

# Practical Application and Empirical Evaluation of Reference Class Forecasting for Project Management

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## ABSTRACT ■

Traditionally, project managers produce cost and time forecasts by predicting the future course of specific events. In contrast, reference class forecasting (RCF) bypasses human judgment by basing forecasts on the actual outcomes of past projects similar to the project being forecasted. The RCF technique is compared with the most common traditional project forecasting methods, such as those based on Monte Carlo simulation and earned value management (EVM). The conducted evaluation is entirely based on real-life project data and shows that RCF indeed performs best, for both cost and time forecasting, and therefore supports the practical relevance of the technique.

**KEYWORDS:** project management; project forecasting; reference class forecasting; earned value management; Monte Carlo simulation; empirical database

## INTRODUCTION ■

**B**efore a project is started, project managers have to make an estimation of how long the project will take and how much it is going to cost. Traditionally, project managers focus on the specifics of the considered project (e.g., its particular activities) to produce these estimations, as they attempt to forecast uncertain events that would influence the future course of the project. Such an “inside view” forecasting approach is obviously based on human judgment. In their studies, Kahneman and Tversky (1979a, 1979b) found that human judgment is biased, as it is generally too optimistic because of overconfidence and insufficient regard to actual previous experience (i.e., “optimism bias”). Moreover, project managers could deliberately and strategically underestimate costs (and durations) to give the impression that they would surpass the competition (i.e., “strategic misinterpretation”). In order to overcome this human bias and the inaccurate forecasts that result from it, Kahneman and Tversky (1979a) and later Lovallo and Kahneman (2003) introduced the method of reference class forecasting (RCF). RCF takes an “outside view” on planned actions rather than an inside view by cutting directly to outcomes through the use of distributional information from other projects similar to the one being forecasted. More specifically, the RCF method consists of a three-step procedure (Flyvbjerg, 2006, 2007):

1. Identifying a relevant reference class of past projects similar to the considered project
2. Establishing a probability distribution for the selected reference class
3. Determining the most likely outcome for the considered project by comparing that project with the reference class distribution

Regarding the first step, Flyvbjerg (2006) states that the reference class must be broad enough to be meaningful, but narrow enough to be truly comparable with the considered project. We will approach this statement from a quantitative point of view by identifying reference classes with different degrees of similarity and evaluating their performance, which has not been done in earlier studies.

Notice that the RCF method, as described by the three-step procedure, does not involve any attempt to forecast specific events that would affect the particular project. Multiple experimental studies (Kahneman, 1994; Kahneman & Tversky, 1979a, 1979b; Lovallo & Kahneman, 2003)

have indicated that RCF is more accurate than traditional forecasting methods. However, these studies were not situated in the field of project management. The first and only instance of RCF in project management was presented by Flyvbjerg (2006), who considered a project in the transportation sector, though no quantitative evaluation of the accuracy of the RCF technique was performed. Therefore, this article will compare the performance of RCF with that of the most common traditional methods for project forecasting. Moreover, this performance evaluation is not based solely on the most important forecasting quality criterion, accuracy (Carbone & Armstrong, 1982), but also on the two other criteria—timeliness and stability (Covach, Haydon, & Reither, 1981)—the latter not being considered by Batselier and Vanhoucke (2015b). Furthermore, and in contrast to Flyvbjerg's (2006) study, RCF will not only be applied for forecasting project cost but also for project duration. As might appear from the above discussion, the focus of this article is on the time and cost aspects of project management. Although these are perhaps the two most important objectives for the project manager, other factors such as safety, sustainability, and especially quality are also of interest. However, it is outside the scope of this article to further elaborate on the latter factors. An overview of studies that incorporate quality, safety, and/or sustainability in the traditional time–cost project control framework is provided by Willems and Vanhoucke (2015). Nevertheless, the expansion of control models through the integration of other performance-defining factors, in addition to time and cost, remains a research path that should receive more attention in the future.

RCF produces forecasts prior to the project start. This corresponds to the budget at completion (BAC) and planned duration (PD) that reflect the final cost and duration of the project, respectively, estimated by the project managers based on their expectations of the future course of the project (i.e., inside view). The BAC

and PD represent the baseline schedule (BLS) of the project (i.e., the planned course of the project) and are, therefore, collectively termed *baseline estimates* here. The baseline estimates are used as inputs for the earned value management (EVM) methodology. EVM is a widely accepted technique for performing project control that integrates the three critical project management elements of cost, schedule, and scope. The technique also implicitly incorporates the quality aspect by taking into account project progress (Willems & Vanhoucke, 2015). Through the application of EVM, the project manager can monitor the performance of the project during execution and receive warning signals for taking corrective actions needed to get the project back on track. Furthermore, the EVM technique can also be used to produce project forecasts. However, because EVM is a technique for performing project control, the forecasts are produced at different tracking periods (TPs) (i.e., evaluation moments) during the project's progress. RCF-based forecasts, on the other hand, are made before the project starts. Nevertheless, the pre-project forecasts from RCF and the intermediately revised forecasts from EVM will be compared. In this light, RCF is seen as a technique for obtaining constant—and, therefore, stable—project forecasts, like the method proposed by Warburton (2011). The results of the RCF method will also be compared with the forecasts obtained from a pre-project Monte Carlo (MC) simulation, the specifics of which will be presented in the next section.

To provide a clear overview of the contributions of this article, we now explicitly summarize the intended objectives:

- Perform a quantitative evaluation of the RCF technique by comparing it with the most common traditional project forecasting methods;
- Apply RCF for project duration forecasting and evaluating the performance;
- Assess the influence of different selections of reference classes with respect to similarity levels;

- Identify other realistic causes for biased forecasts that occur in practice, different from the traditional definitions of optimism bias and strategic misinterpretation; and
- Further support the practical relevance of the RCF technique for real-life applications.

Regarding the first objective, the forecasts used for comparison are those from EVM, Monte Carlo simulation, and baseline estimates. Note that the two latter forecasts have not been explicitly considered in the study of Batselier and Vanhoucke (2015b). In order to achieve the last two objectives, we base our study on a real-life construction project that originates from the empirical project database of Batselier and Vanhoucke (2015a). Furthermore, all projects of the different reference classes are also part of this database. Given the extent of the employed data, it is not our goal to pursue generalizability. Rather, we aim at providing a clear view of the practical application of different project forecasting methods—in particular, RCF—and obtaining a reliable indication of the relevance of RCF in terms of workability and performance with respect to the traditional forecasting methods.

More information about the considered project and the real-life project database is provided in the next section, followed by the presentation of the different project forecasting methods considered in this article. In a subsequent section, the results of these methods are compared and discussed. Conclusively, the most important outcomes of our study are summarized and suggestions for future research are made.

## Methodology

We will start this section with the presentation of the real-life construction project that forms the basis for the current study. Then the empirical database from which the considered project originates is described. Moreover, the reference classes that are selected in this study all consist of projects that are part

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of the said database. After the selection of the different reference classes, the RCF method will be applied. Subsequently, we present the traditional project forecasting approaches that are considered for comparison: first, those that produce pre-project forecasts, and then those that yield forecasts during project execution. More concretely, the consecutive subsections will be about baseline estimates, Monte Carlo simulation, and EVM, respectively. For each forecasting method, both cost and time forecasting are considered.

### Project Description

The study in this article is based on a real-life construction project. More specifically, it concerns the execution of the finishing works inside an office building, comprising the interior joinery and the placement of plaster walls, movable partition walls (also acoustic), raised floors, suspended ceilings, and furniture. The works are performed by a medium-sized finishing construction company with extensive experience in the field. Nevertheless, the considered project comprises a few smaller activities that are rather uncommon for the company, such as the placement of carpets and special glass walls. The complete list of activities, together with their planned costs and durations (i.e., the BLS), is shown in Table 1. Note that the last column of this table contains information that will be considered and discussed later in this article.

The outwardly irregular activity IDs (identification numbers) were chosen by the project manager who was responsible for this project and are therefore retained here. Durations are expressed in standard eight-hour working days. The displayed costs and durations represent the pre-project expectations of the project manager.

The precedence relations between the activities—which express technical constraints—are also displayed in Table 1. When there are no parentheses behind the listed activity IDs, the precedence relation is a finish-start (FS)

ID	Activity Name	Predecessors	Successors	Cost [€]	Duration [d]	Distr Prof
1	Fixed ceilings		4(SS);6(SS);17	2,129	89	symm
2	Metal ceilings		4(SS);6(SS);17	19,509	89	symm
4	Movable partition walls (1)	1(SS);2(SS)		37,641	151	right
6	Plaster walls	1(SS);2(SS)	9(FF);10	36,184	22	left
9	Full subcontracting (1)	6(FF)		1,079	1	no risk
10	Disassembling ceilings	6	12	2,509	7	symm
12	Adjusting raised floor	10	11;21;3	1,800	3	symm
11	Placing carpet	12	13	27,162	5	symm
21	Full subcontracting (2)	12		20,068	67	no risk
13	Placing furniture	11	14;16	36,023	3	symm
14	Placing glass walls	13	17	180	1	symm
3	Acoustic dams	12	20;5;7;8	1,674	2	left
20	Movable partition walls (2)	3	17;15;22	4,926	9	right
5	Movable partition walls (3)	3	17;15;22	619	9	right
7	Doors	3	17;15;22	6,259	3	symm
8	Joinery	3	17;15;22	1,964	3	symm
17	Painting works	1;2;14;20;5;7;8	19(SS)	8,538	41	symm
19	Ancillary works	17(SS)		16,619	3	symm
15	Finishings	20;5;7;8	18(SS)	13,132	71	symm
22	Miscellaneous	20;5;7;8		998	77	right
16	Adjusting furniture	13		312	61	symm
18	Moving reinforcing screens	15(SS)		4,879	3	symm
23	Additional work			0	0	no risk

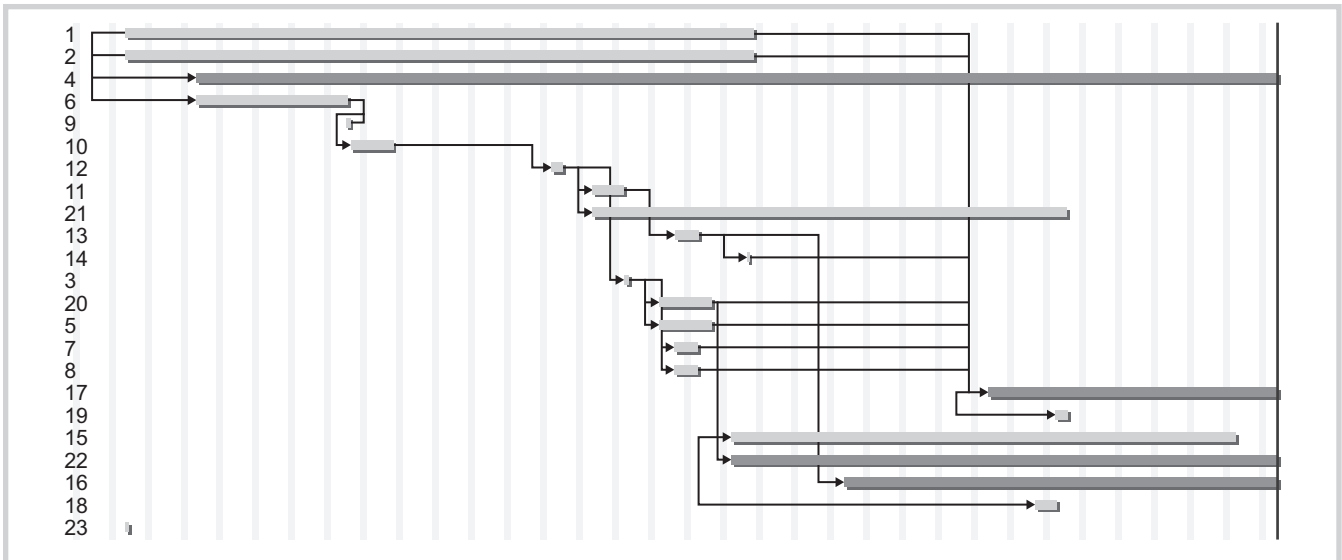
**Table 1:** Activity information for the considered real-life construction project.

relation. An FS relation is the most common type of precedence relation and indicates that an activity can only start after its predecessor(s) has (have) finished. Start-start (SS) and finish-finish (FF) relations, on the other hand, signify that an activity can only start after its predecessor(s) has (have) started and that an activity can only finish after its predecessor(s) has (have) finished, respectively. The precedence relations between the activities can also be identified from the Gantt chart in Figure 1.

Notice that, although all precedence relations have a zero time lag, the

activities almost never directly follow one another in the BLS. This indicates that the project manager has incorporated buffers for activity durations in the project planning.

More extensive data on the considered project can be found at [www.or-as.be/research/database](http://www.or-as.be/research/database), because the project is part of the real-life project database of Batselier and Vanhoucke (2015a). In this database, which will be described in the following section, the considered project is identified by the code C2013-17 and the name Office Finishing Works (5).



**Figure 1:** Gantt chart for the considered real-life construction project.

### Database Description

The real-life project database utilized in this article was constructed by Batselier and Vanhoucke (2015a). At the time of this study, the ever-expanding database consisted of 56 projects, which originate from many different companies from various sectors (mainly construction, but also event management, IT, production, education, etc.) and show wide ranges of project budgets and durations. The quality and authenticity of the project data are guaranteed by the application of a construction and evaluation framework based on so-called project cards, which summarize the most important properties of a certain project and enable its categorization and evaluation (Batselier & Vanhoucke, 2015a). The project card of the project considered here—and of every other project in the database—is available at [www.or-as.be/research/database](http://www.or-as.be/research/database), as are the project data themselves. The data were originally formatted as files from the project management software tool ProTrack ([www.protrack.be](http://www.protrack.be)), but can now also be obtained in Microsoft Excel format, thanks to the novel software tool PMConverter. Furthermore, all projects that constitute the reference classes for the considered project

originate from the presented empirical database. How these different reference classes are composed is described in the next section.

### Reference Class Selection

In order to apply the RCF technique, a reference class of projects similar to the considered project has to be identified. As mentioned in the introduction, it is our objective to assess the influence of the chosen reference class similarity level on the performance of RCF. To this end, we consider four different reference class compositions, ranging from broad sector-based to company-specific. Notice that this approach somewhat resembles the *k*-nearest neighbors (*k*-NN) nonparametric method, in which forecasts are based on the *k* projects closest (i.e., most similar) to the considered project. Paralleling our approach, the fixed number *k* would thus be decreased to reflect the increasing similarity level of the reference class. The explicit implementation of the *k*-NN method is beyond the scope of this article, but can be considered a potential future research topic.

Recall that the project considered in this study is a construction project. Note, however, that the construction

sector is very broad, consisting of the civil, industrial, and building subsectors. The building construction subsector, in turn, can be further subdivided into commercial, institutional, and residential building. Because the considered project comprises the finishing works for an office building, it can be situated within the commercial building construction sector. Thus, three broader reference classes can be identified: projects from construction, building construction, and commercial building construction, in order of increasing specificity and similarity to the considered project. Projects from all of these (sub)sectors can be extracted from the database of Batselier and Vanhoucke (2015a). Logically, the broader the sector, the larger the number of relevant projects; this is also illustrated in Table 2, which shows the project codes and names of the projects within the different reference classes. A number in a column indicates that the project in this study is part of the corresponding reference class (*Constr* is construction, *Build* is building construction, and *Comm* is commercial building construction) for cost and/or time forecasting (C-column and T-column, respectively). Observe that there are four projects that can be

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Code	Name	Reference Class							
		Constr		Build		Comm		OFW	
		C [%]	T [%]	C [%]	T [%]	C [%]	T [%]	C [%]	T [%]
C2013-13	Office Finishing Works (1)	-14.5	-8.1	-14.5	-8.1	-14.5	-8.1	-14.5	-8.1
C2013-14	Office Finishing Works (2)	-12.1	23.8	-12.1	23.8	-12.1	23.8	-12.1	23.8
C2013-15	Office Finishing Works (3)	-9.7	-29.8	-9.7	-29.8	-9.7	-29.8	-9.7	-29.8
C2013-16	Office Finishing Works (4)	-20.0	-33.2	-20.0	-33.2	-20.0	-33.2	-20.0	-33.2
C2011-12	Claeys-Verhelst Premises	—	2.7	—	2.7	—	2.7	—	2.7
C2013-09	Urban Development Project	10.4	23.7	10.4	23.7	10.4	23.7	10.4	23.7
C2013-03	Brussels Finance Tower	5.8	0.2	5.8	0.2	5.8	0.2	5.8	0.2
C2013-04	Kitchen Tower Anderlecht	18.9	36.0	18.9	36.0	18.9	36.0	18.9	36.0
C2013-06	Government Office Building	10.9	-2.3	10.9	-2.3	10.9	-2.3	10.9	-2.3
C2013-07	Family Residence	-3.0	7.6	-3.0	7.6	-3.0	7.6	-3.0	7.6
C2013-08	Timber House	15.1	8.8	15.1	8.8	15.1	8.8	15.1	8.8
C2013-12	Young Cattle Barn	7.5	63.5	7.5	63.5	7.5	63.5	7.5	63.5
C2014-01	Mixed-use Building	2.8	-5.5	2.8	-5.5	2.8	-5.5	2.8	-5.5
C2014-05	Apartment Building (1)	—	20.2	—	20.2	—	20.2	—	20.2
C2014-06	Apartment Building (2)	—	11.7	—	11.7	—	11.7	—	11.7
C2014-07	Apartment Building (3)	—	14.4	—	14.4	—	14.4	—	14.4
C2014-08	Apartment Building (4)	19.5	18.0	19.5	18.0	19.5	18.0	19.5	18.0
C2011-13	Wind Farm	22.0	14.3	22.0	14.3	22.0	14.3	22.0	14.3
C2012-13	Pumping Station Jabbeke	4.2	12.0	4.2	12.0	4.2	12.0	4.2	12.0
C2013-01	Wiedauwkaai Fenders	22.9	0.0	22.9	0.0	22.9	0.0	22.9	0.0
C2013-02	Sewage Plant Hove	-7.3	0.0	-7.3	0.0	-7.3	0.0	-7.3	0.0
C2013-10	Town Square	33.2	-0.1	33.2	-0.1	33.2	-0.1	33.2	-0.1
C2013-11	Recreation Complex	-0.5	-11.4	-0.5	-11.4	-0.5	-11.4	-0.5	-11.4
C2014-04	Compressor Station Zelzate	5.0	62.5	5.0	62.5	5.0	62.5	5.0	62.5
Avg [%]		5.6	9.5	2.4	8.9	-9.2	-3.5	-14.1	-11.8
# projects		20	24	13	17	5	6	4	4

**Table 2:** Reference class selections and deviations between planned and actual outcomes.

used in a reference class for time but not for cost forecasting. This is because authentic actual cost data for these projects are absent. The numbers displayed in Table 2 will be explained and utilized in the next section.

The last two columns of Table 2 present the reference class “OFW” or “office finishing works.” This is the most specific reference class with the highest degree of similarity, as it only comprises the finishing construction projects executed by the same company as the one that did the considered project. Four of these

projects are available in the utilized database. All of them consist of activities that are strongly similar to those of the considered project, with the placement of the movable partition walls as the core activity. Moreover, the four projects were all completed in 2011, in the order indicated by the project codes (C2013-13 to 16) and names (Office Finishing Works [1] to [4]). The considered project C2013-17 Office Finishing Works (5) only started in May 2012, so the OFW reference class for this project is indeed constituted of past projects.

In order to assess the influence of the reference class similarity level on the performance of the RCF technique, all four of the reference classes included in Table 2 will be considered. The resulting cost and time forecasts are presented in the following section.

### Reference Class Forecasting

In terms of the three-step procedure for applying RCF presented in the introduction, we already performed the first step in the previous section (i.e., identifying relevant reference classes of past,

similar projects). Therefore, we can now proceed to the second step. We will not explicitly consider the probability distributions for the selected reference classes as was done by Flyvbjerg (2006). In his research, the goal was to determine the required uplift (i.e., budget increase with respect to the initial estimate or BAC) corresponding to a certain acceptable chance of cost overrun. Because our intention is to compare RCF with traditional forecasting approaches—which are all aimed at providing point estimates of the *most likely* project cost and duration—we are only interested in obtaining the *most likely* outcome for the considered project (i.e., similar to the uplift needed for the 50% percentile of the cost overrun chance in Flyvbjerg [2006]). This corresponds to the third step of the RCF procedure.

We now refer to Table 2, in which the numbers represent the observed deviations of the actual project cost (C-column) and duration (T-column) from their respective baseline estimates (see the next section). A negative percentage deviation indicates that the actual outcome turned out to be lower (i.e., more beneficial) than expected, whereas a positive number obviously signifies the opposite. The most likely cost or time outcome according to a certain reference class can be calculated from the average deviation over all projects in that reference class (see the second to last row of Table 2). More specifically, the desired RCF results are obtained by applying those average deviations to the baseline estimates, that is, to the BAC for cost forecasting and to the PD for time forecasting. Table 3 shows all RCF outcomes for the considered project.

The values of the baseline estimates will be further discussed in the following section.

#### Baseline Estimates

The baseline estimates for the considered project could already be observed from Table 3. More specifically, the BAC appeared to be €244,205 (approximately

	Reference Class							
	Constr		Build		Comm		OFW	
	C [€]	T [d]	C [€]	T [d]	C [€]	T [d]	C [€]	T [d]
Baseline estimate	244,205	161	244,205	161	244,205	161	244,205	161
Avg deviation	+5.6%	+9.5%	+2.4%	+8.9%	-9.2%	-3.5%	-14.1%	-11.8%
RCF outcome	257,771	176.4	250,141	175.4	221,787	155.4	209,833	142.0

**Table 3:** RCF outcomes for the considered project.

US\$323,059) and the PD 161 days. The BAC can quite easily be calculated as the sum of all the activity costs displayed in Table 1. The calculation of the PD, on the other hand, is not as straightforward, because the precedence relations between the different activities have to be respected. Only the activities that are part of the critical path (CP) define the PD. The critical activities of the considered project are indicated by a different shade of gray in Figure 1. In fact, only the very long activity 4 is intrinsically critical, but activities 17, 22, and 16 also become critical because of the as late as possible (ALAP) planning approach adopted by the project management in question. Also note that the start of activity 4 is only planned after 10 days, whereas there is no technical constraint (i.e., precedence relation) that would inhibit the activity from beginning at project launch. The choice for delaying the start of activity 4—and for introducing all other buffers in the project—was made by the project manager, perhaps taking into account the unavailability of a particular team or subcontractor until a certain date. Moreover, all activity costs and durations in Table 1 reflect the project manager's pre-project expectations for the future course of the project. Therefore, the BAC and PD estimates are also completely pre-project.

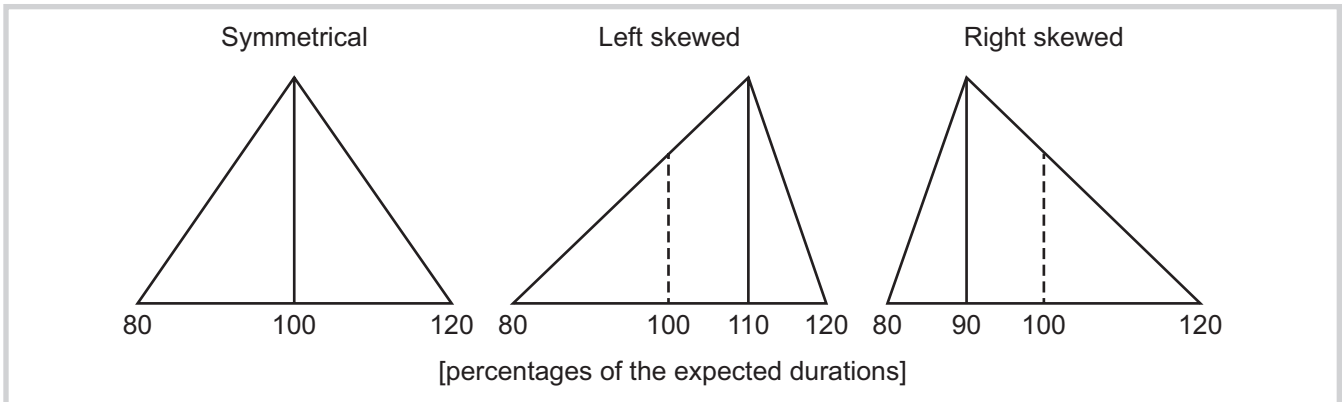
#### Monte Carlo Simulation

An approach for obtaining somewhat more substantiated pre-project estimates of project cost and duration is to use Monte Carlo simulation, which is based on the definition of risk distribution

profiles for the individual activity durations. In this study, we apply triangular distribution profiles, which can be symmetrical, skewed to the left, or skewed to the right. These profiles have predefined shapes (see Figure 2), as also used in earlier research (Batselier & Vanhoucke, 2015b). Furthermore, there is also the possibility that an activity exhibits no risk of its duration deviating from the expected value. The distribution profile in such a case is rather obvious (i.e., one single peak) and is therefore not included in Figure 2.

The worst case/best case duration of an activity is always 20% larger/smaller than its expected duration, regardless of the specific distribution profile (risk-free profile disregarded). Moreover, the expected duration of an activity corresponds to the 100% duration in Figure 2 and represents the duration estimated by the project management prior to the project start. These expected (or planned) activity duration values were already presented in the second to last column of Table 1. Notice that, for an activity with a distribution profile that is skewed to the left, there is a greater chance that the activity will take longer than expected, whereas the opposite is true for an activity with a right skewed distribution profile. It is important to realize that the assignment of distribution profiles to the different activities of the considered project was performed by the project manager on the project based on his experiences from earlier projects that showed similar activities. Because historical data are used for this process, one would be inclined to regard

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**Figure 2:** Activity duration distribution profiles.

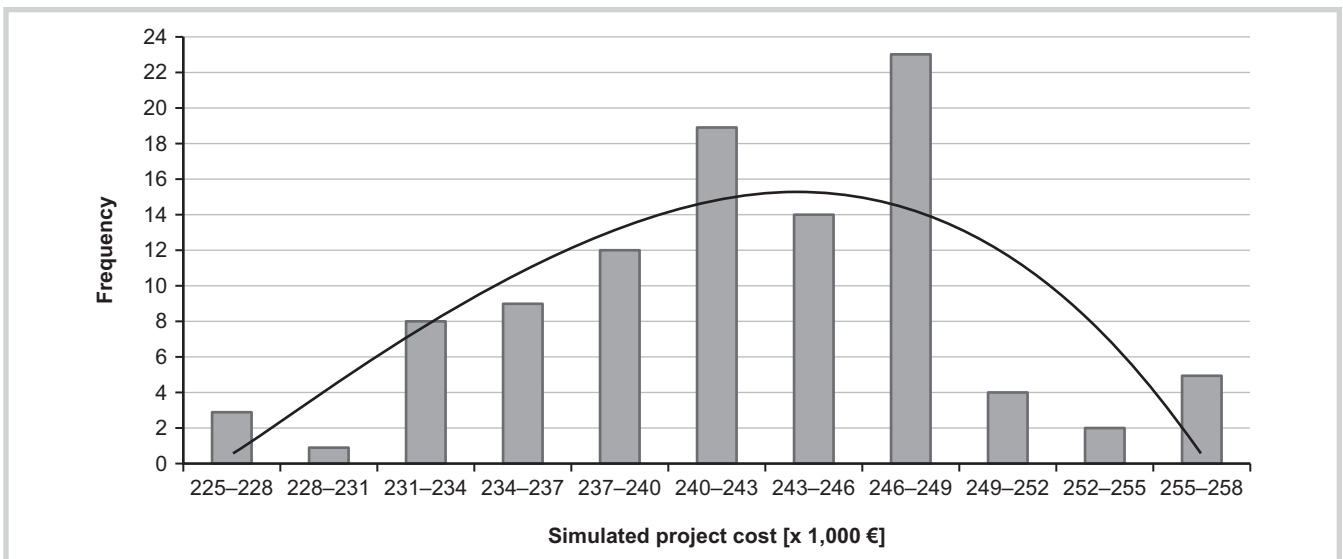
Monte Carlo simulation as an outside view forecasting technique. However, in contrast to RCF, Monte Carlo simulation still requires distributional information for every activity (and not only for the total project), which will often necessitate (unsupported) assumptions from the project manager (e.g., for uncommon activities). Therefore, Monte Carlo simulation could better be identified as a “semi-outside view” on project forecasting. Note that the distribution profiles for activity durations could also be derived in a more analytical manner (Colin & Vanhoucke, 2016; Trietsch, Mazmany, Gevorgyan, & Baker, 2012). However,

these approaches are beyond the scope of this practice-oriented article.

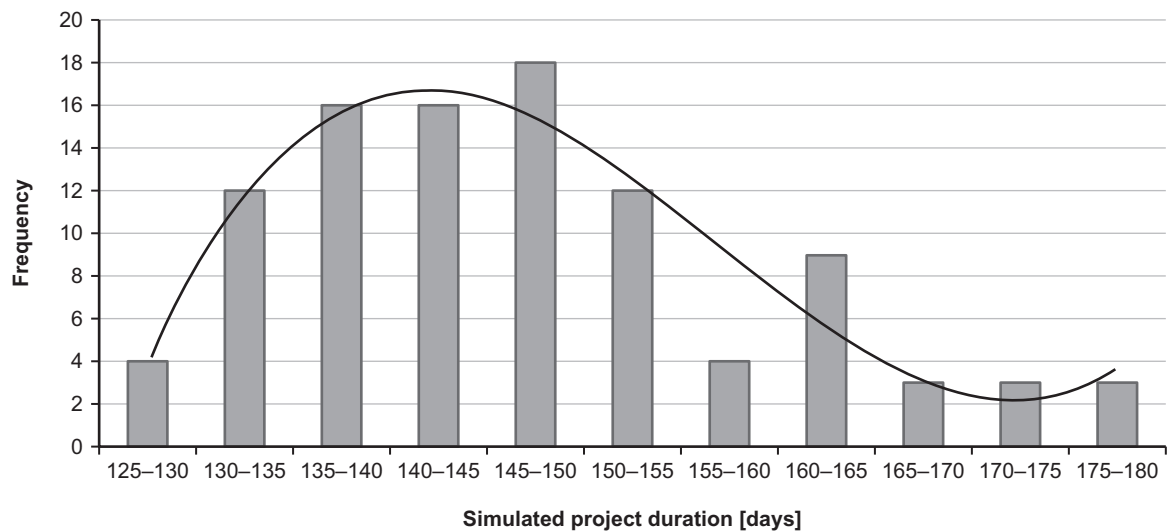
The selected distribution profiles were already included in the last column of Table 1, labeled “Distr prof.” In this column, “symm,” “left,” “right,” and “no risk” indicate symmetrical, left skewed, right skewed, and risk-free distribution profiles, respectively. For the activities that were rather uncommon for the company (e.g., activities 10 to 12) and with which the project manager thus had little to no experience, a standard symmetrical distribution profile was assumed. Furthermore, activity 23 was assigned a risk-free distribution profile

because no additional work—or the risk of it—was taken into account in the initial plan. We also assume that the project only includes variable costs, which correspond well to the actual situation, and that all activity costs thus vary uniformly with the corresponding activity duration.

The Monte Carlo simulation is performed with the project management software tool ProTrack. More specifically, 100 simulation runs are executed. The project costs and durations resulting from these simulation runs are shown in Figure 3 and Figure 4, respectively. For both graphs, the value intervals were chosen in such a way that an equal



**Figure 3:** Project costs from Monte Carlo simulation.



**Figure 4:** Project durations from MC simulation.

and sufficient number (11) of outcome categories could be defined.

For project cost, all activities contribute to the total cost value. Because the cost distribution over the different activities is very close to symmetrical (i.e., a strongly similar percentage of the distribution profiles is left skewed and right skewed—16% and 18%, respectively—while the rest of the profiles are symmetrical or risk-free), we also expect a rather symmetrical distribution of the simulated project costs. The third-degree polynomial in Figure 3 confirms this expectation. On a project level, the BAC represents the expected cost and thus corresponds to the 100% point in the distribution profiles of Figure 2. Recall that for the considered project, the BAC is €244,205 (approximately, US\$323,059). On the other hand, the average project cost over the 100 simulation runs is €242,432 (approximately, US\$320,713). This is the Monte Carlo simulation outcome that will be retained for further evaluation. Notice that this result is modestly lower than the BAC (less than 1% difference), which can be explained by the slightly higher fraction of right skewed distribution profiles (i.e., greater chance of shorter activity duration and thus lower activity cost).

In contradiction to the project cost, only the critical activities (i.e., the activities on the critical path) define the total project duration. In the considered project, activities 4, 17, 22, and 16 are critical, as is indicated by the different shade in Figure 1. From Table 1, one can observe that activities 16 and 17 exhibit a symmetrical distribution profile, whereas the durations of activity 22 and the very significant (i.e., long) activity 4 are skewed to the right. This explains the right skewed distribution of the simulated project duration that can be observed from Figure 4. In correspondence with the cost situation, the PD—which is 161 days for the considered project—reflects the expected duration (100 percentage points in Figure 2) on the project level. Furthermore, the peak of the third-degree polynomial of the simulated project duration distribution occurs around 142 days, which is about 88% of the PD. This indeed corresponds nicely to the right skewed distribution profile as defined in Figure 2, where the peak is situated at 90%. More important, the average project duration from Monte Carlo simulation, which will be the basis for further evaluation, is 147 days. Logically, this value is considerably lower (by 8.7%) than the PD.

### ***Earned Value Management***

In contrast to the forecasting methodologies of RCE, baseline estimates and Monte Carlo simulation, EVM does not provide fixed pre-project predictions, but produces project cost and duration forecasts that are updated every TP based on the actual project progress. For the project considered here, tracking was performed on a monthly basis. For the first TP only, a larger time span of two months was chosen (because of the slow initial progress of the project). The final status date was on 31 October 2012, when the project had already ended. A total of four TPs occurred during the project's execution (i.e., on the last day of June, July, August, and September 2012, respectively). Nevertheless, although the first TP was postponed by one month, the progress made at that point was still not substantial enough to allow for correct calculation of project performance. To avoid the potential bias of EVM forecasting results, the data from the first TP were omitted. Consequently, only the next three TPs (i.e., from July 2012 to September 2012) were considered for the calculation of EVM cost and duration forecasts. Before being able to present the EVM forecasting formulas,



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we first need to provide a brief overview of the basic EVM metrics and their definitions:

- actual time (AT): the current point in time
- planned value (PV): the value that was planned to be earned at the AT
- earned value (EV): the value that has actually been earned at the AT
- actual cost (AC): the costs that have actually been incurred at the AT
- earned schedule (ES): the time at which the EV should have been earned according to the plan, calculated by  $ES = t + \frac{EV - PV_t}{PV_{t+1} - PV_t}$  where  $t$  is the (integer) point in time for which  $EV \geq PV_t$  and  $EV < PV_{t+1}$  (Lipke, 2003)
- cost performance index (CPI):  $CPI = EV/AC$ ; if the CPI is smaller than, equal to, or larger than 1, the project is respectively over, on, or under budget
- schedule performance index (SPI(t)):  $SPI(t) = ES/AT$ ; if the SPI(t) is smaller than, equal to, or larger than 1, the project is respectively late, on time, or early

The above listing is certainly not comprehensive, as only the metrics that are needed for further calculations are presented. For a more extensive overview of the EVM methodology, there are multiple works available for consultation (Anbari, 2003; Fleming & Koppelman, 2010; PMI, 2008; Vanhoucke, 2010, 2014). In this article, the ES methodology proposed by Lipke (2003) is conceived as part of the global EVM technique. The EVM cost and duration forecasting formulas can now be introduced.

The project cost forecast at the AT is called the estimated cost at completion (EAC) and is calculated according to the following generic formula:

$$EAC = AC + \frac{BAC - EV}{PF}$$

Here, PF is the performance factor that reflects the assumptions made for future project performance. In this

article, we only consider the PFs that were shown to provide the most accurate cost forecasts for real-life projects (Batselier & Vanhoucke, 2015b), which are  $PF = 1$  (i.e., future cost performance according to plan) and  $PF = CPI$  (i.e., future cost performance equal to current cost performance). The corresponding methods are indicated by EAC-1 and EAC-CPI, respectively.

The EVM time forecasts are based on Lipke's (2003) earned schedule method (ESM). The dominance of this technique over Anbari's (2003) planned value method (PVM), and the earned duration method (EDM) of Jacob and Kane (2004) has been proven in several studies (Batselier & Vanhoucke, 2015b; Vanhoucke & Vandevorde, 2007). Therefore, the project duration forecast at the AT, termed estimated time at completion (EAC(t)), follows from the generic ESM formula:

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

Just as for cost forecasting, only the PFs with the best real-life performance according to Batselier and Vanhoucke (2015b) are retained. Those are  $PF = 1$  (i.e., future time performance according

to plan) and  $PF = SPI(t)$  (i.e., future time performance equal to current time performance). To clearly indicate the use of the ESM, these methods are represented by ESM-1 and ESM-SPI(t), respectively.

The relevant EVM metrics and all four of the applied cost and time forecasts are presented in Table 4 for all five TPs of the considered project. Recall that only the three middle TPs (i.e., TP2 to TP4) are retained for the upcoming evaluation. The results for TP1 and TP5 are also included in Table 4 for completeness, but are shown in a lighter font.

Note that PC stands for percentage complete and is calculated by  $EV/BAC$ . The PC represents the progress that has already been made on a certain TP. From Table 4, we can see that the PC for TP1 was indeed still very low (i.e., 8%) and does not reach the proposed minimum PC-value of 10% that warrants reliable performance calculation and thus forecasting (Lipke, 2009). Furthermore, the results of TP5 are also not relevant for further evaluation, as this TP occurs after the project has ended. At that time, the actual project outcomes are, of course, already known and forecasting becomes redundant.

	TP1	TP2	TP3	TP4	TP5
Start date	05/01/2012	07/01/2012	08/01/2012	09/01/2012	10/01/2012
Status date	06/30/2012	07/31/2012	08/31/2012	09/30/2012	10/31/2012
PC [%]	8	61	91	98	100
AT [d]	44	66	89	109	132
PV [€]	58,946	77,311	169,890	184,870	226,159
EV [€]	19,535	148,261	222,988	238,834	244,205
AC [€]	27,993	139,833	175,006	202,523	203,606
ES [d]	18.0	79.3	131.6	151.1	161.0
CPI [-]	0.70	1.06	1.27	1.18	1.20
SPI(t) [-]	0.41	1.20	1.48	1.39	1.22
EAC-1 [€]	252,663	235,778	196,223	207,894	203,606
EAC-CPI [€]	349,933	230,324	191,658	207,077	203,606
ESM-1 [d]	187.0	147.6	118.4	118.8	132.0
ESM-SPI(t) [d]	393.5	133.9	108.9	116.0	132.0

**Table 4:** EVM metrics and forecasts for the considered project.

ID	Activity Name	Baseline Cost [€]	Baseline Duration [d]	Real Cost [€]	Real Duration [d]
1	Fixed ceilings	2,129	89	1,929	22
2	Metal ceilings	19,509	89	20,190	62
4	Movable partition walls (1)	37,641	151	33,605	22
6	Plaster walls	36,184	22	34,103	81
9	Full subcontracting (1)	1,079	1	847	1
10	Disassembling ceilings	2,509	7	2,277	7
12	Adjusting raised floor	1,800	3	1,459	3
11	Placing carpet	27,162	5	21,457	5
21	Full subcontracting (2)	20,068	67	15,694	22
13	Placing furniture	36,023	3	29,191	3
14	Placing glass walls	180	1	178	1
3	Acoustic dams	1,674	2	1,520	2
20	Movable partition walls (2)	4,926	9	3,245	9
5	Movable partition walls (3)	619	9	615	9
7	Doors	6,259	3	5,529	3
8	Joinery	1,964	3	1,783	3
17	Painting works	8,538	41	6,185	22
19	Ancillary works	16,619	3	1,374	3
15	Finishings	13,132	71	11,920	65
22	Miscellaneous	998	77	906	22
16	Adjusting furniture	312	61	0	0
18	Moving reinforcing screens	4,879	3	905	3
23	Additional work	0	0	8,695	85
Project total		244,205	161	203,606	132

**Table 5:** Baseline and real activity costs and durations for the considered project.

## Results and Discussion

The considered project was executed and exhibited the real activity outcomes presented in the two last columns of Table 5. The baseline costs and durations (i.e., the as-planned values) in the second and third columns were already shown in Table 1, but are again included here to allow for easier comparison. Furthermore, the project totals for baseline costs and durations are, of course, the BAC and PD, respectively.

On the project level, an eventual cost of €203,606 (approximately, US\$269,350) and eventual duration of 132 days were reached (see the two last columns of project total in Table 5). From now on, these outcomes are referred

to as the real cost (RC) and real duration (RD) of the project, respectively. Thus, the project came in more than €40,000 (approximately, US\$52,916) or 16.6% under budget and was completed 29 days or 18% earlier compared to the baseline estimates. Indeed, one can observe from Table 5 that all critical activities (i.e., activities 4, 17, 22, and 16) were completed significantly faster than planned—especially activity 4, which took only 22 days instead of 151 days, and activity 16, which even appeared to be superfluous (i.e., no adjustments to the furniture were needed). The critical activity for which the duration was least reduced is activity 17. Notice that this activity was only 19 days shorter than

planned, whereas the complete project finished 29 days early. Moreover, most of the predecessors of activity 17 were completed right on time. This means that the buffers introduced in the planning (see Figure 1) were reduced as well and appeared to be oversized. In other words, the start dates of the successor activities could be advanced, as no organizational constraints (e.g., unavailability of a particular team or subcontractor until a certain date) occurred. Therefore, the project was executed even faster than what would result from shortening the activity durations alone. Because of the large fraction of variable costs in the project, the eventual cost is also reduced significantly, with a magnitude quite similar to the reduction in project duration (i.e., 16.6% compared with 18%).

Now reconsider Table 4. This table shows that it could already be seen from TP2 that the project was going to be both under budget and early, as both the CPI and the SPI(t) were consistently higher than 1. Again, it becomes clear that the progress data of TP1 were not yet reliable, as a CPI of 0.70 and SPI(t) of 0.41 incorrectly indicated that the project—when the performance-based EVM forecasting methods EAC-CPI and ESM-SPI(t) are applied—was going to be well over budget, and even more so, overdue. Furthermore, the RC and RD values could already be observed from the last column of Table 4 (i.e., the post-project forecasts of TP5). Because the RC and RD represent the actual project outcomes and, therefore, the optimal forecast values, they form the basis for evaluating the accuracy of the presented cost and time forecasting methods. More specifically, the mean absolute percentage error (MAPE) measure is used to this end. The generic MAPE formula is as follows:

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

In this formula,  $A$  is the actual (eventual) value and  $F_t$  is the forecasted value at time instance  $t$ . In our case, the time instances  $t = 1, \dots, n$  represent

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the  $n$  TPs that were selected for the considered project. Furthermore,  $A$  is substituted by RC and RD for cost and time forecasting, respectively, and  $F_t$  reflects the forecasting outcomes of the different methods. Note, however, that the methodologies of RCF, baseline estimates and Monte Carlo simulation, all produce one fixed forecast prior to the project start that remains constant throughout the entire project. In other words, the forecasts  $F_t$  are the same for every TP  $t$  (i.e.,  $F_t$  can be replaced by  $F$ ). Nevertheless, the MAPE remains a valid accuracy measure in these situations, although its formula is implicitly simplified to  $|A - F|/A$  (i.e., an absolute percentage error). For the EVM forecasting methods, on the other hand, the original MAPE formula, of course, continues to apply, with  $n = 3$  and  $F_1$  to  $F_3$  reflecting the forecasts for TP2 to TP4. It is always true that the lower the MAPE, the more accurate the forecasting method.

In the next two subsections, the performance of the considered forecasting methods is evaluated—first for cost, and then for time. Thereafter, both forecasting dimensions are compared more elaborately. Finally, a qualitative discussion on the underlying causes for the observed performance of the different forecasting approaches is conducted. Note that this discussion emanates from the specific outcomes of the construction

project considered in this article, as do the presented forecasting results.

## Cost Forecasting

The accuracy results for the different cost forecasting methods are presented in Table 6. More specifically, the table shows the difference in MAPEs between the various techniques. A negative number indicates that the horizontal method (row) is more accurate than the vertical method (column), whereas a positive value obviously represents the opposite. All the abbreviations used in the table were already explained earlier in the text.

We will now discuss the results in the order the methods are displayed in Table 6. The BAC represents the pure inside view on project cost forecasting and is used as a first reference value. We see that Monte Carlo simulation yields a more accurate forecast than BAC, albeit modest. The reason that the improvement is only modest might be that symmetrical distribution profiles were assumed for the uncommon activities, whereas the most important of them (i.e., activities 17, 15, and 16) were executed faster—and thus, more cheaply—than planned. This means that right skewed distribution profiles would have been a better option for those activities, although symmetrical profiles were the more logical choice, given the unavailability of distributional

information from past experiences. This also indicates that complete and correct historical data—here, in the form of project manager experience—are crucial to the performance of Monte Carlo simulation. However, for Monte Carlo simulation, one needs distributional data for each activity in the project, whereas for RCF, only the general outcomes of similar projects are required. The latter are obviously much easier to obtain, which is an advantage of the RCF technique.

Moreover, Table 6 even shows that RCF with the most specific reference class of projects from the same company (OFW) is the most accurate cost forecasting method of all those considered. It also becomes apparent that the RCF approach needs a reference class consisting of projects that are highly similar to the considered project, as forecasting accuracy clearly diminishes with decreasing similarity level (i.e., from OFW over Comm and Build to Constr). RCF with a reference class comprising all construction projects (Constr) from the database of Batselier and Vanhoucke (2015a) even proves to be the worst-performing method.

Because RCF with reference class OFW is the overall most accurate technique, it also surpasses both EVM cost forecasting methods (which show very similar results). This is remarkable, as the EVM methodology allows forecasts to be updated during project progress (based on actual progress data), whereas RCF only produces one fixed pre-project forecast that remains constant throughout the entire project.

Because RCF yields constant forecasts, the approach logically exhibits greater forecasting stability than EVM. This is visualized by Figure 5. Since the horizontal line represents the eventual project cost (i.e., RC), the closeness of the markers to this line reflects the forecasting accuracy of the corresponding methods (i.e., the closer, the more accurate).

In terms of timeliness (i.e., the third forecasting quality evaluation criterion according to Covach, Haydon, and

	[MAPE %]	RCF						EVM	
		BAC	MC Sim	Constr	Build	Comm	OFW	EAC-1	EAC-CPI
RCF	BAC	—	0.9	−6.7	−2.9	11.0	16.9	12.8	13.0
	MC Sim	−0.9	—	−7.5	−3.8	10.1	16.0	11.9	12.2
	Constr	6.7	7.5	—	3.7	17.7	23.5	19.4	19.7
	Build	2.9	3.8	−3.7	—	13.9	19.8	15.7	16.0
	Comm	−11.0	−10.1	−17.7	−13.9	—	5.9	1.8	2.0
	OFW	−16.9	−16.0	−23.5	−19.8	−5.9	—	−4.1	−3.8
EVM	EAC-1	−12.8	−11.9	−19.4	−15.7	−1.8	4.1	—	0.3
	EAC-CPI	−13.0	−12.2	−19.7	−16.0	−2.0	3.8	−0.3	—

**Table 6:** Difference in accuracy for the considered cost forecasting approaches.

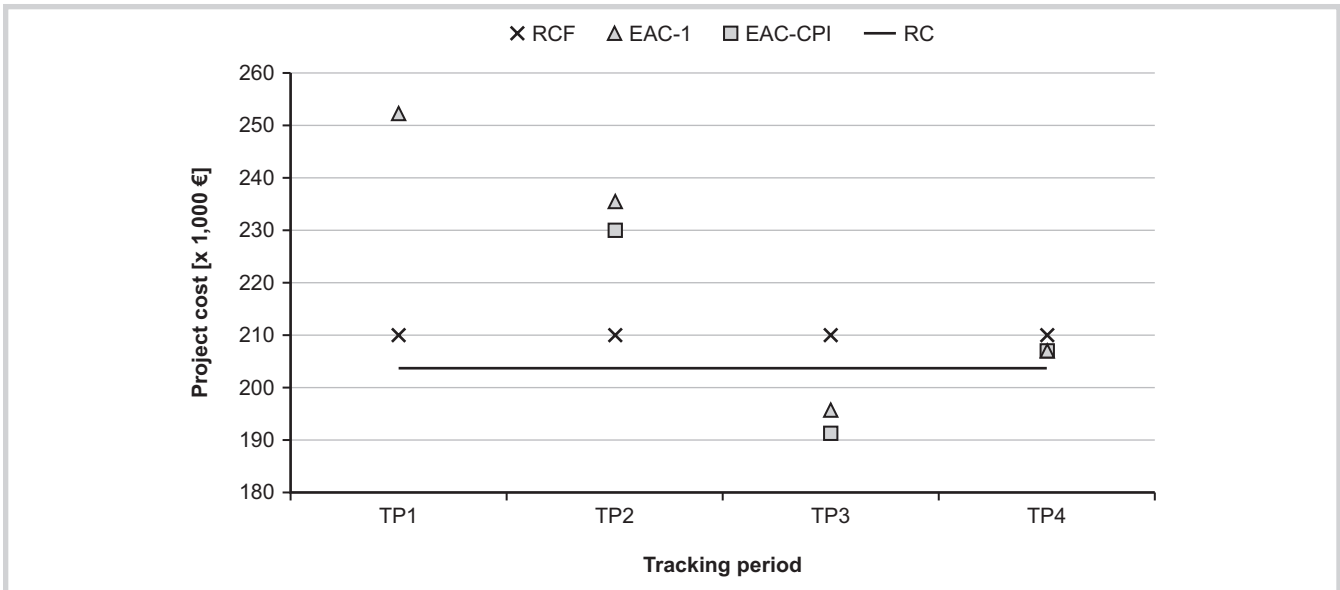


Figure 5: Project cost forecasting results.

Reither [1981], which expresses the ability of a forecasting method to produce accurate forecasts in different stages of the project life cycle), RCF also clearly outperforms EVM. Logically, accurate early-stage forecasts are most important, as they allow adequate corrective actions to be taken in a timely manner (Teicholz, 1993). Following the definitions of Teicholz (1993) and Vanhoucke and Vandevorde (2007), only TP1 (with a PC of 8%) can be situated in the early stage. For this TP, RCF indeed produces a much more accurate forecast than EAC-1 and certainly more accurate than EAC-CPI, which is off the charts in Figure 5 (see the value in Table 4).

### Time Forecasting

Table 7 is very similar to Table 6 in the previous subsection, but now shows the accuracy differences for the considered time forecasting methods.

Again, the outcomes are discussed in the order the methods are presented in the table. When we once again apply the baseline estimate—here, the PD—as a first reference value, we see that Monte Carlo simulation now provides a much greater accuracy improvement than it does for cost forecasting (i.e., 10.6% compared with 0.9%). The reason could

be that two of the four critical activities have a right skewed distribution profile (the two others are symmetrical), which depicts activities that are more likely to be completed faster than planned. Moreover, these two activities—activity 22 and especially activity 4—are the most important (i.e., longest) ones, and thus have the greatest influence on the eventual project duration. Both activities were indeed finished far ahead of schedule, and therefore, so was the project. Again, this indicates the importance of correct activity duration distribution

profiles for Monte Carlo simulation. Also note that these distribution profiles are implicitly based on historical data, as during the construction of these profiles, the concerning project manager is encouraged to take into account experiences from past projects, which would improve forecasting accuracy according to Caron, Ruggeri, and Merli (2013). In other words, the application of Monte Carlo simulation already guides the project manager toward taking more of an outside view on project forecasting. Nevertheless, the technique still

[MAPE %]	PD	RCF					EVM		
		MC Sim	Constr	Build	Comm	OFW	ESM-1	ESM-SPI(t)	
<b>PD</b>	—	10.6	−11.6	−10.9	4.2	14.4	11.2	11.6	
<b>MC Sim</b>	−10.6	—	−22.2	−21.5	−6.4	3.8	0.6	1.0	
<b>Constr</b>	11.6	22.2	—	0.8	15.9	26.1	22.9	23.3	
<b>Build</b>	10.9	21.5	−0.8	—	15.1	25.3	22.1	22.5	
<b>Comm</b>	−4.2	6.4	−15.9	−15.1	—	10.2	7.0	7.4	
<b>OFW</b>	−14.4	−3.8	−26.1	−25.3	−10.2	—	−3.2	−2.8	
<b>ESM-1</b>	−11.2	−0.6	−22.9	−22.1	−7.0	3.2	—	0.4	
<b>ESM-SPI(t)</b>	−11.6	−1.0	−23.3	−22.5	−7.4	2.8	−0.4	—	

Table 7: Difference in accuracy for the considered time forecasting approaches.

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requires the project manager to make some assumptions (e.g., for activities without precedents).

To completely eliminate human judgment and cut directly to the project outcomes, RCF should be applied. The only concern for this approach regards the selection of an adequate reference class. Our study indicates that, also for time forecasting, a reference class should comprise projects that are sufficiently similar to the considered project in order to guarantee accurate forecasts. Indeed, an increasing similarity level of the reference class (i.e., in the order Constr, Build, Comm, and OFW) results in increasing forecasting accuracy.

Moreover, when applying RCF with the most specific reference class of in-company projects (OFW), both EVM methods are outperformed in nearly equal measure. This outcome corresponds perfectly to that for cost forecasting. This is also the case for the comparison between RCF and EVM in terms of stability and timeliness, as for time forecasting, RCF also surpasses EVM. This can be ascertained from Figure 6, which should be interpreted in the exact same way as Figure 5. The theoretical explanation was already provided in the previous subsection and is therefore not repeated here.

The TP1 forecast value for ESM-SPI(t) (see Table 4) is not included in Figure 6 because of the excessive deviation from the eventual outcome, just as for EAC-CPI in Figure 5. The performance-based EVM forecasts (i.e., ESM-SPI(t) and EAC-CPI) thus show a far greater instability than their counterparts, with a  $PF = 1$ .

### Comparing Cost and Time Forecasting

The baseline estimates for cost and time forecasting exhibit a very comparable precision, although the PD is slightly less accurate than the BAC (MAPE of 22% compared with 19.9%). On the other hand, Monte Carlo simulation improves the forecasting accuracy for time to a far greater extent than for cost (MAPE reduction of 10.6% compared with 0.9%). The reasons for this were already given in previous subsections. Of course, these reasons are project-specific, and therefore, the supremacy of Monte Carlo simulation for time with respect to cost should not be generalized.

In this section, we mainly focus on the comparison of the RCF performance for cost and time forecasting. More specifically, we consider the RCF approach based on the reference class of in-company projects (OFW), which

clearly showed the highest accuracy for both dimensions. Traditionally, RCF was introduced to improve the accuracy of cost forecasts and was only applied in this context (Flyvbjerg, 2006; Flyvbjerg & Cowi, 2004). Indeed, our study indicates that the technique succeeds in the cost objective, as the BAC (i.e., inside view) and even the periodically updating EVM methods are surpassed in accuracy. On the other hand, RCF has not been applied to time forecasting up to now. Nevertheless, the technique surpasses all other methods for the time dimension in our study. Furthermore, compared to cost forecasting, a strongly similar accuracy improvement of the RCF approach, with respect to both the baseline estimate (i.e., PD) and the EVM time forecasting methods could be observed. Specifically, the baseline estimate improvement is only 2.5% smaller for time forecasting (MAPE reduction of 14.4% for PD with respect to 16.9% for BAC), and for the best EVM forecasting method (i.e., ESM-SPI(t) for time and EAC-CPI for cost in this case), the difference even remains limited to 1% (MAPE reduction of 2.8% for ESM-SPI(t) with respect to 3.8% for EAC-CPI). Therefore, our results suggest that the RCF approach could just as

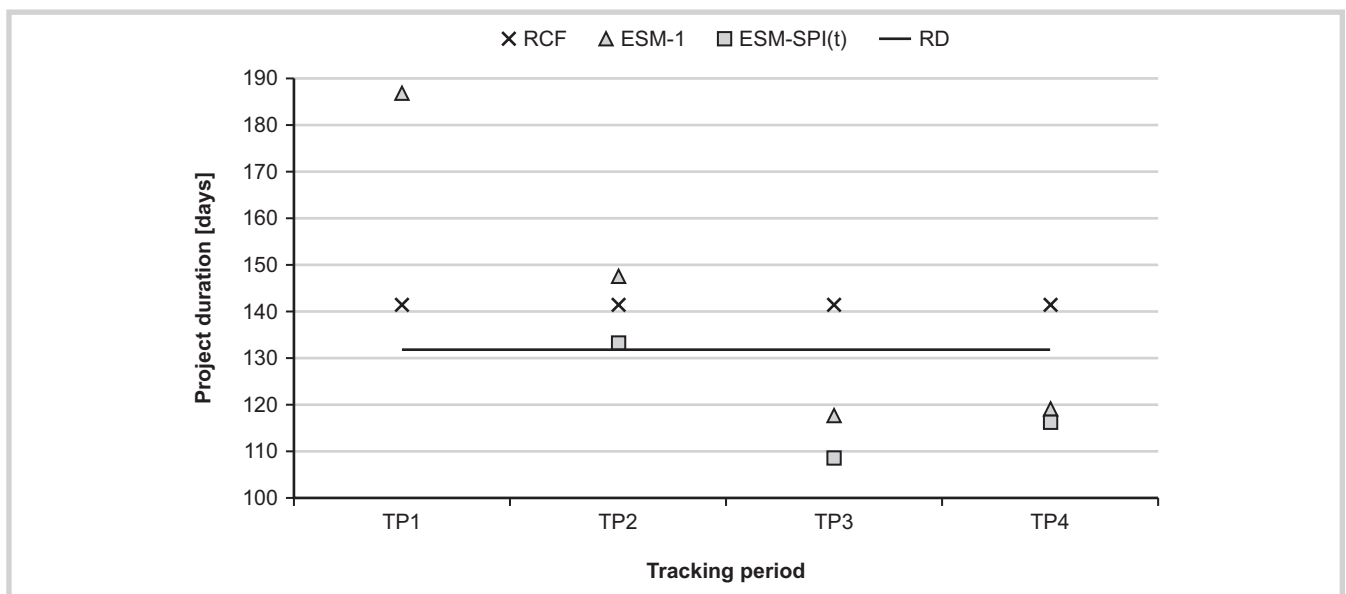


Figure 6: Project duration forecasting results.

well have merit for forecasting project duration.

## Qualitative Discussion

Previous studies (Flyvbjerg, Holm, & Buhl, 2002; 2005; Kahneman & Tversky, 1979b; Lovallo & Kahneman, 2003; Wachs, 1989, 1990) have argued that people—and, therefore, project managers—generally tend to underestimate costs (and durations) when applying an inside view to project forecasting. They identified two reasons: optimism bias (i.e., unintentionally seeing future events in a more positive light than warranted by actual experience) and strategic misinterpretation (i.e., deliberately and strategically making more positive predictions so as to give the impression that the competition would be surpassed). However, when looking at the baseline estimates (i.e., inside view) for the considered project and for similar projects within the same finishing construction company (reference class OFW), we observed exactly the opposite—namely, a structural overestimation of costs and durations. This cannot be explained by the existence of an unintended “negativism bias” (i.e., seeing future events in a more negative light than warranted by actual experience), as this would be in contradiction with the usual manifestations of the human psyche according to the research of Kahneman and Tversky (1979b) and Lovallo and Kahneman (2003). In other words, negativism bias cannot exist alongside positivism bias; they would, by definition, be mutually exclusive. Therefore, strategic misinterpretation must be the root of the structural overestimations within the considered company.

Note that strategic misinterpretation, as also presented by Flyvbjerg (2006), is traditionally defined for the preapproval phase of a project. Project managers would benefit from underestimating costs and durations by increasing the chance of their project—and not that of the competition—would be approved (and funded). However, all considered projects of the finishing construction company had already

been approved, and therefore, underestimating costs and durations would not offer advantages. On the contrary, it would only force the project managers to work faster and more cheaply in order to reach the set goals and the possible bonuses that go with them. Consequently, it is plausible and perhaps even natural that these project managers—with their projects already approved and assigned to them—would rather overestimate the foreseen costs and durations (and build in buffers) so that their targets—and the corresponding bonuses—could be achieved more easily. The exact nature and the effect of strategic misinterpretation thus appear to depend on the phase the project is in when preparing the plan (i.e., producing the baseline estimates): The preapproval phase leads to underestimations, whereas the post-approval phases causes overestimations. Furthermore, the fact that many activities that were planned behind a buffer could actually be started before their foreseen start date not only indicates the absence of organizational constraints (e.g., unavailability of a particular team or subcontractor until a certain date), but also supports the idea of post-approval strategic misinterpretation having occurred for the considered project. In any event, the RCF technique (i.e., outside view) can bypass the biasing effects of this new type of strategic misinterpretation, as our study has shown.

## Conclusions

The main objective of this article was to support the practical relevance of RCF by applying the technique to a real-life project and quantitatively evaluating it through comparison with the most commonly used traditional forecasting methods. More specifically, the considered real-life project is a finishing construction project that was selected from the database of Batselier and Vanhoucke (2015a). The forecasting techniques with which RCF was compared are baseline estimates, Monte Carlo simulation, and EVM. First, practical application

of all these forecasting methods demonstrates that the RCF technique is the most user-friendly, as it does not require a great deal of detailed information (such as distributional data about activity durations for Monte Carlo simulation) or extensive calculations (like the periodical forecast updates for EVM).

Moreover, although RCF produces pre-project forecasts that remain constant throughout project execution (just like baseline estimates and Monte Carlo simulation), it surpasses all the traditional techniques in accuracy, stability, and timeliness. The dominance of RCF in accuracy is especially remarkable, as the competing EVM technique yields forecasts that are updated during project progress. Furthermore, the strong performance of RCF occurs for both cost and time forecasting, and in nearly equal measure. Therefore, our study suggests that RCF could have the same merits for time forecasting as for cost forecasting, for which the technique had already been applied (Flyvbjerg, 2006; Flyvbjerg & Cowi, 2004). However, RCF only outperforms the other techniques when the degree of similarity between the considered project and the projects in the reference class is sufficiently high. More concretely, in our case, the reference class had to consist of projects from the same finishing construction company. A clear decrease in forecasting accuracy could be observed with the gradually declining similarity level of the reference class.

In our specific case, the qualitative reason for the dominance of the outside view on project forecasting over the traditional inside view could be found in the occurrence of a newly identified type of strategic misinterpretation, which suggests that project managers in the post-approval phase are inclined to overestimate the expected costs and durations so that their targets (and bonuses) could be achieved more easily.

This article supports the practical relevance of applying RCF for real-life projects and also shows how the

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technique can be evaluated on a quantitative basis through comparison with other existing forecasting methods. Although this study provides interesting insights into the workings and performance of RCF and other forecasting methods, its results may not be readily generalized because of the restricted number of real-life projects from which the reference classes were selected. To increasingly substantiate the validity of the RCF technique, it should be applied and tested on an ever-growing empirical project database.

Furthermore, following the concept of combining outside view with inside view for project forecasting (Kim & Reinschmidt, 2011), we identify the future research topic of integrating RCF in EVM. By replacing the baseline estimates with the forecasts from RCF, more accurate EVM performance metrics could be obtained. In turn, this would lead to more reliable warning signals and thus more adequate corrective actions. Therefore, it would ensure more effective project control in general. This assertion should, of course, be validated by extensive empirical research.

Although the RCF technique in itself is fairly straightforward, it is relatively difficult to correctly implement in practice because of its strong dependence on the selected reference class. As this research has shown, a reference class of (highly) similar projects is needed to provide (highly) accurate forecasts. Such a collection of (highly) similar projects is not always readily available in practice. Even less often is the collection of adequate size; indeed, forecasting bias increases as the reference class gets smaller, which can undermine the performance and applicability of RCF. That is why it is of great importance to have available many (and correct) real-life project data. Organizations should make a point of collecting their projects' progress and performance data in a structured way, as described, for example, in Batselier and Vanhoucke (2015a) or at [www.or-as.be/research/database](http://www.or-as.be/research/database). This would not only boost the

practical applicability and utility of RCF, but also of many other project management techniques.

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## References

- Anbari, F. (2003). Earned value project management method and extensions. *Project Management Journal*, 34 (4), 12-23.
- Batselier, J., & Vanhoucke, M. (2015a). Construction and evaluation framework for a real-life project database. *International Journal of Project Management*, 33(3), 697-710.
- Batselier, J., & Vanhoucke, M. (2015b). Empirical evaluation of earned value management forecasting accuracy for time and cost. *Journal of Construction Engineering and Management*, 141(11), 05015010.
- Carbone, R., & Armstrong, J. (1982). Evaluation of extrapolative forecasting methods: Results of a survey of academicians and practitioners. *Journal of Forecasting*, 1(2), 215-217.
- Caron, F., Ruggeri, F., & Merli, A. (2013). A Bayesian approach to improve estimate at completion in earned value management. *Project Management Journal*, 44(1), 3-16.
- Colin, J., & Vanhoucke, M. (2016). Empirical perspective on activity durations for project management simulation studies. *Journal of Construction Engineering and Management*, 142(1), 04015047.
- Covach, J., Haydon, J., & Reither, R. (1981). *A study to determine indicators and methods to compute estimate at completion (EAC)*. Fairfax, VA: ManTech International Corporation.
- Fleming, Q., & Koppelman, J. (2010). *Earned value project management* (4th ed.). Newtown Square, PA: Project Management Institute.
- Flyvbjerg, B. (2006). From Nobel Prize to project management: Getting risks right. *Project Management Journal*, 37(3), 5-15.
- Flyvbjerg, B. (2007). Eliminating bias in early project development through reference class forecasting and good governance. In K. J. Sunnevåg (Ed.), *Decisions based on weak information: Approaches and challenges in the early phase of projects* (pp. 90-110). Trondheim, Norway: Concept Program, The Norwegian University of Science and Technology.
- Flyvbjerg, B., & Cowi. (2004). *Procedures for dealing with optimism bias in transport planning: Guidance document*. London, England: UK Department for Transport.
- Flyvbjerg, B., Holm, M., & Buhl, S. (2002). Underestimating costs in public works projects: Error or lie? *Journal of the American Planning Association*, 68(3), 279-295.
- Flyvbjerg, B., Holm, M., & Buhl, S. (2005). How (in)accurate are demand forecasts in public works projects? The case of transportation. *Journal of the American Planning Association*, 71(2), 131-146.
- Jacob, D., & Kane, M. (2004). Forecasting schedule completion using earned value metrics? Revisited. *The Measurable News* (Summer), 11-17.
- Kahneman, D. (1994). New challenges to the rationality assumption. *Journal of Institutional and Theoretical Economics*, 150(1), 18-36.
- Kahneman, D., & Tversky, A. (1979a). Intuitive prediction: Biases and corrective procedures. In S. Makridakis & S. Wheelwright (Eds.), *Studies in the management sciences: Forecasting* (p. 12). Amsterdam, Netherlands: North Holland.
- Kahneman, D., & Tversky, A. (1979b). Prospect theory: An analysis of decisions under risk. *Econometrica*, 47 (2), 313-327.

**Kim, B., & Reinschmidt, K. (2011).** Combination of project cost forecasts in earned value management. *Journal of Construction Engineering and Management*, 137(11), 958–966.

**Lipke, W. (2003).** Schedule is different. *The Measurable News* (Summer), 31–34.

**Lipke, W. (2009).** Project duration forecasting . . . A comparison of earned value management methods to earned schedule. *The Measurable News*, (2), 24–31.

**Lovall, D., & Kahneman, D. (2003, July).** Delusions of success: How optimism undermines executives' decisions. *Harvard Business Review*, 56–63.

**Project Management Institute. (PMI). (2008).** *A guide to the project management body of knowledge (PMBOK® guide) – Third Edition*. Newtown Square, PA: Author.

**Teicholz, P. (1993).** Forecasting final cost and budget of construction projects. *Journal of Computing in Civil Engineering*, 7(4), 511–529.

**Trietsch, D., Mazmanyan, L., Gevorgyan, L., & Baker, K. (2012).** Modeling activity times by the Parkinson distribution with a lognormal core: Theory and validation. *European Journal of Operational Research*, 216(2), 386–396.

**Vanhoucke, M. (2010).** *Measuring time-improving project performance using earned value management* (Vol. 136 of International Series in Operations Research and Management Science). New York, NY: Springer.

**Vanhoucke, M. (2014).** *Integrated project management and control: First comes the theory, then the practice* (Vol. Management for Professionals). New York, NY: Springer.

**Vanhoucke, M., & Vandevorde, S. (2007).** A simulation and evaluation of earned value metrics to forecast the project duration. *Journal of the Operational Research Society*, 58(10), 1361–1374.

**Wachs, M. (1989).** When planners lie with numbers. *Journal of the American Planning Association*, 55(4), 476–479.

**Wachs, M. (1990).** Ethics and advocacy in forecasting for public policy. *Business and Professional Ethics Journal*, 9(1–2), 141–157.

**Warburton, R. (2011).** A time-dependent earned value model for software projects. *International Journal of Project Management*, 29(8), 1082–1090.

**Willems, L., & Vanhoucke, M. (2015).** Classification of articles and journals on project control and earned value management. *International Journal of Project Management*, 33(7), 1610–1634.

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