CRITICAL ANALYSIS OF LINEAR AND NONLINEAR PROJECT DURATION FORECASTING METHODS

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CRITICAL ANALYSIS OF LINEAR AND NONLINEAR PROJECT DURATION FORECASTING METHODS

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ABSTRACT: The accurate estimation of the project duration at completion is still an open issue in project monitoring and control. Earned Value Management (EVM) and Earned Schedule (ES) methods provide alternative solutions, but rely on specific assumptions that may not be satisfied by all projects, thus compromising their reliability. This study provides a profile-based approach to compute the Duration Estimate at Completion (DEAC) that is general and applicable to all projects. First, two nonlinear profiles are introduced, and their DEAC formulae are derived. Then, the ES, the two profile-based, and the EVM forecasting methods are tested on a portfolio of 56 engineering projects by computing each method's DEAC at 5%-progress stage. The collected results are analyzed under both the portfolio and individual project levels. Findings show that the extra effort in using the profile-based methods is valuable in improving the DEAC forecasting performance for specific projects. The correlations between the four DEAC methods' accuracy, the project cumulative work profile, and the final schedule delay are analyzed further to investigate the drivers behind the four approaches' performance. The results confirm that one DEAC method should be prioritized over the others according to the project S-curve shape.

Keywords: project control, earned value management, duration forecasting, schedule delay

1 Introduction

Forecasting the Duration Estimate at Completion (DEAC) for an ongoing project is fundamental to controlling its schedule. As activities are completed, performance data accumulate, and the impact of changes and technical and financial issues is evaluated to make decisions and take appropriate actions. In this regard, the Earned Value Management (EVM) methodology (Fleming & Koppelman, 1997) and the Earned Schedule (ES) approach (Lipke, 2003) are widely used to quantify the schedule delay and compute the project DEAC.

Despite being proven accurate when tested on different case studies (Batselier & Vanhoucke, 2015b; Henderson, 2003; Henderson & Lipke, 2006; Vanhoucke & Vandevoorde, 2007), the two methodologies present major flaws. To begin with, both EVM and ES formulae for the DEAC assume the linearity of the project cost profiles (Warburton & Cioffi, 2016). As for EVM, the delay is expressed as cost units, and the schedule index always converges to one toward completion, compromising DEAC estimates. Although the ES approach fixes such issues, it still relies on the project planned and earned values to quantify the schedule delay. This is because it assumes the physical progress of works and the costs incurred to be linearly related. On this basis, the two methods may prove wrong in two specific situations: first, when the cost of activities is not related to their duration; second, if a large amount of costs is allocated within a limited time window, neither the EVM nor the ES methods would be able to capture the steep rise in the cost profile. Because of the reasons above, a cost-independent approach is needed to estimate the schedule delay and forecast the DEAC.

Barraza, Back, and Mata (2000) criticized the linear assumption upon which the EVM and ES formulae for the project DEAC are based. Several authors, such as Batselier and Vanhoucke (2015a); Cioffi (2005, 2006); Jacob and Kane (2004) and Khamooshi and Golafshani (2014), commented that S-curves, or by extension, any nonlinear profile, should instead be used. Motivated by these criticisms, Warburton and Cioffi (2016) defined a general theoretical foundation for calculating the duration estimate and showed how to generate a DEAC formula for any project cumulative work curve. However, they also reported some exceptions; not all nonlinear profiles resulted in the standard formula. Therefore, there is a need to identify one or more profiles that can fit the project data accurately enough and, at the same time, result in the standard formula, which equals satisfying the delay condition (see Section 3).

According to the shape of their cumulative work profile, projects can be grouped into four categories, as represented in Figure 1.

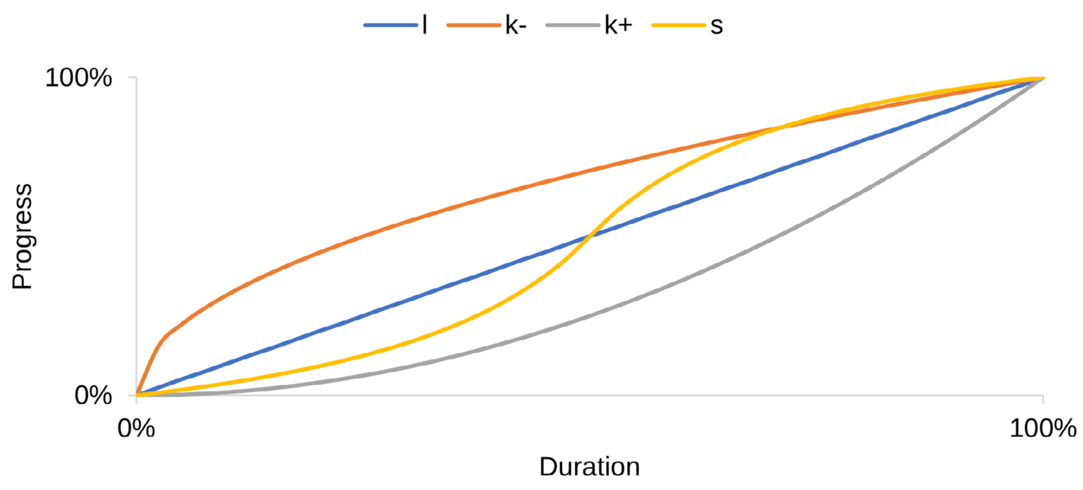

Figure 1: Four projects' cumulative work profiles

The S-shaped (*s*) profile arises when the project phases present a substantial difference in work rate. These types of projects typically undergo an initial slow growth, where the initial activities then seed a multitude of follow-up activities. As a result, there is a rapid rise, after which it reaches a peak -- the middle stage. In the late stage, the work rate declines, reaching zero at the project end. The exponential profile is a valuable add-on as it can represent two practical situations. In the first type of exponential ($0 < k < 1$, referenced as k^-), the highest work rate is reached right at the project start, and in the second case ($k > 1$, referenced as k^+), it occurs during the project last phase. The linear profile (*l*) represents a less common scenario in which the same amount of work is performed in each time interval, i.e., the work rate is constant over the whole project. For clarification, the terms *work*, *labor*, and *progress* will be used interchangeably in the following sections; the same applies to *profile* and *curve*.

The study introduces a profile-based method for quantifying the project delay and computing the DEAC. Two profiles are proposed, the Cioffi and a generic exponential one, and adjusted to fit the project S-curve characteristics. Then, both profile DEAC formulae are derived. The theoretical results are tested in practice by applying the ES, both profile-based and EVM methods, to a portfolio of engineering projects. The four DEAC estimates are compared at 5%-time intervals, resulting in a series of forecasts of the projects' final duration. Then, the linear and distance correlation analyses are performed to investigate the relationship between the methods' DEAC accuracy and the project work profiles. The combined analyses allow an understanding of when a particular DEAC method should be prioritized over the others.

The paper is structured as follows. In Section 2, a review of the relevant theoretical and practical literature is provided. Next, Section 3 describes the Cioffi and exponential profiles and the respective DEAC formula derivation. The algorithmic steps in the four duration estimation methods are provided in Section 4. We present the accuracy and timeliness results of the four methods for the 56 real-world projects in Section 5. While Section 6 provides helpful advice for project managers from results, Section 7 presents practical recommendations and conclusions.

2 Literature Review

In developing the EVM methodology, Fleming and Koppelman (1997) recognized that it is not possible to assess the project schedule performance by using costs as a proxy. To correct this deficiency, Lipke (2003) defined the ES approach and provided a novel DEAC formula, even though it relied on the assumption that the project work profiles are linear. Ward & Litchfield (1980) discussed this issue beforehand, stressing the need to recognize that project progress is continually subject to change, invalidating the linearity assumption. Chang (2001) also claimed an underlying problem in EVM and ES related to using short-term schedule performance indexes to forecast long-term completion. On this matter, Corovic (2007) tested the performance of EVM and ES schedule indicators, confirming that they lead to inaccurate predictions when applied to projects with nonlinear cumulative work profiles.

Several attempts were made to improve the performance of DEAC forecasts. The analytic review conducted by Chen and Zhang (2012) identified three branches of schedule control methods: ES-based (Lipke, 2003) methods, those extending the Planned Value Method (Anbari, 2003), and the ones that are based on the Earned Duration (ED) concept (Jacob & Kane, 2004). Concerning the last stream, Khamooshi and Golfashani (2014) refined the ED approach by removing the time dependency when forecasting project costs, relying on the properties of the network activities. Also, Vanhoucke and Andrade (2017) verified that the ED method is better for measuring the project progress over time. To further improve the reliability of the ED-based DEAC, Yousefi et al. (2019) proposed a two-step framework to develop a control chart of EDM indices that increases the chances of detecting schedule problems beforehand. A statistical project control system designed on Shewhart's and CUmulative SUM control charts was also proposed by Galante, La Fata, and Passannanti (2019) and validated in three case studies. Votto, Lee Ho, and Berssaneti (2021) further improved the control charts technique for project duration monitoring by providing a rationale for identifying the limit width based on repeated schedule simulations.

A subset of studies focused on identifying the drivers behind the DEAC forecasting performance. Elshaer (2013) investigated the effect of sensitivity to activity information on the forecasting accuracy of the ES method and concluded that the framework is subject to failures when parallel, non-critical activities generate incorrect warnings for the project manager. Vanhoucke (2012) confirmed that idea by showing that the network topology is a significant factor in variability. In this regard, both Galvez, Ordieres-Meré, and Capuz-Rizo (2015) and Galvez, Capuz-Rizo, and Ordieres (2017) determined that the duration, interrelationships, and level of parallelism of activities are the sources of inaccuracy in project duration estimates. Vanhoucke and de Koning (2016) proved on a sample of nine projects that the steeper a project S-curve, the later stability of the schedule performance index for reliable DEAC forecasts. On the other hand, Mamghaderi, Khamooshi, and Kwak (2021)'s findings showed that ED is superior to ES regardless of the project characteristics.

The performance of the above techniques for duration estimation has been tested through their application to different project datasets. Lipke et al. (2009) validated that the ES method worked well using statistical prediction and testing methods. Chen (2014) proposed a framework to improve the predictive power of the Planned Value-based forecasting technique by ~ 23.6%. Batselier and Vanhoucke (2015c) compared the accuracy and timeliness of the EVM, ES, and ED methods using the same dataset as used here. Borges Jr and Mário (2017) compared Carr (1993)'s Time Duration Method (TDM) to PVM, ES, and ED, while Ballesteros-Pérez et al. (2020) proposed a method to quantify the accuracy of duration forecasts. All the studies above concluded that all methods are good enough for practical work, but the accuracy of the ES method is slightly superior to the others.

Many regression attempts have been proposed, as straightforward and available algorithms generate reasonable accuracy. Chen (2014) developed a linear model that improved the Earned Value forecasting accuracy by an average of 13% when applied to 131 projects. Salari and Khamooshi (2016) proved the superiority of the ED method when used in conjunction with exponential smoothing techniques. The same technique was adopted by Martens and Vanhoucke (2020) but applied to EVM and ES, who also showed that it could improve the final duration forecasts. In a slightly different approach, Votto, Lee Ho, and Berssaneti (2020) used the ED concept as input to evaluate the duration performance indexes for project duration forecasting purposes. Using a construction project as a case study, both Pan et al. (2022) and Wu et al. (2022) tested the prediction capability of the multiple linear regression and artificial neural network models, respectively, with the former focusing on interpretability and the latter on prediction.

Several studies attempted sophisticated statistical analyses. Using a neural network nonlinear mapping technique, Chao and Chien (2009) evaluated the project S curve with just a few data points, and projected the project S curve for the future. De Marco, Briccarello, and Rafele (2009) found that a nonlinear time estimate better indicates the project's revised duration because the S-curve profile can overcome the EVM schedule performance index bias. Kim and Reinschmidt (2010) employed the Kalman Filter forecasting method (KFFM) to minimize the variance of future forecasts by combining the prior project duration estimate with a one-step-ahead prediction derived from a new observation. Narbaev and De Marco (2014) proposed an index-based formula based on the Gompertz S-profile and nonlinear regression analysis; the model was later validated by Narbaev and De Marco (2017); Warburton, De Marco, and Sciuto (2017) and Huynh et al. (2020). Galvez, Ordieres, and Capuz-Rizo (2017) adopted the Monte Carlo filtering method to identify and regionalize input variables impacting the project schedule performance.

Cheng, Chang, and Korir (2019) developed the neural network–long short-term memory (NN-LSTM) model to estimate the Schedule to Completion, mapping the long temporal dependency of the time-dependent variables, showing the superiority of the proposed model compared to the previous ones in the literature. Sackey, Lee, and Kim (2020) recently proposed a DEAC model which removed the use of cost as a proxy but still relied on linear regression analysis. Assaad, El-Adaway, and Abotaleb (2020) developed a holistic framework to evaluate project progress and predict the DEAC. By fitting predefined distributions to the actual data and calculating schedule overruns, the model exploited risk-related data to increase the accuracy of the duration forecasts. To overcome the main limitation of the EVM methodology, which assumes a linear relationship between the activities' cost and their physical progress, Ngo, Lucko, and Ballesteros-Pérez (2022) reformulated the EVM method through singularity functions. By enabling continuous monitoring of project schedule performance as activities are completed, DEAC estimates become more reliable.

In light of recent studies on the topic, this paper suggests an alternative approach to EVM and ES for computing schedule DEAC at the project level, whose accuracy scales with the goodness of fit of the chosen profile and the project cumulative work shape.

3 Theoretical Development

This section introduces the Cioffi and the generic exponential curves, describes their characteristics, and presents the derivation of the respective DEAC formulae.

The project metrics are expressed using the scientific notation proposed by Cioffi (2006) instead of the traditional EVM nomenclature: the planned and actual durations are denoted, respectively, as T_p and T_a; the budgeted cost at completion is indicated as B; the cumulative planned and earned values are referred to as $C_p(t)$ and $C_e(t)$.

By the EVM assumption, both the planned and earned work profiles must equal the project budgeted cost at completion at T_p and T_a, respectively, as per Equation 1.

$$B=C_p(T_p)=C_e(T_a) \qquad 1$$

Based on the ES concept, the schedule delay, $\delta(t)$, consists of the distance between the actual time, t, and the time, $T_e(t)$, the observed progress should have been achieved according to the baseline schedule, also called the earned duration. Therefore, the delay condition can be represented through the system of equations comprising Equation 2,

$$\delta(t)=t-T_e(t). \qquad 2$$

and Equation 3,

$$C_e(t)=C_p[t-\delta(t)]=C_p[T_e(t)]. \qquad 3$$

These connotations are general and apply to any work profile.

An example of the $T_e(t)$ evaluation, according to the ES theory, is provided in Figure 2, which also shows the substantial difference that may be present between the former and the EVM conception of delay, $SV(t)=C_e(t)-C_p(t)$.

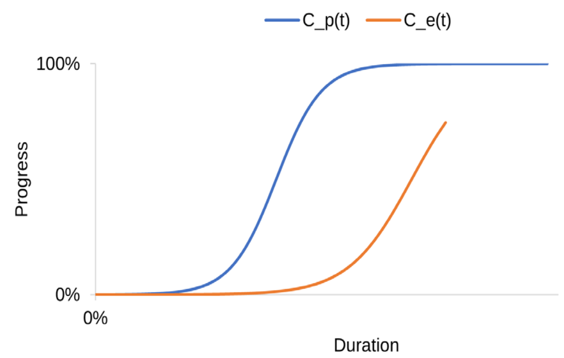

Figure 2: Definition of delay, $\delta(t)$, and earned duration, $T_e(t)$, for a sample project

3.1 Cioffi profile

Equation 4 illustrates the original Cioffi profile.

$$y=y_\infty \frac{1-\exp(-\alpha t)}{1+\gamma_p \exp(-\alpha t)} \qquad 4$$

The adjustments that follow are required for the Cioffi profile to fit a project S-curve characteristics: first, the upper horizontal asymptote, y_∞ should correspond to the project B; second, relating t to the time in which the labor rate profile is at its maximum, T', leads to $\gamma_p=\exp(\alpha T')$; for the same reason, it is convenient to change the constant, α, to $\alpha=\alpha T_p'$. The adjusted Cioffi labor profile, applied to the planned progress, is presented in Equation 5.

$$C_p^c(t)=B\frac{1-\exp[-\alpha(t/T'_p)]}{1+\exp[-\alpha(t/T'_p-1)]} \qquad 5$$

The expression for the earned labor profile, $C_p^c(t)$, has the same functional form, with the peak in the earned labor rate profile, T'_α replacing T'_p. Using the delay condition, Equations 2 and 3, gives Equation 6,

$$C_e^c(t)=C_p^c[t-\delta(t)]\Rightarrow B\frac{1-\exp[-\alpha(\frac{t}{T'_\alpha})]}{1+\exp[-\alpha(\frac{t}{T'_\alpha}-1)]}=B\frac{1-\exp[-\alpha(\frac{t-\delta(t)}{T'_p})]}{1+\exp[-\alpha(\frac{t-\delta(t)}{T'_p})]} \qquad 6$$

which is always satisfied whenever Equation 7 is valid:

$$\frac{t}{T'_a}=\frac{t-\delta(t)}{T'_p}\Rightarrow T'_a=\frac{tT'_p}{t-\delta(t)}=\frac{tT'_p}{T_e(t)} \qquad 7$$

The parameters T'_p and T'_α, representing the peak in the work rate profiles, are proportional to the end times; therefore, Equation 7 can be converted into the standard DEAC formula, Equation 8.

$$T_a(t)=\frac{tT_p}{T_e(t)} \qquad 8$$

3.2 Exponential profile

Since the Cioffi profile does not allow for work rate peaks in the project first or last stage, a second nonlinear profile is proposed based on the generic exponential formula provided in Equation 9.

$$C^x(t)=B\left(\frac{t}{T}\right)^k \qquad 9$$

In this case, the B parameter provides the y-value at T, which indicates the project planned duration (T_p) in the planned progress profile, as in Equation 10,

$$C_p^x(t)=B\left(\frac{t}{T_p}\right)^k, \qquad 10$$

and the actual duration (T_a) in the earned one, as per Equation 11.

$$C_e^x(t)=B\left(\frac{t}{T_a}\right)^k \qquad 11$$

Both Equations 10 and 11 respect the EVM assumption in that they both equal zero at the project start and B at the project end. Applying the delay condition (Equations 2 and 3) to Equations 10 and 11 leads to Equation 12,

$$C_e^x(t)=C_p^x[t-\delta(t)]\Rightarrow B\left(\frac{t}{T_a}\right)^k=B\left[\frac{t-\delta(t)}{T_p}\right]^k \qquad 12$$

which is true whenever the equality in Equation 13 subsists:

$$\frac{t}{T_a}=\frac{t-\delta(t)}{T_p}\Rightarrow T_a=\frac{tT_p}{t-\delta(t)}=\frac{tT_p}{T_e(t)}. \qquad 13$$

Since Equation 13 is identical to Equation 8, both the adjusted Cioffi and exponential profile fit the standard DEAC formula.

4 Research Methodology

4.1 DEAC Estimation Methods

The four methods of estimating the DEAC to be analyzed are the ES (ES), Cioffi (c), exponential (x), and SPI (SPI) methods, to which we will refer as the m methods.

The method is based on the evaluation of the earned duration (or simply, ES) as per Equation 14,

$$T_e^{ES}(t)=c(t)+\frac{C_e(t)-C_p(y)}{C_p(y+1)-C_p(y)} \qquad 14$$

where $c(t)$ is the number of time increments such that $C_e(t)\geq C_p(y)$ with $y\leq t$. Then, the DEAC is computed through Equation 8.

The c and x methods are based on the Cioffi and the exponential profile, respectively. First, the curve is fit to the project planned value data through the nonlinear regression analysis to determine the profile parameters: B, α, and T'_p for the Cioffi profile; the exponent k in the exponential profile. The earned duration at time is obtained through Equations 2 and 3, and then Equation 8 gives the profile-based DEAC.

The SPI method is based on the Practice Standard for EVM (PMI, 2005) relies on the Schedule Performance Index, which is the ratio between the project to-date earned and planned value, $SPI(t)=C_e(t)/C_p(t)$. The DEAC formula is obtained without evaluating the earned duration, as per Equation 15.

$$T_a^{SPI}(t)=\frac{T_p}{SPI(t)}=\frac{T_p}{C_e(t)/C_p(t)} \qquad 15$$

To test their performance, we analyzed a portfolio of $p = 56$ engineering projects available from Ghent University's OR&S Database (Batselier & Vanhoucke, 2015a; Vanhoucke, Coelho, & Batselier, 2016). No data cleaning was required. For each project, the following data were collected: budget at completion (B), planned duration (T_p), actual duration (T_a), and cumulative planned and earned data, $C_p(t_i)$ and $C_e(t_i)$. The m methods were applied to all p projects, computing the respective DEAC at 5%-progress intervals throughout the project, i.e., from 5% to 95%.

4.2 Calculation of the DEAC Errors

The methods' accuracy is compared based on the prediction absolute percentage error criterion, which is calculated for any p project at time t through Equation 16.

$$E^m(p,t)=\left|\frac{T_a^m(t)-T_a}{T_a}\right| \qquad 16$$

Equation 17 provides a project mean DEAC error across all 5%-progress time iterations.

$$\overline{E^m(p)}=\frac{1}{T}\sum_{t=1}^{T_a}E^m(p,t) \qquad 17$$

Instead, Equation 18 represents the project portfolio mean DEAC error at the specific 5%-progress time step.

$$\overline{E^m(t)}=\frac{1}{P}\sum_{p=1}^{P}E^m(p,t) \qquad 18$$

4.3 Calculation of the Deviations

We computed the mean absolute percentage difference between the forecasted and the observed earned values to analyze the accuracy of the different methods in predicting future progress. In the *ES* and *SPI* methods, the $C_e(t)$ points are obtained by dividing the time t in which the $C_p(t)$ points were expected to be reached by the schedule performance indicator, shifting the formers either to the right (delay) or to the left (advance). By the EVM and ES assumption, the work between consecutive points is performed linearly over time, which does not account for the real work profile shape. In the c and x methods instead, the earned profiles are obtained by using the same shape parameters (B and α for Cioffi, k for exponential), but replacing T_p' with $T_a'(t)$ (Cioffi) or T_p with $T_a^x(t)$ (exponential).

For a given p project, the deviation at time t, calculated through the m method, is computed as per Equation 19.

$$D_e^m(p,t) = |C_e(p,t_i) - C_e^m(p,t)| \quad 19$$

For a given p project, at each time t, the mean of the forecasted deviations is obtained through Equation 20.

$$\overline{D_e^m(p)} = \frac{1}{T_a - t}\sum_{t}^{T_a}\overline{D_e^m(p,t)} \quad 20$$

Equation 20 provides the average of the mean future deviations, which further summarizes the m method performance in forecasting the earned value points for a given p project.

$$\overline{\overline{D_e^m(p)}} = \frac{1}{N}\sum_{n=1}^{N}\overline{D_e^m(p,t)} \quad 21$$

Instead, Equation 22 summarizes the m method performance on the portfolio level at the same t time.

$$\overline{\overline{D_e^m(t)}} = \frac{1}{P}\sum_{p=1}^{P}\overline{D_e^m(p,t)} \quad 22$$

5. Results

5.1 Portfolio Perspective

The performance of the m methods is first compared at the portfolio level. The DEAC accuracy results are shown in Figure 3.

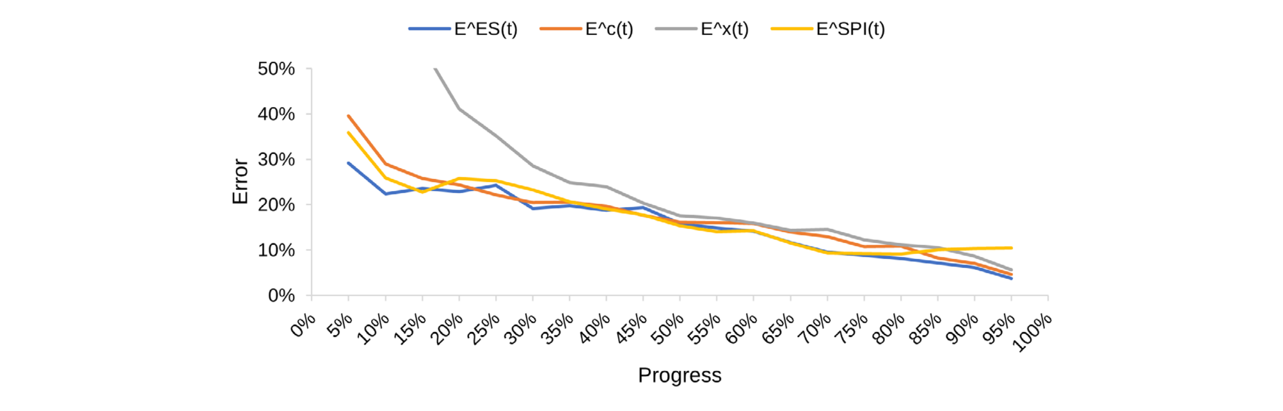

Figure 3: Projects portfolio average DEAC errors

$\overline{E^{ES}(t)}$, $\overline{E^c(t)}$, $\overline{E^x(t)}$, and $\overline{E^{SPI}(t)}$ indicate the portfolio mean m-methods DEAC errors, calculated at the different 5%-time intervals through Equation 17. The four performances are similar, as they all improve along with the project progress. The only exception is the exponential profile-based DEAC, which struggles in the early stages. The average deviations between the earned data points and the forecast values are shown in Figure 4.

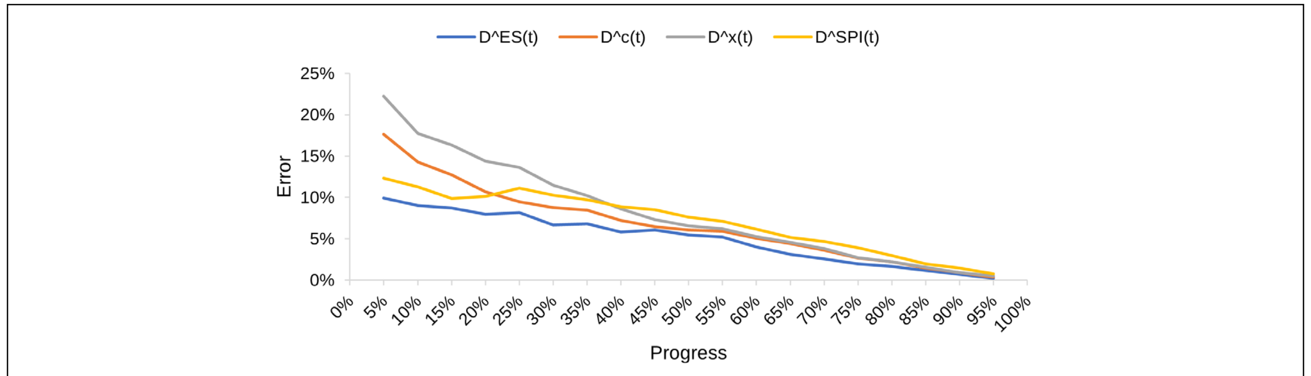

Figure 4: Projects portfolio average earned data deviations

$\overline{\overline{D_e^{ES}(t)}}$, $\overline{\overline{D_e^c(t)}}$, $\overline{\overline{D_e^x(t)}}$, and $\overline{\overline{D_e^{SPI}(t)}}$ correspond to the four methods' portfolio average deviations computed through Equation 21. The results show that the deviations follow the same behavior as the DEAC errors, with the accuracy improving as progress accumulates. In particular, the deviations are more significant early on because of the uncertainties in the earned value data.

5.2 Project Perspective

We now analyze the correlation between the variables at the project level, which allows to identify the drivers behind the four methods' performance. The individual project results are summarized in Table 1.

Table 1. Projects results

p	$\overline{E^{ES}}$	$\overline{E^c}$	$\overline{E^x}$	$\overline{E^{SPI}}$	$\overline{\overline{D_e^{ES}}}$	$\overline{\overline{D_E^c}}$	$\overline{\overline{D_e^x}}$	$\overline{\overline{D_e^{SPI}}}$	R_i^2	R_k^2-	R_k^2+	R_s^2	$\delta_{\%}(Ta)$
1	.13	.14	.22	.14	.08	.08	.09	.08	.88	.88	.93	.96	.11
2	.09	.21	.21	.08	.04	.11	.11	.05	.95	.98	.95	.98	.05
3	.22	.22	.23	.31	.09	.07	.08	.10	.97	.97	.98	.98	.00
4	.05	.05	.06	.36	.07	.05	.08	.50	.36	.36	.97	.98	.15
5	.13	.23	.20	.13	.05	.10	.08	.06	.89	.97	.89	.97	.12
6	.05	.15	.17	.14	.03	.09	.09	.05	.93	.94	.93	.93	.41
7	.02	.04	.04	.03	.01	.04	.04	.02	.93	.93	.98	.98	.00
8	.42	.19	.94	.30	.07	.04	.12	.06	.49	.96	.49	.92	.00
9	.09	.10	.12	.11	.04	.04	.06	.04	.96	.96	.97	1.00	.00
10	.36	.25	.50	.15	.10	.08	.11	.06	.65	.99	.65	.93	.57
11	.37	.24	.49	.21	.07	.06	.09	.06	.80	.97	.80	.96	.18
12	.04	.10	.14	.05	.03	.06	.08	.03	.95	.95	.96	.99	.00
13	.46	.18	.40	.25	.09	.07	.05	.04	.74	.97	.74	.90	.10
14	.20	.21	.28	.21	.05	.07	.06	.05	.89	.90	.89	.96	.33
15	.20	.22	.22	.21	.04	.08	.07	.05	.96	.96	.97	.98	.25
16	.39	.36	.33	.19	.06	.09	.08	.05	.64	.95	.64	.97	.00
17	.11	.15	.16	.13	.05	.08	.09	.07	.86	.86	.97	.97	.00
18	.08	.16	.25	.18	.03	.06	.10	.07	.90	.91	.90	.98	.00
19	.13	.21	.26	.14	.06	.10	.11	.06	.89	.97	.89	.96	.25
20	.19	.18	.34	.22	.05	.05	.08	.06	.93	.95	.93	1.00	.08
21	.19	.23	.27	.20	.07	.09	.11	.08	.98	.99	.98	.99	.50
22	.10	.08	.14	.15	.04	.05	.06	.06	.98	.98	.98	.99	.18
23	.08	.16	.26	.12	.04	.06	.08	.06	.90	.97	.90	.98	.12
24	.03	.12	.26	.16	.02	.06	.09	.07	.96	.96	.96	.98	.17
25	.05	.05	.11	.06	.02	.03	.06	.05	.89	.89	.97	.99	.18
26	.20	.17	.29	.26	.05	.06	.09	.08	.96	.97	.96	.99	.50
27	.43	.45	.73	.52	.07	.10	.09	.11	.89	.94	.89	.99	.13
28	.09	.08	.12	.09	.04	.04	.06	.04	.98	.98	.98	.99	.00
29	.19	.29	.39	.14	.10	.12	.11	.10	.89	.95	.89	.99	.14
30	.08	.09	.47	.09	.03	.03	.11	.03	.82	.96	.82	1.00	.11
31	.11	.12	.18	.11	.06	.07	.06	.07	.95	.95	.95	1.00	.13
32	.05	.06	.44	.05	.02	.03	.10	.02	.70	.94	.70	.99	.00
33	.10	.14	.13	.34	.07	.10	.09	.13	.83	.83	.96	.97	.50
34	.20	.19	.31	.32	.03	.03	.10	.10	.92	.92	.92	1.00	.00
35	.00	.08	.12	.00	.00	.05	.06	.00	.97	.97	.97	.99	.00
36	.18	.15	.18	.15	.04	.07	.06	.04	.95	.98	.95	.97	.00
37	.19	.23	.17	.33	.10	.12	.11	.20	.93	.93	.97	.99	.31
38	.18	.21	.21	.45	.04	.07	.07	.08	.08	.08	.96	.96	.00
39	.02	.05	.07	.08	.01	.04	.06	.07	.87	.87	.98	1.00	.08
40	.08	.15	.17	.13	.05	.08	.08	.07	.97	.97	.97	.99	.17
41	.09	.23	.22	.07	.04	.11	.10	.04	.91	.94	.91	.95	.08
42	.08	.12	.41	.07	.03	.04	.07	.03	.58	.96	.58	.99	.10
43	.03	.15	.15	.02	.01	.06	.06	.02	.94	.95	.94	.96	.00
44	.01	.14	.07	.01	.01	.05	.03	.01	.78	1.00	.78	.98	.00
45	.57	.44	.77	.37	.14	.12	.15	.11	.86	.96	.86	.98	.08
46	.11	.07	.44	.17	.06	.04	.13	.08	.88	.92	.88	.99	.25
47	.41	.28	.72	.33	.09	.07	.11	.07	.76	.99	.76	.97	.00
48	.14	.12	.27	.14	.04	.02	.07	.05	.94	.98	.94	1.00	.00
49	.05	.36	.14	.05	.00	.07	.04	.00	.36	.94	.36	.90	.05
50	.10	.13	.13	.12	.03	.05	.04	.04	.97	.98	.97	.99	.25
51	.10	.30	.28	.04	.03	.14	.13	.03	.78	.86	.78	.80	.00
52	.12	.15	.12	.19	.13	.15	.13	.17	.75	.75	.98	.99	.29
53	.17	.14	.23	.13	.05	.06	.05	.05	.80	.95	.80	.92	.00
54	.08	.09	.17	.14	.03	.04	.10	.07	.87	.87	.96	.99	.10
55	.10	.11	.30	.10	.03	.04	.11	.06	.86	.88	.86	1.00	.25
56	.40	.39	.45	.50	.06	.06	.06	.09	.91	.92	.91	1.00	.50

The first column, p, refers to the project unique identifier. $\overline{E^{ES}}$, $\overline{E^c}$, $\overline{E^x}$, and $\overline{E^{SPI}}$ consist of the average DEAC errors for the ES, Cioffi, exponential, and SPI methods computed through Equation 16. $\overline{\overline{D^{ES}}}$, $\overline{\overline{D^c}}$, $\overline{\overline{D^x}}$, and $\overline{\overline{D^{SPI}}}$ indicate their average earned data deviations, given by Equation 20. R_l^2, $R_{k^+}^2$, $R_{k^-}^2$, and R_s^2 represent the coefficients of determination of the four project profiles and provide the goodness of fit to the planned value data for the linear (l), exponential (k^+), exponential (k^-) and S-shaped (s) profiles. The R^2 metric ranges from 0 (few earned data points close to the profile) to 1 (the profile passes close to all the earned data points). In the last column, $\delta_{\%}(T_a)$, indicates the project final percentage delay, as per Equation 23.

The statistics shown in Table 2 provide a helpful summary of Table 1 results.

$$\delta_{\%}(T_a) = \frac{T_a - T_p}{T_p} \quad 23$$

Table 2. Projects results summary statistics

Code	Variable	M	SD	max	min
1	$\overline{E^{ES}}$	.157	.132	.569	.002
2	$\overline{E^c}$	.177	.096	.450	.039
3	$\overline{E^x}$	.276	.186	.940	.041
4	$\overline{E^{SPI}}$	.174	.121	.524	.004
5	$\overline{\overline{D_e^{ES}}}$	.050	.030	.139	.001
6	$\overline{\overline{D_E^c}}$	.068	.029	.146	.023
7	$\overline{\overline{D_e^x}}$	.082	.026	.152	.028
8	$\overline{\overline{D_e^{SPI}}}$	.070	.069	.505	.001

Columns M and SD indicate the variables' mean and standard deviations, while max and min refer to their maximum and minimum values. The table confirms, with more precision, the same deductions of Figure 3: the four methods' overall performance, in terms of DEAC error, is similar; the only exception being the exponential profile (M_3=.276, SD_3=.186). All other means and standard deviations have roughly the same size, indicating that the methods are equivalent over the entire portfolio. However, the individual DEACs may differ substantially between one project and another. Among the four, the c method is the one that presents the least variability: max_2=.450; it also has the minimum of the four methods' maximum errors and the min_2=.039 is second only to the exponential.

The two profile-based methods can lead to the most consistent forecasts under the DEAC error and future deviation perspectives when applied to specific projects. Therefore, if a project is schedule-dominated, investing additional effort in the nonlinear regression analysis, and employing the more accurate profile-based method may prove worthwhile.

5.3 Correlation Analyses

The results in Table 2 vary substantially from project to project, as differences in the procedures can lead to entirely different predictions; therefore, a more detailed analysis is required. For this purpose, we analyzed the relationships between the DEAC errors, earned profile deviations, the goodness of fit of the project data to the four typical S-curve profiles, and the final project delay percentage. To do so, we evaluated their Pearson correlation (Acton, 1959) and distance correlation (Székely, Rizzo, & Bakirov, 2007) coefficients. The formers provide the strength and direction of the (eventual) linear relationship between variables; the latter, instead, can capture both the linear and nonlinear association between two variables but does not provide its direction. For representation purposes, we omitted from the matrices all coefficients and relative -values referring to the pairs of variables whose relationships are not within the scope of this analysis.

The Pearson correlation matrix is reported in Table 3. The $\rho_{X,Y}$ coefficient ranges from -1 (exact negative linear correlation) to 1 (exact positive linear correlation), where 0 indicates no linear correlation. To each $\rho_{X,Y}$ coefficient corresponds a p value, which indicates the probability of rejecting the null hypothesis that the $\rho_{X,Y}$ coefficient is null.

Table 3. Pearson correlation matrix

Code	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	$\overline{E^{ES}}$	1												
2	$\overline{E^{c}}$		1											
3	$\overline{E^{x}}$			1										
4	$\overline{E^{SPI}}$				1									
5	$\overline{\overline{D_e^{ES}}}$	.69**				1								
6	$\overline{\overline{D_E^{c}}}$		.59**				1							
7	$\overline{\overline{D_e^{x}}}$			.52**				1						
8	$\overline{\overline{D_e^{SPI}}}$				.52**				1					
9	R_l^2	-.15	-.14	-.19	-.26*	-.05	.06	.01	-.28*	1				
10	R_k^2+	-.32**	-.35**	-.51**	.07	.01	.03	-.07	.25*		1			
11	R_k^2-	.11	.10	.19	-.38**	-.05	.03	.03	-.54**			1		
12	R_s^2	-.04	-.21	.02	.05	.00	-.37*	-.06	.09				1	
13	$\delta_{\%}(T_a)$	.14	.14	.02	.28**									1

*$p \leq .10$, **$p \leq .05$

The distance correlation matrix is shown in Table 4. The $dCor_{X,Y}$ coefficient ranges from 0 (X and Y are independent) to 1 (dimensions of the linear sub-spaces delimited by the X and Y are almost the same). The reason why we implement the distance correlation analysis is twofold: first, $dCor_{X,Y}$ may confirm or disprove the considerations made for $\rho_{X,Y}$ second, whenever $\rho_{X,Y}$=0 it is possible that $dCor_{X,Y} \neq 0$, as the two variables may be related but not in a linear way.

Table 4. Distance correlation matrix

Code	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	$\overline{E^{ES}}$	1												
2	$\overline{E^{c}}$		1											
3	$\overline{E^{x}}$			1										
4	$\overline{E^{SPI}}$				1									
5	$\overline{\overline{D_e^{ES}}}$	.69**				1								
6	$\overline{\overline{D_E^{c}}}$		.65**				1							
7	$\overline{\overline{D_e^{x}}}$			.48**				1						
8	$\overline{\overline{D_e^{SPI}}}$				.67**				1					
9	R_l^2	.31*	.25	.37**	.28	.24	.19	.25	.34*	1				
10	R_k^2+	.44**	.39**	.61**	.16	.22	.16	.28	.34*		1			
11	R_k^2-	.21	.21	.26	.38**	.18	.22	.19	.56**			1		
12	R_s^2	.20	.35**	.21	.20	.25	.42*	.24	.26				1	
13	$\delta_{\%}(T_a)$	.22	.21	.18	.33**									1

*$p \leq .10$, **$p \leq .05$

Both analyses confirm the interesting result that the DEAC accuracy ($\overline{E^m}$) is correlated with the earned profile deviation ($\overline{\overline{C_e^m}}$): the better the fit, the more precise the quantification of delay, hence, the more accurate the forecast of the revised duration. Both analyses also show the ES DEAC error to be significantly related to the goodness of fit to the k^+ profile, where $\rho_{10,1}$=-.32 indicates an inverse relationship and $dCor_{10,1}$=.44 further confirms it. The distance correlation coefficient proves a nonlinear association exists with the coefficient of determination of the linear profile ($dCor_{9,1}$=.31), which, according to the Pearson coefficient ($\rho_{9,1}$=-.15) is an inverse relationship.

Similarly to the ES method, the c DEAC error is also related to R_k^2+ ($\rho_{10,2}$=-.35, $dCor_{10,2}$=.39). Also, the Cioffi method is the only one that shows a significant relationship with the goodness of fit to the s profile, where $\rho_{12,2}$=-.21 indicates a negative relationship and $dCor_{12,2}$=.35 confirms the association. This is also supported by the significant relationship between R_s^2 and the Cioffi profile deviations, as $\rho_{12,6}$=-.37 and $dCor_{12,6}$=.42. These results show that the Cioffi method works well for both the cases above, and its flexibility allows the profile to assume either symmetric (s) or back-loaded (k^+) shape, which improves the DEAC accuracy at the portfolio level.

For the exponential method, the DEAC accuracy is related to the goodness of fit to the k^+ profile, with $\rho_{10,3}$=-.51 and $dCor_{10,3}$=.61. Despite the modest significance ($p_{9,3}$=15), it is also shown to be associated with the linear profile fit, as $\rho_{9,3}$=-.19 and $dCor_{10,3}$=.37. The same applies to the exponential k^- case, but in the opposite direction ($\rho_{11,3}$=.19) as the DEAC error E^x tends to increase.

The SPI method behavior is the one that differs the most from the others. First, the DEAC error is not related to the fit to the exponential k^+ profile ($p \leq .1$ in the Pearson and distance correlation cases). Second, the Pearson coefficient would imply an association between the DEAC error and the fit to the linear profile ($\rho_{9,4}$=-.26), but this is denied by the $dCor$ coefficient ($p \leq .1$). Third, it is the only method that shows a significant and inverse relationship with the exponential k^- case ($\rho_{11,4}$=-.38, $dCor_{11,4}$=.38), further confirmed by the correlation between R_k^2- and the earned deviations ($\rho_{12,8}$=-.54, $dCor_{12,8}$=.56). Also, it represents the only DEAC forecasting method that is statistically related to the project final delay ($\rho_{12,8}$=.28, $dCor_{13,4}$=.33).

6. Discussions

The main theoretical and practical contributions of this study are summarized as follows. Figure 3 shows that the standard formula for DEAC forecasting, Equation 8, is accurate and timely. It provides a DEAC accuracy of around 20% when 20% through the project. Therefore, a project manager can confidently start with this DEAC method. If the project has significant schedule constraints, such as penalty clauses or fixed operational dates, additional effort in the DEAC accuracy may be justified.

All methods generate an accurate DEAC for linearly planned projects. This is not a surprise, as the EVM and ES methodologies are explicitly based on the linearity assumption. In addition, the parameters of the Cioffi and exponential profiles can be adapted to the linear case. However, the two profile-based methods are more accurate and timelier when the planned profile is S-shaped, either slightly back-loaded or front-loaded, reducing future earned data deviations. Therefore, when schedule accuracy is at a premium, the additional effort required by these methods may be justified. All methods, but the , are viable options for the rising exponential profile.

This study confirms the following aspects considering the current literature. First, the performance of the EVM and ES methods, despite being proven acceptable in most cases, is still subject to the limitations rooted in their delay and revised project duration formulae. Second, adopting a nonlinear profile-based method that complies with the delay condition provides accurate DEAC forecasts and does not depend on any further assumption that may compromise its reliability. To this end, the nonlinear regression analysis, required by the curve fitting process, is confirmed to be a valuable tool in improving the more realistic, continuous description of the project work profile over time, leading to a better quantification of the project delay. Moreover, the whole study confirms the need for analyzing the network of activities and the variables related to it in deciding which DEAC forecasting method to adopt.

The research also suggests several practical limitations the project manager should be aware of. If the observed earned profile shape differs significantly from the planned shape, duration estimates will be inaccurate. This condition is built into EVM and is necessary for using the standard duration formula. It also means that, in the Cioffi case, the actual value of α must be used for the planned and earned profiles; otherwise, the analysis leading to Equation 11 fails; the same applies to the exponential case, referring to the k parameter. If the planned and earned profile shapes differ, the project manager should find a new, more appropriate formula that matches both planned and emerging earned data. If so, the standard duration formula will apply, and the DEAC accuracy will increase.

7. Conclusions

Research on forecasting project revised durations has mostly focused on developing a sophisticated model based on additional control metrics or simulating the project network schedule. While the extra effort involved may improve the forecasting performance, the leading cause of incorrect estimations is not addressed, which is how to quantify the current schedule delay at the project level, as activity-by-activity analyses are often impossible due to the absence or unreliability of granular data. Also, different DEAC forecasting methods can lead to entirely different predictions, which primarily depend on the geometrical properties of the ES, profile-based, and EVM methods used to calculate the project delay. To answer such a question, we first developed an alternative approach to DEAC calculation: the principles are based on the ES theory, but the actual shape of the profile is considered instead of the standard linear interpolation between successive data points. We introduced two nonlinear profiles, the Cioffi and the exponential, the former to model precisely for S-shaped projects and the latter to model front and back-loaded labor profiles. Both profiles are expressed in dimensionless time units, which is a slight change of notation and does not affect previous analyses nor its effectiveness in practical situations.

After proving that the DEAC formula of ES also works with nonlinear profiles, we compared the accuracy of the ES, c, x, and SPI methods in forecasting the revised duration of the project for a portfolio of real construction projects. The results show that the four methods perform similarly, especially during project development's mid to late stages. To identify the drivers behind each method's accuracy, we analyzed the results at the project level. We verified whether the shape assumed by the cumulative progress curve would impact the method's performance. We identified four typical profiles, namely linear, rising exponential, asymptotic exponential, and S-shaped, and computed the respective criterion per each project. Then, we calculated the DEAC errors and earned data deviations, which we provided as input to the Pearson linear and distance correlation analyses. The results show that it is possible to determine which method is advised to be used both before and during the execution of a project based on its planned profile shape and observed earned data deviations.

There are several exciting avenues for potential future research. First of all, one could use the physical advancement of work curves to quantify the delay, rather than using activities cost (EVM, ES) or duration (ED). Furthermore, it would be desirable to explore the impact of systematic and random deviations on the duration estimate. This is because it would be necessary to select complex profiles that almost perfectly fit the data. Also, since adopting the Cioffi or exponential profile already provides accurate and timely forecasts and is built on top of the project cumulative and rate profiles, the quantified delay can be provided as input to machine learning models or deep learning architectures to further enhance their prediction capability by recognizing different associative patterns between the control variables.

Notation

- B: budget at completion.
- C_e: earned work profile.
- C_p: planned work profile.
- D_e: absolute deviation between observed and forecast earned work profile.
- E: DEAC absolute percentage error.
- k: exponential profile parameter.
- R^2: coefficient of determination.
- T_p: planned duration.
- T_a: actual duration.
- $T_a(t)$: standard DEAC formula (at time).
- T'_a: time that corresponds to earned work rate profile maximum peak.
- T'_p: time that corresponds to planned work rate profile maximum peak.
- $T_e(t)$: earned duration (at time).
- t: time.
- a: Cioffi profile shape parameter.
- $\delta(t)$: delay (at time).

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