Project Duration Forecasting Using Earned Duration Management with Exponential Smoothing Techniques

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Abstract: For decades the project management community has been using forecasting models based on the schedule performance index (SPI) and recently SPI(t), duration based schedule performance index, to predict the duration and completion of an in-progress project. In this paper, the authors have used and recommend the earned duration index (EDI), developed as part of earned duration management (EDM) in conjunction with the well-established exponential smoothing forecasting technique to predict the completion of a project. The study compares several models and provides a comparative analysis of performance of these models using variety of projects at multiple stages of completion. The research findings suggest that using EDI of earned duration management is a preferred option compared to SPI(t). In addition, when EDI is used together with exponential smoothing techniques, the results become even better. **DOI: 10.1061/(ASCE)ME.1943-5479.0000475.**

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Introduction

Forecasting is an essential aspect of decision making within the normally uncertain project environment. A need for forecasting arises simply because there is uncertainty about the future and some aspects of the future cannot be controlled (Armstrong 2002). Forecasting in project management might well be a self-defeating prophecy, but at the same time, that may be good for organizations. Usually, large deviations attract management's attention and result in control actions whereas small deviations are rather left alone. Earned value management (EVM) and similar techniques help managers to focus on projects or work packages that need the most attention, by measuring and highlighting possible future deviations. Forecasting using these techniques provides a reasonable and uniform approach for project tracking and control (Anbari 2003).

To predict the estimated duration at completion [EAC(t)] and the cost estimate at completion (EAC) of a project, several models or equations have been suggested using earned value (EV), earned schedule (ES), and earned duration (ED) data (Anbari 2003; Lipke et al. 2009; Khamooshi and Golafshani 2014). However, a debate continues over the introduction of the most rigorous and reliable method for project-duration and cost forecasting that is applicable at different stages of project completion. Many simple forecasting models (e.g., moving average and exponential smoothing), and or more-advanced and more-complex methods (such as fuzzy time series) could be reasonably used to predict performance indexes for the next periods of a project.

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Project performance indexes like schedule performance index (SPI) and cost performance index (CPI) normally are not constant. The project manager may face a low performance at the beginning of project or things may go wrong or vice versa. Thus, performance of the project in the next reporting period(s) is not necessarily constant and similar to the past, but rather it is flexible, dynamic, and responsive to the past performance (Khamooshi and Golafshani 2014). Moreover, it is possible that current project performance can be ameliorated in the future due to various causes such as productivity improvements, learning, and risk-reduction strategies. For this reason, exponential smoothing often performs better out-of-sample than might otherwise be expected because it is used when the trend as well as the mean is varying slowly over time (Holt 2004).

Taking into account these considerations, in this article, for the first time, the earned duration performance measures in conjunction with exponential smoothing are used to predict the project duration. The principal objective of this study is to combine exponential smoothing method with earned duration management (EDM) as a new model to predict project duration and compare the results obtained versus earned schedule (ES), which according to previous studies (Vandevoorde and Vanhoucke 2006; Lipke et al. 2009) yields more-reliable forecasts than EVM-based techniques. Furthermore, the accuracy of these three methods, EDM, ES, and EDM combined with exponential smoothing is examined in multiple project completion stages (cases/scenarios), using real-life projects data.

To this end, the article is organized as follows. After the introduction, an overview of forecasting equations and models used in EVM, ES, and EDM techniques is presented. The previous related works and literature are reviewed next and the following section explains the research methodology in which the new forecasting approach and case studies used in this work are introduced. In the next section, the results of applying the model to 19 case study projects is presented and discussed. Finally the conclusions are drawn and presented.

Overview of Techniques

The earned value management (EVM) technique has been widely used to monitor and control the performance of a project up to a reporting date and forecasting the project's final duration. EVM was originally developed for cost management. However, recent research trends show an increase of interest in using performance indicators for monitoring project schedule performance as well. Furthermore, using this technique, real data generated during project execution period are used to predict trends for future project performance and forecasting total project duration. A detailed description and depiction of EVM concepts can be found in McConell (1985), Anbari (2003), Fleming and Koppelman (2010), and PMI (2013).

The earned schedule (ES) technique was introduced by Lipke (2003), as an extension to EVM, to ameliorate EVM's accuracy in connection with schedule performance measurement and project duration forecasting.

The earned duration management (EDM) technique, then, was developed by Khamooshi and Golafshani (2014) to overcome some of the issues associated with the use of the aforementioned methods for schedule performance measurement.

In this section, three of the previously mentioned methods are briefly explained, focusing on project duration forecasting.

EVM Forecasting Technique

The essence of EVM could be depicted using graphs. The primary curves on the EVM diagram (Fig. 1) include planned value (PV), actual cost (AC), and EV. The PV curve represents the budgeted cost of planned work. The initially submitted and accepted contractor bid contains the PV information. Meanwhile, the AC curve represents the total actual cost incurred, and the EV curve represents the actual payments received for completed work as per planned values. The EV could be used to indicate how efficiently the project team utilizes the project resources. One of the simplest techniques for measuring the EV is the percent complete (PC) technique: EV $=$ PV $\times$ PC. The AC and EV curves are developed dynamically during a project's execution phase.

In the EV analysis, cost-related information is used to measure project cost and schedule performance. EV analysis uses the following parameters to evaluate project performance and forecast final cost and duration:

- CV = cost variance (CV $=$ EV $-$ AC);
- SV = schedule variance (SV $=$ EV $-$ PV);
- CPI = cost performance index (CPI $=$ EV$/$AC);
- SPI = schedule performance index (SPI $=$ EV$/$PV);
- EAC = estimated cost at completion (EAC $=$ BAC$/$CPI); and
- EAC(t) = where BAC is budget at completion, estimated duration at completion (SAC/SPI).

There are several formulas available to calculate duration estimate at completion, EAC(t). A common formula, which assumes that the future trend of the project performance remains intact, divides the schedule at completion (SAC) [or baseline planned duration (BPD)] by the schedule performance index (SPI). In other words, this formula assumes that duration of remaining work would follow the current SPI trend. There are some other formulas which can be used to derive the EAC(t) based on the EV data (for instance, see Anbari 2003; Vandevoorde and Vanhoucke 2006; PMI 2013).

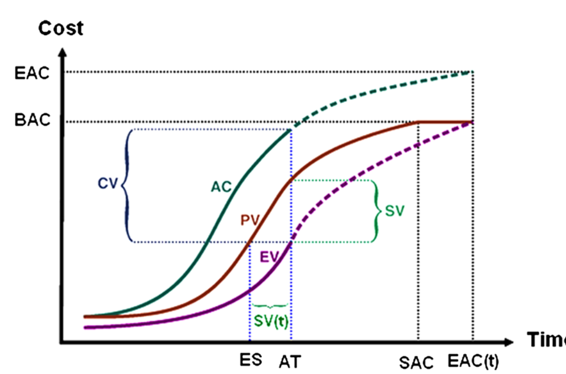


Fig. 1. Graphical representation of EVM and ES quantities

ES Forecasting Technique

SPI and SV are no longer applied as they are both broadly recognized for failing to present status of the project when it continues execution past the planned end-date. For late projects, SPI and SV converge and conclude at the values of 1.00 and 0.00, respectively.

To overcome this limitation, Lipke (2003) and Lipke et al. (2009) proposed use of the concept of earned schedule (ES). ES is the duration or date corresponding to the current earned value on the planned value curve. To compute ES (Fig. 1) at time now (AT), first, the earned value is calculated. This value is then used on the PV curve (cost baseline) to compute the date when EV equals PV. With ES determined, better indicators can be formed by comparing where the project is (duration earned) in contrast with the time actually passed. Actual time (AT) is the duration at which the EV accrued is recorded. The time-based indicators are readily formulated from the two measures, ES and AT:

- SV(t) = schedule variance (time) [SV(t) = ES-AT];
- SPI(t) = schedule performance index (time) [SPI$(t) =$ ES$/$AT]; and
- EAC(t) = estimated duration at completion [SAC$/$SPI(t)].

As discussed previously, the final cost might be predicted from the formula EAC = BAC/CPI. In an analogous manner, final duration may be forecasted from EAC$(t) =$ SAC$/$SPI(t), where SAC is the schedule at completion (planned duration) for the project and EAC(t) is the estimated duration at completion (Lipke et al. 2009).

EDM Forecasting Technique

While it is generally agreed that the ES method and consequently its schedule performance index, SPI(t) offer improvements over EVM and SPI, Khamooshi and Golafshani (2014) argue that the ES technique has some conceptual shortcomings and still there are some issues associated with the use of this method for project schedule/duration performance analysis. Similar to traditional SPI, SPI(t) still uses monetary terms of earned value (EV) and planned value (PV) to measure schedule performance. With regard to *Schedule is different*, where the concept of ES was introduced (Lipke 2003), EV could not necessarily be an accurate measure of schedule/duration performance. More precisely, it is considered the best measure of value earned monetarily. Using the same EV, the earned schedule method gets to the corresponding duration. Despite the fact that activity durations and cost items might be correlated, duration and cost profiles are not generally the same. Therefore, it is unjustifiable to say that performance indicators that use cost profile are accurate measures for schedule performance. In other words, similar to EVM's cost-based indicators, ES is not inherently adequate to handle duration performance measurement and consequently project duration forecasting (Khamooshi and Golafshani 2014).

Concerning this preceding argument against ES, the greater the disparity between duration and cost profiles, the more deficient the schedule performance measures/forecasts. In such cases, SPI and SPI(t) will both show inaccurate results, and at times, SPI(t) could even perform worse than SPI. As a confirmation of this, Lipke et al. (2009) indicated that, although SPI(t) generally performs better, SPI generates reasonably better predictions for large projects (like those of the U.S. Department of Defense projects in which the duration of the project is long and the volume of data used in the forecasting process is large).

Based on the preceding argument, Khamooshi and Golafshani (2014) introduced a new technique called earned duration management (EDM) to measure/forecast project duration by decoupling schedule and cost dimensions. Their approach, as a minimum, does not suffer the previously mentioned deficiency of EVM and ES. However, EDM's concept differs from earned duration (ED) analysis proposed by Jacob (2003, 2006). The earned duration method described by Jacob (2003, 2006) is the product of the actual duration (AD) and the schedule performance index (SPI), i.e., ED = AD × SPI. Therefore, the duration forecasting formula using Jacob's ED and SPI (as the performance factor) is

$$\mathrm{EAC}(t) = \mathrm{AD} + \frac{\mathrm{SAC} - \mathrm{ED}}{\mathrm{SPI}} = \frac{\mathrm{SAC}}{\mathrm{SPI}} \tag{1}$$

which again, suffers from the same problem as ES's shortcoming described earlier.

The total ED proposed in EDM is defined as

$$\mathrm{TED} = \sum_{i=1}^{n} (\mathrm{BPD}_i \times \mathrm{API}_i) \tag{2}$$

where BPD_i = baseline planned duration or the authorized duration assigned to the scheduled work to be accomplished for activity i. BPD_i = independent of the status date. Some may refer to it as the baseline duration for activity i. API_i is an activity progress index which, at any point in time, measures the progress of an activity. The schedule progress of an activity could be defined in two ways. In cases where the progress made on the activity has a linear relationship with time, one can assume percentage complete to be an accurate measure of progress. However, when this is not the case, physical progress could be used as a medium (e.g., labor hours, material quantities, lines of code, etc.) (PMI 2005). Irrespective of the method used, it is agreed that normally there could be challenges in measuring progress. For EDM purposes, one can use progress of an activity similar to EVM. However, an alternative method of calculating schedule progress based on duration is through estimating the remaining duration to complete activity i (i.e., estimated duration to complete for in-progress activity i, EDTC_i) by subject matter experts, then using the API_i equation:

$$\mathrm{API}_i = \frac{\mathrm{AD}_i}{\mathrm{AD}_i + \mathrm{EDTC}_i} \tag{3}$$

where AD_i = actual duration spending on activity i. This measure for EDM method is the duration counterpart or equivalent to AC of an activity in EVM.

Earned duration at time t (time now, data date), ED(t), is the date when the current total earned duration (TED) should have been achieved. To compute ED(t) at time now (AD or AT), first TED is calculated. Then, this value is used on representative S-curve of the cumulative planned duration of all scheduled activities (TPD) to compute the date when TED equals TPD (Fig. 2). TPD can be mathematically represented as follows:

$$\mathrm{TPD} = \sum_{i=1}^{n} \mathrm{PD}_i \tag{4}$$

where n = number of in-progress and completed activities up to that time; and TPD, for the project, at any particular point in time = sum of PD_i for all the planned activities at that time according to the baseline plan. For activities crossing over the status date, only the duration of the activity to the left of the vertical status date line counts toward TPD. ED(t) can be mathematically described as

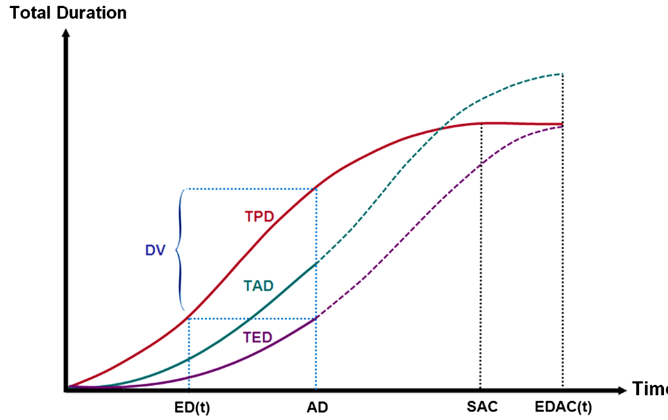


Fig. 2. Graphical representation of EDM quantities

$$\mathrm{ED}(t) = t + \frac{\mathrm{TED} - \mathrm{TPD}_t}{\mathrm{TPD}_{t+1(\text{calendar unit})} - \mathrm{TPD}_t} \times 1(\text{calendar unit}) \tag{5}$$

where ED(t) = earned duration at status date or actual duration (AD); TED = total earned duration at AD; TPD_t = total planned duration at time instant t, and the calendar unit = unit in which time instant t is measured. At the end of the project, ED(t) is the same as SAC (schedule at completion).

For EDM, a naïve forecasting equation can be formulated similar to the classical forecasting approaches used for EVM (assuming a constant performance for the remainder of the project equal to average performance of the past). In the EDM, the total duration variance (TDV) is defined and calculated as TDV = TED − TPD. Using the same parameters, a novel schedule performance indicator, called *earned duration index* (EDI) is defined as

$$\mathrm{EDI} = \frac{\mathrm{TED}}{\mathrm{TPD}} \tag{6}$$

At any reporting date, a project might have achieved more, less, or the same amount of work in comparison with the work planned to be achieved by that time. Thus, EDI can have values of greater than one, lower than one, or equal to one, respectively.

Accordingly, Khamooshi and Golafshani (2014) define estimated duration at completion (EDAC) for EDM method, as a counterpart of EAC(t) in the ES method. EDAC is calculated as

$$\mathrm{EDAC} = \mathrm{AD} + \frac{\mathrm{SAC} - \mathrm{ED}}{\mathrm{EDI}} = \frac{\mathrm{SAC}}{\mathrm{EDI}} \tag{7}$$

Review of the Literature

In recent years, many different methods have been proposed to monitor schedule performance and forecast final project duration. In this section, previous studies in the field of project duration forecasting and comparison between related techniques are reviewed.

Previous Research in EVM Duration Forecasting

To improve the capacity of EVM duration forecasting, several modified forecasting formulas have been suggested. Lipke (1999) proposed cost ratios and schedule ratios to manage the cost and schedule reserves in projects. Zwikael et al. (2000) evaluated five EVM forecasting methods using three performance measures:

mean square error, mean absolute deviation, and mean absolute percentage error. Looking at design operations, Chang (2001) defined cost/schedule performance indexes (C/SPIs) to measure project performance. Kim et al. (2003) studied the implementation of the EV in different types of organizations and projects. Lipke (2004) developed forecasting models using project cost and time performance probabilities. Jacob and Kane (2004) argued that the well-known performance measures of EVM are true indicators for project performance as long as they are used at the activity level, and not on the control account level or higher work breakdown structure (WBS) levels. Using a network-based simulation, Barraza et al. (2004) proposed a probabilistic model to forecast project duration and cost. They have simplified the correlation between past and future performance by adjusting the parameters of probability distributions of future activities with the performance indices of finished works (i.e., CPI in EVM model). However, no empirical or statistical evidence has been presented to support this study. Cioffi (2006) proposed a new notation for the EV analysis to make its mathematics more transparent and flexible.

A formal method was proposed by Warburton (2011) to include time dependence into EVM. The model requires three parameters: (1) reject rate of activities, (2) cost overrun parameter, and (3) time to repair the rejected activities, which map directly to the fundamental triple constraint of scope, cost, and schedule. Time dependent expressions for the PV, EV, and AC are derived along with the CPI and SPI. He claimed that the model accurately predicts the required revised labor profile and the new schedule. By linear modeling approach and data from 131 real projects, Chen (2014) modeled PV quantity and calculated the correlations between PV and EV as well as PV and AC, and claimed that this linear modeling approach considerably improved the forecasting accuracy of EVM metrics. Kim (2015b) developed a probabilistic CPI for earned value analysis of a real-world project and measured the uncertainty of its stability using a simulation technique.

Previous Research in ES Duration Forecasting

Relating to earned schedule forecasting method, Vandevoorde and Vanhoucke (2006) and Vanhoucke and Vandevoorde (2007) summarized some of the cost and schedule forecasting methods and studied their accuracy in real and simulated projects. They compared different EVM-based approaches with the ES method for the estimated duration at completion. The authors reported that the ES method is the best and most-reliable method to forecast project final duration. Lipke et al. (2009) validated the reliability of ES in forecasting the final duration using the statistical prediction and testing methods. In that work, they studied statistical confidence limits to improve estimated duration at completion. Vanhoucke (2010) introduced a dynamic corrective action decision-making model and measured the ability of four basic sensitivity metrics to dynamically improve the schedule performance during project execution, using a large number of simulation runs, which were performed on a large set of fictitious project networks generated under a controlled design. In Vanhoucke (2011), two alternate project tracking methods are presented to detect project problems and their efficiency on the quality of control actions to bring the project back on track is measured. Both a bottom-up and a top-down project tracking approach within a corrective action framework are used on a large and diverse set of fictitious projects that are subject to Monte-Carlo simulations to simulate fictitious project progress under uncertainty. The top-down tracking approach relies on state-of-the-art EVM performance metrics and the bottom-up tracking method makes use of the well-known schedule risk analysis.

Elshaer (2012) investigated the effect of sensitivity of activity information on the forecasting accuracy of the ES method. Additionally, he tested the claim that the SPI(t) index provided by ES is reliable at higher levels of WBS in normal conditions. In order to achieve this objective, activity-based sensitivity measures were used as weighing parameters of the activities to enhance the schedule performance by elimination or mitigation of the negative effects that wrong warning can have in noncritical activities. Running a simulation on a large set of benchmark projects showed that the forecasting accuracy of the ES model can be improved by use of sensitivity information. More recently, Colin and Vanhoucke (2015) using EVM/ES measures and tolerance limits, proposed a new project control approach to improve the discriminative power between progress reports. The tolerance limits were determined from subjective estimates for the project activity durations. This new statistical project control method gives project managers the ability to take corrective actions to return the system to its desired state (or predefined thresholds). Kim and Reinscmidt (2010) and Abdel Azeem et al. (2014) developed a probabilistic model based on the Kalman filter algorithm and earned schedule management to estimate project duration at completion, called the Kalman Filter Forecasting Model (KFFM). They claimed that the KFFM model, which is equipped with probabilistic prediction bounds of project duration at completion, can be employed in different project completion stages and can offer improved accuracy compared with EV and ES forecasting models. Moslemi Naeni et al. (2014) developed new fuzzy-based EVM and ES model with the advantage of developing and analyzing the earned value indexes and estimated duration and cost at completion under uncertainty. Colin and Vanhoucke (2015) integrated the EVM and ES methods with multiple control points inspired by critical chain/buffer management (CC/BM). They showed how the EVM/ES control approach is complementary with the concept of buffers and how they can improve the project control process when cleverly combined. These combined top-down approaches overcome some of the drawbacks of traditional EVM/ES mentioned in the literature.

Other Statistical Approaches

Some researchers have employed other forecasting techniques to provide final performance prediction. Lee (2005) introduced stochastic project scheduling simulation (SPSS) software developed to calculate the probability of project completion in a desired duration determined by the user. Lee and Arditi (2006) described a scheduling system (S3) based on stochastic simulation which integrates the deterministic critical path method (CPM), probabilistic PERT, and stochastic discrete event simulation (DES) approaches into a single system. This system is based upon an earlier version of the system called stochastic project scheduling simulation and applies all the capabilities of this system. Using Bayesian inference and the beta distribution, Kim and Reinschmidt (2009) introduced a new probabilistic forecasting method for schedule performance control of on-going projects that provides confidence bounds on predictions and determines the range of potential outcomes.

By use of statistical regression and sample tests, Abu Hammad et al. (2010) developed a probabilistic model to predict project cost and duration, and applied it to data from 113 public building projects. They reported that the forecasting accuracy of the model improved, reaching an error margin of $\pm 0.035\%$ of the actual cost and time. Narbaev and De Marco (2014) proposed a new forecasting methodology to calculate estimated duration and cost at completion concerning a modified index-based formula predicting expected duration and cost for the remaining work using nonlinear regression curve fitting and an earned schedule approach. The authors claimed that the proposed model is more accurate in different project completion stages (early, middle, and late) than those of traditional EVM index-based methods.

Kim (2014) calculated dynamic control thresholds (DCTs) by developing a quantitative method. The DCTs could be modified based upon the project time and cost performance. Gunduz et al. (2014) presented a fuzzy model in conjunction with the relative importance index (RII) to be used by contractors to calculate the probability of delay in construction projects. Mortaji et al. (2014) proposed an analytical model approach to project cost and duration prediction. Kim (2015a) presented a Bayesian project cost forecasting model that adaptively integrates preproject cost risk assessment and actual performance data into a range of possible project costs at a chosen confidence level.

Published literature shows that, to date, considerable effort has been put into the field of project duration forecasting. The review makes it evident that the earned schedule approach generally outperforms other EVM-based duration forecasting methods. However, the search continues over the introduction of a general method for project duration forecasting which is applicable in different stages of project completion. On the other hand, the accuracy of the EDM technique in predicting final duration (EDAC) has not been examined so far. Furthermore, there are several powerful and less-complex forecasting models that could be utilized in this regard, such as the exponential smoothing method. Therefore, in this research, EDM and ES are compared first, then exponential smoothing method is integrated with EDM, and the results are examined and compared with other existing approaches for accuracy and reliability.

Formulation and Development of the Model

This section explains the formulation of the approach used to conduct this research. To begin with, a brief introduction to exponential smoothing method is presented. Then, forecasting formulae and equations used to integrate exponential smoothing method and ES/EDM techniques are described. Lastly, the comparative analysis method is briefly explained.

Exponential Smoothing

In business, exponential smoothing models are fully automatic forecasting methods that have become very popular because of their relative simplicity and good overall performance as well as taking into account trends, seasonality, and other features of the data without need for human intervention (Hyndman et al. 2002).

In general, exponential smoothing is a weighted average of past values from an observed process that places more weight on recent observations than on earlier ones. The weights for observations decrease exponentially as one moves further into the past. As a result, the older data have less influence on these projections. The rate at which the weights of older observations decrease is determined by the smoothing constant selected. A number of generalizations have found numerous industrial applications for exponential smoothing (Maia and de Carvalho 2011; Gardner 2006). In this paper, both simple (single) and linear (double) exponential smoothing models used are explained next.

Simple (Single) Exponential Smoothing

Simple exponential smoothing (SES) is used when the historical data basically have a stable pattern (mostly horizontal). According to the SES, predicted value at the next period (F_{t+1}) is calculated as follows:

$$F_{t+1} = \alpha x_t + \alpha(1-\alpha)x_{t-1} + \alpha(1-\alpha)^2 x_{t-2} + \cdots \tag{8}$$

where x_t and F_t = real and predicted values, respectively, at time period t before the prediction; and α = smoothing constant ($0 < \alpha < 1$).

This equation illustrates that the prediction is a weighted average based on exponentially decreasing weights. For a high smoothing constant, weights for earlier observations decrease rapidly. For a low smoothing constant, decreases are more moderate.

Linear (Double) Exponential Smoothing

Linear exponential smoothing (LES) is used when the time series is expected to change linearly with time. The algebraic form of the LES model, like that of the SES model, can be expressed in a number of different but equivalent forms (Appendix I). Formally, the SES equation takes the form of (Brown and Meyer 1961)

$$F_t = \alpha x_{t-1} + (1-\alpha)F_{t-1} \tag{9}$$

The standard form of LES model is usually expressed as follows. Let $\bar{F}$ denote the doubly-smoothed series obtained by applying simple exponential smoothing. Then, LES model is defined as

$$\overline{F_t} = \alpha F_t + (1-\alpha)\bar{F}_{t-1}$$

After $\overline{F_t}$ and F_t are calculated, quantities a_t and b_t will be calculated as follows:

$$a_t = 2F_t - \bar{F}_t \qquad b_t = \left(\frac{\alpha}{1-\alpha}\right)(F_t - \bar{F}_t)$$

Finally, prediction value for the next M periods could be obtained using Eq. (10):

$$F_{t+M} = a_t + b_t M \tag{10}$$

The exponential smoothing analysis tool uses the smoothing constant α, the magnitude of which determines how strongly the forecasts respond to errors in the prior forecast. Values between 0.2 and 0.3 of α indicate that the current forecast should be adjusted 20–30% for error in the prior forecast. Larger constants yield a faster response but can produce erratic projections. Smaller constants can result in long lags for forecast values.

Comparative Analysis Procedure

In order to generate the forecasts and assess the accuracy for each of the methods, data from 19 projects are used. A brief description of the type or the industry and number of the projects used are represented in Table 1. Also, some supplemental information on the case studies is presented in Table of the Appendix II. The models are used, forecasts are developed, and the forecasts are then analyzed, evaluated, and compared. The projects used in the study have not undergone any replanning or rebaselining. Also as the earned schedule's SPI(t) is shown to outperform the other EVM-based prediction indexes for project duration, the authors compare the performance of suggested models with that of SPI(t) as well.

Let SPI(t) denotes the schedule performance indicator obtained based on the ES data and SPI′(t) the schedule performance indicator calculated applying SES method using SPI(t) data, whereas EDI′(t) presents the schedule performance indicator calculated applying SES method using EDI data. According to the SES model, SPI′(t) and EDI′(t) are calculated as follows:

$$\mathrm{SPI}'(t) = \alpha\mathrm{SPI}(t) + (1-\alpha)\mathrm{SPI}'(t-1) \tag{11}$$

Table 1. Type and Related Number of Case Studies

Project type	Number
U.S. Armed Forces	1
Telecommunication	4
Information technology	3
Research and development (R&D)	7
Construction	4
Total	19

$$\mathrm{EDI}'(t) = \alpha\mathrm{EDI}(t) + (1-\alpha)\mathrm{EDI}'(t-1) \tag{12}$$

Similar to EAC(t) and EDAC, estimated duration using SES in conjunction with ES and EDM methods is calculated as

$$\mathrm{EAC}'(t) = \mathrm{AT} + \frac{(\mathrm{SAC}-\mathrm{ES})}{\mathrm{SPI}'(t)} \tag{13}$$

$$\mathrm{EDAC}' = \mathrm{AD} + \frac{(\mathrm{SAC}-\mathrm{ED}(t))}{\mathrm{EDI}'(t)} \tag{14}$$

In order to build the LES model similar to EAC$'(t)$ and EDAC$'$, define EAC$''(t)$ and EDAC$''$ as estimated durations using LES model for ES and EDM base data, respectively. Formulas for EAC$''(t)$ and EDAC$''$ are presented in Appendix III.

To understand the impact of selecting a particular value of α in predicting EAC$'(t)$, EDAC$'$, EAC$''(t)$, and EDAC$''$, the projects' forecasts are developed and results are analyzed for a spectrum of values of α. Furthermore, the project data were analyzed and tested for multiple stages of project performance, i.e., early, middle, late, or overall performance. In order to isolate possible forecasting characteristics or tendencies among the methods, according to Lipke et al. (2009), four groupings are formed using the observations within different percent complete ranges to make the determinations, namely: early (10–40%), middle (40–70%), late (70–100%), and overall (10–100%).

Evaluation of the Forecasting Accuracy

In order to evaluate and compare the forecasting accuracy of each method, the root-mean squared error (RMSE), a widely accepted criterion, was used. Clearly, the lower the RMSE, the more accurate the prediction and the method used. RMSE is defined as

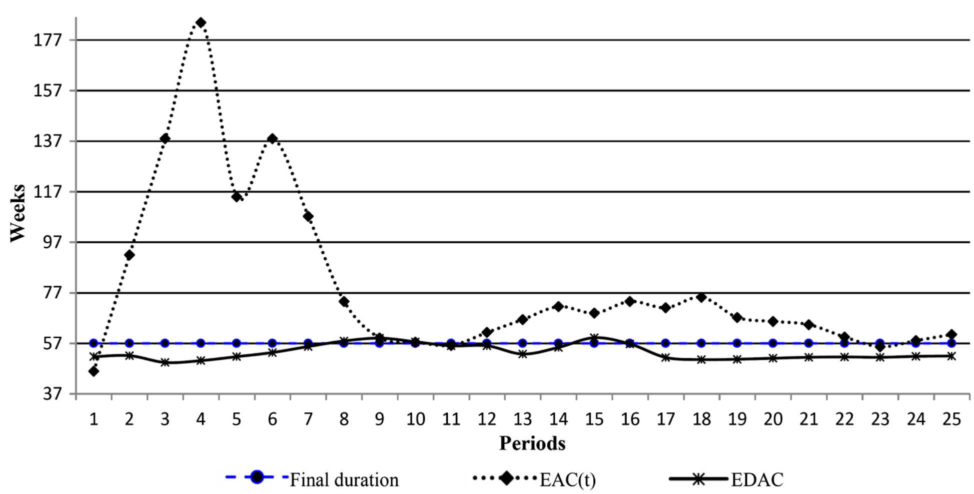
$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(Y_k - P_k)^2} \tag{15}$$

where Y_k = forecast of the real value P_k; and n = number of predicted periods or events (Faria et al. 2009).

Analysis of the Results

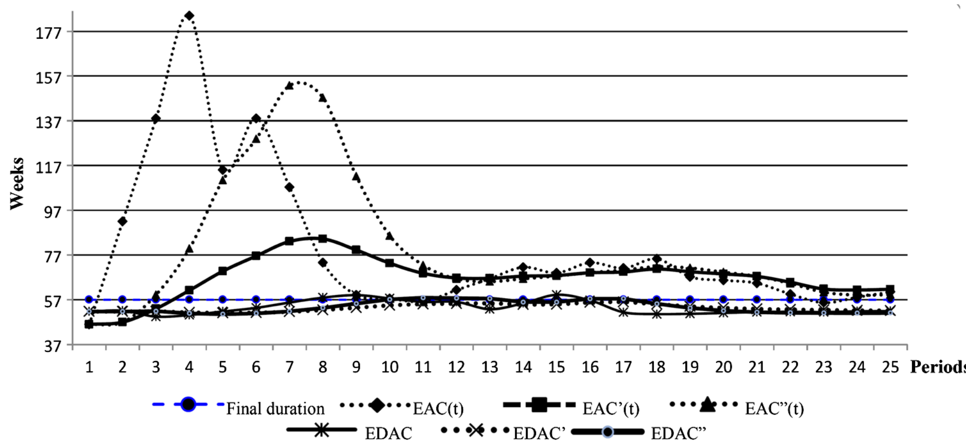
Before presenting the overall forecasting results, it is instructive to show the forecasting performance of methods EAC(t), EDAC, EAC$'(t)$, EAC$''(t)$, EDAC$'$, and EDAC$''$ for a single project (Project 1). This project's scope upgrades the capacity and capability of an old boat maintenance facility to that of a modernly equipped boat handling and maintenance facility in the United States Coast Guard (USCG). As an example project, the results and predictions obtained by ES and EDM techniques [i.e., EAC(t) and EDAC] are portrayed in Fig. 3. The figure makes it evident that in USCG project, forecasting performance of EDM technique is much better than ES technique, especially at the early stages of the project completion. It can be observed that after Period 12, EDAC underestimates the project duration and at the last four periods (i.e., 22–25), EAC(t) tends to be closer to the actual duration than EDAC. However, separate calculation of RMSEs for periods after 12 showed that RMSE of EAC(t) and EDAC are 10.78 and 4.90, respectively. That is to say despite underestimating for those periods, EDAC represented a better overall accuracy.

Applying exponential smoothing models (with $\alpha = 0.2$), predictions for USCG project can be observed in Fig. 4. The graphs show that the fluctuation of EDAC, EDAC$'$, and EDAC$''$ values is much less than those of EAC(t), EAC$'(t)$, and EAC$''(t)$, mainly at the early stages of project completion. Moreover, RMSE values reveal that the predictions obtained by applying SES/LES are seen to be much better than solely ES and EDM techniques. To be more precise, predictions using exponential smoothing technique outperform other predictions provided by EAC(t) and EDAC formulas. Likewise, RMSEs were separately calculated for periods after 12. RMSEs for EAC$'(t)$, EAC$''(t)$, EDAC$'$, and EDAC$''$ were 9.84, 9.44, 3.66, and 4.70, respectively. This means that again,



Method	EAC(t)	EDAC
RMSE	39.14	4.55

Fig. 3. Comparison of the duration forecasting methods EAC(t) and EDAC for USCG project



Method	EAC(t)	EAC'(t)	EAC"(t)	EDAC	EDAC'	EDAC"
RMSE	39.14	13.49	35.57	4.55	4.01	4.27

Fig. 4. Comparison of the duration forecasting of methods $\mathrm{EAC}(t)/\mathrm{EDAC}$, and $\mathrm{EAC}'(t)$, $\mathrm{EAC}''(t)$, EDAC', and EDAC'' (with $\alpha = 0.2$), for USCG project

Table 2. Measuring the Accuracy of the Forecasting Methods Using RMSE Indicator

	RMSE (average for 19 projects) (α)								
Forecasting method	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$\mathrm{EAC}(t)'$	10.78	10.95	11.62	12.46	13.37	14.46	16.07	19.29	29.29
$\mathrm{EAC}(t)''$	11.22	14.19	18.35	25.58	27.17	36.90	32.26	29.30	29.03
EDAC'	9.72	8.57	8.53	8.70	8.91	9.18	9.58	10.35	12.62
EDAC''	9.08	10.79	11.48	12.44	13.08	13.19	11.91	11.47	11.33

SES/LES methods made some improvements in the prediction. However as mentioned earlier, the prediction improvements in the early stages of the project progress are more considerable than those in the middle and late stages.

Now that the process of assessment is established, using the sample cases, the method was implemented to the data from all the 19 projects and forecasts were made adopting a range of values for α. Results of testing yielded a value of $\mathrm{RMSE} = 8.35$ for EDAC and a value of $\mathrm{RMSE} = 14.69$ for $\mathrm{EAC}(t)$. The RMSE for the rest of the methods for the overall region of completion (10–100%) on these projects are given in Table 2. Using minimum RMSE as the criteria, it is obvious that EDAC (with $\mathrm{RMSE} = 8.35$) yields more-accurate predictions than the other methods, particularly in comparison with $\mathrm{EAC}(t)$ with $\mathrm{RMSE} = 14.69$. When combining with exponential smoothing, $\mathrm{EAC}(t)$ improved, especially in the case of conjunction with SES model [$\mathrm{EAC}'(t)$] and for $\alpha \leq 0.3$. Among the set of combined formula, however, it is EDAC' that represents the least RMSEs, with a minimum at $\alpha = 0.3$.

Looking more closely at RMSE values for the combined formulas, it can be observed that the accuracy of both $\mathrm{EAC}'(t)$ and $\mathrm{EAC}''(t)$ has declined gradually, by increase of the value of α constant, with the best duration forecasts at $\alpha = 0.1$. The RMSEs of EDAC' and EDAC'' shows that the accuracy of EDM model combined with the SES and LES did not improve. The results also reveal that when the constant α increases from 0.1 to 0.3, the prediction performance of EDAC' improves, reaching a minimum RMSE in $\alpha = 0.3$. However, for the EDAC'' formula, $\alpha = 0.1$ would represent the best predictions and higher constants would not improve the predictions.

Using minimum RMSE as the criteria, the performance of each method was ranked, a summary of which is provided in Table 3. Without devoting attention to project completion stage, therefore, the main conclusions derived from Tables 2 and 3 are as follows:

- The EDM model (or EDAC) outperforms the ES model [or $\mathrm{EAC}(t)$] in duration forecasting;
- The ES model performs much better when combining with exponential smoothing models, mainly SES (or $\mathrm{EAC}'(t)$ formula); and
- EDAC outperforms the other models for the set of projects under this study. It could fairly be concluded that overall when forecasting duration of a project, the exponential smoothing method could not improve the predictions power of EDM based model consistently.

Fig. 5 represents the RMSE values of $\mathrm{EAC}(t)'$, $\mathrm{EAC}(t)''$, EDAC', and EDAC'', for $\alpha = 0.1, 0.2, \ldots, 0.9$. The purpose of this analysis is to see what range of previous periods should be more appreciated in forecasting the future performance of an on-going project. As shown in Fig. 5, constants near 0.1 account

Table 3. Ranking of Forecasting Methods for Overall Region of Completion (10–100%)

Rank	Forecasting formula	Approaches
1	EDAC	EDM
2	EDAC' ($\alpha = 0.3$)	EDM and SES
3	EDAC' ($\alpha = 0.2$)	EDM and SES
4	EDAC' ($\alpha = 0.4$)	EDM and SES
5	EDAC' ($\alpha = 0.5$)	EDM and SES
6	EDAC'' ($\alpha = 0.1$)	EDM and LES
7	EDAC' ($\alpha = 0.6$)	EDM and SES
8	EDAC' ($\alpha = 0.7$)	EDM and SES
9	EDAC' ($\alpha = 0.1$)	EDM and SES
10	EDAC' ($\alpha = 0.8$)	EDM and SES

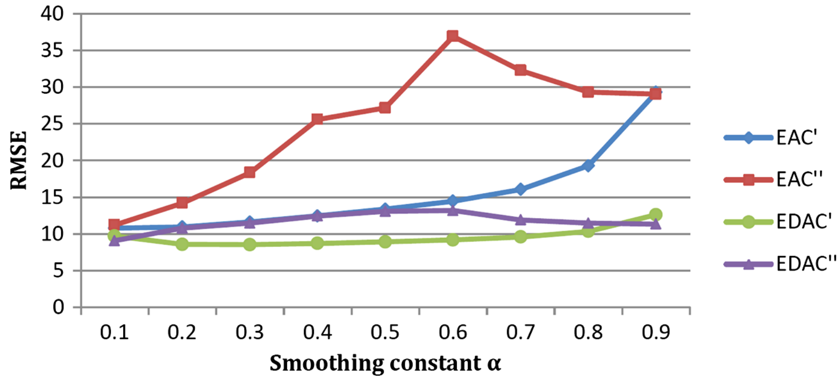


Fig. 5. Effect of the smoothing constant α on RMSE indicator of the combined formulae $\mathrm{EAC}'(t)$, $\mathrm{EAC}''(t)$, EDAC', and EDAC''

for the most-accurate predictions, which mean recently elapsed periods better reflect project performance at completion. It reveals that as the value of α rises, the accuracy of prediction methods generally declines, proving the point that more-recent periods are relevant and not the average of the past. Regarding the rankings, the SES model merged with EDAC performs better than LES model in 19 under-study projects.

In addition to the overall forecasting performance of each method, the methods' performance at different stages of project progress was analyzed and assessed. The ranked results indicated that in the early stages of project completion, EDAC is still the best method to forecast final duration of a project. In the middle stages of project completion, as the projects progress, exponential smoothing techniques, mainly the SES model, could improve the EDM forecasting method marginally. The SES model with $\alpha = 0.2$ merged with EDM (EDAC') could develop and deliver the best forecasts when the project is in its middle phases of completion. Likewise, the EDAC' ($\alpha = 0.2$) provided the most-accurate predictions for the late stages of completion of the projects. It is not unexpected that exponential smoothing has improved the predictions in middle and late stages of projects, as the model possesses the ability to track volatility and variations relating to previous performances, appreciating recent periods. Indeed, it has shown the ability to mirror the effect of management actions and/or project nature on the course of the project.

Regarding the optimum value for α (i.e., 0.2), although it should not rely on an arbitrary preset smoothing parameter, published literature has recommended a choice in the range $0.1 < \alpha < 0.3$ to allow the SES model to change relatively slowly, and such values often work well for series such as sales figures. However, optimal coefficients should be selected by minimizing the RMSE over some initial sample (Gardner 1985, 2006).

Conclusion

In this paper, the performance of EDI from EDM as a parameter or tool for forecasting the duration of a project at completion was assessed. The results strongly support the argument that a duration-based performance measure is a better indicator for use in predicting the duration of a project. In addition, knowing that the naïve forecasting model of using SPI or $\mathrm{SPI}(t)$ could almost always generate highly erroneous forecasts, the authors merged the models with SES and LES to improve the performance of these prediction models. The amalgamation of exponential smoothing and these simple models improved the accuracy of the forecasts and reduced the errors. Based on current study, one could predict that the combination of EDI and SES could deliver improved results most of the time, indicating that the use of EDI from EDM approach is less erroneous than $\mathrm{SPI}(t)$. While there are other advanced or sophisticated forecasting models, the authors recommend SES due to its ease of use and formulation.

The projects used for this study were cases to which authors had access. A more extensive study with a much larger database could be conducted as the extension of this paper and further research. An extension of the proposed method can also concentrate on the constant α and how it can be determined for individual ongoing projects.

Appendix I. Brown's Linear (i.e., Double) Exponential Smoothing

If the *trend* as well as the mean is varying slowly over time, a higher-order smoothing model is needed to track the varying trend. The simplest time-varying trend model is Brown's linear exponential smoothing (LES) model, which uses *two* different smoothed series that are centered at different points in time. The forecasting formula is based on an extrapolation of a line through the two centers.

The algebraic form of the linear exponential smoothing model, like that of the simple exponential smoothing model, can be expressed in a number of different but equivalent forms. The standard form of this model is usually expressed as follows: Let S' denote the *singly-smoothed* series obtained by applying simple exponential smoothing to series Y. That is, the value of S' at period t is given by

$$S'(t) = \alpha Y(t) + (1 - \alpha) S'(t - 1)$$

[Recall that, under simple exponential smoothing, it is assumed that $\acute{Y}(t + 1) = S'(t)$ at this point.] Then, let S'' denote the *doubly-smoothed* series obtained by applying simple exponential smoothing (using the same α) to series S':

$$S''(t) = \alpha S'(t) + (1 - \alpha) S''(t - 1)$$

Finally, the forecast $\acute{Y}(t + 1)$ is given by

$$\acute{Y}(t + 1) = a_t + b_t$$

where a_t = estimated *level* at period t

$$a_t = 2S'(t) - S''(t)$$

and b_t = estimated *trend* at period t

$$b_t = [\alpha/(1 - \alpha)][S'(t) - S''(\mathrm{t})]$$

Forecasts with longer lead times made at period t are obtained by adding multiples of the trend term. For example, the k-period-ahead forecast [i.e., the forecast for $Y(t+k)$ made at period t] would be equal to $a_t + kb_t$. For purposes of model-fitting (i.e., calculating forecasts, residuals, and residual statistics over the estimation period), the model can be started by setting $S'(1) = S''(1) = Y(1)$, i.e., set both smoothed series equal to the observed value at $t = 1$.

A mathematically equivalent form of Brown's linear exponential smoothing model, which emphasizes its nonstationary character and is easier to implement on a spreadsheet, is as follows:

$$\acute{Y}(t) = 2Y(t-1) - Y(t-2) - 2(1-\alpha)e(t-1) + [(1-\alpha)^2]e(t-2)$$

where $e(t) = Y'(t) - Y(t)$ (as the previous errors).

Equivalently

$$\acute{Y}(t) - Y(t-1) = Y(t-1) - Y(t-2) - 2(1-\alpha)e(t-1) + [(1-\alpha)^2]e(t-2)$$

In other words, the predicted difference at period t [namely $\acute{Y}(t) - Y(t-1)$] is equal to the previous observed difference [namely $Y(t-1) - Y(t-2)$] minus a weighted difference of the two previous forecast errors.

This form of the model is rather tricky to start at the beginning of the estimation period. The following convention is recommended: first set $\acute{Y}(1) = Y(1)$, which yields $e(1) = 0$ (i.e., cheat a bit and let the first forecast equal the actual first observation), then also set $\acute{Y}(2) = Y(1)$, which yields $e(2) = Y(2) - Y(1)$, then continue from this point using the preceding equation. This would yield the same fitted values as the formula based on S' and S'' if the latter were started using $S'(1) = S''(1) = Y(1)$.

Appendix II. Supplemental Information on the Case Studies

The following table provides some detail about the cases used for the comparative analysis of the models. For five categories of projects, details such as the country in which the project was implemented, number of activities, original scheduled duration (SAC), and final duration of the project are given.

Number	Category	Country	Number of activities	SAC (days)	Final duration (days)
1	USCG project	U.S.	—	322	399
2	Telecommunication	U.S.	130	183	242
3		U.S.	120	175	203
4		U.S.	150	150	172
5		U.S.	148	110	145
6	Information technology	U.S.	115	450	700
7		U.S.	146	420	690
8		U.S.	98	185	223
9	Research and development (R&D)	U.S.	122	430	510
10		U.S.	43	300	391
11		U.S.	56	112	133
12		U.S.	74	120	187
13		U.S.	110	310	364
14		U.S.	55	140	158
15		U.S.	79	165	182
16	Construction	Iran	225	515	627
17		Iran	510	540	576
18		Iran	84	290	319
19		Iran	150	350	381

Appendix III. Calculation of EAC$''(t)$ and EDAC$''$

Let SPI$''(t)$ denote the schedule performance indicator calculated applying LES method using SPI(t) data, whereas EDI$''(t)$ presents the schedule performance indicator calculated applying LES method using EDI data. According to the LES model, SPI$''(t)$ and EDI$''(t)$ are calculated as follows:

$$\mathrm{SPI}''(t) = 2\mathrm{SPI}'(t) - \bar{\mathrm{SPI}}'(t) + \left(\frac{\alpha}{1-\alpha}\right)\mathrm{SPI}'(t) - \bar{\mathrm{SPI}}'(t)$$

where SPI$'(t)$ and $\bar{\mathrm{SPI}}'(t)$ = *singly-smoothed* series and *doubly-smoothed* series obtained by applying simple exponential smoothing to SPI(t) (using the same α), respectively

$$\mathrm{EDI}''(t) = 2\mathrm{EDI}'(t) - \bar{\mathrm{EDI}}'(t) + \left(\frac{\alpha}{1-\alpha}\right)\mathrm{EDI}'(t) - \bar{\mathrm{EDI}}'(t)$$

where EDI$'(t)$ and EDI$'(t)$ = *singly-smoothed* series and *doubly-smoothed* series obtained by applying simple exponential smoothing to EDI (using the same α), respectively.

Similar to EAC(t) and EDAC, estimated duration using LES in conjunction with ES and EDM methods is calculated as

$$\mathrm{EAC}''(t) = \mathrm{AT} + \frac{(\mathrm{SAC} - \mathrm{ES})}{\mathrm{SPI}''(t)}$$

$$\mathrm{EDAC}'' = \mathrm{AT} + \frac{[\mathrm{SAC} - \mathrm{ED}(t)]}{\mathrm{EDI}''(t)}$$

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