Using exponential smoothing to integrate the impact of corrective actions on project time forecasting

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1 Introduction

During project execution, uncertainty and risks often result in deviations from the plan. Therefore, project time forecasting is an important aspect of project management. The aim of this study is to improve the accuracy of project time forecasting by using exponential smoothing to account for the impact of corrective actions during project execution. The well-known project monitoring methodologies Earned Value Management (EVM, Fleming and Koppelman (2010)) and Earned Duration Management (EDM, Khamooshi and Golafshani (2014)) serve as a basis to forecast the final project duration. The forecasting accuracy of the approach presented in this study is evaluated for eight real-life projects that have been conducted in recent years and have been followed-up in real-time.

2 Project time forecasting

Project time forecasting is used to predict the final project duration during execution, given the current project performance. In recent literature, this topic has been explored in several studies. Barraza *et. al.* (2004) applied the concept of stochastical S-curves to improve the forecasting accuracy. De Marco *et. al.* (2009) reviewed the practicality and predictability of traditional forecasting methods by means of an empirical study. Monte Carlo simulations were used by Elshaer (2013) to incorporate the activity sensitivity measures in the project time forecasting process. Further, Kim and Kim (2014) examined the sensitivity of EVM forecasting methods to the characteristics of the planned value and earned value S-curves. Wauters and Vanhoucke (2015) used historical data and conducted a simulation experiment to study the stability and accuracy of EVM forecasts. Furthermore, Wauters and Vanhoucke (2016) and Wauters and Vanhoucke (2017) applied artificial intelligence methods for project time forecasting. Finally, exponential smoothing for project time forecasting has been applied by Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) to give greater weights to the project performance of recent periods.

Exponential smoothing is a technique for time series forecasting that assigns exponentially decreasing weights from recent to older observations. Both Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017) use simple exponential smoothing, which can be expressed as follows:

$$s_0 = x_0 \tag{1}$$

$$s_t = \alpha x_t + (1-\alpha)s_{t-1} \tag{2}$$

with x_t the raw data, s_t the forecasted values and α the smoothing parameter. The smoothing parameter α indicates the level of forecasting responsiveness to the most recent periods and can vary from 0 to 1. The closer α is set to 1, the more weight is assigned to recent observations.

Since determining an appropriate value for α is important to achieve accurate project time forecasts, Batselier and Vanhoucke (2017) introduced two viewpoints to select a value for α, namely a static viewpoint and a dynamic viewpoint. The *static viewpoint* entails that a constant value for α is selected for the entire project execution. A *dynamic viewpoint* implies that the value for α may vary for different periods during project execution. In this viewpoint, the smoothing parameter may be adjusted based on human insight of the project manager (*qualitative dynamic viewpoint*) or by using a quantitative approach (*quantitative dynamic viewpoint*). While Khamooshi and Abdi (2016) applied the static viewpoint, Batselier and Vanhoucke (2017) applied both the static and the quantitative dynamic viewpoint.

In this study, a qualitative dynamic viewpoint to set the smoothing parameter will be applied in order to account for the impact of corrective actions. More precisely, corrective actions are interventions taken by the project manager to get the project back on track. Since these interventions affect the project progress, the smoothing parameter α will be adapted when a corrective action has been taken during the most recent period. The methodology section describes the applied procedure to select adequate smoothing parameter values and discusses the case study data used to evaluate this procedure.

3 Methodology

3.1 Selection of smoothing parameter values

Since both EVM and EDM are established methodologies for project time forecasting, our approach will be applied to both EVM and EDM project time forecasting. In order to account for the impact of corrective actions on the project outcome, two distinct smoothing parameters will be used (α_1 and α_2). The α_1 smoothing parameter will be used when no corrective actions have been taken in the previous period, otherwise smoothing parameter α_2 is used to forecast the expected project duration with exponential smoothing.

In the empirical experiment, the forecasting accuracy for α_1 and α_2 will be evaluated for values ranging from 0.1 until 1 (in steps of 0.1) in order to determine which values for the smoothing parameters are appropriate. A total of 10×10 combinations of α_1 and α_2 will thus be analysed. The forecasting accuracy of the best performing combination of α_1 and α_2 will be compared to the traditional EVM and EDM forecasting methods and to EVM/EDM project time forecasting with exponential smoothing.

3.2 Case study

Since the presented approach requires the timing of corrective actions throughout the project execution, real-life projects had to be followed up in real time to document the required information on the project progress and timing of corrective actions taken during this progress. Therefore, eight recent projects have been followed up in real-time. The main characteristics of these projects are summarised in Table 1. The columns #acts and #TPs represent the number of activities and the number of tracking periods at which a forecast has been made, respectively.

Table 1. Main characteristics of table

ID	Project description	Baseline start	Baseline end	Industry	BAC (EUR)	# 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

4 Results

In the empirical experiment, the forecasting accuracy is measured using the Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}|\frac{A-F_t}{A}| \tag{3}$$

with T the number of periods, A the project duration at completion and F_t the forecasted project duration at period t. First, the presented approach is evaluated for EVM and EDM. Further, the most adequate combination of values for α_1 and α_2 is determined. Finally, the forecasting accuracy of the presented approach is compared to existing EVM and EDM forecasting methods. This comparison is made over the entire project lifecycle and for different stages of the project (early stage $= <$ 30% completion, middle stage = between 30% and 70 % completion and late stage $= >$ 70% completion).

The first part of the experiment showed that the presented approach applied to EDM resulted in a higher forecasting accuracy than EVM, for each combination of values for α_1 and α_2. More precisely, the MAPE for EDM is on average 14.49% lower than the EVM MAPE. This result is in line with previous studies on project time forecasting (Khamooshi and Abdi 2016, de Andrade *et al.* 2019). Further, the most accurate combination of smoothing parameters consists of a low value for α_1 (0.1) and a high value for α_2 (0.7). The low value for α_1, i.e., the smoothing parameter when no corrective actions have been taken in the previous period, is in line with the results of Khamooshi and Abdi (2016) and Batselier and Vanhoucke (2017). The higher smoothing parameter α_2 allows to emphasise that the project progress has been improved during the previous period due to a corrective action. Finally, compared to the traditional methods and exponential smoothing with a single smoothing parameter, the forecasting accuracy of the presented approach is slightly more accurate. However, when the forecasting accuracy is evaluated over the different project phases, the following observations are made. In the early phase, the accuracy of all forecasting methods is relatively low (average MAPE of 20%). This can be explained by the limited information that is available in this phase. In the middle and late phase, the accuracy of all forecasting methods improves. In these phases, the presented approach clearly outperforms the other forecasting methods. Compared to the standard EDM forecasting methods, the MAPE of the presented approach is more than 50% lower in the middle phase and 10% lower in the late phase. Compared to exponential smoothing with 1 smoothing parameter, the MAPE of the presented approach is 30% lower in the middle phase and 10% lower in the late phase.

To conclude, to obtain the most accurate project time forecasts during project execution, standard EDM forecasting can be used in the early project phase, while it is recommended to use the presented approach with $\alpha_1 = 0.1$ and $\alpha_2 = 0.7$ from the middle phase until project completion.

Future research could focus on collecting on additional projects to improve the currently available data on corrective actions during project execution. With this additional data, the most adequate smoothing parameters for different types of corrective actions and for different types of project can be determined.

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