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Earned value project management: Improving the predictive power of planned value

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Abstract

Earned value project management (EVPM) is an effective tool for managing project performance. However, most studies on extensions and applications of EVPM concentrate on improving final cost and duration estimates rather than improving upon the use of planned value (PV) to predict earned value (EV) and actual cost value (AC). This study proposes a straightforward modeling method for improving the predictive power of PV before executing a project. By using this modeling method, this study develops EV and AC forecasting models for four case projects. Out-of-sample forecasting validation using mean absolute percentage error (MAPE) demonstrates that the proposed method improves forecasting accuracy by an average of 23.66% and 17.39%, respectively, for EV and AC. This improvement on PV's predictive power prior to project execution provides management with more reliable predictive information about EV and AC performance, allowing for effective proactive action to ensure favorable performance outcomes.

Keywords: Earned value management; Planned value; Earned value; Actual cost; Prediction

1. Introduction

Project management studies widely assume that predictions of project performance guide management to engineer critical issues scientifically, allowing for proactive project performance management. Several researchers have proposed predictive models and approaches to better estimate project performance (Brandon, 1998; Brown, 1985; Chen, 2013, 2014; Cioffi, 2005, 2006a, 2006b; Farris et al., 2006; Keil et al., 2003). The level of detail in these models and approaches varies considerably with their various purposes and assumptions about information availability.

Earned value project management (EVPM), a method that employs scope, cost, and schedule to measure and communicate the real physical process of a project (Vanhoucke and Vandevoorde, 2007), is the most commonly used of the project performance forecasting approaches reviewed. EVPM produces variance and performance indices for project costs and schedules, and thus predicts project costs and schedules at completion, providing early indications of expected project performance results. A broad consensus exists among researchers and practitioners (Anbari, 2003, 2004; Christensen, 1998, 1999; Kim, 2014; Lipke, 2003; Lipke et al., 2009; Narbaev and Marco, 2014; Project Management Institute, 2013) about the usefulness of EVPM for monitoring and predicting project performance, and EVPM has become an important component of successful project management (Marshall, 2006, 2007; Marshall

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et al., 2008), with considerable research on the extensions and applications of EVPM being published.

Despite the panoply of EVPM studies, prior studies (Anbari, 2003, 2004; Cioffi, 2006a; Henderson, 2003; Lipke et al., 2009; Vanhoucke and Vandevoorde, 2007) focus on enhancing the accuracy and reliability of predicting the final cost and duration of a project. Relatively few address improving the predictive power of planned values, considered initial estimates of earned values, and actual costs prior to project execution. As a result, there appears to be a lack of models capable of enhancing the prediction accuracy of earned values and actual costs before execution of projects.

The rest of the paper is organized as follows. Section 2 reviews related EVPM studies, Section 3 presents the research question and methodology, and Section 4 depicts the data, model building, and validation. Section 5 presents the research summary and conclusions. Section 6 describes research limitations and direction for future research.

2. Background

We first offer some definitions: planned value (PV) is the cumulative planned value as a continuous or periodic function summing the approved budget for accomplishing the scheduled work (activity, work package, or project) as a function of time. Earned value (EV) is the cumulative earned value either as a continuous or periodic sum of the approved budget for work performed to date. Actual cost (AC) is the cumulative actual cost value either as a continuous or periodic sum of the actual cost of work performed to date. PV, EV, and AC are respectively the budgeted cost of work scheduled (BCWS), the budgeted cost of work performed (BCWP), and the actual cost of work performed (ACWP).

PV, EV, and AC are the fundamental metrics of the earned value project management (EVPM) that generates variance and performance indices for financial performance and schedules. EVPM forecasts project costs and schedules at completion, providing early indications of expected project financial and scheduling results based on current information. Aside from that, the time-phased representation of PV is the performance-management baseline of a project, PV is actually the predictor for both EV and AC.

Specifically, PV predicts EV and AC prior to work performed at a given time in project. EV and AC are then measured subsequent to work performed at that certain point of time. The project manager then uses these measured values of EV and AC to evaluate project performance status.

Considerable research has been devoted to the extensions and applications of EVPM for project cost performance and schedule control (Batselier and Vanhoucke, 2015; Brandon, 1998; Brown, 1985; Christensen and Daniel, 1995; Colin and Vanhoucke, 2014; Kim, 2000; Kim et al., 2003). For example, Anbari (2003, 2004) shows the major aspects of EVPM and provides logical extensions for forecasting project cost (or earnings) and completion time using several scenarios, such as that the original cost (or time) estimate is flawed, that past cost (or time) performance is (or is not) a good predictor, and that the project will meet its original cost (or time) target upon completion, regardless of prior performance.

Cioffi (2006b) provided EVPM with a novel formalism derived from a scientific notation, allowing EVPM to extend easily to predicting project cost (or earnings) and duration. Vandevoorde and Vanhoucke (2006) presented a generic forecasting model based on the earned schedule (ES) method to predict project duration, which is applicable in different situations, including those involving a learning curve. Vanhoucke and Vandevoorde (2007) further validated their generic forecasting model by performing extensive simulations on a large set of 3100 generated networks created with 30 project activities based on nine simulation scenarios.

Subsequent work by Lipke et al. (2009) refined the EVPM and ES methods to include the confidence limits of prediction, thereby placing high and low bounds on forecasted costs (or earnings) and duration and thus improving project managers' abilities to make informed decisions. Chou et al. (2010) developed EVPM into a web-based visualized-implementation system, enabling managers to monitor, evaluate, and estimate project financial and scheduling performance by converting project data into manageable information clusters. Hanna (2012) presented a case study to illustrate the use and applicability of EVPM in the electrical construction industry. He concluded that early determination of probable project outcomes is possible with reasonable forecasting accuracy by EVPM.

Recently, Elshaer (2013) refined the EVPM and ES methods by integrating activity-based sensitivity information into the earned value calculations to remove and/or decrease false warning effects caused by non-critical activities, and thus improved the forecasting accuracy of project durations during project execution. Naeni et al. (2014) further developed EVPM into a fuzzy-based model using linguistic terms and fuzzy theory, enabling management to analyze, evaluate, and estimate project costs and scheduling performance under uncertainty during project execution.

More recently, Chen (2014) proposed a linear data-transformation formula and used data from 131 sample projects to demonstrate that the formula significantly improves the correlations between PV and EV and between PV and AC. He developed a mathematical model which he claimed can improve the prediction accuracy of EV and AC through further modeling PV prior to the project's execution stage.

Acebes et al. (2015) proposed a framework based on EVPM, Monte Carlo simulation, and statistical learning techniques for project control under uncertainty. They used a case project to demonstrate how to estimate the probability of cost overruns and the expected project duration during project execution. They concluded that their framework can detect anomalies with regard to possible correlations between project time and cost.

Vanhoucke and Colin (in press) assessed four multivariate regression methods for monitoring the activity level performance of an ongoing project from EVPM/ES observations. Based on a database of project networks, they concluded that using kernel principal component regression method with a radial base function kernel outperforms the other presented regression methods.

In particular, Chen's (2014) EVPM forecasting approach attempts to improve the forecasting accuracy of PV prior to project execution. However, Chen's (2014) model implicitly assumes the duration estimate of a project prior to its execution to be or nearly be 100% accurate. Such an assumption not only is difficult to meet in practice but also makes the prediction accuracy of PV subject to duration estimation. Thus, we suggest modeling extensions to improve the predictive power of PV prior to project executing. Enhancing PV's predictive power prior to project execution is important, since it provides management with more reliable predictive indications of project performance (EV and AC) before work begins, thus allowing an effective proactive action to advance favorable performance outcomes before it is too late.

3. Research methodology

The previous section suggests that existing extensions of EVPM are inadequate to improve the accuracy of EV and AC predictions prior to project execution. In response to this limitation, this study poses the following research question: *How can we enhance the predictive power of PV prior to project execution?*

A two-fold methodology is adopted to answer this research question. Based on Chen's (2014) logarithm linear transformation (LLT), we first convert the PV data. The LLT equation proposed by Chen (2014) is one of the simplest transformations capable of converting the relationship of PV, EV, and AC into a nearly linear relationship. This equation is found by the natural logarithm of project percentage completion multiplied by project time, which applies to both the dependent and independent variables:

$$\text{Logarithm Linear Transformation} = t\ln\left(PC^{i}_{j}(t)\right)\quad t = 1,\ 2,\ \ldots, n \tag{1}$$

where i denotes the budgeted cost (bc), the work scheduled (ws), the work performed (wp), or the actual cost (ac) of a project; j denotes the project's PV, EV, or AC; t denotes the time between project start and completion; ln is the natural logarithm; and n is the project's duration in days. For example, $PC^{ac}_{AC}(t)$ denotes the percentage completion of the actual cost for a project's AC for time t; $PC^{wp}_{AC}(t)$ denotes the percentage completion of the work performed for a project's AC for time t.

In the second stage, we propose a mathematical modeling procedure that combines time-series and linear regression analysis, starting with the following simple time-series regression model:

$$Y_t = \alpha + \beta X_t + \varepsilon_t \tag{2}$$

where Y_t is the matrix whose tth element is $y(t) = t\ln(PC^{i}_{j}(t))$, denoting a response variable at time t; X_t is the matrix whose tth element is $x(t) = t\ln(PC^{i}_{j}(t))$, denoting explanatory variables at time t; α is the y-intercept; β is the slope; and ε_t is the vector of random errors. The equation for the predicted EV is expressed as follows:

$$P\hat{C}^{wp}_{EV}(t) = EXP\left(\frac{\hat{\alpha}_{PV}}{t}\right) + EXP\left(\hat{\beta}_{PV}\ln\left(PC^{bc}_{PV}(t)\right)\right) \tag{3}$$

where

$$\hat{\beta}_{PV} = \frac{S_{\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)\left(t\ln\left(PC^{ws}_{PV}(t)\right)\right)}}{S_{\left(t\ln\left(PC^{bc}_{PV}(t)\right)\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)\right)}} \text{ and} \tag{4}$$
$$\hat{\alpha}_{PV} = \overline{t\ln\left(PC^{ws}_{PV}(t)\right)} - \hat{\beta}_{PV}\overline{t\ln\left(PC^{bc}_{PV}(t)\right)}$$

where

$$S_{\left(t\ln\left(PC^{bc}_{PV}(t)\right)\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)\right)} = \sum\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)^2 - \frac{\left(\sum t\ln\left(PC^{bc}_{PV}(t)\right)\right)^2}{n}$$

$$S_{\left(t\ln\left(PC^{bc}_{PV}(t)\right)\left(t\ln\left(PC^{ws}_{PV}(t)\right)\right)\right)} = \sum\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)\left(t\ln\left(PC^{ws}_{PV}(t)\right)\right) - \frac{\sum\left(t\ln\left(PC^{bc}_{PV}(t)\right)\right)\sum\left(t\ln\left(PC^{ws}_{PV}(t)\right)\right)}{n}$$

The equation for the predicted AC can be expressed as follows:

$$P\hat{C}^{ac}_{AC}(t) = EXP\left(\frac{\hat{\alpha}_{EV}}{t}\right) + EXP\left(\hat{\beta}_{EV}\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right) \tag{5}$$

where

$$\hat{\beta}_{EV} = \frac{S_{\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\left(t\ln\left(PC^{bc}_{EV}(t)\right)\right)}}{S_{\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)}} \text{ and} \tag{6}$$
$$\hat{\alpha}_{EV} = \overline{t\ln\left(PC^{bc}_{EV}(t)\right)} - \hat{\beta}_{EV}\overline{t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)}$$

where

$$S_{\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)} = \sum\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)^2 - \frac{\left(\sum t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)^2}{n}$$

$$S_{\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\left(t\ln\left(PC^{bc}_{EV}(t)\right)\right)} = \sum\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\left(t\ln\left(PC^{bc}_{EV}(t)\right)\right) - \frac{\sum\left(t\ln\left(P\hat{C}^{wp}_{EV}(t)\right)\right)\sum\left(t\ln\left(PC^{bc}_{EV}(t)\right)\right)}{n}$$

Model restructuring for remedial measures of seasonal cycles ensures that our parameter estimates are efficient. Because the effects of seasonal cycles require tests of a higher-order autoregressive process, the study incorporates the generalized Durbin–Watson statistic (Vinod, 1973) to detect the effects of seasonal cycles (or autocorrelated errors that occur when a correlation between two or more consecutive error terms is

Table 1
Sample projects used to demonstrate the development of EV and AC models.

Project name	Project description	Type of contract	Category	Budget at completion	Cost at completion	Planned duration	Actual duration
ST	Steel tank project for chemical waste storage	Fixed-price contract	Early finish over budget	NTD [a] 3,172,140	NTD 3,212,850	262 days	212 days
GDP	Gas duct and pipe project for a manufacturing company	Fixed-price contract	Early finish under budget	NTD 11,000,000	NTD 10,200,000	345 days	231 days
DP	Distance pipe project for an engineering company	Fixed-price contract	Late finish over budget	NTD 1,803,500	NTD 1,998,500	107 days	231 days
RPS	Raw and product silo project for a manufacturing company	Fixed-price contract	Early finish over budget	NTD 29,103,200	NTD 31,988,200	180 days	177 days

[a] New Taiwan dollars, where 1 New Taiwan dollar = 0.032819 U.S. dollars.

present), specified as:

$$d_p = \frac{\sum_{t=p+1}^{n} \left(\hat{v}_t - \hat{v}_{t-p}\right)^2}{\sum_{t=1}^{n} \hat{v}_t^2} \tag{7}$$

where d_p is the pth order Durbin–Watson statistic and $\hat{v}_t$, $t = 1$ to n are the residuals from $\hat{v} = Y - X\hat{\beta}$. In situations where autocorrelation is present, Yule–Walker estimates (used for autocorrelation correction in regression analysis) are then performed to estimate the set of autoregressive parameters (Shumway and Stoffer, 2000) for model restructuring, specified as:

$$\hat{\phi} = \hat{R}_p^{-1} \hat{\rho}_p, \ \hat{\sigma}_w^2 = \hat{r}(0) - \hat{\phi}' \hat{r}_p \tag{8}$$

where $\hat{\phi}' = (\hat{\phi}_1 \hat{\phi}_2 \ldots \hat{\phi}_p)$ is the vector of autoregressive parameters, $\hat{R}_p = \{\hat{\rho}(k-1)\}_{j,\,k=1}^{p}$ is the matrix of the autocorrelation function (ACF), $\hat{\rho}_p' = (\hat{\rho}(1)\hat{\rho}(2)\cdots\hat{\rho}(p))$ is the ACF vector, $\hat{\sigma}_w^2$ is the autoregressive variance, and $\hat{r}_p = (\hat{r}(1)\hat{r}(2)\cdots\hat{r}(p))$ is the autocovariance vector.

4. Research results

4.1. The data

Data to support analysis were collected on four sample projects using case study research protocols (Yin, 2003), including the use of multiple data sources (where possible) to ensure the quality of the data collected. The names of these projects have been changed at the request of the companies involved. The collected data include detailed scheduling, budget, cost, contract, and characteristic data for the sample projects.

The ST project, a chemical waste storage tank, was finished within schedule but was over budget. ST's respective planned costs, actual costs, planned duration, and actual duration are, respectively, NTD 3,172,140, NTD 3,212,850, 262 days, and 212 days. The GDP project, a gas duct and pipe construction project, was completed early and within budget. GDP's planned costs, actual costs, planned duration, and actual duration are, respectively, NTD 11,000,000, NTD 10,200,000, 345 days, and 231 days.

The DP project, a distance pipe construction project, was finished behind schedule and over budget. DP's respective planned costs, actual costs, planned duration, and actual duration are NTD 1,803,500, NTD 1,998,500, 107 days, and 231 days. The RPS is a raw and product silo project that was finished ahead of schedule but was over budget. The respective planned costs, actual costs, planned duration, and actual duration of RPS are NTD 29,103,200, NTD 31,988,200, 180 days, and 177 days. These sample projects are summarized in Table 1. Due to space limitations, this study only presents a project's complete modeling process, but the rest are available from the authors upon request.

4.2. Model building for EV forecasting

Table 2 summarizes the parameter estimates and Durbin–Watson (DW) statistics of ST's EV prediction using Eqs. (3) and (4). As shown in the left side of Table 2, both $\hat{\alpha}_{PV}$ and $\hat{\beta}_{PV}$ are highly significant with p-values of <0.001, capable of explaining 99.89% of the variation in the $t\ \ln(PC_{PV}^{ws}(t))$ data. As reported in the right side of Table 2, the Durbin–Watson statistics (with a value of 0.0033) suggest a significantly

Table 2
Parameter estimation and Durbin–Watson (DW) statistics of ST's predicted EV, $\hat{PC}_{EV}^{wp}(t)$.

Dependent variable: $t\ \ln(PC_{PV}^{ws}(t))$		Durbin–Watson statistics			
Variables	Coefficient	Order	DW	Probability < DW	Probability > DW
Intercept	$\hat{\alpha}_{PV} = -0.00397$***	1	0.0033	<0.01	1.00
$t\ \ln(PC_{PV}^{bc}(t))$	$\hat{\beta}_{PV} = 0.98450$***				
Total R^2	0.9989				

*$P < 0.05$.
**$P < 0.01$.
***$P < 0.001$.

Table 3
Parameter estimation and Durbin–Watson (DW) statistics of ST's predicted EV, $P\hat{C}_{EV}^{wp}(t)$, subsequent to Yule–Walker estimators.

Yule–Walker estimates				Durbin–Watson statistics after Yule–Walker estimates				Parameter estimation after Yule–Walker estimates	
Source A	Value of source A	Source B	Value of source B	Order	DW	Probability < DW	Probability > DW	Variables	Coefficient
SSE	0.00004	DFE	255.00000	1	0.5230	<0.01	1.00	Intercept	$\hat{\alpha}_{PV}$ = −0.00395***
MSE	0.00001	Root MSE	0.00044					t ln($PC_{PV}^{bc}(t)$)	$\hat{\beta}_{PV}$ = 0.99100***
SBC	−3272.63090	AIC	−3297.60930						
Regress R^2	0.99540	Total R^2	0.99999					Total R^2	0.99999

Note: SSE = sum of squares for error; SBC = Schwarz's Bayesian criterion; DFE = degree of freedom for error; AIC = Akaike's information criterion.
*P < 0.05.
**P < 0.01.
***P < 0.001.

positive autocorrelation in the model on the basis of the 0.05 threshold value.

Yule–Walker estimates were thus performed to estimate the set of autoregressive parameters for model restructuring, shown in the left portion of Table 3. The center portion of Table 3 shows the test results of Durbin–Watson statistics after Yule–Walker estimates, indicating that autocorrelation is largely alleviated from a value of 0.0003 to a value of 0.5230 for the Durbin–Watson statistics, although it is still significant.

The left portion of Table 3 reports the parameter estimates of ST's EV prediction after Yule–Walker estimates. The model explains 99.99% of the variation in the t ln($PC_{PV}^{ws}(t)$) data, which is 0.10% more before model restructuring.

4.3. Model building for AC forecasting

Table 4 reports the parameter estimates and Durbin–Watson (DW) statistics of ST's AC prediction using Eqs. (5) and (6). The left portion of the table reveals that $\hat{\alpha}_{PV}$ and $\hat{\beta}_{PV}$ are highly significant with p-values of <0.001; it explains 99.99% of the variation in the t ln($PC_{EV}^{bc}(t)$) data. As the right side of Table 4 shows, the Durbin–Watson statistics (with a value of 1.9420) suggest an insignificant positive or negative autocorrelation in the model on the basis of the 0.05 threshold value. Therefore, this study concludes that there is no need for model restructuring.

4.4. Evaluation of forecast accuracy

To assess the accuracy of our EV and AC forecasting models, data were analyzed using two independent approaches: pattern-matching logic (Trochim, 1989) and the mean absolute percentage error (MAPE) (Chen, 2010). Pattern-matching logic compares an empirically based pattern with a predicted one. For this study, the historical EV and AC for each project were used as empirical bases for comparison with EV and AC predictions generated from the original PVs and our EV and AC response models. If certain patterns of forecasts and those of historical EV and AC are closely matched, a strong causal inference can be made.

While pattern-matching logic supports analysis of empirical observations, a weakness of the approach is that it does not provide a quantitative measure of the improvement achieved by our models. In contrast, MAPE provides a measure for evaluating out-of-sample forecasting accuracy, which is calculated as:

$$\text{MAPE} = \frac{1}{n}\sum |(y_t - \hat{y}_t)/y_t| \tag{9}$$

where y_t is the actual value of data at time t in the out-of-sample forecasts, $\hat{y}_t$ is the predicted value for y_t, and n is the number of days of out-of-sample forecast data. When autocorrelated errors are not present, the respective EV and AC response models are denoted as $P\hat{C}_{EV}^{wp}(t)$ (Eq. (3)) and $P\hat{C}_{AC}^{ac}(t)$ (Eq. (5)). The EV and AC response models are respectively denoted as $P\hat{C}_{EV}^{wp}(t)_{MR}$ and $P\hat{C}_{AC}^{ac}(t)_{MR}$ after model restructuring for the effect of autocorrelated errors on $P\hat{C}_{EV}^{wp}(t)$ and $P\hat{C}_{AC}^{ac}(t)$.

Fig. 1 plots the PV, EV, and AC curves of the ST project prior to data transformation. Fig. 2 plots the transformed PV, EV, and AC curves of the ST project using Chen's (2014) LLT = $t \times \ln(PC_j^i(t))$. Fig. 3 depicts pattern matching among ST's actual EV (red curve), predicted EV (black curve) created with $P\hat{C}_{EV}^{wp}(t)_{MR}$, and predicted EV (blue curve) created with PV. Fig. 4 depicts pattern matching among ST's actual AC (red curve), predicted AC (black curve) by $P\hat{C}_{AC}^{ac}(t)$, and predicted AC (blue curve) using PV.

Table 4
Parameter estimation and Durbin–Watson (DW) statistics of ST's predicted AC, $P\hat{C}_{AC}^{ac}(t)$.

Dependent variable: t ln($PC_{EV}^{bc}(t)$)		Durbin–Watson statistics			
Variables	Coefficient	Order	DW	Probability < DW	Probability > DW
Intercept	$\hat{\alpha}_{EV}$ = 0.00251***	1	1.9420	0.26	0.68
t ln($P\hat{C}_{EV}^{wp}(t)$)	$\hat{\beta}_{EV}$ = 1.0080***				
Total R^2	0.9999				

*P < 0.05.
**P < 0.01.
***P < 0.001.

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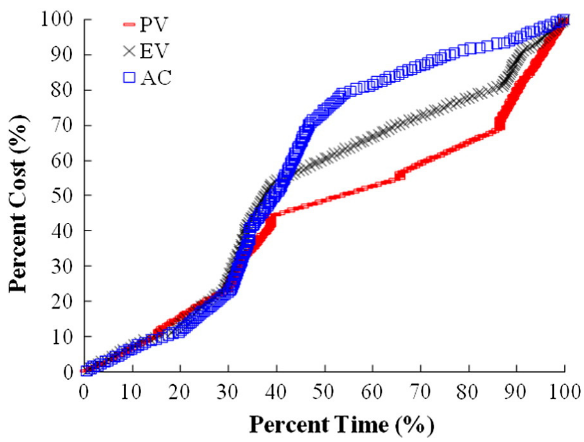

Fig. 1. Scatterplot of the project ST's PV, EV, and AC data.

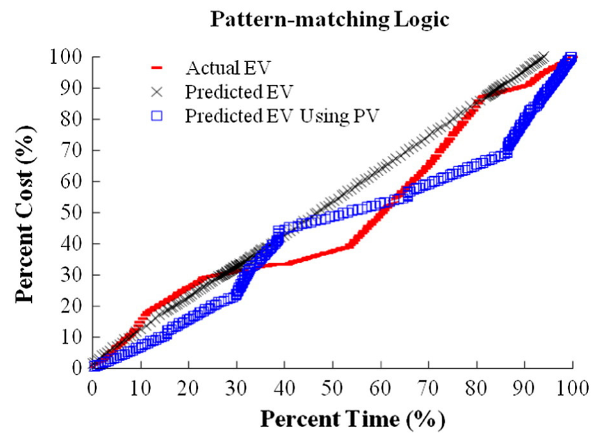

Fig. 3. Pattern matching: comparison of project ST's actual EV, predicted EV by $P\hat{C}^{wp}_{EV}(t)$, and predicted EV by PV.

As seen in Figs. 3 and 4, ST's respective predicted EV (black curve) and AC (black curve) with $P\hat{C}^{wp}_{EV}(t)_{MR}$ and $P\hat{C}_{\bar{A}C}$ *$^{ac}(t)$ appear to have smaller deviations from its actual EV and AC than those (blue curves) by PV.*

The study develops similar EV and AC forecasting models for the other three projects. Table 5 summarizes the analysis of the out-of-sample forecast data sets from the EV and AC models for projects ST, GDP, DP, and RPS. Due to space limitations, the complete modeling details and related figures for those projects are available from the authors upon request.

To evaluate the improved predictive performance, the MAPE values are then compared to the forecasting results of the projects' PV curves, where a project's PV curve is the predictor of EV and AC prior to project execution.

As Table 5 shows, the respective MAPE values of the EV and AC response models for projects ST, GDP, DP, and RPS are (10.80%, 17.99%), (19.61%, 19.71%), (9.69%, 57.60%), and (10.94%, 4.17%), respectively. In contrast, those directly using PV curves are (12.33%, 30.89%), (81.62%, 73.00%), (20.16%, 59.38%), and (31.55%, 5.77%). The proposed models improved EV and AC forecasts by 23.66% and 17.39%, respectively, compared to the initial estimates by PV. This comparison suggests that the proposed models could be viable for enhancing the predictive performance of PV, thus providing more accurate EV and AC predictions before executing a project.

5. Summary and conclusions

This paper presents a step-by-step methodology for enhancing the predictive power of PV. Based on Chen's (2014) logarithm linear transformation, this study combines time-series and regression analysis to develop PV into an EV response model for predicting $P\hat{C}^{wp}_{EV}(t)$. Through modeling the relationship between $P\hat{C}^{wp}_{EV}(t)$ and $PC^{bc}_{EV}(t)$ depicted in the EV response model, this study further develops EV into an AC response model for predicting $P\hat{C}^{ac}_{AC}(t)$. The results show that the proposed models improve the predictive performance of EV and AC by 23.66% and 17.39%, respectively.

Adding to the benefits of current EVPM prediction models that provide management with predictions of project schedules and costs at completion (Anbari, 2003, 2004; Cioffi, 2006b; Henderson, 2003; Lipke et al., 2009; Vanhoucke and Vandevoorde, 2007), this study contributes a methodology capable of improving predictive performance of PV. Specifically, the present research extends the state of knowledge about the predictive power of PV by further modeling PV prior to project

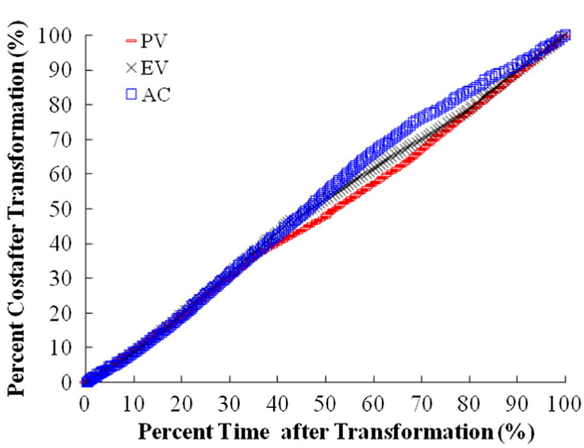

Fig. 2. Scatterplot of the PV, EV, and AC data of project ST using Chen's (2014) logarithm linear transformation = $t \times \ln(PC^i_j(t))$.

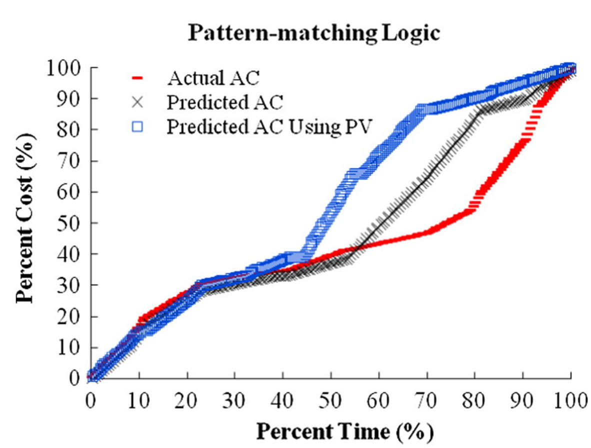

Fig. 4. Pattern matching: comparison of project ST's actual AC, predicted AC by $P\hat{C}^{ac}_{AC}(t)$, and predicted AC by PV.

Table 5
Comparison of the MAPE values of the prediction models to those of the projects' PV curves.

Project	Prediction model	MAPE	MAPE of theprojects' PV curves	Improved MAPE
ST	$P\hat{C}_{EV}^{wp}(t)_{MR}$	10.80%	12.33%	1.52%
	$P\hat{C}_{AC}^{ac}(t)$	17.99%	30.89%	12.90%
GDP	$P\hat{C}_{EV}^{wp}(t)_{MR}$	19.61%	81.62%	62.01%
	$P\hat{C}_{AC}^{ac}(t)$	19.71%	73.00%	53.28%
DP	$P\hat{C}_{EV}^{wp}(t)_{MR}$	9.69%	20.16%	10.47%
	$P\hat{C}_{AC}^{ac}(t)$	57.60%	59.38%	1.78%
RPS	$P\hat{C}_{EV}^{wp}(t)_{MR}$	10.94%	31.55%	20.62%
	$P\hat{C}_{AC}^{ac}(t)$	4.17%	5.77%	1.59%

Note: Computation of MAPEs is based on 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, and 95% completion of project time. The average improvements of the prediction models over the PV curves in EV and AC forecasting performance are 23.66% and 17.39%, respectively.

execution. As such, this paper provides a fundamental improvement in EVPM.

6. Limitations and future research

While the results of this study provide the potential for improving the predictive power of PV prior to project execution, some limitations of this study point to opportunities for future research. First, while this study uses four sample projects with different conditions to demonstrate the proposed methodology and the research results are statistically sound, making generalized claims based on the results would require further empirical testing. Specifically, more research is necessary to generalize the proposed methodology and broaden the area of its applicability.

Second, although this study presents the proposed modeling method systematically and in detail, project managers and/or engineers may still have difficulty applying the method in practice. Future research could further develop the modeling method into a software system to increase ease of use for project management practitioners.

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