurring corrective actions is making status update calls to employees, occurring in five of the eight projects. Using compensation claims in contracts and working overtime, however, both occurred only twice.

Procedure to integrate corrective actions in project time forecasting

In order to account for the effect of managerial interventions on the forecasting accuracy, exponential smoothing for project time forecasting will be used. As mentioned in the literature review, two studies have used exponential smoothing techniques to assign a greater weight to the performance of recent tracking periods and/or to account for potential corrective actions by the management, namely Batselier and Vanhoucke (2017) and Khamooshi and Abdi (2016). The approach used by these studies differs in three ways, namely (i) the procedure to smooth the schedule performance factor, (ii) the selection of an appropriate smoothing parameter value and (iii) the used project monitoring methodology. In the remainder of this section, these three aspects are discussed in greater detail and the choices made in this study are clarified. Table 5 summarises the settings of these aspects for the exponential smoothing procedures of Batselier and Vanhoucke (2017), Khamooshi and Abdi (2016) and this study.

Exponential smoothing procedure

The main difference between the approaches of Batselier and Vanhoucke (2017) and Khamooshi and Abdi (2016) is the most pronounced when smoothing parameter α is set to 1. In this case, equations (3) and (4) reduce to equations (5) and (6), respectively.

$$\mathrm{SPI}(t)'_t = \mathrm{SPI}(t)_t \tag{5}$$

$$\mathrm{SPI}(t)'_t = \frac{\mathrm{ES}_t - \mathrm{ES}_{t-1}}{\mathrm{AT}_t - \mathrm{AT}_{t-1}} \tag{6}$$

Hence, at tracking period t, the smoothed performance factor of Khamooshi and Abdi (2016) is equal to the SPI(t) (i.e., the cumulative progress of the project), while the smoothed performance factor of Batselier and Vanhoucke (2017) is based on the progress of the most recent tracking period only, and is thus more sensitive to changes in the project performance (such as incidents in recent periods causing severe delays or recent corrective actions that temporarily speed up the project progress). Thus, since the approach of Khamooshi and Abdi (2016) for smoothening the performance factor is less volatile than the approach of Batselier and Vanhoucke (2017) when corrective actions temporarily speed up the project progress, the former approach will be used in this study.

Smoothing parameter selection

Since corrective actions during project execution affect the project progress temporarily, the value of the smoothing parameter will be adapted when a corrective action has been taken in the most recent period. This entails that a *qualitative dynamic approach* is applied. More precisely, two distinct smoothing parameters will be used, namely α_1 if no corrective actions have been taken in the previous tracking period and α_2 when corrective actions have been taken in the previous tracking period. In order to review which values for α_1 and α_2 are appropriate, the forecasting accuracy for α_1 and α_2 ranging from 0.1 until 1, in steps of 0.1 will be evaluated. Hence, 10×10 combinations of α_1 and α_2 will be analysed. In the remainder of this paper, the proposed approach will be referred to as EAC(t)-CA and EDAC-CA, with CA indicating ‘Corrective Actions’.

Monitoring methodology

Comparing the performance of EVM and EDM project time forecasting has shown that EDM performance measures are better indicators for future performance than EVM performance measures (Khamooshi and Abdi 2016; de Andrade et al. 2019). In order to validate this observation, both the EAC(t) and EDAC formulas with smoothed performance factors will be evaluated in this study.

Empirical experiment

For each project, the project progress has been measured at each tracking period using EVM and EDM. Using this information, forecasts of the final project duration could be made at each tracking period. For both EVM and EDM, project time forecasts have been made using α_1 and α_2 varying from 0.1 to 1. The performance of EAC(t)-CA and EDAC-CA is compared to the standard EAC(t) formula with PF = 1 and PF = SPI(t), the standard EDAC formula with PF = 1 and PF = DPI, and the static exponential smoothing approach for EAC(t) and EDAC (referred to as EAC(t)-XSM and EDAC-XSM), with $\alpha_1 = \alpha_2$, varying from 0.1 to 1. The latter approach corresponds to the approach of Khamooshi and Abdi (2016). Each of these forecasting methods is evaluated in terms of forecasting accuracy, by means of the Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T} \mid \frac{A - F_t}{A} \mid \tag{7}$$

with A the actual duration at project completion, F_t the forecasted duration at tracking period t and T the number of tracking periods. Thus, the performance of the proposed forecasting approaches is evaluated by determining the average MAPE over all tracking periods of all projects.

RESULTS AND DISCUSSION

In this section, the results of the empirical experiment are discussed. First, the most appropriate values for smoothing parameters α_1 and α_2 are determined. Subsequently, the proposed approach is compared to the standard forecasting formulas and to the static exponential smoothing approach of Khamooshi and Abdi (2016).

Selection of smoothing parameters

Table 6 depicts the forecasting accuracy for the eight projects, with α_1 (columns) and α_2 (rows) varying from 0.1 to 1. Tables 6a and 6b represent the average MAPEs for EAC(t)-CA and EDAC-CA respectively. Table 6c shows the percentage change between the EAC(t)-CA and EDAC-CA MAPEs. In each subtable, the results for equal smoothing parameters α_1 and α_2, which represent the results for static exponential smoothing (EAC(t)-XSM and EDAC-XSM), are highlighted in bold italic.

From table 6, several findings can be conceived. First, the accuracy of EAC(t)-CA can be compared to EDAC-CA. Second, the combination of smoothing parameters α_1 and α_2 resulting in the lowest MAPE and thus the highest accuracy can be determined. Finally, the sensitivity of the forecasting accuracy to changes in α_1 and α_2 can be reviewed. In the remainder of this section, each of these aspects is discussed.

EVM vs EDM

Table 6c shows that, for each combination of α_1 and α_2, EDAC-CA has a lower MAPE and thus a higher forecasting accuracy than EAC(t)-CA. On average, the EDAC-CA MAPE is 14.49% lower than the EAC(t)-CA MAPE. This is in line with other recent empirical studies on project duration forecasting (e.g. Khamooshi and Abdi (2016)). Therefore, in the remainder of this section, the focus lies on the EDAC-CA results of table 6b.

Parameter selection

Table 6b shows that an α_1 and α_2 of respectively 0.1 and 0.7 ensure the highest forecasting accuracy (MAPE = 10.99%). Hence, when no corrective actions have been taken in the most recent period, a low smoothing parameter is preferred ($\alpha_1 = 0.1$), which is in line with the findings of Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017). However, if corrective actions have been taken during the most recent tracking period, a substantially higher smoothing parameter ($\alpha_2 = 0.7$) is recommended. This higher smoothing parameter allows to strike a balance between emphasising that the project progress during the previous tracking period has been improved due to managerial intervention, and recognising that this improved performance is likely to be temporarily.

Sensitivity analysis

Based on table 6b, the importance of selecting the right α_1 and α_2 can be assessed. In general, the forecasting accuracy reduces for increasing α_1. For α_2, the accuracy first increases for increasing α_2 but starts to decrease from a certain moment on (depending on the value of α_1). Further, the highest MAPE (14.89%) is obtained for $\alpha_1 = 1$ and $\alpha_2 = 0.1$. For this combination of smoothing parameters, the MAPE is 1.35 times higher than for the best performing combination. Due to the substantial difference between the forecasting accuracy of the best and worst performing combination of smoothing parameters, it can be concluded that an appropriate parameter selection is important to achieve a high forecasting accuracy. However, table 6b shows that the combinations of smoothing parameters leading to the highest forecasting accuracy are situated in the same area, namely a low α when no corrective actions have been taken (which is in line with recent literature) and a higher α after corrective actions to emphasise the performance of recent periods.

Project specific results

Since Vanhoucke and Vandevoorde (2007) argued that the forecasting accuracy depends on the completion stage of the project, the forecasting accuracy should be assessed for different stages of completion. Therefore, figure 2 depicts the overall MAPE and the MAPE for three project stages, namely the *early stage* ($0\% \leq PC \leq 30\%$), the *middle stage* ($30\% < PC \leq 70\%$) and the *late stage* ($70\% < PC \leq 100\%$) for each of the eight projects. This figure shows that the overall MAPE varies substantially between 2.23% and 26.25%. Further, for most projects (except P2 and P5), the early stage has a MAPE that is substantially higher than the MAPE of the middle and late stages. Moreover, the spread of the early stage MAPE (6.91% - 44.15%) is higher than the spread of the middle and late stages as well (0.01%-13.10% and 1.58%-8.94%), respectively. These observations confirm that the forecasting accuracy depends on the completion stage of the project. Therefore, the most accurate forecasting approach might depend on the completion stage of the project as well.

To summarise, the main conclusions from this section are that (i) EDAC-CA outperforms

EAC(t)-CA for each combination of smoothing parameters, (ii) smoothing parameters $\alpha_1 = 0.1$ and $\alpha_2 = 0.7$ result in the highest forecasting accuracy for EDAC-CA and (iii) the forecasting accuracy depends on the completion stage of the project. Accordingly, the next section compares the accuracy of the EDAC-CA approach with $\alpha_1 = 0.1$ and $\alpha_2 = 0.7$ to the standard forecasting approaches over the different stages of completion.

Comparison with standard methods

In this section, the forecasting accuracy of EDAC-CA is compared to the standard EDAC formulas with performance factors 1 and DPI, and to EDAC-XSM. The results are shown in table 7. The results for EDAC-XSM are defined as the lowest MAPEs from table 6b for $\alpha_1 = \alpha_2$, i.e. $\alpha = 0.2$.

The first row of table 7 represents the average forecasting accuracy over all tracking periods of all projects. The following rows list the results for the early, middle and late project stages. The column Improvement vs. standard methods' presents the percentage change of the EDAC-CA MAPEs to the best performing comparison method (i.e., the EDAC with PF=1, the EDAC with PF=DPI and EDAC-XSM). In order to evaluate the effect of using a qualitative dynamic smoothing parameter instead of a static smoothing parameter, the percentage change of the EDAC-CA MAPEs compared to EDAC-XSM is depicted in the column 'Improvement vs. EDAC-XSM'.

Overall comparison

Over the entire project makespan, table 7 shows that EDAC-CA has the lowest MAPE (10.99% vs. 11.38% for EDAC with PF=1) and is thus the most accurate forecasting method. However, the difference in performance is rather low, i.e. a percentage change of -3.40% compared to EDAC with PF=1. The effect of using a qualitative dynamic smoothing parameter compared to a static parameter is more distinctive (-11.58%). Consequently, considering corrective actions indeed improves the accuracy of project time forecasting with exponential smoothing. However, since the differences between the overall results are not very distinctive, they should be reviewed for the 3 different stages of project completion.

Comparison over different stages

Generally, table 7 shows that the forecasting methods are the least accurate in the early stage of projects. This can be explained by the fact that little information on the project progress is available in this stage. When more information becomes available (i.e., in the middle and late stages), the accuracy of the forecasting methods improves substantially.

More specifically, during the early stage, the standard EDAC formula with PF=1 is the most accurate forecasting method (17.66%) compared to the other EDAC forecasting methods. During the middle phase, EDAC-CA clearly outperforms EDAC-XSM and the standard EDAC formulas with PF=1 and PF=DPI. More precisely, during the middle phase, the EDAC-CA MAPE is 28.73% lower than EDAC-XSM 54.11% lower than the standard EDAC formulas. During the late stage of projects, EDAC-CA has a MAPE that is 9.88% lower than EDAC-XSM and 10.11% lower than the standard EDAC formulas. These results show that, during the early stage of projects, a performance factor of 1 leads to the most accurate forecasts, while from the middle stage on it is substantially more beneficial to use EDAC-CA. Accordingly, incorporating information on the timing of corrective actions during project execution and using exponential smoothing with appropriate values for the adaptive smoothing parameter generally leads to the most accurate project time forecasts.

Limitations

In this study, eight projects during which 19 corrective actions have been taken are considered. For each project, the timing and type of corrective actions has been documented (tables 3 and 4). Due to the unique character of projects, the restricted number of observed corrective actions cannot guarantee that the six identified categories of corrective actions are exhaustive. New categories can be identified by future research studies that document information on corrective actions of additional projects.

Moreover, currently, only the timing of these actions has been integrated in the forecasting process by adapting the smoothing parameter for exponential smoothing when an action has been taken in the most recent period. Although different types of corrective actions might affect the project progress differently, this aspect could not be investigated in this study due to the low number of observed corrective actions per category. In order to examine the impact of these different types of corrective actions and to further improve the forecasting accuracy, additional projects should be followed up and more information on corrective actions should be documented.

CONCLUSION

In this study, exponential smoothing for project time forecasting is used with a qualitative dynamic smoothing parameter to account for the impact of corrective actions on the project outcome. The forecasting accuracy of the proposed approach using EVM and EDM (EAC(t)-CA and EDAC-CA) has been compared to the EAC(t) and EDAC formulas with performance factors 1 and SPI(t) or DPI, and to exponential smoothing for EAC(t) and EDAC time forecasting with a static smoothing parameter.

The results of the experiment showed that the accuracy of the EDAC forecasting formulas is higher than that of the EAC(t) formulas. The most accurate results are obtained for EDAC-CA forecasting when a low smoothing parameter (i.e., 0.1) is used in case no corrective actions occurred during the most recent tracking period and a higher smoothing parameter (i.e., 0.7) is used in a period after corrective actions (MAPE=10.99%). Especially in the middle phase of projects, the EDAC-CA approach (MAPE=4.85%) clearly outperforms the standard EDAC formula with performance factors 1 and DPI and EDAC-XSM, with a percentage change of -28.73%. In the early project phase, however, project time forecasting with a performance factor of 1 leads to the highest forecasting accuracy (MAPE = 17.66%). Therefore, to obtain the most accurate project time forecasts during the entire project life cycle, it is recommended to use standard project time forecasting with PF =1 in the early phase of projects and to apply EDAC-CA from the middle project phase until project completion with a smoothing parameter of 0.7 in case a corrective action has been taken in the most recent period and a smoothing parameter of 0.1 otherwise.

Due to the lack of documented data on corrective actions during project execution, projects had to be followed up in real time from the project start until completion in order to collect the required data for this analysis. Future research could focus on monitoring additional projects to enhance the currently available data on corrective actions during project execution. With this additional data, the impact of different types of corrective actions taken during project execution on the project outcome can be evaluated to improve the project monitoring and forecasting process further.

DATA AVAILABILITY STATEMENT

Some or all data, models or code generated or used during the study are available in a repository online in accordance with funder data retention policies (url: http://www.projectmanagement.ugent.be/research/da

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List of Tables

ID	Project description	Baseline start	Baseline end	Industry	BAC (€)	# acts	#TPs
P1	Apartment complex	30/07/15	14/08/17	Residential building	1.192.979	86	10
P2	Social Housing	20/01/17	28/05/18	Residential building	734.602	18	10
P3	Emergency Department	15/07/16	13/02/18	Civil construction	967.878	17	22
P4	Nuclear Healthcare	06/01/16	09/06/17	Civil construction	4.318.950	33	24
P5	Fuel Tank Filter	09/05/16	20/05/18	Production	1.456.000	15	10
P6	Production line change	31/10/16	01/09/18	Production	1.512.000	23	11
P7	Gluing machine	11/09/17	06/04/18	Production	107.500	8	10
P8	Labeling machine	04/09/17	09/02/18	Production	114.700	7	9

TABLE 1. Overview of projects

ID	PD (workdays)	AD (workdays)	Deviation from PD (%)	BAC (€)	Total Cost	Deviation from BAC (%)
P1	533	672	26.08	1.192.979	1.315.820	10.30
P2	352	355	0.85	734.602	748.556	1.90
P3	413	521	26.15	967.878	1.270.876	31.31
P4	373	519	39.14	4.318.950	4.232.553	-2.00
P5	510	515	0.98	1.456.000	1.476.290	1.39
P6	480	501	4.38	1.512.000	1.534.060	1.46
P7	150	189	26.00	107.500	116.800	8.65
P8	115	182	58.26	114.700	128.200	11.77

TABLE 2. Outcome of projects

Category	Description	Type of action
C1	Status update call employees	variability reduction/activity crashing
C2	Status update call subcontractor	variability reduction/activity crashing
C3	Use new resource/supplier	activity crashing
C4	Use compensation claim in contracts	activity crashing
C5	Involve higher management	variability reduction/activity crashing
C6	Overtime work	activity crashing

TABLE 3. Observed categories of corrective actions

Project	Timing of action (TP)	Type of action
P1	3	C1
P1	6	C3
P1	9	C6
P2	4	C2
P3	1	C1
P3	5	C1
P3	7	C5
P3	15	C4
P4	9	C1
P4	20	C4
P5	3	C3
P5	8	C1
P6	2	C5
P6	4	C2
P6	8	C6
P7	1	C1
P7	7	C5
P8	4	C2
P8	7	C3

TABLE 4. Timing of corrective actions

	Batselier and Vanhoucke (2017)	Khamooshi and Abdi (2016)	This study
Smoothing procedure	equation (4)	equation (3)	$\text{SPI(t)}'_t = \alpha_i \text{SPI(t)}_t + (1 - \alpha_i)\text{SPI(t)}'_{t-1}$ $\text{DPI}'_t = \alpha_i \text{DPI}_t + (1 - \alpha_i)\text{DPI}'_{t-1}$
Smoothing parameter	static / quantitative dynamic	static	qualitative dynamic
Project monitoring	EAC(t)	EAC(t) and EDAC	EAC(t) and EDAC

TABLE 5. Summary exponential smoothing methods for project time forecasting

		α_1									
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
	0.1	***14.92***	14.86	14.92	15.11	15.35	15.63	15.88	16.09	16.23	16.36
	0.2	14.76	***14.68***	14.74	14.95	15.21	15.47	15.71	15.90	16.05	16.18
	0.3	14.62	14.51	***14.61***	14.82	15.08	15.32	15.55	15.74	15.90	16.04
	0.4	14.52	14.43	14.52	***14.72***	15.00	15.22	15.44	15.63	15.77	15.90
	0.5	14.43	14.37	14.44	14.67	***14.93***	15.13	15.34	15.52	15.66	15.86
α_2	**0.6**	14.39	14.31	14.37	14.63	14.86	***15.05***	15.25	15.41	15.55	15.67
	0.7	14.33	**14.25**	14.33	14.59	14.80	14.97	***15.16***	15.32	15.44	15.56
	0.8	14.28	**14.20**	14.34	14.57	14.76	14.92	15.09	***15.24***	15.36	15.48
	0.9	14.26	**14.22**	14.38	14.59	14.77	14.91	15.07	15.22	***15.34***	15.45
	1.0	14.28	14.30	14.43	14.61	14.77	14.90	15.06	15.20	15.31	***15.42***

(a) Impact of α_1 and α_2 on EAC(t)-CA MAPE

		α_1									
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
	0.1	***12.58***	12.75	13.02	13.27	13.52	13.78	14.08	14.40	14.66	14.89
	0.2	12.19	***12.43***	12.73	13.00	13.25	13.52	13.86	14.15	14.41	14.64
	0.3	11.87	12.16	***12.47***	12.75	13.02	13.33	13.65	13.94	14.18	14.41
	0.4	11.60	11.91	12.24	***12.53***	12.82	13.17	13.47	13.74	13.98	14.20
	0.5	11.38	11.71	12.04	12.35	***12.69***	13.02	13.31	13.56	13.79	14.09
α_2	**0.6**	**11.24**	11.58	11.93	12.29	12.61	***12.91***	13.18	13.41	13.63	13.83
	0.7	**10.99**	11.35	11.74	12.12	12.46	12.85	***13.10***	13.32	13.53	13.73
	0.8	**11.17**	11.57	11.94	12.26	12.53	12.79	13.02	***13.24***	13.43	13.63
	0.9	11.35	11.71	12.05	12.33	12.59	12.82	13.04	13.24	***13.43***	13.62
	1.0	11.55	11.87	12.17	12.42	12.65	12.87	13.07	13.26	13.44	***13.63***

(b) Impact of α_1 and α_2 on EDAC-CA MAPE

		α_1									
		0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
	0.1	***-15.68***	-14.17	-12.77	-12.15	-11.91	-11.86	-11.31	-10.53	-9.69	-9.00
	0.2	-31.37	***-15.35***	-13.64	-13.06	-12.88	-12.58	-11.79	-10.98	-10.22	-9.54
	0.3	-18,78	16.23	***-14.64***	-13.99	-13.68	-13.00	-12.19	-11.44	-10.79	-10.18
	0.4	-20.12	-17.46	-15.72	***-14.91***	-14.52	-13.50	-12.74	-12.08	-11.36	-10.71
	0.5	-21.11	-18.51	-16.64	-15.83	***-15.00***	-13.97	-13.26	-12.61	-11.94	-11.15
α_2	**0.6**	-21.91	-19.09	-16.98	-16.02	-15.11	***-14.21***	-13.60	-12.96	-12.36	-11.72
	0.7	-23.31	-20.36	-18.06	-16.94	-15.81	-14.18	***-13.61***	-13.04	-12.38	-11.78
	0.8	-21.75	-18.52	-16.71	-15.88	-15.07	-14.29	-13.71	***-13.15***	-12.54	-11.95
	0.9	-20,39	-17.64	-16.21	-15.48	-14.79	-14.02	-13.49	-13.01	***-12.46***	-11.84
	1.0	-19.15	-17.02	-15.66	-14.98	-14.34	-13.64	-13.22	-12.76	-12.19	***-11.59***

(c) Percentage change between EAC(t) and EDAC

TABLE 6. Impact of α_1 and α_2

	EDAC PF=1	EDAC PF=DPI	EDAC-XSM $\alpha = 0.2$	EDAC-CA $\alpha_1 = 0.1, \alpha_2 = 0.7$	Improvement vs. standard methods	Improvement vs. EDAC-XSM
Overall	11.38	13.03	12.43	10.99	-3.40	-11.58
Early	17.66	21.46	22.47	20.43	15.68	-9.10
Middle	11.92	10.56	6.80	4.85	-54.11	-28.73
Late	6.47	7.11	6.46	5.82	-10.05	-9.88

TABLE 7. Comparison of EDAC MAPEs (in %)

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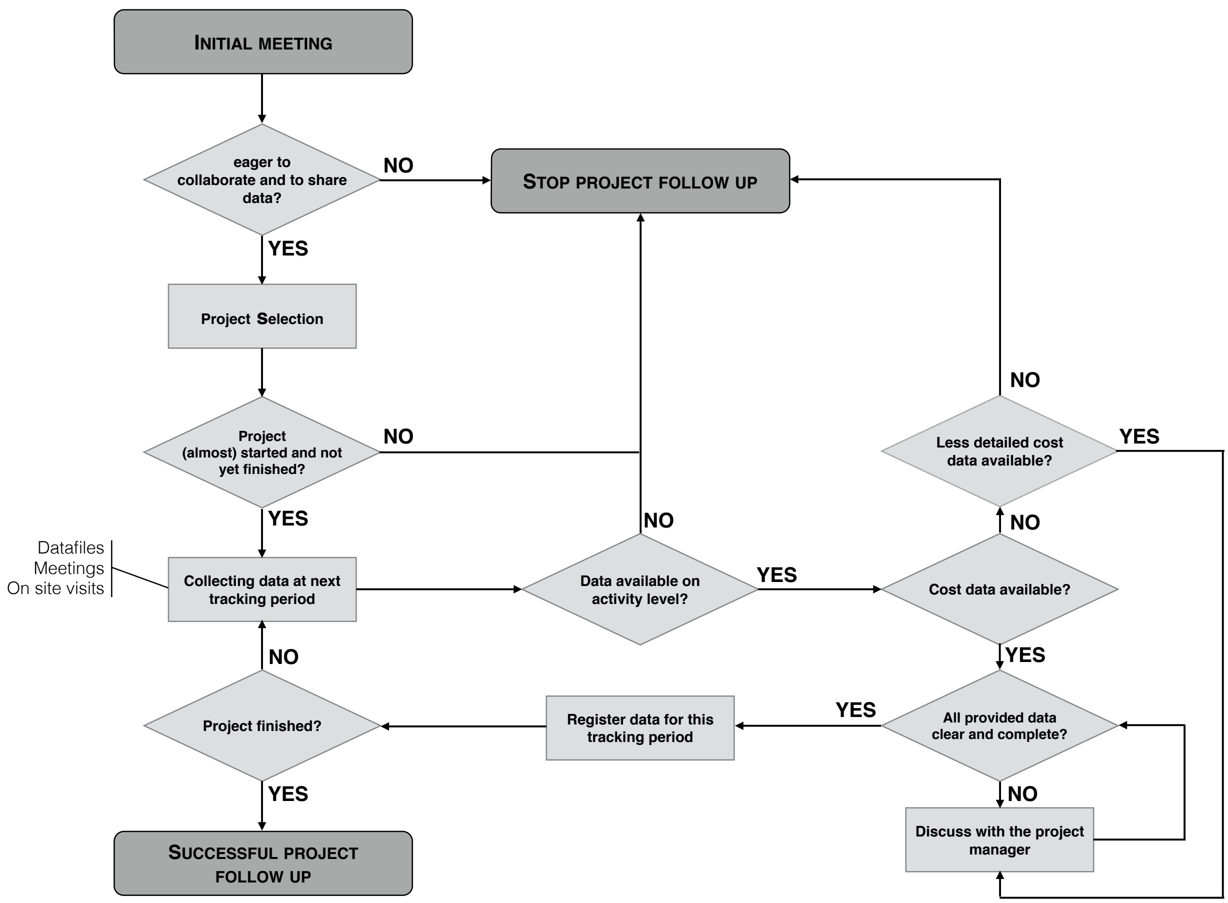

Fig. 1. Data collection process.

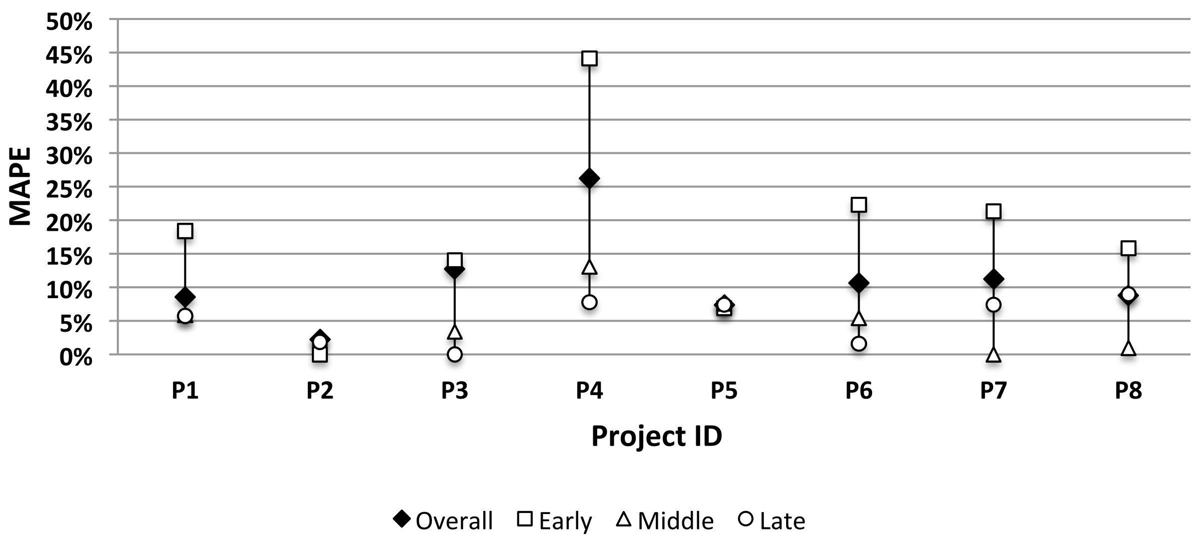

Fig. 2. EDAC-CA MAPEs for the eight projects with α_1 = 0.1 and α_2 = 0.7.