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# Improving project forecast accuracy by integrating earned value management with exponential smoothing and reference class forecasting

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**Abstract**

In this paper, the earned value management (EVM) project control methodology is integrated with the exponential smoothing forecasting approach. This results in an extension of the known EVM and earned schedule (ES) cost and time forecasting formulas. A clear correspondence between the established approaches and the newly introduced method – called the XSM – is identified, which could facilitate future implementation. More specifically, only one smoothing parameter is needed to calculate the enhanced EVM performance factor. Moreover, this parameter can be dynamically adjusted during project progress based on information of past performance and/or anticipated management actions. Additionally, the reference class forecasting (RCF) technique can be incorporated into the XSM. Results from 23 real-life projects show that, for both time and cost forecasting, the XSM exhibits a considerable overall performance improvement with respect to the most accurate project forecasting methods identified by previous research, especially when incorporating the RCF concept.


*Keywords:* Project management; Time series forecasting; Duration forecasting; Cost forecasting; Project control; Empirical database

## 1. Introduction

Forecasting an ongoing project's actual duration and cost is an essential aspect of project management. One of the most widely used and best performing approaches for obtaining such forecasts is that based on the earned value management (EVM) methodology. To ensure the standalone comprehensibility of this paper, a concise summary of EVM's key definitions and formulas is included in Table 1.

The metrics below the middle line in Table 1 can be used to indicate a project's schedule and cost performance at a certain point during project execution (i.e. at a certain tracking period). More specifically, a schedule variance $SV$ or $SV(t) < 0$ ($> 0$) and a schedule performance index $SPI$ or $SPI(t) < 1$ ($> 1$) express that the project is behind (ahead of) schedule. Similarly, regarding project cost, a cost variance $CV < 0$ ($> 0$) and a cost performance index $CPI < 1$ ($> 1$) reflect a project that is over (under) budget. When the schedule or cost variances are equal to zero, the project is right on schedule or on budget, respectively. This corresponds with schedule or cost performance indices that are equal to unity.

The utility and reliability of EVM as a method for evaluating a project's current cost performance and forecasting its actual cost has been endorsed ever since the introduction of the technique in the 1960s. The performance of EVM for the time dimension, however, only got the necessary boost from the introduction of the extending concept of earned schedule (ES)

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Table 1
EVM key metrics and formulas.

| Metric | Definition/formula |
|---|---|
| *PD* | Planned duration, the planned total duration of the project |
| *BAC* | Budget at completion, the budgeted total cost of the project |
| *AT* | Actual time |
| *PV* | Planned value, the value[a] that was planned to be earned at *AT* |
| *EV* | Earned value, the value that has actually been earned at *AT* |
| *AC* | Actual cost, the costs that have actually been incurred at *AT* |
| *ES* | Earned schedule, the time at which the *EV* should have been earned according to plan, $ES = t + \frac{EV - PV_t}{PV_{t+1} - PV_t}$ with *t* the (integer) point in time (i.e. tracking period) for which $EV \geq PV_t$ and $EV < PV_{t+1}$ |
| *EAC*(*t*) | Estimated duration at completion, the prediction of *RD* made at *AT* |
| *EAC*($) | Estimated cost at completion[b], the prediction of *RC* made at *AT* |
| *RD* | Real duration, the actual total duration of the project |
| *RC* | Real cost, the actual total cost of the project |
| *SV* | Schedule variance, $SV = EV - PV$ |
| *SPI* | Schedule performance index, $SPI = \frac{EV}{PV}$ |
| *SV*(*t*) | Schedule variance (time), $SV(t) = ES - AT$ |
| *SPI*(*t*) | Schedule performance index (time), $SPI(t) = \frac{ES}{AT}$ |
| *CV* | Cost variance, $CV = EV - AC$ |
| *CPI* | Cost performance index, $CPI = \frac{EV}{AC}$ |
| *SCI* | Schedule cost index, $SCI = SPI * CPI$ |
| *SCI*(*t*) | Schedule cost index (time), $SCI(t) = SPI(t) * CPI$ |

[a] In these definitions, *value* always alludes to the cumulative value over all activities up to a certain point in time.
[b] In some papers, the estimated cost at completion is simply abbreviated by *EAC*, without the addition of the dollar sign. However, in other papers just as in this one, it is preferred to add the dollar sign anyhow in order to make a clearer distinction between the cost context and the time context (the latter is always indicated by a suffix *t*).

by Lipke (2003). A recent study (Batselier and Vanhoucke, 2015b) explicitly showed that, when implementing ES, EVM time forecasting is at virtually the same accuracy level as EVM cost forecasting. Therefore, the EVM technique can indeed be deemed a viable and valuable basis for the forecasting of both project duration and cost.

Furthermore, multiple extensions of the traditional EVM forecasting approaches have been proposed in literature the past several years (Kim and Reinschmidt, 2010; Lipke, 2011; Elshaer, 2013; Khamooshi and Golafshani, 2014; Mortaji et al., 2014; Baqerin et al., 2015; Chen et al., 2016). This list is obviously not exhaustive, as to provide a complete overview and description of the existing EVM extensions is beyond the scope of this study, and so is the quantitative comparison of all those techniques (including the one developed in this paper). The latter defines an evident subject for future research, similar to the study performed by Batselier and Vanhoucke (2015c), in which three EVM forecasting extensions (Lipke, 2011; Elshaer, 2013; Khamooshi and Golafshani, 2014) are compared and combined.

Another widely used and well-performing technique for making forecasts based on time series data is exponential smoothing. This technique arose in the late 1950s and early 1960s (Brown, 1956, 1959, 1963; Holt, 1957; Holt et al., 1960; Muth, 1960; Winters, 1960)[1] and has formed the basis for some of the most successful forecasting methods ever since. The main feature of an exponential smoothing method is that the produced forecasts are based on weighted averages of past observations, moreover, with the weights decaying exponentially as the observations age. Furthermore, the technique enables forecasting for time series data that display a trend and/or seasonality. For more background information regarding the origins, formulations, variations, applications, and state-of-the-art of exponential smoothing, the reader is referred to Gardner (2006). Nevertheless, the formulations relevant to the study in this paper will also be presented in later sections.

Although the technique of exponential smoothing is mainly used in financial and economic settings, it can in fact be applied to any discrete set of repeated measurements (i.e. to any time series). Since the tracking data gathered during project progress constitute a time series, exponential smoothing can also be applied to forecast project duration and project cost. Intuitively, this shows potential. Indeed, traditional EVM forecasting assigns equal importance (or weight) to all past observations, whereas the exponential smoothing approach makes it possible to gradually decrease the weights of older observations. The latter could be a very useful feature in a project management context, as it allows to account for the effect of both natural performance improvement and corrective management actions that might occur during the course of a project (see Section 2.1 for a more elaborate discussion).

Therefore, a novel forecasting approach for both project duration and project cost based on the integration of well-known EVM metrics in the exponential smoothing forecasting technique is developed in this paper. From now on, this novel approach will be referred to as the XSM, which is an acronym for eXponential Smoothing-based Method. Moreover, note that the general notation of XSM refers to both the time and cost forecasting dimension of the novel technique. As an overview, all notations for the different components of the XSM that will be introduced and discussed later in this paper are presented in Appendix A.

The outline of this paper can be summarized along the following lines. The derivation of the XSM formulations and explanation of their application (static/dynamic) will be the subject of Section 2, preceded by a qualitative discussion on the motivation for adapting the current EVM forecasting methods and why the exponential smoothing technique is appropriate for this. Furthermore, in the same section, we will make the link between the XSM and the established EVM forecasting methods. Section 3 then proposes an evaluation approach for the XSM, based on accuracy comparison with the known EVM top forecasting techniques. Furthermore, the proposition to incorporate the reference class forecasting (RCF) technique – in which a relevant reference class of similar historical projects is used as a basis for making forecasts for the considered project – into the XSM methodology is made in Section 3.2. In Section 4, the results of the evaluation are presented and discussed, for time forecasting as well as for cost forecasting. Moreover, both a static and a dynamic approach to the XSM will be assessed. Finally, Section 5 draws more general conclusions and suggests several future research actions.

[1] The 1957 report by Holt (1957) has been republished as Holt (2004) in order to provide greater accessibility to the paper.

## 2. Development of the XSM

### 2.1. Limitations of the established EVM forecasting methods

First, consider EVM time forecasting. In Batselier and Vanhoucke (2015b), it was shown that the earned schedule method (ESM) introduced by Lipke (2003) and further developed by Henderson (2004) provides the most accurate project duration forecasts, and this compared to the two other commonly used EVM time forecasting approaches, being the planned value method (PVM) by Anbari (2003) and the earned duration method (EDM)[2] by Jacob and Kane (2004). In this paper, we will therefore only focus on the ESM, of which the generic forecasting formula proposed by Vandevoorde and Vanhoucke (2006) is presented here (metrics defined in Table 1):

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

In this formula, the performance factor *PF* can either be 1, *SPI*(*t*) or *SCI*(*t*), respectively reflecting that future schedule performance is expected to follow the baseline schedule, the current time performance, or both the current time and cost performance. In this paper, the less common performance factor of *SCI*(*t*) will not be considered. Regarding the performance factor, empirical studies (Guerrero et al., 2014; Batselier and Vanhoucke, 2015b) showed that, in general, the unweighted ESM ($PF = 1$), referred to as $ESM - 1$ from now on, clearly provides the most accurate time forecasts. However, one could argue that this method is intuitively not realistic as it does not take into account the current schedule performance. On the other hand, the *SPI*(*t*)-weighted method $ESM - SPI(t)$ does take into account past achievements. This method comes out on top in the simulation study of Vanhoucke (2010). Then again, the *SPI*(*t*) reflects the *cumulative* schedule performance, which assumes that the performance of *every* past tracking period has an equal influence on the future expectations. This implies that the *SPI*(*t*) cannot accurately account for the following two possible influences, which are generally not incorporated in simulation studies:

- The occurrence of natural performance improvement during the course of the project due to increasing experience levels of the resources (e.g. workers).
- The effect of corrective management actions that were taken recently with the aim of improving future performance.

Indeed, the *SPI*(*t*) will always drag along the performance of the earliest project phases as well. To overcome these drawbacks, it seems appropriate to assign more weight to the performance of the latest tracking periods as these best represent the effect of experience-driven performance improvement and/or the impact of current management efforts. In contrast to $ESM - SPI(t)$, $ESM - 1$ does more or less incorporate the effect of increasing experience levels and upcoming corrective actions by assuming that future performance will be exactly according to plan (i.e. following the baseline schedule). Obviously, an intuitive problem with this assumption arises from the use of the term *exactly*. First of all, there is no guarantee that an experience-driven performance improvement would appear (so that future productivity would increase of itself) or that any corrective action for improving future performance will actually be taken. Moreover, if such occasions were to occur, it is highly unlikely that they would result in an exact future compliance with the original plan.

Above discussion identifies the need for a novel time forecasting method that is situated somewhere in between $ESM - 1$ and $ESM - SPI(t)$. Moreover, this method should be able to assign more weight to the more recent tracking periods, accounting for the potential effect of increasing experience levels of resources and/or corrective actions by management. Furthermore, we add the additional requirement that the novel method should be able to express *anticipated* changes in management attention (note the difference with management actions that have already effectively taken place) through an adjustable parameter. Taking all these prerequisites into account, the technique of exponential smoothing soon arises as the ideal base for the development of the desired new time forecasting method. More (mathematical) details on the exponential smoothing technique and its applications in project forecasting will be provided in Section 2.2.

Note that the discussion in previous paragraphs only concerned time forecasting. Now consider EVM cost forecasting. The generic cost forecasting formula is very similar to Eq. (1) for time forecasting (metrics defined in Table 1):

$$EAC(\$) = AC + \frac{BAC - EV}{PF} \quad (2)$$

The performance factors *PF* that are considered here are 1 and *CPI*. These are two of the most commonly used performance factors for cost forecasting and, moreover, according to Batselier and Vanhoucke (2015b) the ones also leading to the highest forecasting accuracy. From now on, we will designate both methods by $EAC - 1$ and $EAC - CPI$, respectively.

First of all, note the obvious resemblance between *SPI*(*t*) for time (expressing the project's *schedule* performance) and *CPI* for cost (expressing the project's *cost* performance). Therefore, the drawbacks identified for $ESM - 1$ and $ESM - SPI(t)$ also apply for $EAC - 1$ and $EAC - CPI$, respectively. In other words, the discussion on $ESM - 1$ also holds for $EAC - 1$, and similarly, the comments made on $ESM - SPI(t)$ are also true for $EAC - CPI$. Of course, the discussion has to be placed in a cost context instead of a time context (i.e. *SPI*(*t*) becomes *CPI*), but nonetheless, the fundamental ideas remain the same. However, the drawback of *SPI*(*t*) of it not being able to account for the presence of experience-driven performance improvement might be sensed as less relevant for *CPI*, as cost evolutions in a project are not intuitively linked to experience.

[2] This EDM should not be confused with the earned duration management methodology – also abbreviated as EDM – proposed by Khamooshi and Golafshani (2014) and examined by Batselier and Vanhoucke (2015c) and Vanhoucke et al. (2015).

Nevertheless, when resources begin to work more efficiently due to increased experience levels, the resource costs (and other variable costs) reduce as the tasks being performed take less time to complete. Moreover, *CPI* does certainly exhibit the same disadvantage as *SPI*(*t*) that it cannot effectively take into account the impact of recently implemented management actions on future performance. Therefore, parallel to time forecasting, we can state that there is a need for a novel cost forecasting method that is situated somewhere in between *EAC* − 1 and *EAC* − *CPI*. Correspondingly, the exponential smoothing technique can serve as a basis here as well, ensuring that the novel cost forecasting method will meet the same requirements as were imposed on the novel time forecasting method (i.e. the ability to assign more weight to more recent tracking periods, and the ability to express anticipated changes in management attention through an adjustable parameter). In order to make a clear distinction between the exponential smoothing-based forecasting method for project duration and that for project cost, these methods are from now on denoted by XSM(t) and XSM($), respectively. Recall that an overview of the utilized notations for the different components of the XSM can be found in Appendix A.

## 2.2. Derivation of the XSM formulations

As mentioned repeatedly in previous sections, the technique of exponential smoothing will provide the basis for both the novel time and cost forecasting methods developed here. It was already indicated that the XSM would be built by incorporating the known EVM metrics into the exponential smoothing formulas. Since all EVM key metrics (see Table 1), both those related to time (*AT* and *ES*) and to cost (*AC* and *EV*), show an obvious and intrinsic upward trend – but no seasonality – we can apply Holt's double exponential smoothing method (Holt, 1957, 2004). The basic formula is:

$$F_{t+k} = L_t + kT_t \tag{3}$$

with $t$ the current time period, $k$ the number of periods over which we want to forecast, $F_{t+k}$ the forecasted value for time period $t+k$, $L_t$ the long-term level or base value, and $T_t$ the trend per period. $L_t$ and $T_t$ can be calculated as follows:

$$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{4}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{5}$$

where $\alpha$ and $\beta$ are the smoothing constants and $y_t$ is the actual value at time period $t$.

In this case, the actual values $y_t$ are represented by $AT_t$ and $ES_t$ for time forecasting, and $AC_t$ and $EV_t$ for cost forecasting.[3]

[3] In fact, the notations $AT_t$, $ES_t$, $AC_t$ and $EV_t$ have exactly the same meaning as the respective standard notations *AT*, *ES*, *AC* and *EV* without the subscript *t*, as presented in Table 1. However, the subscript *t*, indicating that it concerns the values for the current tracking period (notice that *tracking* period is a project management concretization of the general term *time* period), is included here, as it will be needed in upcoming formulations. For example, $ES_{t-1}$ will indicate the *ES* value for the previous tracking period.

It can be deemed logical here to use the unadapted actual values as a base for both time and cost forecasts. Indeed, one can never go back in time and incurred costs can never be undone, so the actual values (i.e. *AT*, *ES*, *AC* and *EV*) will never decrease. Therefore, $\alpha$ is fixed to 1 for both time and cost forecasting, meaning that the actual values are not smoothed. Hence, Eq. (4) is simplified to $L_t = y_t$. The trend $T_t$, however, remains available for smoothing via the parameter $\beta$.

In the next two subsections, the above general formulas will be concretized for time forecasting (i.e. XSM(t)) and cost forecasting (i.e. XSM($)), respectively, through the introduction of the corresponding EVM metrics. Then, in a last subsection, a possible approach for the dynamic use of the XSM during project progress is proposed.

### 2.2.1. Time forecasting: XSM(t)

Eqs. (3)–(5) can now be concretized for time forecasting. Note that Eq. (4) is no longer explicitly mentioned but rather directly substituted into Eq. (3), as this becomes quite straightforward through the simplification of $L_t = y_t$. Furthermore, we can identify two situations: the real situation according to the actual project progress represented by Eqs. (6) and (7), and the planned situation according to the baseline schedule represented by Eqs. (8) and (9).

$$EAC(t) = AT_t + kT_{t,AT} \tag{6}$$

$$T_{t,AT} = \beta(AT_t - AT_{t-1}) + (1-\beta)T_{t-1,AT} \tag{7}$$

$$PD = ES_t + kT_{t,ES} \tag{8}$$

$$T_{t,ES} = \beta(ES_t - ES_{t-1}) + (1-\beta)T_{t-1,ES} \tag{9}$$

Note that we define $T_{0,AT} = T_{0,ES} = PD/N$ with $N$ the expected number of tracking periods according to the baseline schedule.

Eq. (6) is the formula needed for obtaining a forecasted project duration. However, at a certain tracking period $t$ during the project, one cannot know in advance how many tracking periods $k$ there are still to come. To obtain a time-based estimate of the expected number of upcoming tracking periods, Eq. (8) is reshaped into:

$$k = \frac{PD - ES_t}{T_{t,ES}} \tag{10}$$

This $k$ can then be substituted into Eq. (6), so that we obtain:

$$EAC(t) = AT_t + \frac{PD - ES_t}{T_{t,ES}} T_{t,AT} \tag{11}$$

or

$$EAC(t) = AT_t + \frac{PD - ES_t}{T_{t,ES}/T_{t,AT}} \tag{12}$$

Notice that Eq. (12) seems to perfectly correspond to the generic ESM time forecasting formula of Eq. (1). Indeed, fully equal expressions are obtained when the performance factor of Eq. (13) is introduced into Eq. (1).

$$PF = \frac{T_{t,ES}}{T_{t,AT}} = \frac{\beta(ES_t - ES_{t-1}) + (1-\beta)T_{t-1,ES}}{\beta(AT_t - AT_{t-1}) + (1-\beta)T_{t-1,AT}} \tag{13}$$

As such, it can be stated that the exponential smoothing technique has in fact been integrated in the established EVM time forecasting approach. Let us now elaborate on the derived performance factor of Eq. (13), more specifically, on how it is influenced by the smoothing parameter $\beta$. Two extreme cases can be identified.

First, if $\beta=1$ (maximum responsiveness to the current schedule performance) then $PF=SPI(t)_{inst}$.[4] In this case, the effect of a corrective management action performed during the current tracking interval would be integrally extrapolated to the remaining portion of the project. For example, consider a situation where management has assigned extra resources to a particular project during the last tracking interval. Assume this has lead to a considerable increase in schedule performance for this last interval, compared to the performance earlier in the project. In this case, a choice of $\beta=1$ ($PF=SPI(t)_{inst}$) would imply the assumption that the recently achieved augmented schedule performance will be maintained for the rest of the project's life (i.e. this would reflect a situation where the extra resources remain in service until the very end of the project and maintain the current performance level).

On the other hand, if $\beta=0$ (no responsiveness to the current schedule performance) then $PF=T_{t-1,ES}/T_{t-1,AT}=T_{0,ES}/T_{0,AT}=1$, producing the well-known $ESM-1$ method, which assumes that future progress will be exactly according to plan (i.e. according to the baseline schedule). The XSM(t) thus also covers the method that, according to earlier studies, produces the most accurate project duration forecasts.

Obviously, one is not limited to only using one of these two extreme $\beta$s. There is an entire spectrum of $\beta$ values, ranging from 0 to 1, possible for selection. The general rule is that the closer $\beta$ is chosen to 1, the more weight is assigned to the more recent tracking periods. The extremum is of course $\beta=1$, for which only the very latest tracking interval is taken into account. The parameter $\beta$ of the proposed method thus provides the required possibility of adjusting the level of forecast responsiveness to the more recent schedule performance of the project.

#### 2.2.2. Cost forecasting: XSM($)

The derivation of the cost forecasting formulations is very similar to that performed for time forecasting in previous subsection. Therefore, some repetition may be observed. However, explicit derivation of the novel cost forecasting formulas is needed to ensure the comprehensibility of the method.

Parallel to time forecasting, Eqs. (3)–(5) are now concretized for cost forecasting, with Eq. (4) no longer explicitly mentioned but rather directly substituted into Eq. (3). Again, we can identify two situations: the real situation according to the actual project expenditures represented by Eqs. (14) and (15), and the planned situation according to the baseline costs represented by Eqs. (16) and (17).

$$EAC(\$) = AC_t + kT_{t,AC} \tag{14}$$

$$T_{t,AC} = \beta(AC_t - AC_{t-1}) + (1-\beta)T_{t-1,AC} \tag{15}$$

$$BAC = EV_t + kT_{t,EV} \tag{16}$$

$$T_{t,EV} = \beta(EV_t - EV_{t-1}) + (1-\beta)T_{t-1,EV} \tag{17}$$

Here, we define $T_{0,AC}=T_{0,EV}=BAC/N$ with $N$ the expected number of tracking periods according to the baseline schedule.

Eq. (14) will provide the forecasted project cost. However, a cost-based estimate of the expected number of upcoming tracking periods $k$ is first required. Therefore, Eq. (16) is reshaped into:

$$k = \frac{BAC - EV_t}{T_{t,EV}} \tag{18}$$

This $k$ can be substituted into Eq. (14), yielding:

$$EAC(\$) = AC_t + \frac{BAC - EV_t}{T_{t,EV}} T_{t,AC} \tag{19}$$

or

$$EAC(\$) = AC_t + \frac{BAC - EV_t}{T_{t,EV}/T_{t,AC}} \tag{20}$$

Notice that introducing the performance factor of Eq. (21) into the generic EVM cost forecasting formula of Eq. (2) produces the exact same expression as Eq. (20).

$$PF = \frac{T_{t,EV}}{T_{t,AC}} = \frac{\beta(EV_t - EV_{t-1}) + (1-\beta)T_{t-1,EV}}{\beta(AC_t - AC_{t-1}) + (1-\beta)T_{t-1,AC}} \tag{21}$$

Therefore, it can be stated that – just as for time forecasting – the exponential smoothing technique has hereby been integrated in the established EVM cost forecasting approach. The following discussion on the influence of the smoothing parameter $\beta$ on the derived performance factor of Eq. (21) is similar to that conducted in Section 2.2.1, but now situated in a cost context. Again, two extreme cases can be identified, and $\beta$ can be chosen anywhere between these two extremes.

First, if $\beta=1$ (maximum responsiveness to the current cost performance) then $PF=CPI_{inst}$.[5] The effect of a corrective management action performed during the current tracking

[4] $SPI(t)_{inst}$ is the instantaneous $SPI(t)$, reflecting the schedule performance over the last tracking interval. More specifically, $SPI(t)_{inst}$ is calculated by dividing the increase in $ES$ during the last tracking interval by the corresponding increment of $AT$, or $(ES_t-ES_{t-1})/(AT_t-AT_{t-1})$. Notice the difference between $SPI(t)_{inst}$and the standard cumulative $SPI(t)$, which represents the schedule performance over the *entire* project up to the current tracking period.

[5] $CPI_{inst}$ is the instantaneous $CPI$, reflecting the cost performance over the last tracking interval. More specifically, $CPI_{inst}$ is calculated by dividing the increase in $EV$ during the last tracking interval by the corresponding increase in $AC$. Notice the difference between $CPI_{inst}$ and the standard cumulative $CPI$, which represents the cost performance over the *entire* project up to the current tracking period.

interval would then integrally be extrapolated to the remaining portion of the project. For illustration purposes, now consider the same example as introduced for time forecasting in Section 2.2.1. As a reminder, it concerns a situation where management has assigned extra resources to a particular project during the last tracking interval. This intervention has lead to a considerable increase in schedule performance for this last interval, but since hiring extra resources incurs extra expenses, cost performance has deteriorated significantly. In this case, having set the cost-related $\beta$ to 1 ($PF=CPI_{inst}$) would imply the assumption that the recent deterioration in cost performance will continue for the rest of the project's life (i.e. this would reflect a situation where the extra resources remain in service – and thus incur extra costs – until the very end of the project).

On the other hand, if $\beta=0$ (no responsiveness to the current cost performance) then $PF=T_{t-1,EV}/T_{t-1,AC}=T_{0,EV}/T_{0,AC}=1$, producing the well-known $EAC-1$ method, which assumes that future spending will be exactly according to plan (i.e. in accordance with the baseline costs). Parallel to time forecasting, the XSM($) thus also covers the method that delivers the most accurate project cost forecasts according to earlier studies.

### 2.2.3. Dynamic application of the XSM

The previous sections may have left the impression that the value for the smoothing parameter should be chosen before the project starts and then remains constant throughout the entire project. This is indeed a possible approach, which we will call the *static* approach. However, $\beta$ values do not necessarily have to be the same for every tracking period. For example, we can set $\beta=1/t$, with $t$ the respective tracking period number. In this way, we obtain the exact same forecasts as $ESM-SPI(t)$ for time, and as $EAC-CPI$ for cost. Notice, however, that it is not our intention to use either $SPI(t)$ or $CPI$ as a performance factor, as our goal was to create forecasting methods that assign more weight to the performance of the latest tracking periods, to which end the standard cumulative $SPI(t)$ and $CPI$ are not fit. Anyhow, the novel XSM methodology can be said to provide a universal definition for both the main schedule ($SPI(t)$, $SPI(t)_{inst}$ and 1) and cost ($CPI$, $CPI_{inst}$ and 1) performance factors as a function of just one parameter $\beta$.

Note, however, that setting $\beta$ to $1/t$ for every tracking period can still be seen as a static approach; although the $\beta$ values will be different for every tracking period, they are still fixed prior to the project start and are not adapted during project progress. However, as $SPI(t)$ and $CPI$ are undesirable performance factors in the context of this paper, the term *static* approach will from now on only be used to refer to the case where $\beta$ indeed retains a constant value for every tracking period. On the other hand, an approach where the smoothing parameter can be adjusted every tracking period is called a *dynamic* approach and the corresponding variable parameter is denoted by $\beta_{dyn}$.[6] There are two versions of the dynamic approach.

A first one is based on quantitative analysis. More concretely, the $\beta_{dyn}$ value for a certain tracking period is defined as the $\beta$ – so a constant value equal for all preceding tracking periods – that would have produced the most accurateforecasts over all of these preceding tracking periods. The performance data of these passed tracking periods are of course known, so a nonlinear optimization problem can be modeled of which the solution defines the optimal $\beta$ (i.e. the $\beta$ that would have yielded the highest forecasting accuracy) over all past tracking periods. This calculated optimal $\beta$ is then adopted as the $\beta_{dyn}$ value for the current tracking period, following the principle that the historic optimal $\beta$ is the best estimate for the future optimum. When we perform this procedure for every tracking period during the project, a sequential series of potentially different values of $\beta_{dyn}$ is obtained. We then say to apply the *quantitative* dynamic approach to the proposed XSM forecasting methodology.

Notice that previous approach does not require any human insights. However, in some situations it might be appropriate not to eliminate the possibility of allowing personal assumptions to influence the choice of $\beta_{dyn}$ at a certain point in time. For example, consider a project that is about halfway but showed very poor schedule[7] performance during this first half. However, management was aware of the problem and has now taken some corrective actions, which after a first evaluation seem to greatly improve the schedule performance. Since the improved schedule performance is, however, only a very recent phenomenon, quantitative dynamic calculations will not yet take it into account. At this point, management can decide that the higher schedule performance in fact best reflects the expected future performance (i.e. this means stating that the higher performance will be maintained in the future). To produce time forecasts that reflect this vision, management can increase the $\beta_{dyn}$ (set it closer to 1) so that the forecasts become strongly based on the more recent tracking periods, and thus on the improved schedule performance. Of course, this approach cannot rely on the support of quantitative calculations. Instead, management has to select the most appropriate $\beta_{dyn}$ value at a certain time based on their own experience and insight. Therefore, this approach can be seen as a *qualitative* dynamic implementation of the XSM.

## 3. Evaluation approach

The main objective of the remainder of this paper is to compare the accuracies[8] of the XSM with those of the most common and best performing established EVM forecasting methods, and this for both time and cost. Therefore, we make use of a selection of projects from the real-life project database of Batselier and Vanhoucke (2015a), which are presented in Section 3.1. Regarding the evaluation of the XSM, both the static approach (Section 3.2) – including the incorporation of

[6] It is important to realize that the general smoothing parameter notation "$\beta$"" (without subscript) reflects a constant value and therefore expresses the application of the static approach, whereas "$\beta_{dyn}$"" indicates that it concerns a variable value and thus the dynamic approach. This is also made clear in Appendix A.

[7] A completely similar reasoning can be followed for the cost dimension.

[8] Accuracy is generally accepted as the most important criterium for evaluating the performance of forecasting methods (Carbone and Armstrong, 1982). The other quality-determining aspects of forecasts, namely stability and timeliness (Covach et al., 1981), are not considered in this paper. The evaluation of these aspect is left to future research.

the RCF concept – and the dynamic approach (Section 3.3) will be considered. Note that the discussions in these sections always apply to both time and cost forecasting. Furthermore, the applied approach for evaluating forecasting accuracy is explained in Section 3.4.

### 3.1. Project data

23 real-life projects from the database of Batselier and Vanhoucke (2015a) were considered fit for the upcoming study. All of these projects contain fully authentic baseline schedule and tracking data that were received directly from the actual project owners.[9] 21 of the projects can be situated within the broad construction sector,[10] the other two are IT projects. Furthermore, project durations range from only two months to more than three years, and project budgets from less than € 200,000 to over € 60,000,000. More detailed information for the individual projects is presented in Table 2. Moreover, a more extended presentation of the considered projects together with all corresponding project data are publicly available at www.or-as.be/research/database, both in ProTrack (www.protrack.be) and MS Excel format thanks to the novel software tool PMConverter. The concerning projects can be retrieved through the project codes indicated in the first column of Table 2.

### 3.2. Static approach

For every project, it is assessed which constant $\beta$ value produces the most accurate forecasts (i.e. $\beta_{opt}$). Moreover, the optimal $\beta$ over all projects (i.e. $\beta_{opt,oa}$) is determined and the resulting overall accuracies are compared to those for the most common and best performing established EVM forecasting methods.

However, it is very important to realize that utilizing $\beta_{opt,oa}$ does not entail any intelligent methodology for assigning the most appropriate $\beta$ to a certain project prior to the project start, as $\beta_{opt,oa}$ is simply determined as the $\beta$ that yields the best forecasting accuracy over *all* 23 projects in the database. These projects are – as indicated in Table 2 – quite diverse with regard to sector, budget, duration, etc. As no significant similarities exist between the entirety of projects (beside the fact that the vast majority is situated within the broad construction sector), there is no reason why the $\beta_{opt}$ of a certain project should be considered for the determination of the most appropriate $\beta$ for another – unrelated – project. Nevertheless, this is exactly what is done when $\beta_{opt,oa}$ is applied.

Table 2
Properties of the considered projects.

| Project code | Project name | Sector | PD [days][a] | BAC [€] |
|---|---|---|---|---|
| C2011–05 | Telecom System Agnes | IT (medical applications) | 43 | 180,485 |
| C2011–07 | Patient Transport System | IT (medical applications) | 389 | 180,759 |
| C2011–12 | Claeys-Verhelst Premises | Construction (commercial building) | 442 | 3,027,133 |
| C2011–13 | Wind Farm | Construction (industrial) | 525 | 21,369,836 |
| C2012–13 | Pumping Station Jabbeke | Construction (civil) | 125 | 336,410 |
| C2013–01 | Wiedauwkaai Fenders | Construction (civil) | 152 | 1,069,533 |
| C2013–02 | Sewage Plant Hove | Construction (civil) | 403 | 1,236,604 |
| C2013–03 | Brussels Finance Tower | Construction (institutional building) | 425 | 15,440,865 |
| C2013–04 | Kitchen Tower Anderlecht | Construction (institutional building) | 333 | 2,113,684 |
| C2013–06 | Government Office Building | Construction (institutional building) | 352 | 19,429,808 |
| C2013–07 | Family Residence | Construction (residential building) | 170 | 180,476 |
| C2013–08 | Timber House | Construction (residential building) | 216 | 501,030 |
| C2013–09 | Urban Development Project | Construction (commercial building) | 291 | 1,537,398 |
| C2013–10 | Town Square | Construction (civil) | 786 | 11,421,890 |
| C2013–11 | Recreation Complex | Construction (civil) | 359 | 5,480,520 |
| C2013–12 | Young Cattle Barn | Construction (institutional building) | 115 | 818,440 |
| C2013–13 | Office Finishing Works (1) | Construction (commercial building) | 236 | 1,118,497 |
| C2013–15 | Office Finishing Works (3) | Construction (commercial building) | 171 | 341,468 |
| C2014–04 | Compressor Station Zelzate | Construction (industrial) | 522 | 62,385,600 |
| C2014–05 | Apartment Building (1) | Construction (residential building) | 228 | 532,410 |
| C2014–06 | Apartment Building (2) | Construction (residential building) | 547 | 3,486,376 |
| C2014–07 | Apartment Building (3) | Construction (residential building) | 353 | 1,102,537 |
| C2014–08 | Apartment Building (4) | Construction (residential building) | 233 | 1,992,222 |

[a] Standard eight-hour working days.

Therefore, a more customized pre-project $\beta$ allocation is proposed, in which the $\beta$ is determined based on the optimal $\beta$s of historical projects with the same characteristics as the considered project, producing a far better tuned $\beta_{opt,rc}$. The *rc* in this notation expresses the link with the *r*eference *c*lass forecasting (RCF) methodology, which was presented by Kahneman and Tversky (1979a) and later by Lovallo and Kahneman (2003). The basis of RCF lies in the identification of a relevant reference class of similar historical projects in order to produce more accurate forecasts for the considered project, which is also the idea behind the $\beta_{opt,rc}$ approach. The RCF concept was originally proposed by Kahneman and Tversky

[9] For more information about the concepts of *project authenticity* and *tracking authenticity* and their integration within the database construction and evaluation framework of *project cards*, the reader is referred to Batselier and Vanhoucke (2015a).

[10] Note that the construction industry is very wide and comprises various subdivisions that exhibit mutually different characteristics. As such, we can break down the construction sector into civil, industrial and building construction. Furthermore, building construction can, in its turn, further be split into commercial, institutional and residential building. The subsector to which a certain construction project belongs is specified in Table 2.

(1979a, 1979b) to overcome human bias – which can take the form of optimism bias (i.e. the general overoptimistic nature of human judgment with respect to upcoming events) and strategic misinterpretation (i.e. deliberately making optimistic estimations of future events to give the impression of surpassing the competition) – by taking an outside view on planned actions rather than an inside view. Indeed, RCF does not zoom in on the specifics of a certain project (e.g. activity information) in order to predict uncertain events (e.g. activity delay) that would influence the course of the project, which of course, is exactly what traditional EVM does. Flyvbjerg (2006) and Batselier and Vanhoucke (in press-a) performed a first practical application of the RCF technique, and furthermore, the latter paper successfully compared RCF with the established EVM forecasting technique. For a more elaborate discussion on the foundations and the performance of RCF as a methodology in itself, we refer to the works mentioned above in this paragraph.

With respect to the newly introduced technique of this paper, it is expected that the $\beta_{opt,rc}$ would yield more accurate forecasts than the $\beta_{opt,oa}$, as it could better exploit the full potential of the XSM by selecting a $\beta$ that should be closer to the eventual $\beta_{opt}$ of the considered project, and therefore, would presumably show greater advantage with respect to the best established EVM forecasting method. However, obtaining a pool of projects sufficiently similar to a certain project is not an easy task, certainly not as Batselier and Vanhoucke (in press-a) found that the highest degree of similarity is required to yield the highest forecasting accuracies. More concretely, the reference class should consist of similar projects from within the same company. In our study, this advice is followed and a selection of four projects from the same company (i.e. projects C2014–05 to C2014–08) – all concerning the construction of an apartment building – is considered for the calculation of $\beta_{opt,rc}$.

### 3.3. Dynamic approach

For the dynamic approach, only the version based on *quantitative* analysis will be considered. The approach is applied as described in Section 2.2.3. More concretely, the nonlinear programming problems (i.e. finding the instantaneous optimal $\beta_{dyn}$ based on past performance) that emerge for every tracking period are solved by making use of the MS Excel Solver. As the application of the quantitative dynamic approach for a certain project does not require data from other projects (i.e. it only uses the progress of the considered project itself as input), an incorporation of the RCF technique is not relevant here and is therefore omitted.

Also remark that implementation of the *qualitative* dynamic approach would have required the live and permanent monitoring of a project, including the ascertaining of the visions and prognoses of management at certain times during the project. These efforts have not been made in the context of this paper and are left to future research. However, this paper does point out the possibility of in-project $\beta_{dyn}$ adapting based on personal assumptions or prognoses in situations where this is appropriate.

### 3.4. Forecasting accuracy evaluation

The forecasting accuracy of the different methods will be expressed in terms of mean absolute percentage error (MAPE), for which the general formulation is as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A-P_t}{A}\right| \qquad (22)$$

Here, $A$ represents the actual value at the end of the project and $P_t$ the forecasted (predicted) value at tracking period $t$. Furthermore, $n$ corresponds to the number of tracking periods that were actually performed during the considered project.[11] When particularizing Eq. (22) for time forecasting (referring to Table 1 for the abbreviations), $A$ and $P_t$ are substituted by $RD$ and $EAC(t)$, respectively. For cost forecasting, this becomes $RC$ and $EAC$, respectively. Obviously, the lower the MAPE of a particular forecasting method, the higher the accuracy of that method. The MAPE has also been used in many other EVM accuracy evaluation studies (Batselier and Vanhoucke, 2015b; Batselier and Vanhoucke, 2015c; Batselier and Vanhoucke, in press-a, in press-b; Elshaer, 2013; Guerrero et al., 2014; Rujirayanyong, 2009; Vanhoucke, 2010; Vanhoucke and Vandevoorde, 2007; Zwikael et al., 2000).

## 4. Results and discussion

In this section, the results for the newly developed exponential smoothing-based time and cost forecasting methods are presented and discussed. The established EVM time and cost forecasting methods that are considered for comparison with the XSM will be presented in the respective subsections 4.1 and 4.2. In both subsections, the static approach – including the version with incorporation of the RCF concept – as well as the dynamic approach to the XSM will be evaluated. We reiterate that the concrete notations for the different approaches within the general technique of XSM are summarized in Appendix A and will be used throughout this section.

### 4.1. Time forecasting: XSM(t)

The accuracies of the XSM(t) – both the static (Section 4.1.1) and the dynamic (Section 4.1.2) approach – are now compared with the performances of *ESM-1* and *ESM-SPI(t)*, two of the most commonly used and also most accurate established EVM time forecasting methods. All results are summarized in Table 3.

#### 4.1.1. Static approach: $XSM(t)-\beta_{opt}$, $XSM(t)-\beta_{opt,oa}$, $XSM(t)-\beta_{opt,rc}$

First, consider the results for the static approach. The optimal $\beta$ value for a certain project is indicated by $\beta_{opt}$, and the corresponding exponential smoothing-based method by $XSM(t)-\beta_{opt}$. Recall that for the static approach, $\beta$ – thus also

[11] Recall that $N$ was defined as the *expected* number of tracking periods according to the baseline schedule, which is a number that can be calculated prior to the project start, whereas $n$ is only known after the project has finished.

Table 3
Time forecasting results (accuracies in MAPE %).

| | EVM methods | | Static approach | | | | Dynamic approach | |
|---|---|---|---|---|---|---|---|---|
| Project code | *ESM-1* | *ESM- SPI(t)* | $\beta_{opt}$ | $\beta_{opt}$ accuracy | $\beta_{opt,oa}$ accuracy | $\beta_{opt,rc}$ accuracy | accuracy | timeliness |
| C2011–05 | 12.22 | 11.18 | 0.650 | 9.50 | 12.05 | / | 12.22 | 100% |
| C2011–07 | 7.95 | 7.16 | 0.118 | 7.01 | 7.35 | / | 7.95 | 90% |
| C2011–12 | 3.39 | 8.14 | 0.000 | 3.39 | 4.09 | / | 3.39 | / |
| C2011–13 | 7.83 | 6.80 | 0.065 | 6.80 | 6.84 | / | 8.24 | 85% |
| C2012–13 | 7.76 | 10.38 | 0.000 | 7.76 | 8.44 | / | 7.76 | / |
| C2013–01 | 1.73 | 3.81 | 0.023 | 1.72 | 1.73 | / | 1.73 | 100% |
| C2013–02 | 5.36 | 16.35 | 0.000 | 5.36 | 7.34 | / | 5.36 | / |
| C2013–03 | 4.25 | 8.08 | 0.000 | 4.25 | 5.64 | / | 4.33 | / |
| C2013–04 | 5.71 | 7.74 | 0.129 | 3.26 | 4.68 | / | 5.33 | 60% |
| C2013–06 | 2.46 | 4.12 | 0.062 | 2.14 | 2.15 | / | 2.48 | 85% |
| C2013–07 | 3.09 | 4.97 | 0.000 | 3.09 | 3.52 | / | 3.09 | / |
| C2013–08 | 8.91 | 8.67 | 0.691 | 7.80 | 8.84 | / | 8.91 | 100% |
| C2013–09 | 11.86 | 10.94 | 0.853 | 10.76 | 11.77 | / | 11.75 | 85% |
| C2013–10 | 3.26 | 6.52 | 0.000 | 3.26 | 3.73 | / | 3.27 | / |
| C2013–11 | 6.59 | 6.90 | 0.085 | 6.29 | 6.38 | / | 6.59 | 100% |
| C2013–12 | 6.93 | 8.82 | 0.130 | 6.03 | 6.51 | / | 6.83 | 75% |
| C2013–13 | 5.61 | 9.51 | 0.000 | 5.61 | 6.54 | / | 5.61 | / |
| C2013–15 | 12.89 | 10.56 | 0.159 | 10.43 | 12.09 | / | 12.89 | 100% |
| C2014–04 | 26.99 | 17.61 | 0.188 | 20.80 | 24.17 | / | 26.85 | 75% |
| C2014–05 | 4.84 | 10.82 | 0.106 | 3.02 | 3.50 | 3.05 | 5.77 | 75% |
| C2014–06 | 2.35 | 6.55 | 0.028 | 1.70 | 1.98 | 2.74 | 2.27 | 65% |
| C2014–07 | 4.46 | 13.64 | 0.093 | 3.39 | 3.53 | 3.39 | 4.46 | 85% |
| C2014–08 | 8.80 | 7.05 | 0.666 | 7.41 | 8.63 | 8.42 | 8.74 | 90% |
| **Overall** | 7.18 | 8.97 | *0.050* | 6.12 | 7.02 | / | 7.21 | 85% |
| **Ref. class** | 5.11 | 9.52 | *0.100* | 3.88 | / | 4.40 | / | / |

$\beta_{opt}$ – remains constant throughout the entire project. If this $\beta_{opt}$ is different from 0, it means that $XSM(t)-\beta_{opt}$ can provide more accurate forecasts than *ESM-1*. On the other hand, if $\beta_{opt}$ is equal to 0, the performance factor of Eq. (13) is reduced to 1 and *ESM-1* thus remains the most accurate time forecasting method. Table 3 indicates that $\beta_{opt}$ is different from 0 for 16 of the 23 considered projects (i.e. in about 70% of the cases), providing a first indication that $XSM(t)-\beta_{opt}$ indeed shows potential for improving the accuracy of project duration forecasts with respect to the established EVM methods. We now further examine this statement.

When $\beta_{opt}$ is introduced for every project, the average forecasting accuracy over all projects (second last row of Table 3) is reflected by a MAPE of 6.12%. Meanwhile, *ESM*-1, indisputably the best EVM time forecasting method according to previous empirical research (Batselier and Vanhoucke, 2015b; Guerrero et al., 2014), displays an overall MAPE of 7.18%. This implies that, if for each project the optimal $\beta$ was used, $XSM(t)-\beta_{opt}$ could produce time forecasts that are 14.8% more accurate than those obtained from *ESM*-1. With respect to *ESM-SPI(t)*, the relative improvement even rises up to 31.8%. These are indeed considerable potential improvements. Note, however, that in practice it would be very difficult to exploit the full potential as the $\beta_{opt}$ that induces the maximally improved time forecasts is only known after the project has ended. And since we are considering the static approach here, where $\beta$ has to be fixed prior to the project start, an assumption for the $\beta$ value has to be made. A logical approach would be to base the choice of $\beta$ on the historical performance data from earlier projects. Therefore, we calculate the $\beta$ that, on average, produces the most accurate forecasts over all projects and call this value $\beta_{opt,oa}$. The method applying this $\beta_{opt,oa}$ is referred to as $XSM(t)-\beta_{opt,oa}$. Fig. 1 displays the overall MAPEs for different values of $\beta$ (with increments of 0.05) and allows the identification of $\beta_{opt,oa}$.

From Fig. 1, we can conclude that $\beta_{opt,oa}=0.05$ here (vertical line). Moreover, this $\beta$ value yields a MAPE of 7.02%, as could already be seen from Table 3. This MAPE suggests quite a considerable reduction in accuracy (of almost one absolute percent) with respect to the case where the project-specific optimal $\beta$ (i.e. $\beta_{opt}$) is applied for every project. Nevertheless, $XSM(t)-\beta_{opt,oa}$ is still more accurate than *ESM*-1, but only by 2.3%.[12]

However, recall from Section 3.2 that utilizing $\beta_{opt,oa}$ does not entail any intelligent methodology for assigning the most appropriate $\beta$ to a certain project prior to the project start, whereas the approach that applies $beta_{opt,rc}$ and thus identifies a reference class of similar projects was expected to improve forecasting accuracy. Therefore, the $XSM(t)-\beta_{opt,rc}$ was performed for four strongly similar projects from the used database (i.e. projects C2014–05 to −08) and the results were summarized in the last row of Table 3. Remark that the values in this last row only reflect the (average) outcomes for the four projects in the selected reference class. For this reference class, we see that the optimal $\beta$ (i.e. $\beta_{opt,rc}$) is now 0.10, which is not the same as the $\beta_{opt,oa}$ of 0.05 over all 23 projects. Consequently, the $\beta_{opt,rc}$ accuracy is different from the $\beta_{opt,oa}$

[12] The relative accuracy gain with respect to $ESM-SPI(t)$ is still more than 20%. Hence, $ESM-SPI(t)$ is not deemed a viable alternative for time forecasting and will therefore not be considered in the upcoming discussions of this section.

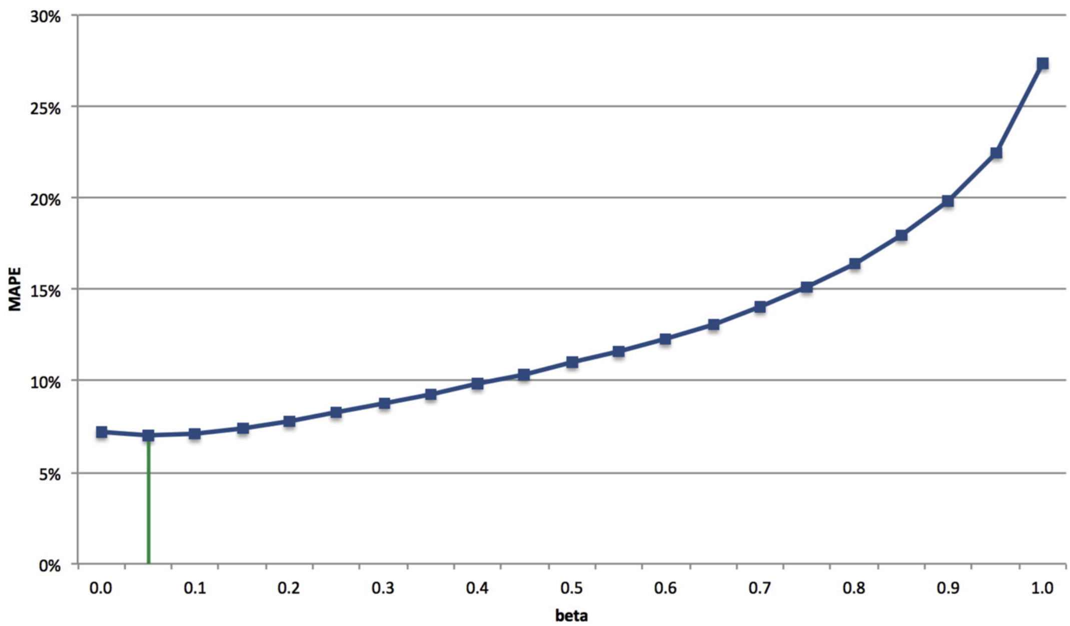


Fig. 1. Determination of $\beta_{opt,oa}$ for time forecasting.

accuracy for the four reference class projects. A MAPE of 4.40% has been obtained by $XSM(t)-\beta_{opt,rc}$, which is 13.9% lower than that of $ESM$-1 (MAPE of 5.11%). This is a considerable accuracy improvement with respect to the traditionally best performing EVM time forecasting method, and furthermore, also with respect to $XSM(t)-\beta_{opt,oa}$. The latter observation confirms the expectation that incorporation of the RCF concept would better exploit the full potential of the XSM. Indeed, when comparing with *ESM-1*, $XSM(t)-\beta_{opt,rc}$ attains 13.9% improvement from the maximum of 24.1% (i.e. when using $\beta_{opt}$ for every project), whereas for $XSM(t)-\beta_{opt,oa}$ this was only 2.3% from the maximum of 14.8%.

### *4.1.2. Dynamic approach: XSM(t)* $-\beta_{dyn}$

Now consider the results for the dynamic approach to the novel time forecasting method, referred to as $XSM(t)-\beta_{dyn}$. More specifically, we are considering the dynamic approach based on quantitative analysis, as was presented in Section 2.2.3. Table 3 indicates that the time forecasting accuracy obtained by applying $XSM(t)-\beta_{dyn}$ is reflected by a MAPE of 7.21%. Although this is considerably more accurate than *ESM-SPI(t)* (19.6% relative improvement), it is almost identical to $ESM$-1 (0.4% relative deterioration). $XSM(t)-\beta_{opt,oa}$ thus exhibits a better performance than $XSM(t)-\beta_{dyn}$ (2.7% relative improvement), and furthermore, the more advanced $XSM(t)-\beta_{opt,rc}$ even shows a relative improvement of 17.8%. Therefore, it could be concluded that the static approach to the XSM shows a greater potential for time forecasting than its dynamic counterpart.

A reason for the weaker performance of the latter approach could lie with the timeliness of the method. The observed timeliness for a certain project is defined here as the point in time (i.e. the tracking period) for which $\beta_{dyn}$ differs from0 for the first time, and remains different from 0 for all subsequent tracking periods, right up to the end of the project. For example, if a certain project contains 20 tracking periods and the dynamic approach yields a non-zero value for $\beta_{dyn}$ for the first time on tracking period 14, than the timeliness of the dynamic approach for this project is said to be 70% (= 14/20). Note that we thus express the timeliness as a percentage of the total number of tracking periods, rounded to the nearest 5% for clarity.

The timeliness results for $XSM(t)-\beta_{dyn}$ are presented in the last column of Table 3. For the projects where $\beta_{opt}$ is 0, with $\beta_{opt}$ always corresponding to the $\beta_{dyn}$ calculated for the final tracking period, there are no timeliness results as the concept is not relevant when $\beta_{dyn}$ remains 0 throughout the entire project. Note that in such a situation, $XSM(t)-\beta_{dyn}$ becomes completely identical to $ESM$-1. A timeliness percentage of 100%, on the other hand, indicates that the dynamic approach yields a non-zero $\beta_{dyn}$ – equal to $\beta_{opt}$ – only at the very last tracking period. In such a case, $XSM(t)-\beta_{dyn}$ again produces the exact same time forecasts as $ESM$-1, as $\beta_{dyn}$ only differs from 0 at the final tracking period (where it can no longer be applied since the project is already finished at this point) and was equal to 0 for the entire preceding portion of the project, just as for $ESM$-1. Thus, when the timeliness percentage is 100%, $XSM(t)-\beta_{dyn}$ has no advantage over $ESM$-1 for that specific project. From this statement, one may deduce that the dynamic approach becomes more beneficial for lower timeliness percentages. Indeed, the lower the timeliness percentage, the more tracking periods there are for which time forecasts can be made that are based on an accuracy-improving non-zero $\beta_{dyn}$.

From Table 3, however, we notice that quite a few projects (5 out of the 16 with a non-zero $\beta_{opt}$) exhibit a 100% timeliness percentage for $XSM(t)-\beta_{dyn}$. Moreover, the other relevant projects also show fairly high timeliness percentages. With the exception of two projects, all experience a first non-zero $\beta_{dyn}$ outcome only in the last quarter of the project (i.e. on or after the 75% timeliness percentage). This is reflected by an overall timeliness percentage of 85%. From this figure, and from the preceding discussion, it could indeed be expected that $XSM(t)-$

$\beta_{dyn}$ would not produce time forecasts that are significantly better than those of the established *ESM*-1.

Furthermore, $XSM(t)-\beta_{dyn}$ can sometimes even prove less accurate than *ESM*-1 (compare the MAPE values in the second and next to last column of Table 3). This is due to the occurrence of misleading spikes in the course of $\beta_{dyn}$ calculated for the different tracking periods. There are two possible situations. In a first, the dynamic approach falsely indicates an non-zero $\beta_{dyn}$ for one or more tracking periods during the project, whereas the eventual $\beta_{opt}$ is in fact equal to 0 (i.e. *ESM-1* is the best method). This situation appears for projects C2013–03 (Fig. 2a) and C2013–10 (Fig. 2b), both for which a rather modest spike occurs for the penultimate tracking period.

A second possibility is that, although the eventual $\beta_{opt}$ is different from 0 (i.e. *ESM-1* is not the best method), the dynamic approach yields non-zero $\beta_{dyn}$ values during the project that are (way) too high and thus produce forecasts that are less accurate than those using a simple *ESM*-1 (i.e. setting $\beta=0$) for the corresponding tracking periods. This is the case for projects C2011–13 (Fig. 2c) and C2014–05 (Fig. 2d). Note that the occurrence of spikes does not necessarily has to be disadvantageous in the situation where $\beta_{opt}$ is different from zero (on the other hand, in the case where $\beta_{opt}=0$, it always is disadvantageous), as the non-zero $\bar{e}ta_{dyn}$ values obtained during the project (more specifically, for tracking periods for which the tracking progress is less than the timeliness percentage)

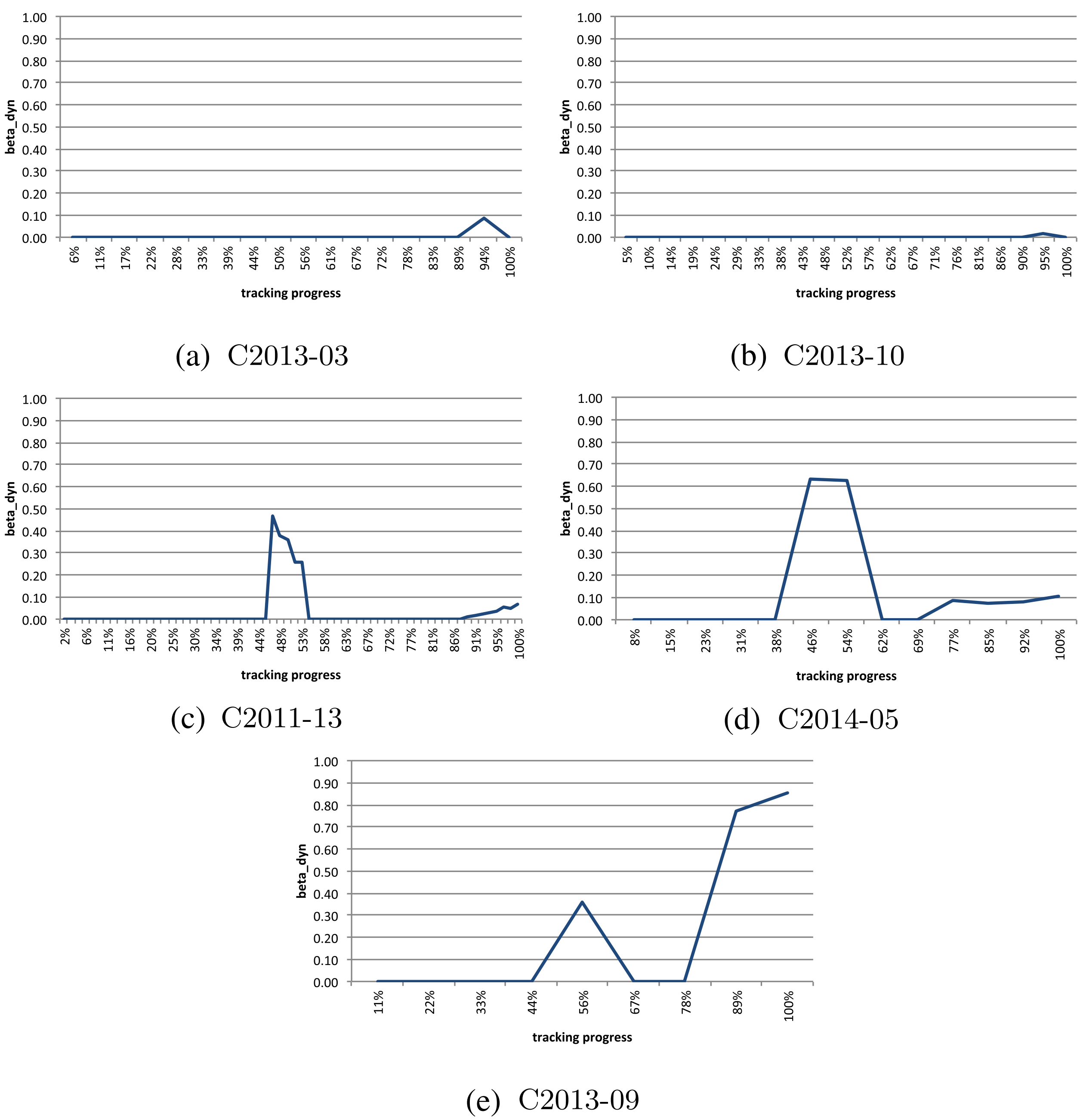


Fig. 2. Course of $\beta_{dyn}$ according to the dynamic time forecasting approach for different projects from the database.

could provide a reasonably accurate approximation of the eventual $\beta_{opt}$ and thus also yield more accurate forecasts than when setting $\beta_{dyn}=0$ for the respective tracking periods. An example of this situation is given by project C2013–09 (Fig. 2e). Here, the spike is smaller than the eventual $\beta_{opt}$, and thus closer to $\beta_{opt}$ than $\beta_{dyn}=0$, therefore always producing a more accurate time forecast than *ESM*-1 for the corresponding tracking period.

### 4.2. Cost forecasting: XSM($)

Similar to what was done for time forecasting in Section 4.1, the accuracies of the exponential smoothing-based cost forecasting methods are now compared with the performances of two of the most commonly used and also most accurate established EVM cost forecasting methods, namely *EAC-1* and *EAC-CPI*. Again, both the static (Section 4.2.1) and the dynamic (Section 4.2.2) approach are considered. Table 4 summarizes all relevant results.

Notice that no results are displayed for projects C2011–05 and C2013–10. The reason is that these projects do not contain adequate cost data to allow a correct execution of the upcoming analysis. Consequently, only 21 projects – instead of 23 – are considered for the assessment of the XSM($). Other than that, the performed evaluation for the cost dimension is completely similar to that performed for time forecasting. Therefore, the discussion in following subsections will be strongly parallel to that of Sections 4.1.1 and 4.1.2. Moreover, definitions of recurring parameters and concepts will not be repeated for the purpose of conciseness, unless needed for clarity.

#### 4.2.1. Static approach: $XSM(\$)-\beta_{opt}$, $XSM(\$)-\beta_{opt,oa}$, $XSM(\$)-\beta_{opt,rc}$

First, consider the results for the static approach in Table 4. Analogous to time forecasting, a $\beta_{opt}$ different from 0 expresses that the corresponding exponential smoothing-based cost forecasting method, denoted by $XSM(\$)-beta_{opt}$, can provide more accurate forecasts than *EAC*-1. On the other hand, if $\beta_{opt}$ is equal to 0, the performance factor of Eq. (21) is reduced to 1 and *EAC-1* thus remains the most accurate cost forecasting method. From Table 4, it appears that $\beta_{opt}$ is different from 0 for 19 of the 21 considered projects (i.e. in about 90% of the cases). This observation provides a first indication that the XSM might have great potential for improving the accuracy of project cost forecasts, and even more so than was the case for time forecasts. We now further examine this statement.

When $\beta_{opt}$ is introduced for every project, the average forecasting accuracy over all projects (second last row of Table 4) is reflected by a MAPE of 3.71%. Meanwhile, *EAC*-1 displays an overall MAPE of 5.04%. This implies that, if for each project the optimal $\beta$ was used, $XSM(\$)-\beta_{opt}$ could produce cost forecasts that are 26.4% more accurate than those obtained from *EAC*-1. This outcome indeed endorses the greater potential of the XSM for cost forecasting compared to time forecasting, where the maximum relative improvement with respect to *ESM*-1 was limited to 14.8%. However, whereas *ESM*-1 is the undisputed EVM top forecasting method for project duration, EAC-1 does experience competition from other established EVM cost forecasting methods, and then mainly from *EAC-CPI*. For the 19 considered projects, *EAC-CPI* even yields forecasts that are, on average, better

Table 4
Cost forecasting results (accuracies in MAPE %).

| | EVM methods | | Static approach | | | | Dynamic approach | |
|---|---|---|---|---|---|---|---|---|
| Project code | *EAC-1* | *EAC- CPI* | $\beta_{opt}$ | $\beta_{opt}$ accuracy | $\beta_{opt,oa}$ accuracy | $\beta_{opt,rc}$ accuracy | Accuracy | Timeliness |
| C2011–05 | / | / | / | / | / | / | / | / |
| C2011–07 | 3.46 | 1.32 | 0.455 | 1.74 | 2.30 | / | 3.26 | 65% |
| C2011–12 | 1.04 | 1.38 | 0.187 | 0.86 | 0.87 | / | 1.08 | 85% |
| C2011–13 | 12.84 | 16.11 | 0.012 | 10.63 | 17.51 | / | 12.74 | 85% |
| C2012–13 | 2.44 | 2.64 | 0.108 | 2.17 | 2.27 | / | 2.44 | 100% |
| C2013–01 | 10.54 | 9.11 | 0.232 | 8.67 | 8.78 | / | 10.54 | 100% |
| C2013–02 | 2.56 | 1.69 | 0.140 | 1.35 | 1.47 | / | 2.17 | 50% |
| C2013–03 | 4.61 | 4.47 | 0.359 | 4.14 | 4.33 | / | 4.61 | 100% |
| C2013–04 | 6.73 | 3.96 | 1.000 | 1.98 | 5.06 | / | 4.35 | 35% |
| C2013–06 | 6.33 | 5.27 | 0.817 | 4.67 | 5.44 | / | 6.14 | 75% |
| C2013–07 | 0.44 | 1.49 | 0.000 | 0.44 | 1.04 | / | 0.44 | / |
| C2013–08 | 8.88 | 8.34 | 1.000 | 7.99 | 8.43 | / | 8.78 | 70% |
| C2013–09 | 4.90 | 3.65 | 0.920 | 2.87 | 4.07 | / | 4.78 | 75% |
| C2013–10 | / | / | / | / | / | / | / | / |
| C2013–11 | 0.57 | 1.33 | 0.014 | 0.56 | 0.97 | / | 0.57 | 90% |
| C2013–12 | 3.53 | 2.75 | 0.320 | 2.49 | 2.83 | / | 3.53 | 100% |
| C2013–13 | 6.75 | 10.40 | 0.000 | 6.75 | 8.46 | / | 6.75 | / |
| C2013–15 | 8.08 | 8.09 | 0.099 | 7.36 | 7.78 | / | 8.08 | 100% |
| C2014–04 | 3.33 | 3.13 | 0.223 | 3.05 | 3.05 | / | 3.48 | 95% |
| C2014–05 | 2.92 | 8.07 | 0.071 | 1.98 | 3.00 | 2.47 | 2.90 | 75% |
| C2014–06 | 0.75 | 1.83 | 0.025 | 0.47 | 1.06 | 0.92 | 0.70 | 60% |
| C2014–07 | 5.85 | 5.17 | 0.444 | 3.21 | 3.69 | 3.83 | 5.59 | 40% |
| C2014–08 | 9.33 | 3.88 | 0.975 | 4.59 | 7.03 | 7.44 | 8.66 | 65% |
| **Overall** | 5.04 | 4.96 | *0.200* | 3.71 | 4.74 | / | 4.84 | 75% |
| **Ref. class** | 4.71 | 4.74 | *0.150* | 2.56 | / | 3.67 | / | / |

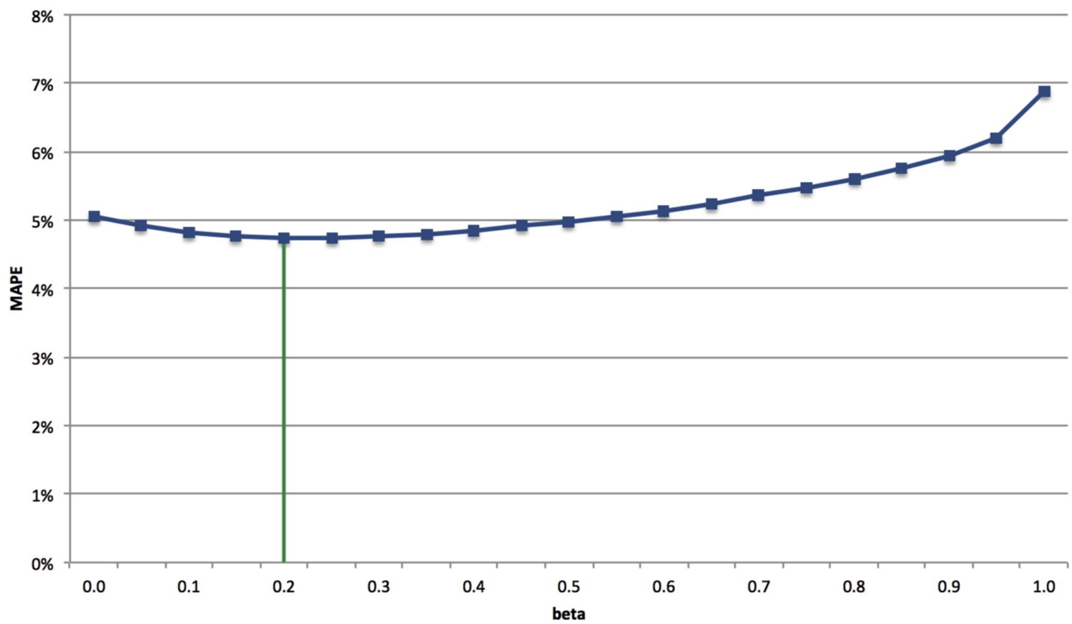


Fig. 3. Determination of $\beta_{opt,oa}$ for cost forecasting.

than those producedby *EAC-1*, which is in line with the findings of (Zwikael et al., 2000). Indeed, *EAC-CPI* exhibits an overall MAPE of 4.96%, which is lower than the 5.04% observed for *EAC-1*. Nevertheless, $XSM(\$)-\beta_{opt}$ still shows a substantial potential accuracy gain of 25.1% over *EAC-CPI*.

However, note that the above results are only obtained when the optimal $\beta$ (i.e. $\beta_{opt}$) is applied for every project. Just as for time forecasting, the $\beta_{opt}$ cannot be known before the start of the project, which implies that it would be very difficult to fully exploit the above-mentioned potential of the novel method in practice, as the static approach requires the pre-project selection of a fixed $\beta$. A more realistic approach would again be to base the choice of the fixed $\beta$ on the historical performance data from earlier projects. Hence, $\beta_{opt,oa}$ is the $\beta$ value that, on average, produces the most accurate forecasts over all projects relevant for cost forecasting. The corresponding method is indicated by $XSM(\$)-\beta_{opt,oa}$. Fig. 3 displays the overall MAPEs for different values of $\beta$ (with increments of 0.05) and enables the identification of $\beta_{opt,oa}$.

From Fig. 3, we can conclude that $\beta_{opt,oa}=0.20$ here (vertical line). Note that this $\beta_{opt,oa}$ is remarkably higher than the corresponding value of 0.05 for time forecasting, anew indicating that the exponential smoothing-based approach might be intrinsically more beneficial for cost forecasting than for time forecasting. Indeed, in a cost context, the produced optimized forecast is expected to deviate more from the standard case of $\beta=0$ and thus to entail greater potential improvement with respect to it. Table 4 indicates that the application of $\beta_{opt,oa}$ yields a MAPE of 4.74%. This MAPE suggests quite a considerable reduction in accuracy (again, of about one absolute percent) with respect to the case where $\beta_{opt}$ is applied for every project. Nevertheless, $XSM(\$)-\beta_{opt,oa}$ is still more accurate than *EAC-1* (relative improvement of 6.1%), and more importantly, than *EAC-CPI*. The relative accuracy gain compared to the latter is only 4.5%. However, this is still more than 2% better than the performance of $XSM(t)-\beta_{opt,oa}$ with respect to *ESM-1* in the time forecasting case.

Furthermore, when applying the more advanced $\beta_{opt,rc}$, the observed forecasting accuracy improvements reach new heights (see last row of Table 4). Indeed, $XSM(\$)-\beta_{opt,rc}$ displays an average MAPE of 3.67% over the four projects of the reference class, which is a relative 22.2% and 22.6% lower compared to *EAC-1* and *EAC-CPI*, respectively. These forecasting accuracy increases are considerable, and even more significant than those observed for the time dimension, where the relative improvement of $XSM(t)-\beta_{opt,rc}$ with respect to *ESM-1* did not surpass 14%. Furthermore, note that $\beta_{opt,rc}$ is now equal to 0.15, whereas $\beta_{opt,oa}$ was slightly higher with 0.20. This indicates that $\beta$ should not necessarily increase to obtain higher accuracies, as this depends on the characteristics of the considered projects (i.e. the four reference class projects in this case). Moreover, the results again showthat application of $\beta_{opt,rc}$ better exploits the full potential of the XSM, as comparison with *EAC-CPI*[13] shows that $XSM(\$)-\beta_{opt,rc}$ attains 22.6% improvement from the maximum of 45.9% (i.e. when using $\beta_{opt}$ for every project), whereas for $XSM(\$)-\beta_{opt,oa}$ this was only 4.5% from the maximum of 25.1%. Therefore, all statements made in Section 4.1.1 (time dimension) concerning the benefits of incorporating RCF into the novel XSM are thus confirmed – and even reinforced – for cost forecasting.

### 4.2.2. Dynamic approach: $XSM(\$)-\beta_{dyn}$

Now consider the results for the (quantitative) dynamic approach to the *XSM($)* in Table 4. It appears that this approach, denoted by $XSM(\$)-\beta_{dyn}$, yields an overall forecasting accuracy of 4.84 MAPE %. Notice that this accuracy is slightly lower than that of $XSM(\$)-\beta_{opt,oa}$ (relative deterioration of 2.1%) and significantly lower than that of $XSM(\$)-\beta_{opt,rc}$ (relative deterioration of 16.9%), which corresponds to

[13] Comparison with $EAC-1$ yields almost identical results.

the observations made for time forecasting. Again, the static approach to the XSM thus shows greater potential than its dynamic counterpart.

However, in contrast with the time forecasting situation, the dynamic approach does perform better than both established EVM methods, as its forecasting accuracy is 4.1% and 2.4% higher than that of *EAC-1* and *EAC-CPI*, respectively. An explanation for this could be found in the observed timeliness of $XSM(\$)-\beta_{dyn}$ (see last column of Table 4). First of all, in comparison with time forecasting, less projects exhibit a 100% timeliness percentage (only 5out of the 19 with a non-zero $\beta_{opt}$). Moreover, the other relevant projects generally show lower timeliness percentages and seven projects (instead of only two for the time context) experience a first non-zero $\beta_{dyn}$ outcome before the 75% timeliness percentage. Not surprisingly, the overall timeliness percentage is lower for cost than that for time forecasting, namely 75% instead of 85%. Recall that, the lower the timeliness percentage, the more tracking periods there are for which forecasts can be made that are based on an accuracy-improving non-zero $\beta_{dyn}$. From the above discussion, one could indeed apprehend the better performance of the dynamic approach to the XSM for cost forecasting.

Furthermore, only one project (C2014–04) contains a misleading spike in the course of the $\beta_{dyn}$ calculated for the different tracking periods, which anew positively influences the forecasting accuracy in comparison with the time forecasting situation (where there were four such cases). It concerns a project for which the eventual $\beta_{opt}$ is different from 0, but where the dynamic approach produces non-zero $\beta_{dyn}$ values during the project that are way too high and thus yield cost forecasts that are less accurate than those using a simple *EAC-1* (i.e. setting $\beta=0$) for the corresponding tracking periods. Fig. 4 shows the course of $\beta_{dyn}$ for this project.

## 5. Conclusions

In this paper, a novel forecasting approach for project duration and cost based on the incorporation of the EVM metrics into the exponential smoothing technique is developed. This novel approach is referred to as the XSM (an acronym for eXponential Smoothing-based Method) and exhibits a strong similarity to the traditional EVM forecasting methodology. Indeed, the rather cumbersome exponential smoothing technique can very straightforwardly be implemented for project management forecasting simply by introducing a new performance factor based on only one smoothing parameter $\beta$ into the established EVM forecasting approach. Thus, the exponential smoothing technique can be fully integrated in the existing EVM framework – for both time and cost forecasting – which endorses the practical applicability of the newly developed methodology.

Concerning the technicalities of the XSM, the applied smoothing parameter $\beta$ always lies between 0 and 1, with the extreme values respectively reflecting no and maximum responsiveness to the current time/cost performance of the project. This means that the closer $\beta$ is chosen to 1, the higher the responsiveness to the performance of the latest tracking periods. The ability to base forecasts on the more recent project performance was one of the main drivers for developing the XSM. Indeed, the XSM makes it possible to tune time and cost forecasts by accounting for experience-driven performance improvement and/orrecently taken corrective management actions. Traditional EVM forecasting methods, on the other hand, cannot adequately account for such influences. Moreover, the most important EVM forecasting methods (i.e. *ESM-1* and *ESM-SPI(t)* for time and *EAC-1* and *EAC-CPI* for cost) can be expressed in terms of XSM formulations. Therefore, it can be stated that the XSM incorporates these established methods and thus expands and generalizes traditional EVM forecasting.

Furthermore, the XSM can be applied in both a static and a dynamic way. For the static approach, the value for $\beta$ is chosen before the project starts and then remains constant throughout the entire project. Moreover, three versions of the static approach can be identified: a first one is based on the constant $\beta$ value that produces the most accurate forecasts for the considered project (i.e. $\beta_{opt}$); a second version relies on the optimal $\beta$ over *all* projects in the database (i.e. $\beta_{opt,oa}$); and a third version only considers *related* projects with similar characteristics to define the optimal $\beta$ (i.e. $\beta_{opt,rc}$). The latter approach in fact incorporates the RCF concept into the XSM. Furthermore, it should be noted that the $\beta_{opt}$ for a certain project cannot be known prior to the start of that project, whereas $\beta_{opt,oa}$ and $\beta_{opt,rc}$ can be calculated from historical projects in the database. Therefore, the XSM based on $\beta_{opt}$ can be said to reflect the maximum potential of the novel methodology, whereas the approaches based on the other $\beta$s reflect realistically attainable performances.

For the dynamic approach, the smoothing parameter can be adapted during the project and can thus take a different value for

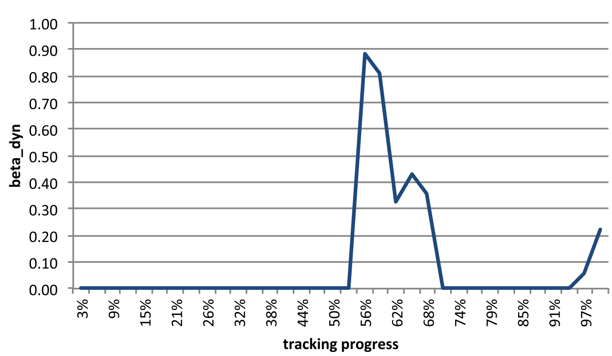


Fig. 4. Course of $\beta_{dyn}$ according to the dynamic cost forecasting approach for project C2014–04.

every tracking period. In this case, the smoothing parameter is indicated by $\beta_{dyn}$. There are two possible versions of the dynamic approach. The first one is based on a quantitative analysis. More concretely, the $\beta_{dyn}$ value for a certain tracking period is calculated as the $\beta$ that would have produced the most accurate forecasts over all of the preceding tracking periods. On the other hand, a qualitative dynamic approach would allow management to select the most appropriate $\beta_{dyn}$ value at a certain time, not based on quantitative calculations, but rather on their own experiences and insights (e.g. with respect to the effect of anticipated corrective actions). The possible merits of this second option are not evaluated in this paper, nevertheless, the reader should recognize the possibility of incorporating human insights into the XSM.

The forecasting accuracies of the static and the dynamic approach to the XSM were compared with the accuracies of the most common and best performing established EVM forecasting methods, and this for both time and cost. To this end, data from 23 real-life projects from the database of (Batselier and Vanhoucke, 2015a), and available at www.or-as.be/research/database, were used. MAPE comparison indicates that the XSM has the potential to produce forecasts that are on average 14.8% more accurate with respect to the best EVM time forecasting method (i.e. *ESM-1*) and even 25.1% more accurate compared to the best EVMcost forecasting method (i.e. *EAC-CPI*). However, in practice it would be difficult to exploit the full potential of the XSM as this would require the knowledge of $\beta_{opt}$ prior to the project start. Nevertheless, even for the most rudimentary static application of the XSM (i.e. based on $\beta_{opt,oa}$), there is still an average performance improvement with respect to the top EVM time and cost forecasting methods of 2.3% and 4.5%, respectively. The quantitative dynamic approach, on the other hand, yields accuracy results that are slightly worse than those just presented and cannot be further improved. In contrast, the performance of the static approach can be enhanced through consideration of reference classes. Indeed, when applying $\beta_{opt,rc}$ for a reference class of similar projects within the used database, the accuracy gains with respect to the best EVM forecasting methods rise up to 13.9% for time and 22.2% for cost. Remark that the XSM seems to perform better for cost than for time forecasting, although the improvements can be deemed considerable in both contexts.

The obtained results thus indicate that the XSM, which integrates the EVM methodology with the exponential smoothing technique, exhibits great potential for improving the accuracy of project forecasts, certainly when also incorporating the RCF concept. The objective reflected by the title of this paper can therefore be deemed achieved. However, it is important to note that the current evaluation was performed on a data set of 23 projects. Therefore, it is not our intention to provide generalizable conclusions, but rather a trustworthy indication of the potential of a newly developed forecasting technique. The XSM – and especially the most promising version based on $\beta_{opt,rc}$ – should thus further be tested on a larger pool of (real-life) projects. Other topics for future research are the comparison of the XSM with other state-of-the-art forecasting methods (based on EVM), the assessment of the effect of tracking frequency and regularity on the XSM performance, the investigation into the possibilities of the qualitative dynamic approach to the XSM, and the evaluation of the effect of project seriality and project regularity (Batselier and Vanhoucke, in press-b) on the accuracy of XSM time and cost forecasts.

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## Appendix A. Notations for the different components of the XSM

The notations for the different components of the exponential smoothing-based method developed in this paper are now listed in the order in which they appear in the text:

| | |
|---|---|
| XSM | The exponential smoothing-based method in general, comprising both time and cost forecasting. |
| XSM(t) | The time forecasting component of the XSM. |
| XSM($) | The cost forecasting component of the XSM. |
| $\beta$ | The general smoothing parameter used in the XSM; we assume that this $\beta$ is chosen prior to the project start and remains constant over all tracking periods.[14] |
| $\boldsymbol{\beta_{opt}}$ | The optimal value for $\beta$ for a certain project in the database. |
| $\boldsymbol{\beta_{opt,oa}}$ | The optimal value for $\beta$ over all projects in the database. |
| $\boldsymbol{\beta_{opt,rc}}$ | The optimal value for $\beta$ over all projects within a same reference class, i.e. with similar characteristics w.r.t. sector, budget, duration, etc. |
| $\boldsymbol{\beta_{dyn}}$ | The variable smoothing parameter value that is calculated for every tracking period (based on the performance of the past tracking periods); this $\beta_{dyn}$ can thus be different for every tracking period. Note: It is important to realize that $\beta_{opt}$, $\beta_{opt,oa}$ and $\beta_{opt,rc}$ are in fact specifications of the general $\beta$. Therefore, $\beta_{opt}$, $\beta_{opt,oa}$ and $\beta_{opt,rc}$ are all fixed for the entire course of the project and retain the same value for every tracking period. On the other hand, $\beta_{dyn}$ can change during the project and can thus take on different values for different tracking periods, as it is dynamically adjusted over the course of the project. Table A.5 further illustrates the difference in possible courses of $\beta$ (or $\beta_{opt}$, $\beta_{opt,oa}$ or $\beta_{opt,rc}$) and $\beta_{dyn}$ on a notional example project with seven tracking periods (TPs) |

[14] As an exception, $\beta$ can for example also be set equal to $1/t$, with $t$ the respective tracking period number, as to produce the exact same forecasts as $ESM-SPI(t)$ and $EAC-CPI$ for time and cost, respectively (see Section 2.2.3). In such a case, the $\beta$ values are not the same for every tracking period, although they are fixed and unadaptable as from the start of the project. However, the definition of $\beta$ retaining the same value for every tracking period is much more common, and is also adopted in the discussions of this paper.

**Table A.5.** A possible course of $\beta$ and $\beta_{dyn}$

| | TP1 | TP2 | TP3 | TP4 | TP5 | TP6 | TP7 |
|---|---|---|---|---|---|---|---|
| $\beta$ | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 |
| $\beta_{dyn}$ | 0.00 | 0.00 | 0.07 | 0.00 | 0.08 | 0.16 | 0.21 |

$XSM(t)-\beta_{opt}$ The static approach to the XSM(t) based on $\beta_{opt}$.
$XSM(t)-\beta_{opt,oa}$ The static approach to the XSM(t) based on $\beta_{opt,oa}$.
$XSM(t)-\beta_{opt,rc}$ The static approach to the XSM(t) based on $\beta_{opt,rc}$.
$XSM(t)-\beta_{dyn}$ The dynamic approach to the XSM(t), obviously based on $\beta_{dyn}$.
$XSM(\$)-\beta_{opt}$ The static approach to the XSM($) based on $\beta_{opt}$.
$XSM(\$)-\beta_{opt,oa}$ The static approach to the XSM($) based on $\beta_{opt,oa}$.
$XSM(\$)-\beta_{opt,rc}$ The static approach to the XSM($) based on $\beta_{opt,rc}$.
$XSM(\$)-\beta_{dyn}$ The dynamic approach to the XSM($), obviously based on $\beta_{dyn}$.

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