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Evaluation of deterministic state-of-the-art forecasting approaches for project duration based on earned value management

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Abstract

In recent years, a variety of novel approaches for fulfilling the important management task of accurately forecasting project duration have been proposed, with many of them based on the earned value management (EVM) methodology. However, these state-of-the-art approaches have often not been adequately tested on a large database, nor has their validity been empirically proven. Therefore, we evaluate the accuracy and timeliness of three promising deterministic techniques and their mutual combinations on a real-life project database. More specifically, two techniques respectively integrate rework and activity sensitivity in EVM time forecasting as extensions, while a third innovatively calculates schedule performance from time-based metrics and is appropriately called earned duration management or EDM(t). The results indicate that all three of the considered techniques are relevant. More concretely, the two EVM extensions exhibit accuracy-enhancing power for different applications, while EDM(t) performs very similar to the best EVM methods and shows potential to improve them.

Keywords: Project management; Time forecasting; Earned value management; Earned duration management; Rework; Sensitivity measures; Empirical database; Project control

1. Introduction

Being able to accurately predict the final duration of a project is essential to good project management. The widely-used project control technique of earned value management (EVM) provides a basis for obtaining such project duration forecasts. A presentation of the basic and more thoroughgoing aspects of the EVM methodology can be found in several works (Anbari, 2003; Fleming and Koppelman, 2010; PMI, 2008; Vanhoucke, 2010a, 2014). The traditional EVM time[1] forecasting approaches — 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) — have recently been evaluated by Batselier and Vanhoucke (2015b) based on the real-life project database constructed by Batselier and Vanhoucke (2015a). The said empirical research supported the findings of the simulation study of Vanhoucke and Vandevoorde (2007) by also indicating ESM as the most accurate method.

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[1] Following earlier works related to this paper (Batselier and Vanhoucke, 2015b; Elshaer, 2013; Khamooshi and Golafshani, 2014; Vanhoucke and Vandevoorde, 2007, etc.), the terms "time" and "duration" are interchangeable when used in the context of EVM forecasting (apart from linguistic preferences).

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However, a variety of novel EVM-based time forecasting approaches has been developed in the last five years. These state-of-the-art techniques can be subdivided into two major categories, namely deterministic and probabilistic approaches (Barraza et al., 2004). Deterministic approaches — like the three traditional EVM time forecasting methods — yield a point estimate of the eventual project duration, whereas probabilistic techniques provide confidence intervals and/or distributions of possible durations. The latter techniques can, for example, make use of stochastic S-curves, which produce upper and lower bounds for the range of acceptable outcomes based on the uncertainty about the predictions (Barraza et al., 2004). Moreover, an extending probabilistic approach is provided by the fuzzy methodology, which can overcome vagueness of data by introducing linguistic terms that can be translated into fuzzy numbers through a membership function (Naeni et al., 2011). An extensive overview of the existing literature on both deterministic and probabilistic[2] approaches is given by Willems and Vanhoucke (under submission). The said paper also provides a summary of other recently developed project forecasting methods, like those based on neural networks (e.g. Pewdum et al., 2009; Rujirayanyong, 2009) and support vector machines (e.g. Cheng et al., 2010; Wauters and Vanhoucke, 2014). Although these methods have been proven useful for making project forecasts, an extensive survey is beyond the scope of this paper, as the current focus is on deterministic EVM-based forecasting approaches for project duration. More specifically, three recent and promising techniques are considered. The logical basic principles on which they build are as follows:

- Lipke (2011) integrates the effect of rework in ESM time forecasting.
- Elshaer (2013) integrates activity sensitivity information in ESM time forecasting.
- Khamooshi and Golafshani (2014) introduce earned duration management or EDM(t)[3], where schedule performance is calculated from metrics expressed in time units (and not in cost units).

These logical basic principles in fact demonstrate the relevance of introducing the three selected methods. A more concrete presentation of the three techniques is provided in Section 2. Moreover, the last two papers in the list above are also included in the overview of Willems and Vanhoucke (2015), of course under the category of deterministic approaches.

In the respective papers, all three of the methods are said to have the potential to improve the accuracy of the traditional EVM time forecasting methods. Nevertheless, these assertions have not yet been adequately tested on a large database, nor has the validity of the considered techniques been empirically proven. More concretely, Lipke (2011) and Khamooshi and Golafshani (2014) apply their technique on just one real-life project, whereas Elshaer (2013) only considers projects generated by the RanGen project network generator (Demeulemeester et al., 2003; Vanhoucke et al., 2008) that were already used in many earlier project management studies (Vandevoorde and Vanhoucke, 2006; Vanhoucke, 2010a,2010b, 2011, 2012; Vanhoucke and Vandevoorde, 2007).

Moreover, it is not known which one of the three considered methods — or which combination of the methods — would yield the best results, overall and in different stages of the project. Therefore, the goal of this paper is to compare the forecasting accuracy and timeliness of the three novel time forecasting techniques and all of their mutual combinations based on the real-life project data of Batselier and Vanhoucke (2015a). As such, recommendations can be made concerning which method — or combination of methods — best to use in a certain situation and which future research actions to take to further improve the methods' utility. Furthermore, the proposed combination of the three novel techniques for time forecasting is innovative in itself and can therefore also be seen as a contribution of this paper.

The remainder of the paper is organized as follows. In Section 2, the three considered state-of-the-art time forecasting methods are presented. Section 3 then proposes the methodology for evaluating the accuracy and timeliness of these methods on real-life project data. Subsequently, the results of this evaluation are presented and discussed in Section 4. And finally, in Section 5, conclusions are drawn and suggestions for future research actions are made.

2. Presentation of the three state-of-the-art time forecasting methods

In this section, the three considered state-of-the-art time forecasting methods (Elshaer, 2013; Khamooshi and Golafshani, 2014; Lipke, 2011) are presented in chronological order. The concerning subsections are assigned a name which reflects the basic principle of the respective method. We restrict ourselves to a brief explanation of the three methods. Although the provided explanation should suffice for understanding the techniques, if desired, the reader can find more elaborate discussions on the different methodologies in the originating papers. However, before we can present the three novel time forecasting methods — which are all based on EVM — a more general discussion needs to be conducted.

Since earlier studies on EVM forecasting accuracy (Batselier and Vanhoucke, 2015b; Vanhoucke and Vandevoorde, 2007) have proven the dominance of ESM over PVM and EDM, the former method is used as a basis (and benchmark) for all three novel deterministic approaches. The generic ESM formula for obtaining the project duration forecast or estimated time at completion $EAC(t)$ is given by:

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

[2] In Willems and Vanhoucke (2015), the probabilistic approaches are further subdivided into stochastic and fuzzy techniques.

[3] Khamooshi and Golafshani (2014) in fact use the abbreviation EDM for earned duration management. However, this abbreviation was already introduced for the earned duration method of Jacob and Kane (2004). In order to avoid confusion, we therefore refer to earned duration management by EDM(t). Furthermore, the suffix (t) also clearly indicates that the technique is based on time metrics instead of cost metrics.

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AT represents the actual time (at the current tracking period), *PD* the planned duration of the project according to the baseline schedule, and *ES* the earned schedule (i.e. the time at which the current project progress should actually have been achieved according to the plan). Furthermore, *PF* expresses the performance factor that is assumed. Vandevoorde and Vanhoucke (2006) and Vanhoucke (2010a) provide an extensive overview of the performance factors that can be applied for EVM time forecasting. Nevertheless, the most commonly used performance factors — which will also be considered in this study — are 1 (i.e. it is assumed that future schedule performance will be as planned) and the ES-based schedule performance index $SPI(t)$ (i.e. it is assumed that future schedule performance will be equal to the current schedule performance; $SPI(t) = ES/AT$). Whereas the simulation study of Vanhoucke and Vandevoorde (2007) indicated $SPI(t)$ as the best performing performance factor, Batselier and Vanhoucke (2015b) showed that setting $PF = 1$ produces the most accurate time forecasts for the considered real-life project data.

Building on this basis, a brief discussion of the three deterministic state-of-the-art methods for project duration forecasting can now be provided.

2.1. Integrating rework in ESM (Lipke, 2011)

While Lipke et al. (2009) applied statistical methods to ESM, Lipke (2011) extends the technique by taking into account schedule adherence, which can lead to the occurrence of rework (Lipke, 2004; Vanhoucke, 2010a). More specifically, the earned value *EV* is adjusted to the effective earned value $EV(e)$ through the formula $EV(e) = EV - R$ where *R* represents the rework that can be calculated as:

$$R = \left(1 - PC^n \cdot e^{-m(1-PC)}\right) \cdot (1-p) \cdot EV. \tag{2}$$

PC is the percentage complete of the project (= EV/BAC, with *BAC* the budget at completion) and *P* is the so-called p-factor (Lipke, 2004), which expresses the degree of schedule adherence (i.e. $P = 1$ indicates perfect schedule adherence, $P = 0$ signifies no schedule adherence at all). The assessment of the influence of schedule adherence (i.e. the p-factor) on EVM time forecasting accuracy has already been the subject of a few simulation studies (Vanhoucke, 2010a, 2013).

The exponents n and m in Eq. (2) are traditionally set to 1 and 0.5, respectively, yielding a nearly linear decrease of the rework fraction (i.e. the percentage of the work not performed according to schedule that has to be redone) as the percentage complete increases (Lipke, 2011). The adapted $EV(e)$ can then be used to calculate $ES(e)$, and through that, $SPI(t)(e) = ES(e)/AT$. The targeted project duration forecast can then be obtained by substituting *ES* by $ES(e)$ and using $SPI(t)(e)$ as a performance factor in the generic ESM formula (Eq. (1)). Of course, 1 can also be used as a performance factor here.

2.2. Integrating activity sensitivity in ESM (Elshaer, 2013)

Elaborating on the idea of integrating schedule risk analysis (SRA) and EVM as proposed by Vanhoucke (2010a); Vanhoucke (2010b); Vanhoucke (2011); Vanhoucke (2012); Elshaer (2013) suggests to take into account activity sensitivity information (i.e. SRA) for the calculation of project duration forecasts (i.e. EVM). More specifically, activity-based sensitivity measures are used as weighing parameters for the *PV* and *EV* of the activities. The rationale is that this would lead to a more accurate schedule performance by removing or decreasing the negative effect of false warning signals caused by non-critical activities. The criticality index *CI* appeared to yield the best results as a weighing parameter (Elshaer, 2013). Therefore, this activity sensitivity measure — which can be calculated by performing Monte Carlo simulations based on the activity duration distribution profiles (i.e. triangular distributions which can be either symmetrical or skewed to the left or to the right, depending on the characteristics of the activity) — will be applied here. Moreover, since weighing *PV* and *EV* results in an adjusted *ES* and $SPI(t)$, the $EAC(t)$ will also change (see Eq. (1)), both with $PF = 1$ and $PF = SPI(t)$.

2.3. Calculating schedule performance in time units: EDM(t) (Khamooshi and Golafshani, 2014)

Khamooshi and Golafshani (2014) argue that time forecasting with ESM could still yield misleading results as the technique keeps using costs as a proxy to measure schedule performance (i.e. *ES* is calculated based on *EV* and *PV* values, which are both expressed in cost units). Therefore, they developed the technique of earned duration management or EDM(t), in which schedule and cost performance measures are completely decoupled. More specifically, the *ES* metric is replaced by earned duration $ED(t)$, which is calculated as the projection of the total earned duration *TED* (i.e. the sum of the earned durations of all the in-progress and completed activities at *AT*[4]) on the total planned duration *TPD* (i.e. the sum of the planned durations of all the planned activities at *AT* according to the baseline schedule) instead of the projection of *EV* on *PV*, which yields *ES*. Besides the fact that the calculation of $ED(t)$ is based on metrics that are expressed in time units (i.e. *TED* and *TPD*) instead of cost units (i.e. *EV* and *PV*), it is completely similar to the calculation of *ES*. To obtain time forecasts from the EDM(t) methodology, we apply following formula[5]:

$$EAC(t) = \frac{PD}{DPI}. \tag{3}$$

This formula is strongly parallel to that of the traditional PVM (i.e. PVM-SPI: $EAC(t) = PD/SPI$), but with the performance factor changed to the duration performance index *DPI*,

[4] The earned duration of an in-progress (or completed) activity at *AT* is the planned baseline duration of that activity multiplied by the actual percentage complete (or physical progress) of that activity at *AT*.

[5] Khamooshi and Golafshani (2014) actually use the notation *EDAC* for the estimated duration (or time) at completion, which is substantially exactly the same as $EAC(t)$.

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which can be calculated very similar to $SPI(t)$ as $ED(t)/AT$. Obviously, using a $PF = 1$ would not be useful when applying the EDM(t) formulas as proposed by Khamooshi and Golafshani (2014), since this would simply yield the planned duration as a forecast (see Eq. (3)).

3. Methodology

Recall that the goal of this paper is to compare the forecasting accuracy and timeliness of the three novel deterministic time forecasting techniques and all of their mutual combinations based on real-life project data. The real-life projects that are used for this study originate from the database of Batselier and Vanhoucke (2015a) and are briefly presented in Section 3.1. Section 3.2 then describes the applied forecasting accuracy and timeliness evaluation approach. Finally, the concrete approach for combining the three considered state-of-the-art time forecasting methods is presented in Section 3.3.

3.1. Real-life project database

For the current study, we make use of the empirical project database constructed by Batselier and Vanhoucke (2015a). This database is intended to grow continuously. Therefore, it should be mentioned that at the time of this study, the database consisted of 51 projects (i.e. the projects with codes C2011-01 to C2014-03). Moreover, the entire database can be consulted freely at www.or-as.be/research/database (OR-AS, 2015). We also mention the availability of so-called *project cards*, which summarize the data of every project in the database. More importantly, these project cards provide a framework for data validation, as they evaluate both the authenticity and completeness of the project data. More information on this database evaluation framework can be found in Batselier and Vanhoucke (2015a).

Here, the framework is applied to select only those projects from the considered database that are relevant for the current study, that is, projects that include authentic (time) tracking data. More specifically, only those projects that contain tracking data (i.e. complete projects) that were obtained directly from the actual project owner (i.e. authentic projects) are retained. Under these conditions, 24 projects — of which validity is guaranteed through application of the project cards — are still eligible. However, one of these projects (C2013-14) contains less than three tracking periods (i.e. the minimum required amount to allow meaningful results, as was also defined by Batselier and Vanhoucke (2015b)) and is thus discarded. Therefore, 23 projects from the empirical database of Batselier and Vanhoucke (2015a) form the basis for the upcoming evaluations. A brief overview of the most important properties (i.e. name, sector, planned duration, budget at completion) of the 23 considered projects is provided in Table 1. Via the project codes displayed in the first column (also see the first column of Table 2), these projects can be retrieved on the associated website (OR-AS, 2015), if more elaborate information would be desired.

3.2. Forecasting accuracy and timeliness evaluation approach

The forecasting accuracy of the considered forecasting techniques is evaluated based on the mean absolute percentage error or MAPE. This measure has already been used in multiple studies on EVM forecasting accuracy (Batselier and Vanhoucke, 2015b; Elshaer, 2013; Rujirayanyong, 2009; Vanhoucke, 2010a;

Table 1
Overview of the considered real-life projects.

Project code	Project name	Sector	PD [days] [a]	BAC [euro]
C2011-07	Patient transport system	IT	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	366,410
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
C2013-05	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
C2013-15	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 eight-hour working days.

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Table 2
Overall accuracy results of the three deterministic state-of-the-art time forecasting approaches and their combinations for all considered projects of the database.

[MAPE %]		ESM-1				ESM-SPI(t)				EDM(t)-DPI			
Lipke, (2011)		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Elshaer, (2013)		N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Proj code	# TPs												
C2011-07	9	6.7	6.6	9.2	8.9	13.2	13.2	10.6	10.1	8.5	8.5	9.8	8.1
C2011-12	5	4.2	4.3	4.4	4.3	11.1	11.3	11.1	11.2	11.3	11.5	11.5	12.9
C2011-13	9	6.4	5.8	11.7	11.7	5.0	4.2	11.2	11.2	7.1	8.5	17.8	19.8
C2012-13	9	9.7	9.3	10.0	9.1	13.2	12.2	14.5	12.3	14.4	12.7	14.6	13.2
C2013-01	*5*	*2.0*	*3.8*	*0.0*	*0.0*	*14.8*	*104.5*	*0.0*	*0.0*	*28.5*	*23.6*	*57.6*	*57.5*
C2013-02	9	6.8	7.2	0.6	1.5	30.4	38.9	1.6	6.3	64.7	95.6	1.6	6.3
C2013-03	9	4.4	5.5	18.7	16.0	8.2	9.7	29.0	25.7	12.4	12.7	29.0	25.7
C2013-04	7	7.5	7.4	11.1	10.9	13.5	14.0	9.5	9.1	9.5	10.0	9.5	9.3
C2013-05	9	6.5	5.4	22.6	22.6	51.8	66.2	22.6	22.6	12.3	20.0	17.3	14.7
C2013-06	9	2.4	3.9	2.3	3.5	7.1	9.8	7.6	8.9	4.1	4.3	8.9	6.6
C2013-07	7	2.8	2.1	2.8	4.2	11.5	13.5	10.7	17.6	22.8	21.8	22.6	27.0
C2013-08	7	4.9	4.9	5.1	4.6	5.4	5.4	4.5	4.5	4.5	4.4	4.0	3.7
C2013-09	8	14.5	14.4	14.3	14.2	16.1	15.8	15.8	15.5	17.0	16.9	16.6	16.3
C2013-10	9	3.2	3.6	0.2	3.2	3.8	4.4	0.2	3.8	3.6	4.1	0.8	0.6
C2013-11	9	10.4	11.2	14.5	19.4	9.3	10.5	16.5	25.7	15.8	18.8	21.5	26.5
C2013-12	*4*	*17.8*	*17.7*	*18.5*	*19.0*	*191.2*	*191.8*	*16.2*	*18.1*	*41.0*	*62.8*	*12.4*	*21.9*
C2013-13	*6*	*5.3*	*5.2*	*4.5*	*4.7*	*21.5*	*20.4*	*20.5*	*19.3*	*109.9*	*116.9*	*100.4*	*107.3*
C2013-15	*3*	*17.2*	*22.6*	*49.1*	*48.2*	*32.6*	*22.1*	/	/	*8.5*	*58.8*	/	/
C2013-16	3	51.8	52.3	51.1	51.6	55.6	57.2	53.4	54.9	39.5	42.4	27.3	29.9
C2013-17	*4*	*18.4*	*19.5*	*24.8*	*22.5*	*57.2*	*82.6*	*M*[a]	*M*	*85.9*	*136.0*	*M*	*M*
C2014-01	9	5.4	5.5	5.2	5.2	6.9	6.7	7.1	6.9	5.9	7.3	7.5	9.9
C2014-02	8	7.4	7.4	7.4	7.4	7.9	7.9	7.9	7.9	7.7	7.7	8.4	8.4
C2014-03	8	7.5	8.2	7.1	8.0	16.6	26.8	19.3	29.7	13.9	23.1	19.0	29.0

[a] The big *M* represents a very large number of which displaying would overload the table.

Vanhoucke and Vandevoorde, 2007). The MAPE is calculated according to the following formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A-F_t}{A}\right| \quad (4)$$

where A is the actual final value and F_t the forecasted value at time t. The time points $t = 1,..., n$ represent the n tracking periods that were selected for the considered project. More information on the selection procedure applied for the tracking periods is provided in the next paragraph. Furthermore, Eq. ((4)) can be particularized for time forecasting by substituting A and F_t by the actual total duration of the project (also referred to as the real duration *RD*) and *EAC*(t), respectively. Logically, the lower the MAPE for a certain forecasting method, the higher the accuracy of that method.

Covach et al. (1981) state that, besides overall accuracy (i.e. the average accuracy over the entire course of a project), timeliness is also an essential criterion for the assessment of forecasting methods. Therefore, we perform a stage-wise comparison of the accuracies of the considered time forecasting methods based on the timeliness evaluation approach from Vanhoucke and Vandevoorde (2007). To allow this comparison, three project completion stages are defined according to the *PC*:

- $0\% \leq PC < 30\%$: early stage
- $30\% \leq PC \leq 70\%$: middle stage
- $70\% < PC \leq 100\%$: late stage

The above categorization corresponds to the basic subdivision made by Vanhoucke and Vandevoorde (2007) and was also applied by Batselier and Vanhoucke (2015b). Notice that the middle stage was assigned a *PC*-interval that is larger than that of the other completion stages. This was done to account for the faster progress near the middle of a project that is typically observed in many situations (Kim and Kim, 2014). By assigning a larger *PC*-interval to the middle stage, we thus increase the probability of having ample tracking periods situated in this stage. More specifically, we aim at having data from three tracking periods for every completion stage of the project.

Moreover, we attempt to select the tracking periods for a certain completion stage in such a way that their *PC*-values are distributed as evenly as possible within the appropriate interval. Furthermore, tracking periods with a *PC* close to the boundary values of the stages are avoided, in order to allow a clear and distinctive comparison between the stages. More concretely, for the early stage we try to select three tracking periods with a *PC* of approximately 5%, 15% and 25%, respectively. For the middle stage this becomes 40%, 50% and 60%, respectively, and for the late stage 75%, 85% and 95%, respectively. Obviously, these optimal *PC*-distributions are not always readily applicable for the projects in the employed database. Nevertheless, we always seek to approach them as well as possible.

Furthermore, for some of the considered projects, it is not possible to find three tracking periods for one (or more)

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completion stages, regardless of the optimal *PC*-distribution. For these projects, the total number of considered tracking periods — needed for the overall forecasting accuracy evaluation — will thus be lower than nine (i.e. worse than the best case situation of three tracking periods for all three completion stages), which can be seen from the second column of Table 2. Moreover, we already mention that no results will be taken into account for a certain stage of a project if it does not contain the desired amount of three tracking periods.

3.3. Combination of the three state-of-the-art time forecasting methods

Notice that the methods proposed by Lipke (2011) and Elshaer (2013) are in fact extensions of the traditional ESM. This is also indicated by the expression of the basic principle of the methods, namely “integration of activity sensitivity in ESM” and “integration of activity sensitivity in ESM”, respectively. Indeed, both methods still produce forecasts based on the generic formula (Eq. (1)). Khamooshi and Golafshani (2014), on the other hand, actually developed an approach sprouting from ESM but with a different definition of the key metrics (i.e. time-based instead of cost-based). Therefore, ESM and EDM(t) can be seen as two separate methodologies for obtaining project duration forecasts and can thus both be used in combination with the approaches of Lipke (2011) and Elshaer (2013). The implementation of the two extending techniques — in what follows sometimes referred to as “extensions” — is completely similar for EDM(t) as for ESM (see explanation in Sections 2.1 and 2.2). Also note that the techniques of Lipke (2011) and Elshaer (2013) cannot only be applied separately, but also combined.

Furthermore, since both the performance factors 1 and $SPI(t)$ are relevant for ESM — whereas only $PF = DPI$ is useful in the current EDM(t) formulas — there is a total of 12 time forecasting variations to be evaluated, as appears from Table 2. Notice that the traditional ESM-1 and ESM-SPI(t) are indeed used as a benchmark, as they respectively correspond to the third and seventh column of Table 2, where neither of the two extensions are applied to ESM. This is indicated by the two Ns (“No”) in the second and third row of the table. Oppositely, a Y (“Yes”) in one of these rows signifies that the corresponding technique is indeed applied.

4. Results and discussion

The overall accuracy results (i.e. the average accuracy over the entire course of a project, so over all tracking periods of all stages) of the three deterministic state-of-the-art time forecasting approaches and their combinations are shown in Table 2, for all 23 considered projects of the database of Batselier and Vanhoucke (2015a). However, the results for some projects (marked in italics in Table 2) are not relevant for overall accuracy evaluation due to various reasons, which are now listed.

For projects C2013-01, C2013-12 and C2013-17, the results for the first tracking period (at a *PC* of 3%, 6% and 8%, respectively) are too sensitive to variations in *EV* and $ED(t)$ because of the low levels of *PV* and *TPD* at these very early completion stages. Therefore, the overall results for these projects also become biased (with MAPEs of over 100%), as they include the outcomes of the first tracking period. For project C2013-15, the method of Elshaer (2013) could not be applied to ESM-SPI(t) and EDM(t)-DPI. More specifically, for the first two tracking periods (at a *PC* of 4% and 22%, respectively), the activities with a $CI > 0$ had not started yet, yielding an *ES* and $ED(t)$ equal to zero and therefore an $SPI(t) = DPI = 0$. If these performance factors are inserted in Eqs. (1) and (3), respectively, it indeed appears that $EAC(t)$ cannot be calculated (division by zero) and thus no time forecasts can be obtained. Therefore, just as projects C2013-01, C2013-12 and C2013-17, project C2013-15 is discarded for the overall evaluation of the forecasting accuracy of the considered methods. Note, however, that for all four projects the biasing results only occur in the early stage (i.e. $PC < 30\%$). Hence, these projects can still be considered for accuracy evaluations in the middle and late stages.

Project C2013-13 displays biasing results for EDM(t)-DPI due to the existence of a very expensive activity (about 85% of the *BAC*) with a duration that is strongly disproportionate to the high cost. In such situations, EDM(t)-DPI thus appears to be less appropriate for forecasting project duration. Nevertheless, this situation is rather exceptional, and therefore, project C2013-13 is discarded for all stages to allow a fair comparison between EDM(t)-DPI and the ESM techniques. A total of five projects are thus discarded for the overal accuracy evaluation of the three deterministic state-of-the-art time forecasting approaches and their combinations. The summarized overall results (i.e. over the entire project course) for the 18 retained projects are shown on the first row of MAPE-outcomes of Table 3 and are now discussed.

It clearly appears that ESM-1 provides the best basis for making accurate time forecasts over all stages of the project. The ESM-1 without extensions shows the lowest MAPE of 9.0% and thus dominates both ESM-SPI(t) and EDM(t)-DPI, which attain a maximum accuracy of 14.1% and 13.8% MAPE, respectively, both with application of the method of Elshaer (2013). These outcomes are not entirely unexpected, as Batselier and Vanhoucke (2015b) already indicated that for ESM a $PF = 1$ yields more accurate forecasts than a $PF = SPI(t)$. By extension, it could thus be stated that unweighted time forecasting methods (i.e. future performance is assumed to be as planned) outdo their performance-based counterparts (i.e. future performance is assumed to be equal to the current performance), which also include EDM(t)-DPI. The main reason for the supremacy of unweighted forecasting methods — such as ESM-1 here — is that they implicitly take into account potential corrective actions performed by management in order to improve lagging project performance. The effects of these management actions are obviously comprised in the real-life project data. Therefore, the current (poor) performance expressed by the $SPI(t)$ or *DPI* does not adequately reflect the actual future performance, which is subject to the corrective actions.

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Table 3
Summarized accuracy results of the three deterministic state-of-the-art time forecasting approaches and their combinations.

[MAPE %]		ESM-1				ESM-SPI(t)				EDM(t)-DPI			
(Lipke, 2011)		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
(Elshaer, 2013)		N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
	# projs												
Overall	18	9.0	9.2	11.0	11.5	15.9	18.2	14.1	15.8	15.3	18.4	13.8	14.9
	(10)	(6.2)	(6.4)	(9.5)	(10.1)	(14.9)	(17.6)	(12.1)	(13.4)	(14.9)	(19.3)	(12.9)	(13.1)
Early stage	10	7.4	7.5	10.8	10.4	25.2	27.1	16.0	15.9	26.6	35.3	17.4	17.7
	(12)	(8.4)	(8.3)	(11.1)	(10.7)	(24.1)	(26.6)	(17.0)	(17.8)	(24.9)	(32.8)	(17.9)	(18.8)
Middle stage	10	6.0	6.4	10.3	10.8	12.7	18.6	12.3	13.2	12.0	16.1	13.2	13.8
	(16)	(6.6)	(6.8)	(9.5)	(9.8)	(12.9)	(17.8)	(12.0)	(14.1)	(12.5)	(15.8)	(13.2)	(14.9)
Late stage	10	5.2	5.4	7.5	9.2	6.8	7.0	8.0	11.0	6.0	6.3	8.0	8.0
	(14)	(4.5)	(4.6)	(6.4)	(7.8)	(5.4)	(5.6)	(6.3)	(8.8)	(4.8)	(5.0)	(6.3)	(6.5)

Furthermore, the extension of Lipke (2011) does show potential for ESM-1. Although the overall MAPE is slightly higher than that of the traditional ESM-1 (9.2% > 9.0%), the extending technique does provide better results for half of the projects (also see Table 2). Moreover, note that for the calculation of rework according to Eq. (2), the exponents n and m were fixed to 1 and 0.5 as proposed by Lipke (2011). However, these values could be optimized, in general as well as for a specific selection of projects (w.r.t. sector, duration, budget, etc.). Through further research, the benefits of applying the method of Lipke (2011) for ESM-1 could thus be increased, potentially making this approach overall the most accurate.

In contrast to the extension of Lipke (2011), the extension of Elshaer (2013) appears disadvantageous for ESM-1 (MAPE of 11.0% > 9.0%). For the performance-based forecasting methods (i.e. ESM-SPI(t) and EDM(t)-DPI), on the other hand, the situation is completely opposite. While the technique of Lipke (2011) has an adverse effect on forecasting accuracy compared to the traditional methods without extensions (MAPEs of 18.2% > 15.9% and 18.4% > 15.3% for ESM-SPI(t) and EDM(t)-DPI, respectively), the technique of Elshaer (2013) produces forecasts of improved accuracy for both ESM-SPI(t) and EDM(t)-DPI (MAPEs of 14.1% < 15.9% and 13.8% < 15.3%, respectively). These observations also imply that combining the techniques of Lipke (2011) and Elshaer (2013) is not beneficial for any of the three base methods. More concretely, for ESM-1 it is preferable just to use the extension of Lipke (2011), whereas for ESM-SPI(t) and EDM(t)-DPI it is better to only apply the technique of Elshaer (2013). Therefore, in following discussions, only these preferred combinations will be considered.

In order compare ESM and EDM(t), we focus on the performance-based time forecasting methods ESM-SPI(t) and EDM(t)-DPI. These two methods adhere to the same principle of basing forecasts of future performance on the performance of past activities, and therefore, allow a fair comparison of the general methodologies of ESM and EDM(t), which would not be the case when comparing ESM-1 and EDM(t)-DPI. Although EDM(t)-DPI performs slightly better than ESM-SPI(t), both methods display strongly similar overall accuracies (MAPEs of 15.3% and 15.9%, respectively). Furthermore, the beneficial effect of applying the method of Elshaer (2013) is almost equal for both methods (accuracy improvement of 1.8% and 1.5% MAPE for ESM-SPI(t) and EDM(t)-DPI, respectively). Consequently, EDM(t) as proposed by Khamooshi and Golafshani (2014) certainly proves to be a valid methodology for forecasting project duration, as it can compete with the currently most recommended methodology of ESM. Even more, since EDM(t)-DPI appears to slightly outperform ESM-SPI(t) for the 18 considered projects, the modification of the EDM(t) formulas to allow the application of a $PF = 1$ might improve the forecasting accuracy of ESM-1 and thus give rise to a new overall best performing method. Obviously, this is an interesting topic for future research.

In addition, we now only consider those projects in the database that include the optimal number of nine tracking periods. According to Table 2, ten such projects can be identified. If a project contains a total of nine tracking periods, it means that the data of three tracking periods are available for all three stages (i.e. early, middle, and late) for that project. This is a prerequisite to allow a correct comparison of the accuracy outcomes for different stages (i.e. the same projects and same amount of tracking periods are needed for every stage). Therefore, the said ten projects will form the basis for the timeliness evaluation. First, however, note that strongly similar conclusions regarding the overall accuracy results can be drawn from these ten projects (see second 'Overall' results row of Table 3 with values in brackets) with respect to the 18 initially considered projects.

We now perform the stage-wise comparison of the accuracies of the three state-of-the-art time forecasting methods based on the approach of Vanhoucke and Vandevoorde (2007). The definition of the different completion stages was provided in Section 3.2. Now consider the results on the first row of every stage in Table 3 (no brackets, ten projects). As expected, the forecasting accuracy of every method and combination monotonically increases towards the later stages. Consequently, there are only minor accuracy differences between the various approaches in the late stage. This observation indicates that the identification of the most accurate time forecasting method is less crucial in the later stages of the project. Indeed, Teicholz (1993) stated that it is particularly important to get accurate warnings about significant delays (i.e. accurate forecasts) during the early stages of the project so that adequate (and timely) corrective actions can be taken.

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We thus focus on the early stage forecasting results. First of all, the dominance of ESM-1 without extensions and the potential of the technique of Lipke (2011) in combination with ESM-1 still exist. A more remarkable observation, however, is that the application of the method of Elshaer (2013) proves much more beneficial for ESM-SPI(t) and EDM(t)-DPI in the early stage than over all stages of the project (MAPE reductions of 9.2% for both methods instead of 1.8% and 1.5%, respectively). This means that the observed overall benefits of the extension of Elshaer (2013) for ESM-SPI(t) and EDM(t)-DPI are mostly due to the very good performance of the technique in the early stage. Indeed, the technique even appears to have a negative effect on the accuracy of both performance-based time forecasting methods for the later stages. Nevertheless, given the great importance of accurate early stage forecasts (Teicholz, 1993), the method of Elshaer (2013) can certainly be deemed relevant.

In order to expand the set of considered projects for the timeliness evaluation, for every completion stage, we now include all projects that contain three tracking periods for that specific stage (condition already mentioned in Section 3.2). This implies that we can now take into account more than ten projects for the three stages (i.e. 12, 16 and 14 projects for the early, middle and late stage, respectively), but that we can no longer use the outcomes to make comparisons between the stages. Nevertheless, for a certain stage, the forecasting accuracies of the different methods and combinations can still be compared. The corresponding results are displayed on the second row of every stage in Table 3 (in brackets). Completely similar conclusions regarding the methods' accuracy can be drawn with respect to the timeliness results presented earlier, and this for every completion stage.

5. Conclusions

The goal of this paper was to compare the forecasting accuracy and timeliness of three deterministic state-of-the-art time forecasting techniques and their mutual combinations based on real-life project data. The three techniques that were considered are those proposed by Lipke (2011); Elshaer (2013) and Khamooshi and Golafshani (2014) and are all based on the EVM methodology. More specifically, Lipke (2011) and Elshaer (2013) respectively integrate rework and activity sensitivity in ESM time forecasting, while Khamooshi and Golafshani (2014) introduce earned duration management or EDM(t), a technique that calculates schedule performance from time-based instead of cost-based metrics. EDM(t) can thus be seen as a novel base methodology for forecasting project duration (i.e. an alternative for ESM), whereas the methods of Lipke (2011) and Elshaer (2013) are extensions of the base methods (i.e. of ESM, but also of EDM(t)). Moreover, these extensions cannot only be applied separately, but also combined. Furthermore, the real-life project data that were used for the current study originate from the empirical project database of Batselier and Vanhoucke (2015a), of which 23 projects were retained.

The accuracy of the considered forecasting methods is assessed based on the MAPE. Moreover, timeliness is evaluated according to the stage-wise comparison approach of Vanhoucke and Vandevoorde (2007). We also mention that the ESM technique is applied with the performance factors 1 and *SPI*(*t*), whereas only *PF* = *DPI* is useful for EDM(t) under the current definitions. When also considering the extensions of Lipke (2011) and Elshaer (2013) (and their combination), a total of 12 time forecasting approaches could be evaluated.

From this evaluation, it clearly appears that ESM-1 dominates the performance-based time forecasting methods ESM-SPI(t) and EDM(t)-DPI, both overall (i.e. over the entire course of the project) and for every specific completion stage (i.e. early, middle, and late). Furthermore, the extension of Lipke (2011) does show potential for ESM-1, whereas the technique of Elshaer (2013) proves disadvantageous. In contrast, for the performance-based methods, the observations are completely reversed. Here, the method of Lipke (2011) has an adverse effect on forecasting accuracy, whereas the technique of Elshaer (2013) can produce improved forecasts with respect to the standard methods without extensions. However, the positive effect of the extension of Elshaer (2013) mainly occurs in the early stage of the project, and not in the later stages. Nevertheless, the method of Elshaer (2013) can certainly be deemed relevant considering the great importance of accurate early stage forecasts (Teicholz, 1993). The above discussion also implies that, for none of the three base methods (i.e. ESM-1, ESM-SPI(t) and EDM(t)-DPI), it appears beneficial to combine the techniques of Lipke (2011) and Elshaer (2013).

The performance-based time forecasting methods EDM(t)-DPI and ESM-SPI(t) (and not ESM-1) are considered in order to allow a fair comparison of the ESM and EDM(t) methodologies. The forecasting accuracy of the standard versions (i.e. without extensions) of ESM-SPI(t) and EDM(t)-DPI is strongly similar, and moreover, the positive influence of the extension of Elshaer (2013) is almost identical for both methods, both overall and for the important early stages. Consequently, EDM(t) as proposed by Khamooshi and Golafshani (2014) certainly proves to be a valid methodology for forecasting project duration, as it can compete with — and potentially improve — the currently most recommended methodology of ESM.

Since the overall results of our study show a slight advantage of EDM(t)-DPI over ESM-SPI(t), the introduction of an unweighted EDM(t)-based method (i.e. *PF* = 1; EDM(t)-1) might yield a new overall best performing method if the forecasting accuracy of ESM-1 can be surpassed. Another interesting topic for future research is the optimization of the approach of Lipke (2011) through fine-tuning of the parameters needed for the calculation of the rework fraction, which were now set to fixed values proposed by the author. As such, the benefits of applying the said approach for ESM-1 (and for other methods, perhaps EDM(t)-1) could be increased.

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