Case Study

Empirical Evaluation of Earned Value Management Forecasting Accuracy for Time and Cost

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Abstract: The ability to accurately forecast a project's final duration and cost is essential to successful project management. The technique of earned value management (EVM) is considered to provide an effective methodology for obtaining such forecasts; however, this has not yet been adequately tested on empirical data. Therefore, the accuracy of the most commonly used EVM time and cost forecasting methods is evaluated on a diverse and qualitative database consisting of 51 real-life projects. As most projects originate from the construction industry, an explicit focus on these construction projects is provided. Moreover, the desired real forecasting outcomes based on the actual project progress data are also supported by a Monte Carlo simulation study. It is demonstrated that highly accurate time and cost forecasts can be obtained by applying the EVM methodology. Furthermore, the best performing forecasting methods for the projects in the considered database are identified, also taking into account timeliness and the influence of the project network structure. **DOI:** 10.1061/(ASCE)CO.1943-7862.0001008.

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Introduction

Since project management is primarily concerned with decisions affecting the future, time and cost forecasts are essential to the adequate management of projects and therefore to project success. Furthermore, project managers—particularly in construction—perceive the capability of predicting time and cost to complete as the most important utility of a project control technique (Kim et al. 2003). A widely accepted technique for making such project forecasts is earned value management (EVM). The EVM method was developed by the United States Department of Defense (U.S. DoD) in the 1960s as an integral part of the cost/schedule control system criteria (C/SCSC) and was brought to a wider attention by the book and pioneering article by Fleming and Koppelman (2003, 2005). A more extensive description of the origins of the EVM methodology is provided by Morin (2009) and Kwak and Anbari (2012). Furthermore, EVM's usefulness to and acceptance by project managers have been explicitly evidenced by Christensen (1998), Kim et al. (2003), and Marshall (2007), the latter two also specifically considering the construction sector. Moreover, numerous other publications confirm the benefits of EVM (Anbari 2003; Henderson 2007; Van De Velde 2007; Egnot 2011).

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Conceptually, the EVM technique integrates the three critical project management elements of cost, schedule, and scope. A more concrete summary of EVM's key definitions and formulas is included in Fig. 1. For a detailed discussion of the more thoroughgoing aspects of EVM, the reader can consult several works [Anbari 2003; Project Management Institute (PMI) 2008; Fleming and Koppelman 2010; Vanhoucke 2010a; Vanhoucke 2014].

The metrics below the bold line in Fig. 1 are in fact measures that are used to indicate a project's schedule and cost performance at a certain point during project execution. 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. Moreover, note that all performance measures described here are cumulative measures. For an overview of other possibilities, the reader is referred to the paper by Christensen (1993).

Besides assessing and communicating current project schedule and cost performance, EVM can thus also be used for predicting the eventual project duration and budget. The commonly used methods for time and cost forecasting based on the earned value metrics from Fig. 1 were identified from Vanhoucke (2012a) and are presented in Fig. 2. The latter figure shows the notations and formulations for nine time and eight cost forecasting methods. For time forecasting, the nine methods can be grouped into three overarching methodologies, namely, the planned value method (PVM) by Anbari (2003), the earned duration method (EDM) by Jacob and Kane (2004), and the earned schedule method (ESM) by Lipke (2003). All the methods, also those for cost forecasting, rely on a specific performance factor (PF), which refers to the assumption about the expected performance of future work. The different assumptions and their related performance factors are indicated in the first two rows of Fig. 2, with the corresponding specified methods listed underneath.

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Metric	Definition
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 for which $EV \geq PV_t$ and $EV < PV_{t+1}$
RD	Real duration, the actual total duration of the project
RC	Real cost, the actual total cost of the project
$EAC(t)$	Estimated time at completion, the prediction of RD made at AT
EAC	Estimated cost at completion, the prediction of RC made at AT
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.

Fig. 1. Definitions of the EVM key metrics

Assessing the accuracy of the forecasts obtained from (a selection of) the methods presented in Fig. 2 and thus identifying the most advisable method for time or cost forecasting has been the goal of multiple studies in the literature. Generally, these papers only focus on one of the two forecasting dimensions, i.e., either time (Vandevoorde and Vanhoucke 2006, 2007) or cost (Christensen 1993; Zwikael et al. 2000). In this paper, both forecasting dimensions will be considered.

Previous studies have performed EVM forecasting evaluations on both generated and real-life project data. However, Batselier and Vanhoucke (2015) already noted that in the case of empirical studies "the data set was often of insufficient size and always of inadequate diversity." They also stated that many authors recognize the need for performing profound EVM (forecasting) research on a large and diverse data set of real-life projects (Zwikael et al. 2000; Henderson 2003, 2004, 2005; Lipke 2009, 2013; Tzaveas et al. 2010; Vanhoucke 2011). Nevertheless, no such study has been undertaken previous to this paper. Therefore, the main objective of this paper is to assess the accuracy of the different EVM forecasting methods for both time and cost based on a large and diverse database consisting of qualitative real-life project data.

The only database that is both fit and available for such a study is the one constructed by Batselier and Vanhoucke (2015) and to be consulted at the Operations Research-Applications and Solutions (OR-AS 2014) database. At the time of this study, the continuously expanding database comprised 51 real-life projects. An overview of the considered projects is provided in the Appendix, including specific project data [i.e., planned value (PV), earned value (EV) and actual cost (AC) for multiple tracking periods] for a number of them. The average project in the database has a duration of about 10 months and a budget of just under 130 million Euro. However, the entirety of projects covers a wide range of durations (i.e., from about 2 weeks to 5 years) and budgets (i.e., from about 30,000 Euro to 5 billion Euro).

Furthermore, the projects originate from many different companies situated in various sectors (Table 10 in the Appendix). This is in contrast with, for example, the defense acquisition executive summary (DAES) database used in the EVM cost performance and forecasting studies of Dr. David Christensen (Christensen and Heise 1993; Christensen and Rees 2002; Christensen and Templin 2002). Despite the considerable size of this database, which is claimed to contain more than 500 projects, it exclusively consists of U.S. defense acquisition contracts. Furthermore, the DAES database is not available to the public, so that verification of the reported results is prevented. A more elaborate comparison of the size and diversity of other existing project databases applied for studies on EVM can be found in Batselier and Vanhoucke (2015).

Note that the database of Batselier and Vanhoucke (2015) does show a dominant sector, being construction with 39 of the 51 projects. Nevertheless, the large share of construction projects does not compromise the diversity of the database, as the construction industry is very wide and thus comprises various subdivisions that exhibit mutually different characteristics. More specifically, the construction sector can be segmented into civil, industrial, and building construction. Furthermore, building construction can, in turn, be further segmented into commercial, institutional, and residential buildings. This subdivision of the construction sector has also been made in Table 10 of the Appendix. Moreover, according to Tzaveas et al. (2010), the prevalence of construction projects in the database can be deemed desirable, as earlier studies on EVM (forecasting) were mainly limited to IT and high-tech projects. In order to fill this research gap, the forecasting results for the

	According to plan	According to current time performance	According to current cost performance	According to current time/cost performance	According to weighted time/cost performance
	PF = 1	PF = SPI or SPI(t)	PF = CPI	PF = SCI or SCI(t)	PF = 0.8CPI+0.2SPI or 0.8CPI+0.2SPI(t)
Time					
PVM $EAC(t) =$	**PVM-1** $PD - \frac{SV * PD}{BAC}$	**PVM-SPI** $\frac{PD}{SPI}$		**PVM-SCI** $\frac{PD}{SCI}$	
EDM $EAC(t) =$	**EDM-1** $PD + AT * (1 - SPI)$	**EDM-SPI** $\frac{PD}{SPI}$		**EDM-SCI** $\frac{PD}{SCI} + AT * (1 - \frac{1}{CPI})$	
ESM $EAC(t) =$	**ESM-1** $AT + PD - ES$	**ESM-SPI(t)** $AT + \frac{PD - ES}{SPI(t)}$		**ESM-SCI(t)** $AT + \frac{PD - ES}{SCI(t)}$	
Cost					
EAC $EAC =$	**EAC-1** $AC + BAC - EV$	**EAC-SPI** $AC + \frac{BAC - EV}{SPI}$	**EAC-CPI** $AC + \frac{BAC - EV}{CPI}$	**EAC-SCI** $AC + \frac{BAC - EV}{SCI}$	**EAC-0.8CPI+0.2SPI** $AC + \frac{BAC - EV}{0.8CPI + 0.2SPI}$
$EAC =$		**EAC-SPI(t)** $AC + \frac{BAC - EV}{SPI(t)}$		**EAC-SCI(t)** $AC + \frac{BAC - EV}{SCI(t)}$	**EAC-0.8CPI+0.2SPI(t)** $AC + \frac{BAC - EV}{0.8CPI + 0.2SPI(t)}$

Fig. 2. EVM time and cost forecasting methods

construction projects will be considered separately and explicitly in this paper.

It has been repeatedly claimed in the literature that research on and application of EVM have primarily been focused on the cost management aspect (Anbari 2003; Jacob 2003; Fleming and Koppelman 2004, 2006; Henderson 2005, 2007; Vandevoorde and Vanhoucke 2006, 2007; Naeni et al. 2011; Vanhoucke 2011; Kwak and Anbari 2012; Lipke 2012a, 2013). However, a chronological overview of the existing EVM studies appears to abandoned these claims, as in more recent years, researchers seem to have turned their attention to the time dimension (Henderson 2003, 2005; Vandevoorde and Vanhoucke 2006; Hecht 2007; Lipke 2009; Rujirayanyong 2009; Tzaveas et al. 2010), whereas all the older studies are on cost management (Bright and Howard 1981; Covach et al. 1981; Riedel and Chance 1989; Zwikael et al. 2000). Therefore, let this paper be the first to argue that considering the research efforts made thus far, EVM time forecasting can be placed on equal footing with cost forecasting. This assertion will be further supported by more quantitative results in later sections of this paper.

Summarized, the contribution of this paper is three-fold:

- To the best of the authors' knowledge, this paper is the first to perform an adequate empirical evaluation of EVM forecasting accuracy. Previous studies either were based on simulations or empirical data used that were too limited in size and/or diversity.
- Also to the best of the authors' knowledge, this paper is the first to consider both time and cost forecasting, enabling the comparison of both forecasting dimensions. Previous studies focused either on costs or on schedule.
- There is an explicit focus on construction, a sector that has hitherto often been neglected in the EVM literature. It is assessed whether general observations on EVM forecasting accuracy also apply for construction projects specifically.

The outline of the rest of the paper is as follows: First, the methodology for attaining this paper's research goals is described. The results of the forecasting accuracy evaluation are presented and discussed in the subsequent section. Not only the overall accuracy and timeliness of the different time and cost forecasting methods will be considered, but also the influence of the important project characteristic of seriality on the forecasting accuracy is assessed. Note that there are other possible factors that can have an impact on forecasting accuracy, such as the nonlinearity of progress curves (i.e., PV curves) and schedule delay patterns (Kim and Kim 2014). However, the empirical assessment of these other influencing factors is left to future research. At the end of the "Results and Discussion" section, some expanding topics are addressed. Finally, conclusions are drawn and actions for further research are suggested.

Methodology

The presentation of the methodology is divided into three subsections: First, the important difference between simulated and real forecasting is clarified. Then, the applied evaluation approach for the different time and cost forecasting methods is presented. More specifically, the methods of the mean absolute percentage error (MAPE) comparison and accuracy ranking are explained, and two approaches for timeliness evaluation are proposed. Finally, the paper concludes with a description of the characteristic of project seriality.

Simulated and Real Forecasting

The important difference between simulated and real forecasting has already been indicated by Batselier and Vanhoucke (2015). In their paper, they identified the comparison of both types of forecasting results as an interesting topic for future research. This comparison has not yet been made in the literature—mainly because it can only be performed for real-life projects—and will therefore be part of this study. However, the simulation results should primarily be regarded as support for the real forecasting results. The explanation of simulated and real forecasting in this section is similar to that provided by Batselier and Vanhoucke (2015) but has been included here to ensure the standalone comprehensibility of this paper.

Simulated forecasting comprises the definition of risk distribution profiles for the individual activity durations, which are then used as input for a number of Monte Carlo simulation runs. In this study, the simulation runs are performed with the project management software tool *ProTrack*. The applied simulations make use of triangular risk distribution profiles for activity durations that can be either symmetrical, skewed to the left, or skewed to the right, according to the specific activity characteristics. It is assumed that the variable costs of an activity vary uniformly with the corresponding activity duration. In contrast, the fixed cost figures always remain constant. Furthermore, the standard symmetric profiles are assumed when the data providers did not include any information about the specific activity risk distributions. One-hundred Monte Carlo simulation runs are performed for each project; the simulated forecasting results presented later on are thus the average over these 100 runs. Moreover, the results for every individual Monte Carlo run are based on simulated progress data over 20 tracking periods. This implies that the tracking periods for simulation are assigned a length of $\lfloor PD/20 \rfloor$, with PD the planned duration of the project. Note that the presented simulation approach does not take into account potential corrective actions by management, as was the case for simulations performed by Vanhoucke (2010b, 2011, 2012b).

It is important to realize that for projects that have been generated by a project network generator (Kolisch et al. 1995; Schwindt 1995; Agrawal et al. 1996; Tavares 1999; Demeulemeester et al. 2003; Vanhoucke et al. 2008) and/or are part of a benchmark dataset (Boctor 1993; Kolisch and Sprecher 1996; Van Peteghem and Vanhoucke 2014), only the above described simulated forecasting can be performed due to the inherent absence of real tracking data for those projects. In contrast, for real-life projects that include tracking information obtained directly from the actual project owner, *real forecasting* results can also be obtained. The accuracy of a real time or cost forecast is assessed by comparing the forecasted values, obtained from a certain forecasting method, with the actual final project duration or cost and this at predefined times throughout the project (i.e., at the end of each tracking period). This approach for accuracy assessment is expressed by the MAPE, which is defined in next subsection. Also, in contrast to simulated forecasting, which can already be performed *before* the project starts, the real forecasting accuracy can only be calculated *after* the project has ended, since the actual project duration and cost needed for calculation are only known from that point.

Forecasting Accuracy Evaluation Approach

As already mentioned, the MAPE forms the basis for expressing the real forecasting accuracy of a certain forecasting technique. The MAPE has also been used in EVM accuracy evaluations performed by Vanhoucke and Vandevoorde (2007), Rujirayanyong (2009), Vanhoucke (2010a), and Elshaer (2012). The measure is calculated as follows:

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

Here A is the actual final value and F_t the forecasted value at time t. The time instances $t = 1, \ldots, n$ correspond to the n tracking periods that were set for the considered project. Furthermore, particularizing Eq. (1) for time forecasting, A and F_t are substituted by the real duration RD and the estimated time at completion EAC(t), respectively. For cost forecasting, this becomes the real cost RC and the estimated cost at completion EAC, respectively. Obviously, the lower the MAPE for a particular forecasting method, the higher the accuracy of that method. The MAPE was presented here in the context of real forecasting. However, simulated forecasting accuracies are also expressed as MAPEs and are therefore based on the same Eq. (1). The only difference is that for simulated forecasting, RD and RC originate from simulations, whereas for real forecasting, they represented the actual final project outcomes. Moreover, the MAPEs for simulated forecasting can be directly calculated by the software tool *ProTrack*.

In this paper, the accuracy of the different time and cost forecasting methods is also evaluated using an alternative technique complementing the standard approach of MAPE-comparison. This approach, which this study calls the accuracy ranking method, is similar to the ranking method used by Lipke (2009). For a certain project, the time or cost forecasting methods are ranked by increasing MAPE. More concretely, the method with the lowest MAPE is assigned rank 1, the method with the second lowest MAPE is assigned rank 2, and so on. When two or more methods show an equal MAPE, they are all assigned the same most optimistic rank and the method following the tied set in the ranking receives its normal rank. For a particular time or cost forecasting method, the average rank over all considered projects can then be calculated and compared with the average ranks of the other methods in order to evaluate its relative accuracy.

Besides overall accuracy (i.e., the average accuracy over the entire course of a project), timeliness is also an essential evaluation criterion for forecasting methods (Covach et al. 1981). Indeed, it is important that a time or cost forecasting method can provide reliable early warnings of schedule or cost overruns, respectively.

More concretely, Teicholz (1993) states that it is particularly important to get accurate warnings about significant overruns during the first half of a project so that adequate corrective action can be taken. Therefore, this study explicitly assesses the accuracy of the EVM time and cost forecasting methods during the first 50% completion of the projects. The percentage complete (PC) of a project at a certain tracking period is expressed by EV/BAC, with the EV calculated for that particular tracking period and BAC representing the budget at completion of the project. Thus, in other words, only the tracking periods with a PC < 50% are considered. The methods that exhibit the lowest MAPEs for this first timeliness evaluation approach are said to provide the most reliable early warning signals.

A second timeliness evaluation approach follows from Vanhoucke and Vandevoorde (2007), who state that the accuracy of forecasts depends on the completion stage of the project. Therefore, a stage-wise comparison of the accuracies of the EVM time and cost forecasting methods can be performed. To this end, three completion stages are defined according to the PC:

- 0% ≤ PC < 30%: Early stage;
- 30% ≤ PC ≤ 70%: Middle stage; and
- 70% < PC ≤ 100%: Late stage.

This categorization corresponds to the basic subdivision made by Vanhoucke and Vandevoorde (2007). Moreover, since typical (construction) projects exhibit the fastest progress near the middle of the project (Kim and Kim 2014), it can be deemed logical to assign the largest PC interval to the middle stage in order to have ample tracking periods situated in this stage. Contemplation of the available tracking data from Batselier and Vanhoucke (2015) supports this approach.

Logically, a tracking period of a project is situated in a certain stage if the PC calculated for it lies within the boundaries of that stage. Nevertheless, no results are taken into account for a certain stage of a project if it contains less than three tracking periods. This is the case for six projects in the early stage, five projects in the middle stage, and two projects in the late stage. Concluding this section, it is noted that only the real forecasting results are considered for both timeliness evaluation approaches; that reflecting early warnings (Teicholz 1993) and that based on stage-wise comparison (Vanhoucke and Vandevoorde 2007).

Project Seriality

The characteristic of *project seriality* enables the description of a project's network structure in terms of how close the network is to a serial (or parallel) network. Project seriality is represented by the so-called serial/parallel-indicator (SP) which ranges from 0 to 1 with SP = 0, indicating that all activities are in parallel and SP = 1 signifying that the project network is completely serial (Tavares et al. 1999; Vanhoucke et al. 2008). Between these two extreme values, networks can be closer to either a serial or a parallel network. The SP can be calculated by the next formula

$$\text{SP} = \frac{n_s - 1}{n_t - 1} \qquad (2)$$

Here, n_s is the maximum number of subsequent activities in the network (also known as the maximum progressive level) and n_t is the total number of activities. Note that for a project consisting of only one activity, SP is obviously equal to unity (completely serial project) and Eq. (2) does not apply.

In order to fulfill the intended research objectives regarding the assessment of the effect of seriality on forecasting accuracy, all projects in the database are subdivided into three categories according to their SP value. The following concrete subdivision is made:

- 0% ≤ SP < 40%: Parallel projects;
- 40% ≤ SP ≤ 60%: Serial-parallel projects; and
- 60% < SP ≤ 100%: Serial projects.

The category intervals are situated symmetrically with respect to the midpoint of SP = 50%. This is a reasonable assumption, since the likelihood of a project's SP being closer to 1 is just as great as it being closer to 0. However, there is a higher probability of the SP lying closer to 50% than it being nearer to either the serial or the parallel extreme. Therefore, the intermediate serial-parallel category is assigned a smaller interval of SP values than the border categories. In this way, it is ensured that the number of projects in each category will not show too great a difference, so that meaningful evaluations could be made later on in this paper. Moreover, note that the same SP categorization has been made by Batselier and Vanhoucke (2015).

Results and Discussion

The results for EVM time and cost forecasting are now presented and discussed in two separate sections. Both sections are structured the same, with the presentation of the overall results first, followed by the timeliness evaluation and finally, the assessment of the influence of project seriality on forecasting accuracy. The techniques of MAPE comparison and accuracy ranking are used to evaluate the results. Moreover, both simulated and real forecasting outcomes are considered where relevant. Note, nevertheless, that simulation results are of secondary importance in this study; rather, they provide support to the real forecasting results. Also, notice that in the first two sections, all 51 projects in the database are considered. In a third expanded section, this study explicitly focuses on the construction projects in the database. Another expanded topic is the comparison of EVM time and cost forecasting.

It should be clearly noted that this paper does not attempt to generalize the obtained results and thus does not aim at making conclusions and recommendations that would apply for all projects in general (or for all construction projects in specific). Rather, it seeks to present and discuss the EVM forecasting outcomes for the projects in the database used and come to useful related observations. In the following sections, the term *overall* does not therefore refer to the entirety of all projects, but to all projects *in the considered database*.

Time Forecasting

Overall Results

Table 1 indicates that ESM-1 is the most accurate method for time forecasting over all projects in the database, based on both MAPE and accuracy rank evaluation. Moreover, this is true for both simulated and real forecasting.

However, apart from the top method, the top three looks remarkably different: for simulation, it is completely occupied by the ESMs, whereas for real forecasting the unweighted methods (i.e., methods with a PF = 1) come out on top. There are two reasons for this.

First, the calculation of EDM-1 (see its formula in Fig. 2) produces biased results in combination with the chosen simulation approach when a project displays a relatively long initial period of very low PV accrue. More concretely, empirical observations point out that it concerns projects that still have a PV lower than 1% of the BAC at 15% of the PD. Such projects show exuberant MAPEs for simulated forecasting, indicated by the big M value in Table 1. Subsequent studies should elaborate on the root causes of the observed effect. Nevertheless, it can be stated that simulated EDM-1 accuracies are biased and that the method's real potential is not reflected by the overall simulation results.

The second reason is of a more qualitative nature. As was already mentioned, this study's simulation approach does not take into account possible corrective actions by management. This implies that current performance cannot be influenced by any external factor and thus is likely to be maintained in the future. Since SPI(t) reflects the current schedule performance, it was to be expected that ESM-SPI(t)—and by extension ESM-SCI(t) based on the schedule cost index—would perform well in the simulations. On the other hand, real project data obviously contain the effect of possible corrective actions that were performed by management during project execution. More specifically, project managers are considered to take improvement actions when project performance is lagging (Anbari 2003). This would mean that the current performance [i.e., the current SPI(t)] does not adequately reflect the expected future performance. Forecasting in project management may therefore well be a self-defeating prophecy (Anbari 2003), just as the resulting predictions may well be self-negating (Kim and Reinschmidt 2009). However, this is not necessarily a disadvantageous property as it might be good for the organization that a project manager takes action inspired by a negative forecast, and through this, gets the project back on track (Anbari 2003; Kim and Reinschmidt 2009). Furthermore, regarding forecasting accuracy, the above discussion suggests the main reason for the unweighted methods—which assume that future performance will be as planned and thus implicitly take into account potential corrective actions—to come out on top for real-time forecasting.

Note that for both simulated and real forecasting, the ESMs perform significantly better than the PVMs and the EDMs for the considered projects. The same conclusion has already been drawn in the extensive simulation study of Vanhoucke and Vandevoorde (2007) and could be regarded as commonly accepted. Therefore, this subject will not be elaborated upon further. However, note that this study is the first—apart from the very basic preliminary study of Batselier and Vanhoucke (2015)—to evidence the supremacy of ESM for a wide real-life project database and, moreover, to explicitly argue that ESM-1 performs better than ESM-SPI(t) in many cases. In the recent literature, however, it has become common practice to only use SPI(t) as a performance factor when studying the ESM technique (Rujirayanyong 2009; Tzaveas et al. 2010; Vanhoucke 2011; Elshaer 2012; Lipke 2012b; Vanhoucke 2012b; Crumrine and Ritschel 2013). This paper's findings thus indicate that this research approach might be incomplete; future studies are encouraged to at least also consider ESM-1 in addition to ESM-SPI(t).

Furthermore, Table 1 shows that the time forecasting methods based on the traditional SPI (PVM-SPI, PVM-SCI, EDM-SPI, and EDM-SCI) do not perform very well here. This also appears from Table 2, which displays the number of times that a certain method proves to be the best [these results correspond to the outcomes presented by Batselier and Vanhoucke (2015)] or is one of the three most accurate methods for time forecasting. Moreover, the table once again indicates the supremacy of the unweighted methods, and most importantly, the indisputable first place of ESM-1 as most accurate method for forecasting project duration for the considered projects. The displayed results are those for real forecasting.

Note that the observed supremacy of the unweighted methods for time forecasting is not entirely unexpected. Indeed, these methods follow the same assumption as the critical path method (CPM)—the historically preferred approach for predicting a project's duration—namely, that future schedule performance will be as planned. Anbari (2003) already explicitly pointed out the similarity between the CPM and the unweighted EVM time forecasting methods. Then again, many other authors have indicated that EVM is

Table 1. Overall Accuracies of EVM Time Forecasting Methods

	PVM			EDM			ESM		
Criterion	1	SPI	SCI	1	SPI	SCI	1	SPI(t)	SCI(t)
Simulated									
MAPE (%)	22.1	31.0	31.6	M	30.9	31.1	14.3	20.4	20.7
Rank (-)	3.4	5.4	6.6	5.2	4.8	5.2	2.2	4.1	4.6
Real									
MAPE (%)	12.4	30.2	38.1	12.5	28.5	31.8	8.5	16.9	20.7
Rank (-)	3.8	7.0	7.5	3.0	5.9	6.0	1.7	4.3	4.9

Table 2. Frequencies of EVM Time Forecasting Methods As Best or Top Three Methods

	PVM			EDM			ESM		
Freq (-)	1	SPI	SCI	1	SPI	SCI	1	SPI(t)	SCI(t)
# best	1	0	0	4	0	1	16	1	2
# top three	15	0	1	17	1	2	21	8	8

Table 3. Timeliness Evaluation of EVM Time Forecasting Methods

MAPE (%)	PVM 1	PVM SPI	PVM SCI	EDM 1	EDM SPI	EDM SCI	ESM 1	ESM SPI(t)	ESM SCI(t)
Early warnings									
(PC 0–50%)	13.2	39.1	47.5	18.0	39.1	43.4	11.3	26.5	30.4
Completion stages									
Early (PC 0–30%)	11.2	34.3	43.6	15.4	34.3	39.2	10.5	26.9	30.5
Middle (PC 30–70%)	8.9	17.6	27.8	9.3	17.6	20.9	6.1	12.3	15.6
Late (PC 70–100%)	12.4	12.8	17.3	8.7	9.0	9.1	5.7	7.0	8.3

often perceived as less appropriate for time forecasting and that there is a belief among some researchers and practitioners that other techniques—mainly alluding to the CPM by this—should be utilized in order to obtain more plausible forecasts of project duration (Jacob 2003; Kim et al. 2003; Henderson 2004; Lipke et al. 2009; Vanhoucke 2011; Kwak and Anbari 2012; Crumrine and Ritschel 2013; Lipke 2013). However, since the unweighted EVM time forecasting methods are based on the same principles as the trusted CPM, there seems to be no apparent reason why these EVM time forecasting methods should not be used. Moreover, the statements regarding the inferiority of EVM in a time context were largely nullified through the introduction of earned schedule (ES) by Lipke (2003), which is supported by the superiority of ESM-1 observed in this study. Therefore, EVM should be considered an appropriate and self-contained technique for forecasting project duration. An explicit comparison with project cost forecasting, for which EVM is already widely used and accepted, is performed later in this paper and will support this last statement.

Timeliness Evaluation

For the timeliness evaluation of the EVM time forecasting methods, the methods' ability to provide reliable early warnings (Teicholz 1993) is assessed and their accuracies are compared over different project completion stages (Vanhoucke and Vandevoorde 2007). The results are shown in Table 3.

In accordance to the overall results of the previous subsection, the unweighted methods provide the most accurate early warning signals for the projects in the database used. Moreover, the ESMs also dominate the PVMs and the EDMs in the first half of the projects. Consequently, ESM-1 again is found to be the best performing method. Similar observations can be made when considering the different completion stages. However, notice that the relative advantage of the unweighted methods with respect to the methods based on past schedule (and cost) performance decreases toward the later stages of the project. This is of course is largely due to the fact that the forecasting accuracies of all methods show an expected increase toward the end of the project, as was also observed by Vanhoucke and Vandevoorde (2007). However, the results for PVM-1 do not follow this logical evolution. The main reason lies with the definitions of the PVM formulas, which in some cases yield biased outcomes at the end of the project. In conclusion of this section, notice that ESM-1—the top time forecasting method according to this paper's empirical study—provides middle stage forecasts that are almost as accurate as those for the late stage, which is of course favorable regarding the timeliness of the method.

Influence of Project Seriality

In order to allow a correct assessment of the influence of project seriality on time forecasting accuracy, the projects with a relatively long initial period of very low PV accrue are eliminated and thus the biased simulation results for EDM-1, which appeared in previous subsection, are removed. More specifically, seven projects with a PV lower than 1% of the BAC at 15% of the PD are eliminated.

Table 4. Accuracies of EVM Time Forecasting Methods with Respect to Project Seriality

MAPE (%)	PVM 1	PVM SPI	PVM SCI	EDM 1	EDM SPI	EDM SCI	ESM 1	ESM SPI(t)	ESM SCI(t)
Simulated									
Serial	8.8	12.5	14.5	9.5	12.2	13.6	7.9	12.1	13.2
Ser.-para.	12.8	16.2	16.5	13.4	15.9	16.1	11.1	16.5	16.7
Parallel	17.7	29.7	29.9	27.5	29.6	29.7	15.4	20.2	20.3
Real									
Serial	16.2	13.4	11.9	11.1	9.4	8.9	10.4	12.2	13.5
Ser.-para.	8.1	16.0	23.7	4.7	12.0	15.8	3.7	12.9	17.1
Parallel	9.5	22.7	47.1	8.9	22.0	36.3	8.7	17.1	30.1

Now refer to Table 4. From the simulation results, it quite clearly appears that time forecasting accuracy increases with the growing level of seriality. This confirms the results of Vanhoucke and Vandevoorde (2007), which were also based on a simulation study. Moreover, all SPI- and SPI(t)-based forecasting methods demonstrate the mentioned relation between accuracy and seriality for real forecasting as well.

The individual unweighted methods, however, produce more inconsistent results here. Three reasons can be found. First, for more parallel projects, delays in noncritical activities will not have such a biasing effect on time forecasts when an unweighted method is used, since the incorrect current performance reflected by SPI or SPI(t) is not accounted for. This qualitative reasoning provides yet another indication that unweighted forecasting methods could be expected to produce the most reliable time forecasts. Second, since the unweighted methods already exhibit a lower MAPE than the other methods considered in this study—certainly for real forecasting—even small absolute variations in MAPE can influence the accuracy relations with respect to seriality. And third, the currently considered pool of projects with real tracking might still be too limited in size in order to eliminate possible distorting effects from outliers. Nevertheless, apart from the explicable inconsistencies for real forecasting unweighted methods, the relation between time forecasting accuracy and project seriality appears to have been validated on this study's real-life database.

Cost Forecasting

Overall Results

The overall simulation results for the considered projects (Table 5) show the indisputable dominance of EAC-1 and EAC-CPI for cost forecasting, with average MAPEs of even less than 1%. This very beneficial outcome is primarily due to the nature of this study's simulation approach, more specifically, to the way that costs are

Table 5. Overall Accuracies of EVM Cost Forecasting Methods

Criterion	EAC 1	CPI	SPI	SPI(t)	SCI	SCI(t)	0.8CPI + 0.2SPI	0.8CPI + 0.2SPI(t)
				Simulated				
MAPE (%)	0.9	0.9	12.8	11.6	13.2	12.0	6.6	4.7
Rank (-)	1.3	1.4	5.9	5.7	6.4	6.3	3.6	3.4
				Real				
MAPE (%)	8.3	9.9	24.9	13.6	27.3	15.7	10.0	8.6
Rank (-)	3.1	3.2	5.9	5.0	6.2	5.5	3.3	2.9

simulated. Recall that variable activity costs are assumed to vary uniformly with the activity duration, whereas fixed activity costs remain the same as planned. This implies that if a project only contains fixed costs, EAC-1 and EAC-CPI will per definition yield a MAPE of 0%, which would suggest a perfect forecast. Obviously, this scenario is rather unrealistic. Nevertheless, the projects with a smaller proportion of fixed costs still indicate EAC-1 and EAC-CPI as the top methods.

More importance should be attached, however, to the real forecasting results. Again, EAC-1 and EAC-CPI are among the most accurate methods here. However, displaying a very similar accuracy according to both MAPE and ranking evaluation, the so-called composite methods EAC-0.8 CPI + 0.2 SPI and EAC-0.8 CPI + 0.2 SPI(t) join the selection of top cost forecasting methods. This is not entirely unexpected, as both methods already exhibited satisfactory results for simulations. The four other cost forecasting methods make the rather illogical assumptions that cost forecasts should be based only on schedule performance [i.e., EAC-SPI and EAC-SPI(t)] or as much on schedule performance as on cost performance [i.e., EAC-SCI and EAC-SCI(t)], and therefore, are not expected to achieve a performance comparable to that of the top four, which is supported by this study's empirical results.

The latter statement is also reflected in Table 6, which presents the frequencies of the different methods being the best or one of the three most accurate methods for cost forecasting in the considered database. Indeed, the supremacy of EAC-1, EAC-CPI and the composite methods is clearly shown in this table. However, a noticeable advantage can be observed for the two former methods—which exhibit completely identical results here—regarding the probability of being the number one method [also see Batselier and Vanhoucke (2015)]. Then again, EAC-0.8 CPI + 0.2 SPI(t) appears to most frequently be part of the top three. Note that the displayed results are those for real forecasting.

In a previous study, Zwikael et al. (2000) concluded that EAC-CPI is the most advisable method for cost forecasting. Today, this conclusion is more or less accepted as a general truth, which resulted in EAC-CPI becoming the standard method for forecasting cost when using EVM. This appears evident in a way, as the method fully takes into account the current cost performance.

Table 6. Frequencies of EVM Cost Forecasting Methods As Best or Top 3 Method

Freq (-)	EAC 1	CPI	SPI	SPI(t)	SCI	SCI(t)	0.8CPI + 0.2SPI	0.8CPI + 0.2SPI(t)
# best	8	8	1	1	2	1	3	3
# top three	13	13	4	3	2	3	11	16

In this study, however, EAC-1 is found to be the most accurate method according to the MAPE values. Similar to the reasoning for the unweighted time forecasting methods, it could be stated that EAC-1 accounts for possible management actions—of which the effect is included in real tracking data—by assuming that future performance will be as planned [i.e., management will improve the project's currently poor cost performance (Anbari 2003)].

Apart from EAC-1 and EAC-CPI, the composite methods also show good cost forecasting accuracies for the considered projects. Concerning these two methods, the following reflections can be made. The dominance of the ESM over the PVM and the EDM was already indicated earlier in this paper and in many previous studies. This also implies that SPI(t) dominates SPI as a measure for schedule performance. Therefore, it is logical that EAC-0.8 CPI + 0.2 SPI(t) would generally be expected to perform better than EAC-0.8 CPI + 0.2 SPI, and thus, the latter method would never be recommended. On the other hand, EAC-0.8 CPI + 0.2 SPI(t) certainly shows its advantages with respect to EAC-1 and EAC-CPI; the method even proves to be the best based on the accuracy ranking evaluation performed for the projects in the database.

A qualitative explanation can be found for this observation. Exemplary, think of a project exhibiting severe delays while the currently incurred costs are more or less as planned [i.e., SPI(t) ≪ CPI]. It should be recognized that this project will probably cost more than expected from the current cost performance (i.e., CPI) as additional costs induced by management actions for getting the project back on track (i.e., hiring more workers and/or allowing overtime) or simply by the project taking longer (i.e., workers have to be paid for a longer period) are not counted for in EAC-CPI. On the other hand, EAC-0.8 CPI + 0.2 SPI(t) does take into account this effect. Of course, current cost performance (i.e., CPI) should remain the primary indicator of future cost performance for obvious reasons. The addition of SPI(t) to the forecasting method performance factor can be understood as taking into account a secondary effect, being that of potential schedule distortions.

In this respect, the 80/20 distribution is one traditionally made in the literature (Wallender 1986; Riedel and Chance 1989; Christensen 1993; Vanhoucke 2012a) and is not claimed to be optimal here. The evaluation of other possible distributions has already been performed in earlier studies [see Christensen et al. (1995) for an overview], but remains a possible topic for extended research [e.g., with consideration of SPI(t) instead of SPI]. It is interesting to know is that Wallender (1986) already argued that the 80/20 composite method should produce the best EVM cost forecasts. Riedel and Chance (1989) and Christensen (1993) contested this statement in the following years. However, at that time, the earned schedule concept had not yet been developed and the 80/20 composite method of Wallender (1986) was thus referred to as EAC-0.8 CPI + 0.2 SPI. According to this study's results, this method indeed does not perform better than EAC-CPI. However, EAC-0.8 CPI + 0.2 SPI(t) does, and therefore, the discussion on the possible advantage of using a composite performance factor for EVM cost forecasting could be reopened. Moreover, the contribution of the earned schedule concept again appears from previous exposition, now even for the cost aspect.

Timeliness Evaluation

The timeliness evaluation of the EVM cost forecasting methods is completely similar to that performed for the time dimension. The results are displayed in Table 7.

It clearly appears that EAC-1 and EAC-0.8 CPI + 0.2 SPI(t) can provide the most accurate early warning signals for the considered

Table 7. Timeliness Evaluation of EVM Cost Forecasting Methods

MAPE (%)	EAC 1	CPI	SPI	SPI(t)	SCI	SCI(t)	0.8CPI + 0.2SPI	0.8CPI + 0.2SPI(t)
				Early warnings				
(PC 0–50%)	12.4	17.1	31.9	22.3	34.9	23.7	16.2	12.9
				Completion stages				
Early (PC 0–30%)	12.2	17.2	25.3	22.4	29.1	23.3	15.5	12.7
Middle (PC 30–70%)	9.7	10.1	11.6	10.9	14.5	12.5	9.0	9.1
Late (PC 70–100%)	3.9	4.1	3.5	4.0	4.0	4.6	3.9	3.9

projects. Furthermore, these two methods seem to exhibit a greater advantage over EAC-CPI in terms of timeliness than in terms of overall accuracy (see previous subsection). Again, this indicates that the dominance of the traditionally preferred EAC-CPI can be questioned for cost forecasting. Just like for time forecasting, all methods show a logical accuracy increase toward the end of the project. In fact, at the late stage, there is hardly any difference (i.e., of maximum 1% MAPE) between the eight methods, and all of them are extremely accurate. Notice that especially EAC-SPI exhibits a strong increase in accuracy toward the later stages of the project. At the late stage, it even becomes the most accurate method in this study. This is largely due to the fact that SPI always goes to 1 at the end of the project, thus implying that EAC-SPI produces forecasts that are increasingly similar to EAC-1 as the project progresses.

Influence of Project Seriality

Just as was done for time forecasting, the potential biasing effect caused by projects with an initial period of very low PV accrue is eliminated through the omission of the same seven projects so that a correct and uniform assessment of the influence of project seriality on cost forecasting accuracy can be performed.

Now refer to Table 8. Different from what was the case for time forecasting, no obvious relation between the level of seriality and the cost forecasting accuracy can be identified for simulated forecasting, and certainly not for the top four methods. For real forecasting, there are also results contradicting a possible relation, most importantly, those for EAC-1 and EAC-CPI. From these observations, it might be concluded that the cost forecasting accuracy is largely independent of project seriality.

Moreover, no qualitative reason could be found for such a dependence to exist. Indeed, the nature of the schedule, or more specifically the character of the network structure, does not intrinsically influence the total project cost because the project cost always comprises *every* individual activity cost. Whether a project is more serial or more parallel, all activity costs are always included in the calculation of the project cost. For the determination of the project duration, however, this is not the case; only the durations of the activities that are on the critical path are counted and the project's network structure can thus indeed influence the project duration. More concretely, a perfectly serial project can only have one critical path, whereas for a more parallel project there are several potential critical paths. The more uncertainty there is about the critical path, the more uncertainty there is about the eventual project duration, and hence, the less accurate time forecasting will be. Previous argumentations thus provide a qualitative explanation of why project seriality has an influence on time forecasting accuracy but not on cost forecasting accuracy.

Expanding Topics

Focus on Construction Projects

In the preceding sections, all 51 projects of the database were considered. Here, this study explicitly focuses on the construction projects in the database and the results are compared with the overall outcomes. Now consider Table 9. Note that all the MAPEs presented in this table refer to the real forecasting accuracies, which is a prerequisite for allowing empirical evaluation.

It immediately appears that both for time and cost forecasting and both on average (i.e., over all forecasting methods) and for only the best method according to this study (i.e., ESM-1 for time and EAC-1 for cost), the results over all projects in the database and those for the construction projects specifically are strongly similar. In fact, there is a maximum accuracy difference of only about half a percent. Of course, this outcome was to be expected as more than three-quarters of the considered projects (i.e., 39 of the 51) are from the construction industry. Nevertheless, this observation does indicate that all of the discussions on the overall results that were performed in the preceding sections also apply in a construction context. However, this does not readily imply that there are no significant differences between construction projects and nonconstruction projects (e.g., from IT, event management, education, production) with respect to EVM forecasting performance. The currently used database contains too few nonconstruction projects (i.e., 12 projects) to make any meaningful statements on this matter. Therefore, the explicit comparison of EVM forecasting accuracies for construction and nonconstruction projects can be an interesting

Table 8. Accuracies of EVM Cost Forecasting Methods with Respect to Project Seriality

MAPE (%)	EAC 1	CPI	SPI	SPI(t)	SCI	SCI(t)	0.8CPI + 0.2SPI	0.8CPI + 0.2SPI(t)
				Simulated				
Serial	1.4	1.3	6.6	7.8	9.0	10.1	2.7	3.1
Serial-parallel	0.8	1.0	6.9	8.4	7.2	8.7	2.7	2.6
Parallel	0.3	0.3	15.9	14.0	16.0	14.0	8.3	5.6
				Real				
Serial	2.1	2.0	10.9	10.8	12.1	12.6	2.3	2.8
Serial-parallel	8.6	7.8	10.8	12.4	11.4	13.0	6.0	5.8
Parallel	8.1	6.9	15.6	13.1	21.0	16.6	7.6	7.6

Table 9. EVM Forecasting Accuracies for All Projects and for Construction Projects

MAPE (%)	Overall	Construction
	Time	
Average	22.2	21.9
Best	8.5	8.8
	Cost	
Average	14.8	15.4
Best	8.3	7.9

research topic after sufficient expansion of the database of Batselier and Vanhoucke (2015).

Comparing Time and Cost Forecasting

Regarding the difference in performance of EVM time and cost forecasting, several authors explicitly stated that EVM has always been considered an excellent cost predictor, but that it has a questionable reputation for forecasting project duration (Van De Velde 2007; Vanhoucke and Vandevoorde 2007; Tzaveas et al. 2010; Egnot 2011; Crumrine and Ritschel 2013). However, their statement refers to the pre-ES period, and moreover, expresses a belief adopted by some researchers and practitioners rather than a general truth based on thorough research.

The results of this paper suggest that EVM can provide project duration forecasts that are just as accurate as the forecasts of project cost. Illustrated by concrete real forecasting figures from Table 9, it can be seen that the best time forecasting method (i.e., ESM-1) exhibits an overall MAPE of 8.5%, which is virtually identical to the overall MAPE of 8.3% of the top cost forecasting method (i.e., EAC-1). Concerning timeliness, ESM-1 even provides slightly more accurate early warning signals than EAC-1 in this study (MAPEs of 11.3 and 12.4%, respectively). Similar observations can be made for the construction projects specifically. Therefore, EVM can be considered an appropriate technique for forecasting project duration. Consequently, there seems to be no need for reluctance to use EVM in a time context.

Conclusions

The main objective of this paper was to assess the accuracy of the most commonly used EVM forecasting methods for both time and cost based on a large and diverse real-life project database. To this end, the database of Batselier and Vanhoucke (2015) was used. At the time of the study, the concerning database comprised 51 projects from various sectors—but with a focus on the construction sector—and with very different durations and budgets, therefore outranking previous real-life databases from the literature in both size and diversity. Moreover, the entire database is publicly available at OR-AS.

Concerning the actual EVM forecasting research, the accuracies of the considered forecasting methods [selection based on Vanhoucke (2012a)] were evaluated through the techniques of MAPE-comparison and accuracy ranking. Furthermore, the methods' timeliness was assessed based on early warning reliability (Teicholz 1993) and accuracy comparison for different completion stages (Vanhoucke and Vandevoorde 2007). The real forecasting results (i.e., based on the actual project progress data) following from these evaluations are always supported by a Monte Carlo simulation study when relevant. Moreover, it is important to note that all of the overall outcomes (i.e., over all projects in the database used) presented below also apply for the specific set of construction projects in the database.

For time forecasting, ESM-1 clearly proved the best method for the considered projects, regarding both overall accuracy and timeliness. In the recent literature, however, the standard approach is to only consider ESM-SPI(t) for time forecasting. This tradition could thus be contested. Nevertheless, the ESM as a global methodology indeed outperforms the PVM and the EDM in this study, confirming the conclusions made by Vanhoucke and Vandevoorde (2007). Furthermore, the main reason for unweighted time forecasting methods being more accurate than those with an SPI- or SPI(t)-related performance factor could be that the former methods can partially take into account possible corrective actions by management whereas the latter cannot. Moreover, the unweighted time forecasting methods were shown to correspond closely with the CPM, which is the traditionally preferred technique for forecasting a project's duration.

For cost forecasting, EAC-1, EAC-CPI and EAC-0.8 CPI + 0.2 SPI(t) come out best according to the performed empirical study. Only minor differences in accuracy can be detected between these methods—although EAC-CPI was found to be less timely—and all three display an apparent advantage: EAC-1 can partially take into account possible corrective actions by management; EAC-CPI only accounts for cost performance and was considered best by Zwikael et al. (2000); and EAC-0.8 CPI + 0.2 SPI(t) can include the cost-increasing effect induced by (severe) schedule delays. Again, the dominance of the traditionally preferred method (i.e., EAC-CPI) could thus be questioned here.

Furthermore, the results of this paper suggest that EVM can provide project duration forecasts that are just as accurate and timely as the forecasts of project cost, which is mainly due to the introduction of ES (Lipke 2003). Therefore, EVM can be considered an appropriate technique for forecasting project duration. Consequently, there seems to be no need for reluctance to use EVM in a time context.

The influence of project seriality on forecasting accuracy was also assessed. Project seriality is expressed by the serial/parallel-indicator SP, which defines whether a project's network structure is more serial or more parallel. For time forecasting, a relation of increasing forecasting accuracy with growing degree of seriality (i.e., increasing SP) was discovered, confirming the results of Vanhoucke and Vandevoorde (2007). For cost forecasting, however, no apparent indications of the existence of such a relation could be observed for the considered projects. This is not surprising as, by its definition, project seriality only refers to the schedule and not to the cost aspects of a project.

Future research efforts should be focused on improving the existing EVM forecasting techniques, preferably starting from those methods that currently appear to perform best according to this study and earlier studies (e.g., ESM-1 for time forecasting). Moreover, an empirical investigation should be performed concerning the effect of irregularities in the course of the PV curve (e.g., a relatively long initial period of very low value accrue) on EVM forecasting accuracy. This study would be related to previous research into the effect of nonlinearity of progress curves on the forecasting accuracy of deterministic methods (Kim and Kim 2014). Possibly, this effect could be quantified and related to a novel project characteristic similar to project seriality.

Appendix. Database Overview

Table 10 provides an overview of the real-life project database of Batselier and Vanhoucke (2015) that is utilized in this paper. More specifically, the table shows the most important characteristics of the projects in the database (i.e., sector, planned duration, budget at completion). The projects are identified by a suitable name and a code that reflects the year in which the project data were received and the sequence number of the project.

Whereas Table 10 gives a more general view on the database used, Table 11 shows the specific tracking data (i.e., PV, EV and AC) for a selection of 13 projects. Not all projects in the database could be considered here due to space limitations. For the same reason, the data for only nine tracking periods are presented, with three tracking periods in every completion stage (i.e., early, middle, and late) distributed as uniformly as possible according to the PC.

Note, however, that a uniform spread of PCs cannot be obtained for every project, nor do the PC distributions within the stages

Table 10. Overview of the Real-Life Project Database

Project code	Project name	Sector	PD (days)[a]	BAC (€)
C2011-01	Nursing home Noordhinder	Construction (commercial building)	766	4,679,795
C2011-02	Social housing Kortrijk	Construction (residential building)	276	366,457
C2011-03	Family day	Event management	97	31,675
C2011-04	Railway station Sint-Joost	Construction (civil)	125	59,831
C2011-05	Telecom system Agnes	IT	43	180,485
C2011-06	Veterinary exposition	Event management	314	54,350
C2011-07	Patient transport system	IT	389	180,759
C2011-08	Sports Center Tielt	Construction (civil)	72	254,564
C2011-09	Commercial IT project	IT	57	33,623
C2011-10	Building a house	Construction (commercial building)	195	484,398
C2011-11	Eating Belgium	Event management	299	37,760
C2011-12	Claeys-Verhelst Premises	Construction (commercial building)	442	3,027,133
C2011-13	Wind farm	Construction (industrial)	525	21,369,836
C2011-14	Hotel Reylof	Construction (commercial building)	252	—
C2012-01	Manufacturing tool cost module	IT	45	61,699
C2012-02	Nut mixing station	Construction (industrial)	22	1,056,501
C2012-03	Day care	Construction (institutional building)	128	—
C2012-04	Asti-Cuneo Highway	Construction (civil)	272	6,230,691
C2012-05	Tappan Zee bridge	Construction (civil)	1,289	4,999,958,016
C2012-06	Youth hostel Merkenveld	Construction (commercial building)	197	—
C2012-07	Solar park	Construction (industrial)	711	—
C2012-08	Sea electricity	Construction (industrial)	468	139,062,144
C2012-09	Digipolis talent management suite	IT	162	4,899,912
C2012-10	Gabala resort outdoor pool	Construction (commercial building)	54	47,413
C2012-11	MIVB SeSaMe	Construction (civil)	13	1,535,854
C2012-12	Railway station Ghent	Construction (civil)	440	—
C2012-13	Pumping station Jabbeke	Construction (civil)	125	366,410
C2012-14	Sluiskil tunnel	Construction (civil)	1,299	528,569,216
C2012-15	The master project	Education	32	185,472
C2012-16	Metal extraction	Construction (industrial)	88	—
C2012-17	Building a dream	Construction (residential building)	145	241,015
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
C2013-05	PET packaging	Production	521	874,554
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
C2013-14	Office finishing works (2)	Construction (commercial building)	80	85,848
C2013-15	Office finishing works (3)	Construction (commercial building)	171	341,468
C2013-16	Office finishing works (4)	Construction (commercial building)	196	248,204
C2013-17	Office finishing works (5)	Construction (commercial building)	161	244,205
C2014-01	Mixed-use building	Construction (residential building)	474	38,697,824
C2014-02	Playing cards	Production	124	192,493
C2014-03	Organizational development	Education	229	43,170

[a]The planned duration is expressed in standard 8-h working days.

perfectly correspond for different projects. This is a direct consequence of working with real-life project data. First, all tracking data were obtained directly from the project managers responsible and are therefore always fully authentic and complete (Batselier and Vanhoucke 2015). The considered tracking periods represent all time points at which the performance of the project was actually monitored and evaluated by the concerning project manager. Based on project-specific characteristics (e.g., sector, company, project size) and/or personal preference, the project manager could choose to track monthly, weekly, or even randomly.

An even greater impact on the PC distributions in Table 11 is brought about by the presence of nonregular PV curves for real-life projects. When generating tailor-made projects by means of a project network generator [e.g., RanGen by Demeulemeester et al. (2003) and Vanhoucke et al. (2008)], these projects will typically show a value accrue that follows the course of an S-curve (Cioffi 2005). Such an S-curve exhibits very smooth progress without irregularities (i.e., no *jumps* in the curve). Consequently, as the EV largely follows the planned value accrue (i.e., the PV curve), the PCs for the different tracking periods can adopt almost every value and can thus be distributed very evenly over the completion stages.

Table 11. Specific Project Data

Project code	Metric	Early stage			Middle stage			Late stage		
		TP1	TP2	TP3	TP4	TP5	TP6	TP7	TP8	TP9
C2011-07	PC (%)	5	10	15	66	67	68	93	94	95
	PV (€)	9,434	38,351	46,549	127,255	170,569	170,569	170,569	180,759	180,759
	EV (€)	9,434	17,622	27,930	118,517	121,851	123,540	168,964	170,569	172,251
	AC (€)	10,156	18,594	29,152	124,272	128,867	131,386	176,988	178,593	181,673
C2011-13	PC (%)	5	15	25	36	49	58	76	85	97
	PV (€)	2,049,601	8,237,890	8,744,706	14,433,044	17,822,314	20,956,414	21,322,914	21,369,822	21,369,822
	EV (€)	580,559	3,281,992	5,244,324	8,712,000	10,464,060	12,386,025	16,164,093	18,130,786	20,693,642
	AC (€)	593,655	5,513,843	7,533,609	11,132,412	13,201,363	15,437,723	19,692,670	22,152,458	25,131,422
C2012-13	PC (%)	16	21	27	37	50	64	76	84	95
	PV (€)	53,725	69,157	76,657	99,501	161,456	213,658	258,507	313,983	336,410
	EV (€)	53,725	71,032	89,351	124,536	168,204	213,658	257,249	313,983	318,423
	AC (€)	54,635	71,357	87,800	123,370	168,154	216,154	265,056	292,887	334,261
C2013-02	PC (%)	11	16	25	47	57	66	76	84	96
	PV (€)	250,891	322,098	454,729	799,212	838,047	873,387	924,342	1,020,356	1,140,911
	EV (€)	140,467	196,212	308,445	575,047	705,494	812,925	935,041	1,041,878	1,182,930
	AC (€)	130,421	186,180	272,954	513,543	653,353	752,402	864,755	962,570	1,101,470
C2013-03	PC (%)	7	15	24	36	49	60	73	80	93
	PV (€)	785,118	2,194,453	3,908,924	6,086,410	8,327,449	10,071,796	12,782,984	14,234,384	15,335,572
	EV (€)	1,023,378	2,392,802	3,709,426	5,582,047	7,574,281	9,225,139	11,262,578	12,335,084	14,397,406
	AC (€)	1,019,681	2,384,410	3,738,624	5,643,739	7,665,293	8,788,952	11,552,952	12,724,860	14,936,088
C2013-05	PC (%)	14	17	18	44	53	66	72	83	97
	PV (€)	190,726	306,549	488,486	494,156	592,988	870,527	870,527	874,544	874,544
	EV (€)	126,783	148,097	159,439	384,186	467,856	577,646	633,293	725,895	847,513
	AC (€)	126,783	148,097	159,439	384,186	467,856	577,646	633,293	725,895	847,513
C2013-06	PC (%)	5	13	27	40	47	56	74	86	95
	PV (€)	1,018,793	3,246,082	6,572,150	7,099,991	9,218,184	10,793,115	14,017,132	16,907,758	18,451,262
	EV (€)	1,009,399	2,442,850	5,249,586	7,753,528	9,042,878	10,822,827	14,317,299	16,614,468	18,442,148
	AC (€)	1,111,851	2,594,640	5,539,355	8,029,809	9,332,822	11,044,432	15,184,268	17,911,574	20,222,842
C2013-09	PC (%)	14	24	28	38	66	69	94	96	—
	PV (€)	138,800	368,676	427,297	579,667	1,037,325	1,223,853	1,537,398	1,537,398	—
	EV (€)	211,395	368,676	427,297	579,667	1,014,730	1,059,920	1,448,300	1,478,105	—
	AC (€)	216,156	381,082	447,206	600,882	1,100,325	1,147,891	1,595,320	1,629,745	—
C2013-10	PC (%)	17	23	26	40	50	61	73	90	95
	PV (€)	2,432,704	3,077,109	3,975,754	6,138,893	7,489,933	9,212,382	10,517,688	11,186,199	11,186,199
	EV (€)	1,917,382	2,679,751	3,009,468	4,589,737	5,676,719	6,955,995	8,355,398	10,237,942	10,823,679
	AC (€)	784,813	875,312	1,109,113	1,779,428	2,406,219	3,450,094	5,557,796	6,763,673	8,646,406
C2013-11	PC (%)	8	17	25	39	56	65	77	84	97
	PV (€)	222,523	716,854	1,383,558	2,206,828	2,444,847	3,043,593	3,964,948	4,247,569	4,891,782
	EV (€)	433,762	935,376	1,368,565	2,144,138	3,052,817	3,538,728	4,207,922	4,619,141	5,297,283
	AC (€)	433,762	929,879	1,357,685	2,124,144	3,028,513	3,494,943	4,329,939	4,695,562	5,308,152
C2014-01	PC (%)	4	15	20	32	52	67	78	86	92
	PV (€)	1,627,216	6,203,439	7,766,087	8,902,558	12,948,258	16,440,791	27,342,556	32,131,146	38,382,500
	EV (€)	1,627,216	5,919,321	7,766,087	12,380,022	20,077,040	26,008,984	30,229,338	33,434,314	35,569,052
	AC (€)	1,695,199	6,166,622	8,090,544	12,758,539	23,473,918	29,653,688	34,050,364	37,389,240	39,592,992
C2014-02	PC (%)	3	11	—	38	49	65	72	86	95
	PV (€)	5,772	21,357	—	72,986	125,272	150,106	163,957	191,493	191,493
	EV (€)	5,772	21,357	—	72,986	93,064	125,272	137,868	163,957	182,314
	AC (€)	5,772	21,357	—	72,986	93,064	124,659	137,255	161,731	181,088
C2014-03	PC (%)	4	17	23	41	57	64	81	89	—
	PV (€)	1,995	10,323	15,013	25,239	30,408	40,364	43,071	43,170	—
	EV (€)	1,704	7,302	9,925	17,492	24,417	27,485	35,149	38,329	—
	AC (€)	2,400	13,362	17,697	30,717	41,175	60,408	75,447	80,721	—

However, in reality, the value accrue within a project hardly ever follows the course of an S-curve or even shows a gradual rise, as can be clearly seen from the projects in the database of Batselier and Vanhoucke (2015).

For example, project C2011-07 shows many sudden climbs in the PV curve (Fig. 3), interspersed with periods of very low value accrue. This irregular course of the PV curve reflects the characteristics of this specific project; in this case, the presence of a few activities with very high fixed costs that produce the jumps. These jumps, in turn, cause long periods of very low value accrue. As a result, the EV—and the PC—will be virtually the same for many subsequent tracking periods. This can indeed be observed for the PC values in the middle and late stages of project C2011-07 (Table 11).

Nevertheless, there still are projects in the considered database that do display a rather uniform value accrue. For project C2012-13, for example, the PV curve (Fig. 4) climbs quite evenly without much irregularity. The PCs within the different stages can thus be distributed very uniformly, as almost all values for EV—and thus for PC—may occur. Table 11 supports this

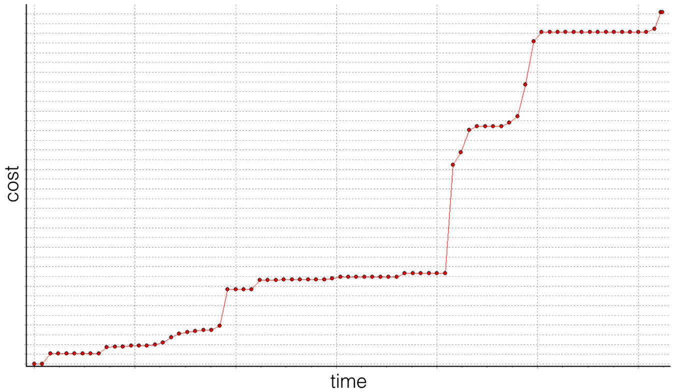

Fig. 3. PV curve for project C2011-07

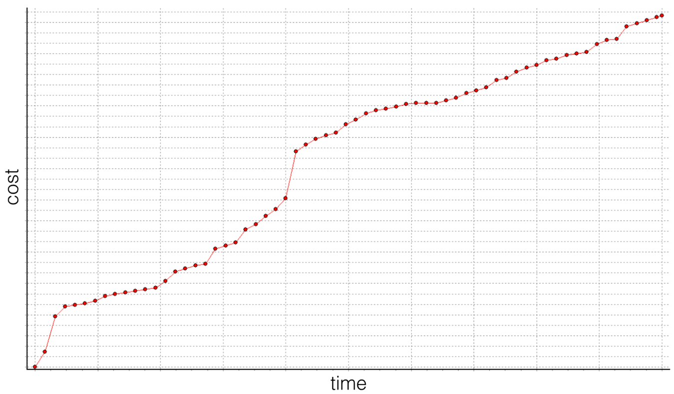

Fig. 4. PV curve for project C2012-13

statement. However, note that even for this rather *regular* project, the PCs in the early stage are less evenly spread. This is due to the initial steep rise of the PV curve, which also yields a relatively high EV for the first tracking period, and thus a higher PC.

Conclusively, the uneven formats of the PCs for the different completion stages in Table 11 are a direct manifestation of the real-life characteristics of the considered projects (i.e., tracking frequency chosen by the concerning project manager and actual value accrue within the project).

Moreover, at the end of the discussion of the applied timeliness evaluation approach of Vanhoucke and Vandevoorde (2007), it has already been mentioned that some projects contain less than three tracking periods for a certain stage. From Table 11, it can be seen that this is indeed the case for projects C2014-02 (early stage) and C2013-09 and C2014-03 (late stage).

Furthermore, it is important to note that the complete tracking data (i.e., for all tracking periods) for the projects considered in Table 11 and for all other projects in the database of Batselier and Vanhoucke (2015) for which real tracking was performed can be found at the OR-AS database.

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