HBRC Journal (2014) 10, 35–42

Housing and Building National Research Center

HBRC Journal

http://ees.elsevier.com/hbrcj

FULL LENGTH ARTICLE

Forecasting project schedule performance using probabilistic and deterministic models

Abdel Azeem S.A. *, Hossam E. Hosny, Ahmed H. Ibrahim

Department of Construction Engineering, Faculty of Engineering, Zagazig University, Egypt

Received 20 January 2013; revised 14 August 2013; accepted 2 September 2013

KEYWORDS

Cost control;
Construction;
Earned value;
Forecasting;
Kalman;
Probabilistic

Abstract Earned value management (EVM) was originally developed for cost management and has not widely been used for forecasting project duration. In addition, EVM based formulas for cost or schedule forecasting are still deterministic and do not provide any information about the range of possible outcomes and the probability of meeting the project objectives. The objective of this paper is to develop three models to forecast the estimated duration at completion. Two of these models are deterministic; earned value (EV) and earned schedule (ES) models. The third model is a probabilistic model and developed based on Kalman filter algorithm and earned schedule management. Hence, the accuracies of the EV, ES and Kalman Filter Forecasting Model (KFFM) through the different project periods will be assessed and compared with the other forecasting methods such as the Critical Path Method (CPM), which makes the time forecast at activity level by revising the actual reporting data for each activity at a certain data date. A case study project is used to validate the results of the three models. Hence, the best model is selected based on the lowest average percentage of error. The results showed that the KFFM developed in this study provides probabilistic prediction bounds of project duration at completion and can be applied through the different project periods with smaller errors than those observed in EV and ES forecasting models.

Introduction

A typical project control process consists of monitoring actual performance, comparing it with planned performance, analyzing the difference, and forecasting the final outcomes at completion resulting from management actions [1]. EVM was originally developed for cost management and has not widely been used for forecasting project duration [2]. Three fundamental limitations arise in EVM-based cost or schedule forecasting. First, EVM based formulas for cost or schedule forecasting are deterministic and do not provide any information about the range of possible outcomes and the probability

* Corresponding author. Tel.: +20 1002835881.
E-mail addresses: eng_abdel82@yahoo.com (S.A. Abdel Azeem), hosny_hosm@yahoo.com (H.E. Hosny), mekky69@yahoo.com (A.H. Ibrahim).

Peer review under responsibility of Housing and Building National Research Center.

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http://dx.doi.org/10.1016/j.hbrcj.2013.09.002

Notation

CPM	Critical Path Method
EDAC	Estimated Duration At Completion
ES	earned schedule
EV	earned value
KFFM	Kalman filter forecasting model
PD	planned duration
PV	planned value
SPI(t)	schedule performance index calculated by earned schedule
SPI	schedule performance index calculated by earned value
SV	schedule variance
TV(t)	time variation calculated by earned schedule

of meeting the project objectives. Second, EVM have some measurement errors because of the difficulty of measuring the progress on projects exactly. Such these measurement errors make the forecast unreliable for the project managers [1]. Third, the schedule variance calculated by the EVM does not measure time but is expressed in a monetary unit [2]. Recently, Naeini, and Heravi developed a probabilistic project control concept based on stochastic S curves to assure an acceptable forecast of project cost performance [3]. Vandevoorde and Vanhoucke [2] compared three different EV-based approaches for schedule forecasting and demonstrated that the Earned Schedule Management (ESM) is the only method among those tested methods that provides reliable forecasting results. Kim and Reinschmidt [1] compared the results of Kalman filter forecasting model (KFFM) against the results of the ES model and such the comparison showed that the ES model produced more erratic responses to reported performance than the KFFM, resulting in large changes to the forecasted Estimated Duration At Completion (EDAC). The EV, ES and KFFM models make the time forecast at the project level by comparing the EV cost versus the planned value cost (PV) at a certain data date. Therefore, the accuracies of the three developed models from the start of a project to the completion will be assessed and compared with the other time forecasting methods such as the Critical Path Method (CPM) that makes the time forecast at activity level through updating the planned original network by actual report data for each activity at a specified data date. In this paper, a new forecasting method will be developed based on Kalman filter and the earned schedule method. The ESM serves as a basic performance measurement system and the KFFM proposed in this paper is based on time variation in the time dimension and provides confidence bounds on the time predictions, which can be used as an effective tool to predict the time forecast at the project level. The outline of this paper is as follows. In the next section, research objectives, EV and ES forecasting methods are reviewed, with a discussion of their limitations for practical implementation. Then, the ESM and the Kalman filter are briefly described in order to facilitate the understanding of the formulation of the KFFM. Based on the reviews of ESM, and Kalman filter, the KFFM is formulated. Numerical example is presented to validate the three models against the most accurate method (CPM).

Research objectives

This study presents a probabilistic project time forecast concept to assure an acceptable forecast of project time performance. Three models will be developed to forecast the estimated duration at completion. Two deterministic models were developed, based on the EV, ES principles. The results of those models were compared with the similar results of a suggested probabilistic model that was developed based on Kalman filter algorithm and earned schedule management. Hence, the accuracies of the EV, ES, and KFFM models through the different project periods will be assessed and compared with the other forecasting methods such as the traditional Critical Path Method (CPM), which makes the time forecast at the activity level. Subsequently, the best time forecasting model will be selected based on the lowest mean absolute invalidity percent. In the next section of this paper, the principles of the earned value, earned schedule, and Kalman filter will be discussed. Hence, a case study project will be used to validate the results of the three models. Finally, based on the results of such case study, some conclusions regarding the best model for project duration forecasting will be provided.

Methodology

Earned value management

The Project Management Institute (PMI, 2008) [4] defined EVM as a management methodology for integrating the project's scope, schedule, and resources, and for objectively measuring project performance and progress from project initiation through closeout. EVM relies on three basic performance variables earned value (EV), actual cost (AC), and planned value (PV), to evaluate where a project is and where it was supposed to be. The schedule variance (SV), schedule performance index (SPI), Estimated Duration At Completion is calculated by EV model ($EDAC_{(EV)}$) as

$$SV = EV - PV \tag{1}$$

$$SPI = EV/PV \tag{2}$$

$$EDAC_{(EV)} = PD/SPI \tag{3}$$

where PD is planned duration. At the end of a project, the EV = PV = BAC (budget at completion), and hence, the SV and SPI always equals 0 and 1, respectively. If SV = 0 and SPI = 1, the earned work is exactly as planned, regardless of the real project status (behind, on schedule or ahead) [1,5]. Fig. 1 shows a graphical representation of the two variables (EV and PV) regarding to the time forecast.

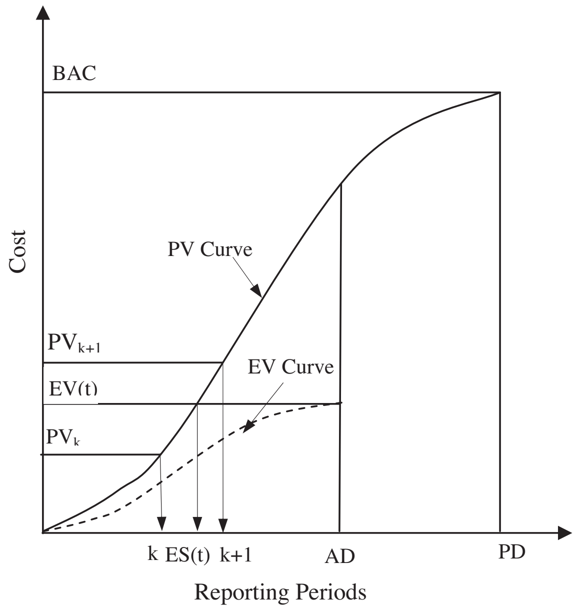

Fig. 1 EV metrics [1].

Earned schedule management

The term earned schedule was first introduced by Lipke [6] as an extended EV metric to overcome the deficiencies of the EVM schedule indicator SPI. The earned schedule at a specific time can be approximated by interpolation between two consecutive PVs that satisfy $EV(t) \geqslant PV(k)$ and $EV(t) < PV(k+1)$. the earned schedule is calculated from the linear interpolation as shown in Fig. 1 [1,4].

$$ES_{(t)} = k + \frac{EV_{(t)} - PV_{(k)}}{PV_{(k+1)} - PV_{(k)}}, \tag{4}$$

where, k is the time increment of the PV that is less than current PV, PV_k the planned value at time k and PV_{k+1} is the planned value at time $k+1$, ES is the number of completed PV time increments that EV exceeds plus the fraction of the incomplete PV increment. $EV(t)$ is the earned value at the actual data date. Once the earned schedule is calculated, the time variation $TV(t)$, which is defined as the deviation between an actual reporting time and the earned schedule at that reporting time [7]. The $TV(t)$ and Schedule Performance Index $SPI(t)$ can be calculated in terms of ES and AD (Actual data date) as [5]:

$$TV(t) = ES(t) - AD \tag{5}$$

$$SPI(t) = ES(t)/AD \tag{6}$$

$$EDAC_{(ESM)} = PD/SPI(t) \tag{7}$$

Kalman filter principles

Accurate project time are difficult to forecast when considering the impact of such events as the inherent uncertainty in the plan and in the execution of plan [7],[1]. The Kalman filter is named after Rudolph Kalman, who in 1960 published his famous paper describing a recursive solution to the discrete-data linear filtering problem [8]. A probabilistic time forecasting in this paper has been proposed based on Kalman filter algorithm and earned schedule management. The Kalman filter estimates a state of a dynamic of system in a way that minimizes the mean of the squared error. This dynamic of system can be disturbed by some noises because the observations or actual measurements we make are always uncertain, mostly the noise assumed to be white noise (noise has a zero mean) [9,10].

Good introduction to the Kalman filter will be found in Whyte [9], Kleinbauer [7] and Welch and Bishop [8]. Within the Kalman filter framework, the state of a dynamic system is represented at time k by two sets of variables: the state variables x_k and the error covariance P_k. The state variables describes the state of the dynamic model. The error covariance represents the inherited uncertainty in the estimates of the state variables. In the Kalman filter algorithm, The variables of the state model cannot be measured directly but they can be inferred from the values that measurable [10]. The state variable has two values at the same time. The first variable is a *priori* variable x^- and the second is a *posterior* variable x^+ as shown in Fig. 2. Fig. 2 shows the two steps of the Kalman filter model; prediction process and correction process. The prediction process predicted the current state estimate in a certain time (x_k). The measurement update equations are responsible for updating a priori estimate x^- by a new measurement (z_k) to obtain an improved a posteriori estimate x^+ [10,8,9]. In the KFFM, cumulative

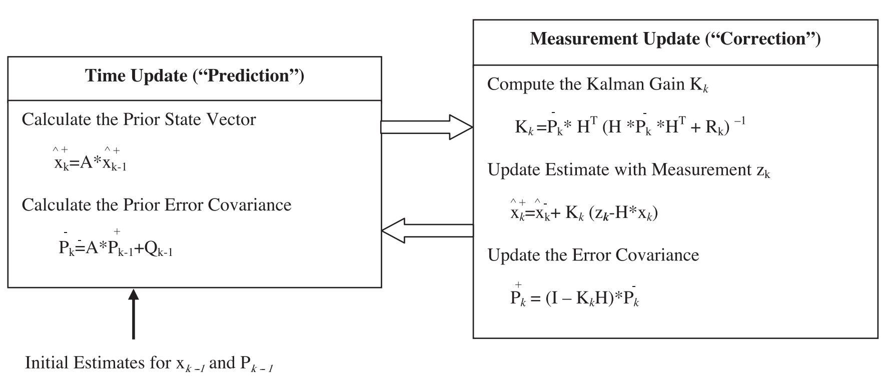

Fig. 2 The recursive learning cycle of the Kalman filter [8], [10].

progress of a project is modeled as a system with two states that evolve over time: the TV_k and its rate of change over a reporting period (dTV_k/dt). Kim and Reinschmidt [1] defined the state vector of the KFFM as,

$$x_k = \begin{Bmatrix} TV_k \\ dTV_k/dt \end{Bmatrix} \tag{8}$$

The Kalman filter is a recursive process of estimating a state vector when the state vector (x_k) and new observations (z_k) are governed by the following equations

$$x_k = Ax_{k-1} + w_{k-1} \tag{9}$$

$$z_k = Hx_k + v_k \tag{10}$$

where where w_{k-1} = random error that represents change in the derivative of the TV over one reporting period and w^2_{k-1} represents the variance of the random process noise. The process noise variance represents the inherited uncertainty in the process model. The term (v_k) represents the measurement noise that represents the error in actual measurement, A is the known square transition matrix of the process, dt is the difference between two

$$A = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} \qquad W_{k-1} = \begin{bmatrix} 0 \\ W_{k-1} \end{bmatrix} \tag{11}$$

consecutive months, and H is the rectangular measurement matrix [1 0] [8]. The measurement model updates prior information using new observations (z_k) to obtain an improved a posteriori estimate x_k.

Kalman filter forecasting model step by step

In the KFFM, the initial state estimate x_o and its error covariance P_o are set to be zero because the project performance forecasting has or should have a clear starting start time, and initial cost, which are likely to be initialized at zero [1].

$$x_k = \begin{bmatrix} 0 \\ 0 \end{bmatrix}; \qquad P_o = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{12}$$

The process noise variable Q shown in Fig. 2 in the Kalman filter acts as in the role of controlling the bandwidth and modulates the Kalman gain (K). Abnormal choice of noise covariance is one of the most important factors which make Kalman filters diverge [11].

$$Q = [w_{k-1}]\overline{[w_{k-1}]} = \begin{pmatrix} 0 \\ w_{k-1} \end{pmatrix} \begin{pmatrix} 0 & W_{k-1} \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & W^2_{k-1} \end{pmatrix} \tag{13}$$

Estimating the process noise variable (Q) is based on the prior distribution of the project duration [1]. The prior distribution of the project duration is estimated by use of three point estimate (PERT method) by assuming the optimistic time estimate (O), most likely time estimate (ML), and pessimistic time estimate (P) as O = 0.95% PD, ML = PD, and P = 1.05% PD, respectively, where PD = planned duration. The mean and the standard deviation of the prior distribution of the project duration are then determined using the three point estimate (PERT formula) [3]. The mean of the project duration is calculated by the PERT formula as

$$\begin{aligned} \text{Mean of project duration} &= \frac{(O + 4^* M + P)}{6} \\ &= \frac{0.95 * 24 + 4 * 24 + 1.05 * 24}{6} \\ &= 24\,\text{days} \end{aligned} \tag{14}$$

$$\text{Standard deviation of project duration} - \frac{(P - O)}{6} = \frac{1.05 * 24 - 0.95 * 24}{6} = 0.40\,\text{day} \tag{15}$$

Then the variance of the project duration is calculated by squaring Standard deviation of project duration $(0.4)^2 = 0.160$.

The random process noise variable w_{k-1} is estimated to be 0.060 to make the error covariance of the TV at k = last reporting period, which is predicted by the Kalman filter method, equal to the prior estimate of the variance of the project duration (variance = 0.16). The measurement noise covariance R_k, indicated in Fig. 2 in Kalman gain equation, is a most significant factor when designing a Kalman filter. The Kalman filter can diverge with an incorrect selection of R_k [11]. R_k in the calculation of the Kalman gain in Fig. 2 represents the accuracy of actual performance measurements and is determined as ($a^2/9$), where the term a is the maximum or minimum measurement error. In this paper the maximum possible error is (+3) days for ahead schedule and is (−3) days for behind schedule. By setting an appropriate value for the measurement error, the sensitivity of the forecasts to the actual performance data may be adjusted by the project manager [1]. At any time t_k, the estimate of time variation TV_k is obtained from the Kalman filter analysis as $x_{(k,1)}$. Consequently, the terms earned schedule and EDAC by the Kalman filter forecasting model can be calculated according to Eqs. (5) and (7), respectively.

Case study project

The KFFM formulated in previous sections has been programmed in Matlab Progam Version 2009 (Matlab R2009a). Using this program, the three models KFFM, EVM, and ESM, requires the PV metric, EV Metric, and Actual Data Date as a input data. The only one output of the three models is the EDAC. Moreover, the EDAC calculated from KFFM is a probabilistic output and have three point estimate, lower bound (LB), mean (M), upper bound (UP).

A case study example is illustrated here to compare the results of the three models against the results of the CPM and facilitate the validation process for the three models. Fig. 3 shows the precedence network of the case study, the activity duration, early dates and the budgeted cost of each activity. The actual reporting data are also indicated (Tables 1–5). Each table shows the actual percentage of completion and the actual dates for each activity, which are stated at a given actual data date. The earned value for each activity is calculated as the actual percentage of completion multiple by the estimated cost for each activity. The cumulative earned value cost is then calculated by the summation of the earned value cost of each activity. The planned value cost for each activity is calculated as the planned percentage of completion multiple by the planned value cost for each activity. The cumulative planned value

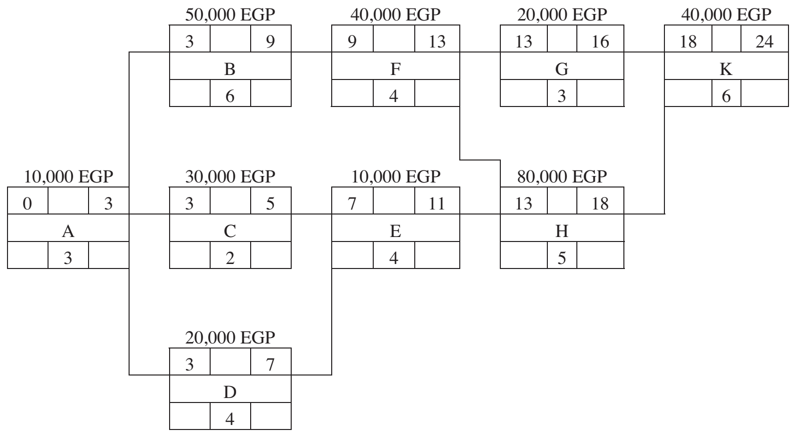

Fig. 3 The precedence network of the case study.

Table 1 Actual project data at the end of the 4th day.

Activity	% work completed	Actual start date	Finish or actual date
A	100	0	3
B	10	3	4
C	50	3	4
D	25	3	4
E	0	–	–
F	0	–	–
G	0	–	–
H	0	–	–
K	0	–	–

Earned value cost = 35,000 EGP.
Planned value cost = 38,333 EGP.
$EDAC_{(CPM)}$ = 24.40 day.

Table 2 Actual project data at the end of the 8th day.

Activity	% work completed	Actual start date	Finish or actual date
A	100	0	3
B	83.33	3	8
C	100	3	6
D	100	3	8
E	10	8	8
F	0	–	–
G	0	–	–
H	0	–	–
K	0	–	–

Earned value cost = 102,666 EGP.
Planned value cost = 104,166.7 EGP.
$EDAC_{(CPM)}$ = 24 day.

Table 3 Actual project data at the end of the 12th day.

Activity	% work completed	Actual start date	Finish or actual date
A	100	0	3
B	83.33	3	8
C	100	3	6
D	100	3	8
E	100	8	12
F	60	9	12
G	0	–	–
H	0	–	–
K	0	–	–

Earned value cost = 144,000 EGP.
Planned value cost = 150,000 EGP.
$EDAC_{(CPM)}$ = 24.60 day.

Table 4 Actual project data at the end of the 16th day.

Activity	% work completed	Actual start date	Finish or actual date
A	100	0	3
B	100	3	9
C	100	3	6
D	100	3	8
E	100	8	12
F	100	9	13.60
G	67	13.60	16
H	40	13.60	16
K	0	–	–

Earned value cost = 205,400 EGP.
Planned value cost = 228,000 EGP.
$EDAC_{(CPM)}$ = 25 day.

is calculated by the summation of planned value of each activity. The project is updated at each given data date based on the actual reporting data given in each table. The estimated duration at completion predicted by CPM is indicated at the last row of each table (Tables 1–5) by updating the project at each data date according to the actual report data stated in each table. The forecasted duration by CPM is not approximated to the nearest integer number because this approximation will badly affect the validation process.

The results of the three models

A case study project is to compare and assess the EDAC by the three models against the EDAC by the CPM and to facilitate the validation process for the three models. The EDAC forecasted from the CPM method is obtained from project time updating according to actual data given from Tables from 1 to 5. The EDAC produced by EV and ES models is calculated from the Eqs. (3) and (7), respectively. On the other hand, the

Table 5 Actual project data at the end of the 20th day.

Activity	% work completed	Actual start date	Finish or actual date
A	100	0	3
B	100	3	9
C	100	3	5
D	100	3	8
E	100	8	12
F	100	9	13.60
G	100	13.60	17
H	100	13.60	19
K	40	19	20

Earned value cost = 284,000 EGP.
Planned value cost = 273,333 EGP.
$EDAC_{(CPM)}$ = 23.60 day.

Kalman filter forecasting model was developed by Matlab Program. The prediction bounds of the EDAC can be obtained directly from the Kalman filter results in terms of the error covariance matrix $\mathbf{P}_k$ [12].

A probabilistic EDAC profile from the KFFM consists of three curves: M, UB, and LB curves. These curves represent the history of probabilistic predictions for the project duration from the start of a project to the point of forecasting.

The comparison of the three models

Fig. 4 shows the EDAC profile produced by the two deterministic models EV and ES, while on the other hand, Fig. 5 shows the EDAC profile produced by the KFFM. The percentage of error (PE) between the EDAC forecasted by the three models against the $EDAC_{(CPM)}$ calculated as

$$PE = \left| \frac{EDAC(t) - EDAC_{(CPM)}}{EDAC_{(CPM)}} \right| * 100 \tag{16}$$

where EDAC(t) is the estimated duration at completion produced by the three models and $EDAC_{(CPM)}$ is the estimated duration at completion produced by the CPM. The average percentage of error is calculated by average the summation of all percentage of errors values as indicated in Table 6. As

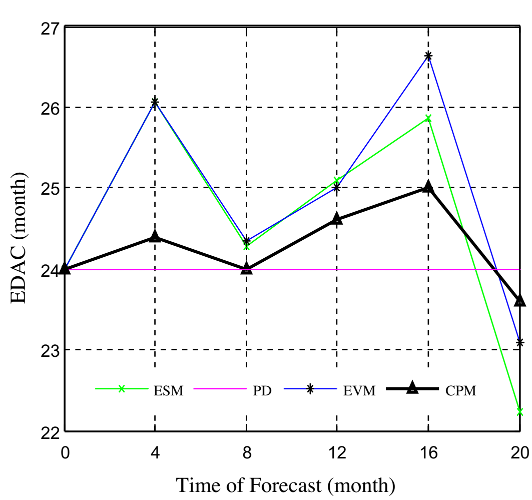

Fig. 4 Forecasted EDAC using EV and ES models.

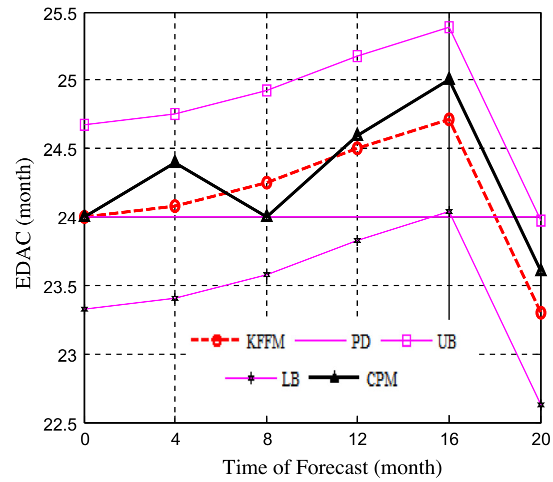

Fig. 5 Forecasted EDAC using KFFM.

shown in both Figs. 4 and 5, the thick black solid line represents the EDAC profile produced by CPM that supposed to be the most accurate forecast because it makes the time forecast at the activity level. It is noted that the EDAC profile produced by the KFFM had better closeness to EDAC profile produced by CPM than the other two EDAC profiles produced by the EV and ES models. In other words, as indicated Table 6, the KFFM is the best model because its EDAC profile had the lowest deviation from the EDAC profile produced by CPM Profile (0.86%), while EDAC profile produced by the EV and ES models have a greater deviation (3.09%) and (3.21%), respectively. Therefore, based on such the comparison, it should be concluded that the KFFM provides more reliable and robust time predictions than the EV and ES models.

EDAC profile produced by the KFFM

Fig. 5 shows the probabilistic EDAC profile produced by KFFM that consists of three curves: M, UB, and LB curves. The thick red dash line EDAC, shown in Fig. 5, represents the estimated duration at completion calculated as the mean of the posterior distribution of project duration. The three curves of KFFM represent the history of probabilistic predictions for the project duration from the start of a project to the point of forecasting. The UB and LB are determined at the confidence level selected by the user. In this paper, a 90% confidence interval is used. When combined together, these three curves the M, LB, and UB show the range of possible completion dates at a given confidence level at a specific time. It is noted that the EDAC produced by CPM located within the UP and LB profiles produced by the KFFM. The probabilistic EDAC profile shows early warning about a possible future schedule delay, for example, at the day No. 16 shown in Fig. 5, the LB profile exceeded the planned duration line (Just behind of schedule at day no. 16 under the worst scenario).

Probability of success graph

The prior and posterior probability distribution curves, as shown in Fig. 6, represent the probability of finishing the project at a given project duration. The prior distribution is the probability distribution for the planned duration before the

Table 6 The forecasted EDAC of the three models versus the forecasted EDAC by CPM.

Time of forecast	EDAC				Percentage of error		
	CPM	ES	EV	KFFM	ES (%)	EV (%)	KFFM (%)
0	24.00	24.00	24.00	24.00	0.00	0.00	0.00
4	24.40	26.06	26.06	24.08	6.79	6.79	1.31
8	24.00	24.28	24.35	24.26	1.15	1.46	1.07
12	24.60	25.10	25.00	24.50	2.01	1.63	0.39
16	25.00	25.87	26.64	24.71	3.50	6.56	1.16
20	23.60	22.22	23.10	23.30	5.84	2.12	1.26
Average percentage of error					3.21	3.09	0.86

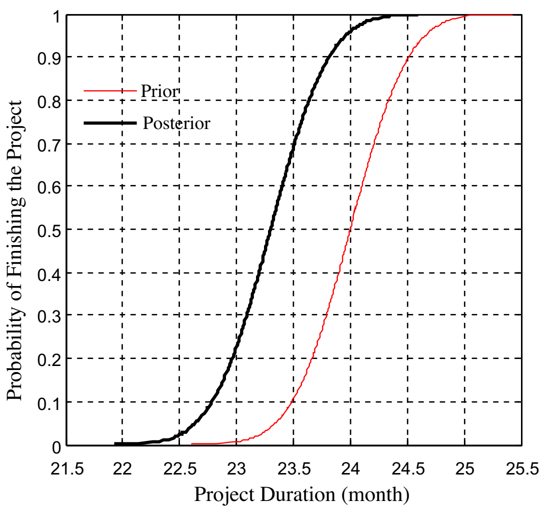

Fig. 6 Probability of success graph.

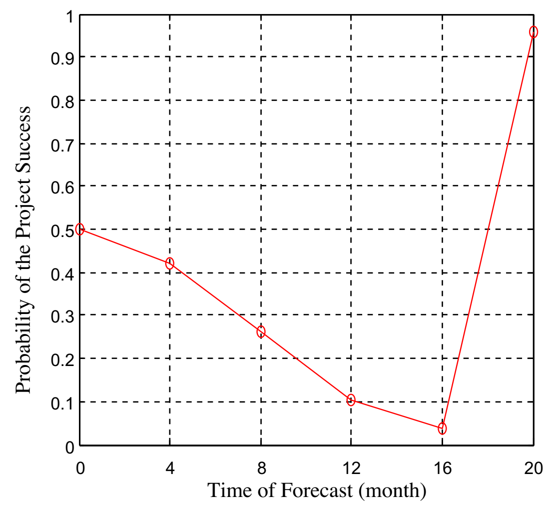

Fig. 7 Probability of success profile.

start of project based on the estimated variance specified by the user judgment and experience. The poster distribution is the probability distribution for the EDAC duration during the execution stage of project at a certain data date. The prior variance of the project duration were estimated previously by three point estimate (PERT formula). The posterior variance of the project duration should be estimated based on the judgment and experience of the project manager. In this paper, the prior variance of project duration is assumed to be equal the posterior variance. Both probability distribution curves are estimated based on cumulative distribution function (CDF) in Matlab. At 50% chance, as shown in Fig. 6, the forecasted duration at the 20th day is 23.3 day, this means that the project performance efficiency regard to time is a head schedule by 0.70 day. Under a worst-case scenario given at the 99% probability level, the EDAC is 24.2 days, then the time project performance efficiency at 1% risk level is 0.2 day behind schedule. The Probability of Success Graph helps the project managers to estimate the probability of completing the project within its different forecasted duration, according to the prior and/or the posterior probability distribution.

Probability of success profile

Fig. 7 shows probability of success profile which is defined as the changes in the probability of meeting the project objective (planned duration). This profile also can be used to detect an early warning point at a specific risk level. As shown Fig. 7, The probability of success has declined from 50% at the beginning to 4% at day no. 16. During this period, the project is behind of schedule. After that period, the probability of success profile improved sharply to reach 96% at the 20th day. The project status is ahead of schedule with 96% chance of finishing on its planned duration (24 day). The probability of success profile can help project managers to make better informed decisions as to corrective and/or preventive actions [13].

Conclusion

The first objective of this paper is to develop three models to forecast the estimated duration at completion. Two of these models were deterministic; earned value (EV) and earned schedule (ES) models. The third model was a probabilistic model and developed based on Kalman filter algorithm and earned schedule principles. The second objective is to identify the most reliable time forecasting model among the three time forecasting methods, earned value, earned schedule and Kalman filter model. Therefore, the accuracies of the EV, ES, and KFFM through the different project periods were assessed and compared with the other forecasting methods such as the CPM, which makes the time forecast at the activity level. Such comparison showed clearly that the KFFM was the best model because it had the lowest average percentage of error (0.86%), while the EV and ES models had 3.09% and 3.21%, respectively. Therefore, It should be concluded that the KFFM provides more reliable and robust time predictions than the other two deterministic EV and ES models. The KFFM developed in this study provides probabilistic prediction bounds of project duration at completion and can be applied in a project with smaller errors than those observed in EV and ES forecasting methods. In addition, KFFM for time forecasting is a probabilistic, provide information about the range of possible outcomes, and the probability of meeting the project objectives (duration only). A limitation of the KFFM is that it is applicable only to the prediction of project duration at completion, not to the prediction of project cost at completion (EAC). However, Kalman filter approach can be extended to forecast of the cost at completion so that schedule and cost forecasting can be integrated within a consistent methodology.

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