Earned Schedule Forecasting Method Selection[1]

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Abstract

Recent research indicates Earned Schedule (ES) forecasting from Earned Value Management data is generally improved when the performance factor, PF=1, is used. However, the use of the ES schedule performance index, SPI(t), remains as accepted practice and, at times, provides the better deterministic forecast. It is postulated that there may be recognizable conditions for which one method is preferable. This paper is an investigation to discern those conditions.

Introduction

The authors, Batselier and Vanhoucke (B&V) examined several methods of forecasting in their paper, "Empirical Evaluation of Earned Value Management Forecasting Accuracy for Time and Cost" [Batselier et al, 2015]. Their research comprehensively evaluated forecasting using Earned Value Management (EVM) data from 51 projects, predominantly construction. The results of the research demonstrated the use of performance factor, PF=1, with the Earned Schedule (ES) method often provides the more accurate deterministic forecast.

Independently, the B&V finding was corroborated, albeit with a smaller amount of data [Lipke, 2017]. Of the 16 projects examined, ES forecasting using PF=1 was shown to provide better results for 12. Beyond affirming the B&V research, the application of PF=1 to statistical forecasting was examined. Additionally, an observation was made that when performance variation is small, forecasting with the ES schedule performance index, SPI(t), is usually better.

The good showing by PF=1, in both cited papers, was surprising and unexpected. Although PF=1 more often provides the better forecast, curiosity was created as to why it is not always so; there are several instances when SPI(t) is preferred. Because the examinations involved real data, there was some concern as to whether the data sets

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represented a very localized set of conditions, or if there were anomalies. That is, do peculiarities within the data examined cause the forecasting performance of PF=1 to be enhanced? For instance, management actions, such as re-plans, can obscure performance and cause the SPI(t) value to be close to 1.0. Of course, when the index value is close to 1.0, it is very likely that PF=1 provides the better forecast.

Certainly management actions can perturb the forecast and assuredly there are disturbances imbedded in the data. Nevertheless, examination of the data from the second paper did not reveal significant issues causing PF=1 to be preferred. It is now believed that the results from the two studies are reasonably broad-based and representative.

Nevertheless, there is reason to explore; there may be performance characteristics useful for identifying which method is more likely to provide the better forecast. We know by inspection that when performance is close to planned, PF=1 should provide the better forecast. As well, it is easily shown that when performance has little variation, the forecast from SPI(t) is better.

From these observations, the research proposition is made:

Two characteristics determine the selection of the more accurate forecasting method, either PF=1 or SPI(t):

1) *Performance deviation from SPI(t) = 1.0*
2) *Periodic variation in ES*

This paper examines simulated and real data to seek and establish the selection criteria for choosing between PF=1 and SPI(t) forecasting methods. Presuming selection criteria can be established, it is reasoned ES deterministic forecasting will yield increased accuracy and thereby improve decision-making by project managers.

Earned Schedule Review

Earned Schedule is dependent upon EVM; the ES measure is derived from the accrued earned value (EV) and the performance measurement baseline (PMB) [Lipke, 2003].[2] As shown in figure 1, "…the idea is to determine the time at which the EV accrued should have occurred." The time duration from project start to the point on the PMB

[2] It is presumed the reader has knowledge of Earned Value Management.

where the planned value (PV) equals the EV accrued is the earned portion of the planned duration (PD), i.e. ES.

As diagrammed in the figure, determining the value of ES is a simple matter of interpreting the graph. In practice, however, a calculation method is applied. Its description is explained, in detail, in the *Earned Schedule* book [Lipke, 2009].

Having the capability to determine ES and the actual time (AT) at which the EV is reported, the time-based indicators for schedule performance index, SPI(t), and schedule variance, SV(t), are created:

SPI(t) = ES / AT
SV(t) = ES – AT

The index, SPI(t), describes the efficiency of achieving the PD for the time invested. When the value of SPI(t) is 1.0 or greater, schedule performance is good. And, when the indicator value is less than 1.0, performance problems need investigating and correcting. Similarly, when the value of SV(t) is positive, performance is ahead of schedule and when negative, performance is lagging.

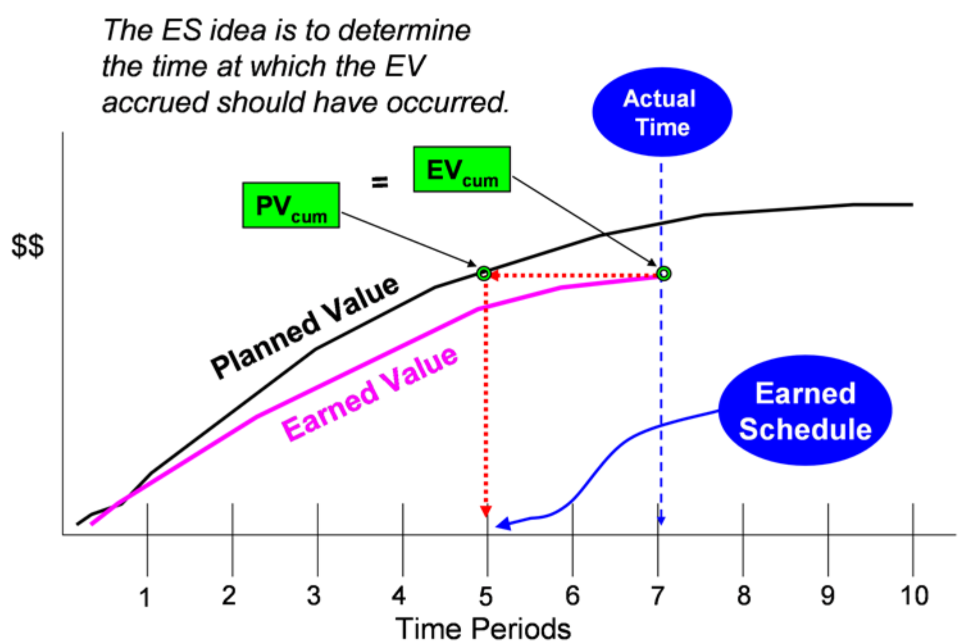

Figure 1. Earned Schedule Concept

Beyond assessing current status, the forecasting of project duration and completion date is made possible using the formulas below:

1) IEAC(t) = PD / SPI(t)

2) IEAC(t) = AT + (PD – ES) / PF

IEAC(t) is the independent estimate at completion (time), i.e. the forecast duration; adding the computed duration to the project start date can be used to forecast the completion date. The PF term, appearing in formula 2, is a performance factor; for example, PF=1, could be used when believed it better represents the expected future execution efficiency.

Methodology

The approach to determine criteria for forecasting selection was a two-step process. The first step simulated project performance, applying variation over a range of values and biasing the outcome from early to late finish. Thirty nine scenarios, representing combinations of variation and bias, were induced in the execution of twenty five simulated projects. The simulated projects were limited to a final duration no greater than 50 periods.

For the simulation, fixed values and variable multipliers were used to create periodic ES values (ESp). The fixed values ranged from 0.15 to 0.80, while the variable multipliers were 0.1, 0.5, and 0.9. Each was applied through a random number, ranging from zero to one. To further explain, let's use the fixed value 0.8; ESp is either 1.8 or 0.2, dependent upon whether the bias is plus or minus. That is, the fixed value is either added to, or subtracted from 1.0. When a variable multiplier is used, it is coupled to a random number to produce the value added or subtracted from 1.0 in the calculation of ESp.

Nine bias values were used, ranging from 0.1, at 0.1 increments, through 0.9. Bias is produced by comparing a random number to the bias value; when the random number is less than one minus the bias value, the periodic ES variation is subtracted from 1.0. Conversely, the variation is added. Bias values above 0.5 cause SPI(t) to be greater than 1.0, while values below 0.5 induce SPI(t) to be less than 1.0.

Utilizing the specified variation and bias values, four sets of examination scenarios were created. The first set viewed large variation over the full range of bias values. The second set examined the range of variation multipliers in three subsets of bias values (0.1, 0.5, and 0.9). Similarly, the third set applied fixed variation multipliers (0.8, 0.5, and 0.2) in three subsets of bias values. Lastly, the fourth set examined combinations of variation and bias to clarify results observed in the three control sets.

For the second step, the tabulated results were inspected for patterns favoring one of the forecasting methods, PF=1 or SPI(t). A process of filtering and graphical analysis was applied for deducing possible forecast method selection rules.

The simulation results for the 39 scenarios were evaluated using the Mean Absolute Percent Error (MAPE) for each forecasting formula. The MAPE for a specific scenario is the computed average across the performance results of the 25 simulated projects.

The scenarios having MAPE favorable to PF=1 were grouped, while those favorable to SPI(t) were likewise placed together. Scatter plot graphs were created for each grouping. The scatter plots are the paired values of the two proposed selection characteristics: natural logarithm (ln) of SPI(t) and the standard deviation (σ) of the natural logarithm of ESp. Just as for MAPE, the two characteristics are represented by the average across the simulations for each scenario.

The patterns recognized in the graphs were used to propose forecasting selection rules. The proposed forecasting method selection rules were then tested using both simulated and real data.

Results/Analysis

An example of the results from the simulations of the 39 scenarios is represented in table 1. The inputs creating distinctive performance scenarios include the following variables:

1) SPI(t) – the initial Schedule Performance Index (time) value for the simulation
2) PD - Planned Duration
3) Fixed Var – Fixed Variable, the value of the fixed variation
4) F or V - choice between fixed (F) or variable (V) type variation
5) Var Mult – Variation Multiplier, the multiplier value when V is chosen
6) Bias “+” - bias value to induce late to early finish performance
7) Trigger – performance stability value

The trigger value was used to determine whether performance stability had influence in the analysis and selection of the forecasting method. There is no further discussion of trigger value; applying performance stability of 0.10 did not significantly impact MAPE results.

	Scenario Inputs							Outcome Averages			Error Results	
Scenario	SPI(t)	PD	Fixed Var	F or V	Var Mult	Bias "+"	Trigger	FD	lnESp σ	lnSPI(t)	MAPE(1)	MAPE(S)
B1	1.000	44	NA	V	0.10	0.10	0.10	46	0.157	-0.034	0.0297	0.0156
B2	1.000	35	NA	V	0.50	0.10	0.10	44	0.299	-0.199	0.1087	0.0463
B3	1.000	24	NA	V	0.90	0.10	0.10	36	0.678	-0.384	0.1694	0.0899
B4	1.000	45	NA	V	0.10	0.50	0.10	46	0.143	-0.002	0.0118	0.0126
B5	1.000	42	NA	V	0.50	0.50	0.10	43	0.336	0.003	0.0271	0.0413
B6	1.000	39	NA	V	0.90	0.50	0.10	40	0.711	-0.001	0.0427	0.0660
B7	1.000	48	NA	V	0.10	0.90	0.10	47	0.126	0.036	0.0126	0.0126
B8	1.000	52	NA	V	0.50	0.90	0.10	44	0.256	0.153	0.0836	0.0295
B9	1.000	56	NA	V	0.90	0.90	0.10	42	0.443	0.287	0.1510	0.0454

Table 1. Scenario Results

As well, the output values from the scenario simulations, Output Averages and Error Results, are depicted in table 1. The definitions of the sub-headings are:

1) FD – Final Duration
2) lnESp σ –the standard deviation of the natural logarithm of the periodic values of ES
3) lnSPI(t) – natural logarithm of cumulative value of SPI(t)
4) MAPE(1) – mean absolute percent error for PF=1 forecasting
5) MAPE(S) – mean absolute percent error for SPI(t) forecasting

A few general observations can be made from analysis of table 1. As expected, the Variation Multiplier induces lnESp σ values; as the multiplier value increases, so does the standard deviation. And, similarly, Bias is reflected in the lnSPI(t) values; bias of 0.1 induces negative numbers (late finish), while 0.9 creates positive numbers (early completion).

Further analysis of table 1 indicates there may be correlation between lnESp σ and MAPE; error increases as variation becomes larger. Additionally, for scenario results having lnSPI(t) values near 0.0, MAPE(1) is seen to be less than MAPE(S); i.e., when SPI(t) is very near the value of 1.0, PF=1 provides the better forecast, although the error difference is very small. This finding was an expectation.

Scatter Plots

With the simulation results for the 39 scenarios, two outcome data sets were created. One contained those having more accurate forecasts from using performance factor PF=1. Of course, the second set contained results when SPI(t) forecasting was more accurate. For each of these sets, scatter plots were made, graphing the paired values of lnSPI(t) and lnESp σ. The scatter plots are shown in figures 2 and 3.

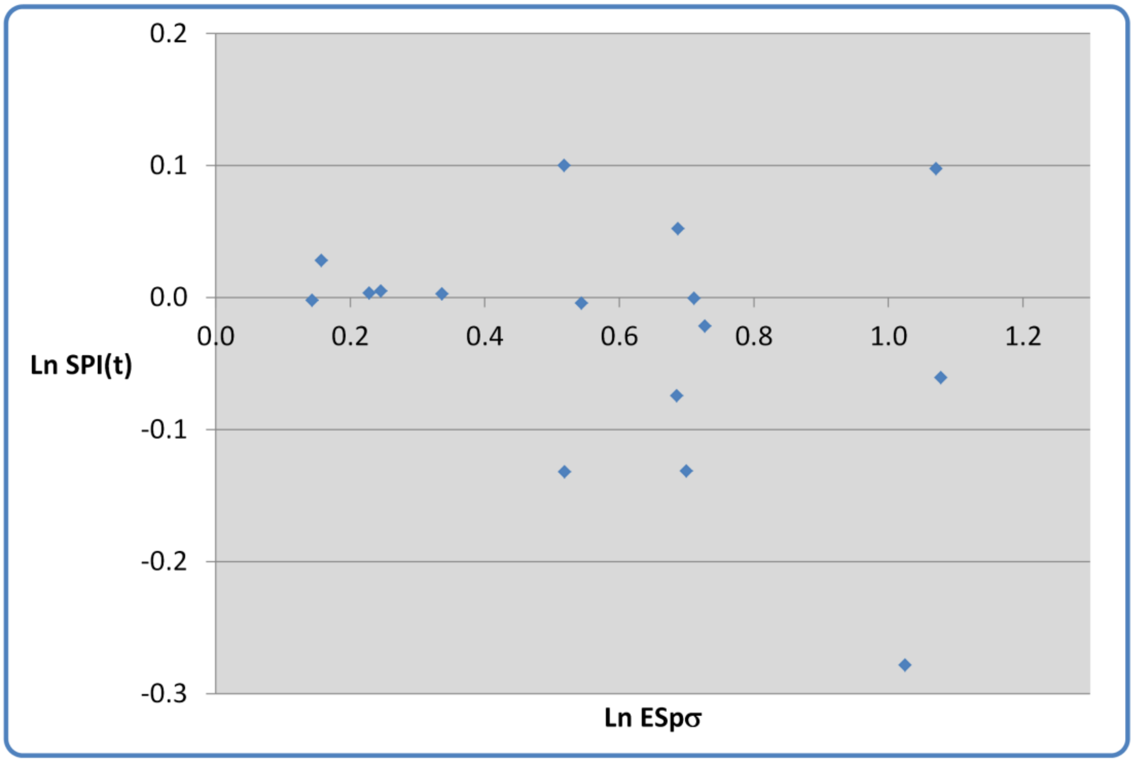

Figure 2. Scatter Plot of PF=1 Set

The scatter plot of figure 2 contains results from 16 scenarios. Clearly, the majority of data points lie between lnSPI(t) values of 0.1 and -0.1. Two of three points outside of this range are near the -0.1 value, while the third appears to be an outlier. All of the results in figure 2, favor PF=1 forecasting by a small percentage, usually less than 2 percent.

Figure 3 is the plot of 23 results favoring SPI(t) forecasting. With one exception, the points reside in the lnESp σ range of 0.0 to 0.8. The one point outside of the range has extremely high variation with an extremely low value for SPI(t). The error results for this point are excessively high; 29.4 percent for PF=1 and 16.7 percent for SPI(t). Similar to analysis of figure 2, this point is considered an outlier. As well, it is observed that all of the points, excluding the outlier, lie in the region of SPI(t) values between, 0.6 and -0.6.

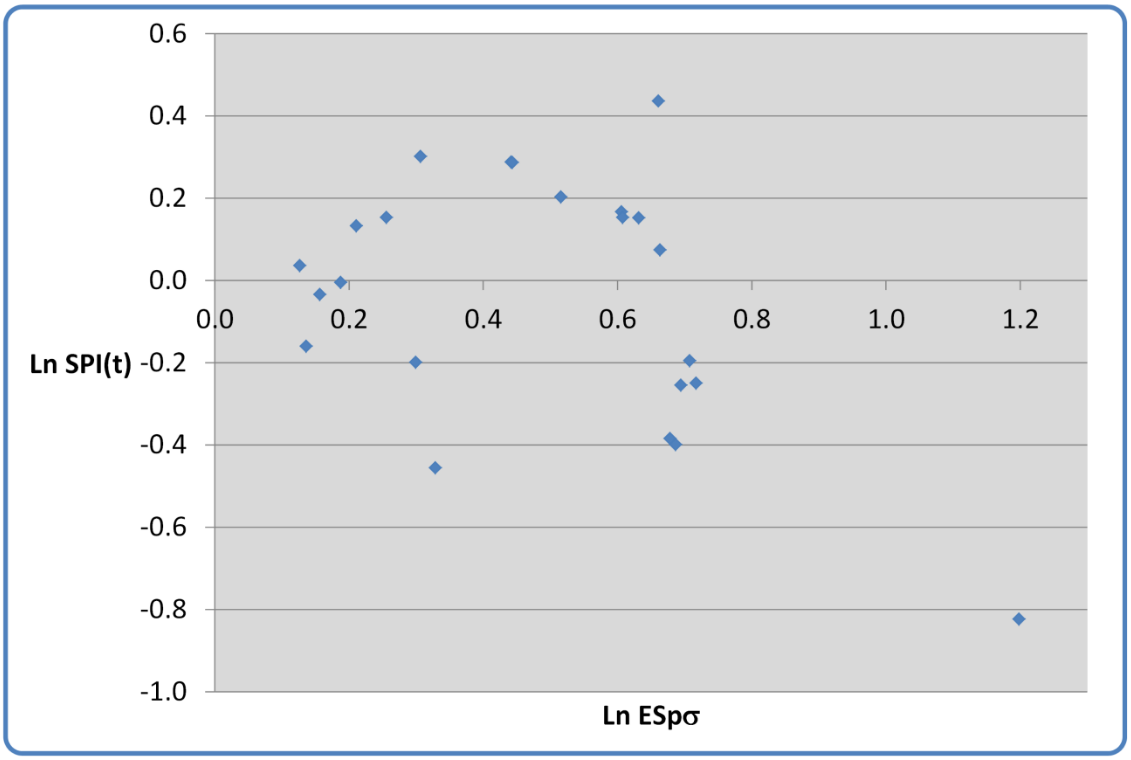

Figure 3. Scatter Plot of SPI(t) Set

Examining the scenario results graphed in figure 3, the following findings were compiled:

1) Three points have nearly the same value of error with PF=1 forecasting
2) Seven points indicate superior SPI(t) forecasting by 10 percent or greater
3) Six points indicate better SPI(t) forecasting in the range of 5 to 10 percent
4) Remaining seven points have a small difference from PF=1 forecasting, generally between 1 to 3 percent difference

Thus, from analysis of the data for the two graphs, 26 of 39 scenarios produce very similar forecasts. Approximately 18 percent of the SPI(t) forecasts are significantly better, while another 15 percent show moderate improvement.

The implication from the above analysis is PF=1 deterministic forecasting is generally good. This statement further confirms the results from the two cited studies. However, there are instances when PF=1 results are significantly less accurate. Obviously then, there is value in being able to discern when SPI(t) forecasting should be used.

Using the observations from figures 2 and 3 scatter plots, selection rules are proposed in table 2. Fundamentally, project managers should use SPI(t) when the indicator's value has some amount of separation from 1.0 and when performance variation is not large. When this is not the situation, PF=1 is preferred. It is to be noted that when out of control performance is encountered, PF=1 is the recommended choice. As identified in table 2, the out of control condition is characterized by extreme performance values for lnSPI(t) and lnESp σ. For this condition, it is usually the case that neither method provides accurate forecasts; generally, the SPI(t) method is worse.

SPI(t) & PF=1 Selection Rules		
Use PF=1	when	-0.1 ≤ lnSPI(t) ≤ 0.1 & lnESpσ ≤ 0.8
Use SPI(t)	when	lnSPI(t) > 0.1 or < -0.1 & lnESpσ ≤ 0.8
Use SPI(t)	when	lnSPI(t) ≤ 0.6 or ≥ -0.6 & lnESpσ ≤ 0.8
Use PF=1	when	-0.6 > lnSPI(t) > 0.6 or lnESpσ > 0.8 = Out of Control

Table 2. Selection Rules

Selection Rules Testing

The proposed rules for selecting between the SPI(t) and PF=1 forecasting methods, specified in table 2, were tested using both simulated and real data, 10 projects each. Analysis information from the testing is compiled in tables 3 and 4. The attributes of interest are identified below:

1) Planned and Final Duration
2) The maximum and minimum values for lnSPI(t) and lnESp σ
3) The number of correct and incorrect selections made, at both zero and five percent tolerance. When the SPI(t) and PF=1 forecasts are within tolerance (i.e., difference between MAPE values), the selection from application of the rules is counted as correct.
4) The number of out of control conditions encountered
5) Four forecasting error modes are tabulated for comparison: Err-SPI(t), Err-PF1, Err-Selection, and Err-Best.

For clarity, each error mode is computed as MAPE. The terminology is defined below:

1) Err-SPI(t) is the error when forecasts are made using only SPI(t)
2) Err-PF1 is the forecasting error when only PF=1 is used
3) Err-Selection is the error when the forecasting selection rules are applied
4) Err-Best represents the least forecasting error possible; i.e., the method (PF=1 or SPI(t)) producing the better forecast is selected at every period of performance

From review of table 3, Selection Rules Test – Simulated Data, the use of the selection rules appears to provide good results in comparison to the other forecasting modes. For eight of the 10 projects, the error shown for Err-Selection is within 1.6 percent of the best forecast, Err-Best. The largest difference is 3.6 percent shown for project 6.

Four projects (1, 2, 3, and 5) have large error when the PF=1 forecasting formula is used. For these projects, application of the selection rules improved the forecasts, on average, by nearly 13 percent, a significant improvement.

Simulated Data										
Project	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PD	24	56	66	39	25	29	35	39	35	52
FD	34	41	43	47	43	33	38	37	43	45
Max lnSPI(t)	0.030	0.364	0.556	-0.105	-0.288	0.113	-0.047	0.197	-0.083	0.163
Min lnSPI(t)	-0.348	0.196	0.336	-0.211	-0.619	-0.264	-0.558	-0.226	-0.271	0.033
Max lnESp σ	0.778	0.690	0.778	0.158	0.490	0.739	1.365	0.679	0.456	0.278
Min lnESp σ	0.483	0.239	0.157	0.050	0.192	0.103	0.607	0.342	0.249	0.089
# Correct - 0%	32	35	32	46	39	10	16	12	40	28
# Wrong - 0%	1	5	10	0	3	22	21	24	2	16
# Correct - 5%	32	40	40	46	39	21	35	31	40	38
# Wrong - 5%	1	0	2	0	3	11	2	5	2	6
# Out of Cntrl	0	0	0	0	3	0	13	0	0	0
Err-SPI(t)	0.082	0.029	0.064	0.012	0.049	0.061	0.082	0.049	0.040	0.023
Err-PF1	0.162	0.167	0.213	0.082	0.209	0.050	0.030	0.033	0.099	0.074
Err-Selection	0.083	0.029	0.064	0.012	0.065	0.068	0.036	0.051	0.043	0.034
Err-Best	0.081	0.027	0.057	0.012	0.049	0.032	0.023	0.026	0.040	0.021

Table 3. Selection Rules Test – Simulated Data

From comparison of the correct and wrong selections at zero and five percent tolerance, it can be deduced that there are many times when PF=1 and SPI(t) methods compute nearly the same forecast values. For 5 percent tolerance, a significant increase in the number correct is seen for six projects (2, 3, 6, 7, 8, and 10).

Project number 7 is shown to have thirteen out of control periods. As could be expected, there is a large difference between maximum and minimum lnSPI(t), 0.511. As well, the variation indicated by lnESp σ is incredibly large. The maximum is equal to 1.365, while the minimum is 0.607. Although 13 of 38 periods were identified to be out of control, the selection rules forecast was very good at 3.6 percent error.

The real EVM data used for the selection rules testing come from high technology projects; it is a subset of the data examined in the second paper cited [Lipke, 2017]. Table 4 compiles the testing results in the same format used for table 3. A characteristic of the data is project performance is highly erratic. The range of values for lnSPI(t) and lnESp σ is large for several projects. As well, four projects (3, 5, 7, and 9) have a large number of out of control performance periods. Thus, as should be expected, the forecasting error values are somewhat larger than are those for the simulated data, on average 3.7 percent higher for the best forecasts.

Eight of the 10 projects have selection forecasts comparing favorably to their corresponding best forecasts; they are within a difference of five percent. The two remaining have differences of 7.2 and 7.8 percent, not excessively large values.

Real Data										
Project	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
PD	21	32	43	24	41	29	43	17	44	42
FD	24	38	47	24	50	30	50	23	50	50
Max lnSPI(t)	0.668	0.130	0.000	0.079	-0.060	0.053	0.000	0.005	0.505	0.021
Min lnSPI(t)	-0.134	-0.343	-0.539	-0.134	-0.693	-0.273	-0.431	-0.480	-0.524	-0.693
Max lnESp σ	1.014	0.630	0.933	0.343	1.564	0.602	1.224	0.739	0.951	0.946
Min lnESp σ	0.435	0.034	0.285	0.200	0.631	0.000	0.000	0.042	0.380	0.443
# Correct - 0%	9	14	18	20	15	21	24	8	14	27
# Wrong - 0%	14	23	28	3	33	8	25	14	35	22
# Correct - 5%	17	35	31	20	31	23	43	14	37	39
# Wrong - 5%	6	2	15	3	17	6	6	8	12	10
# Out of Cntrl	3	0	23	0	22	0	31	0	20	2
Err-SPI(t)	0.187	0.090	0.134	0.041	0.077	0.067	0.058	0.138	0.156	0.100
Err-PF1	0.129	0.093	0.050	0.015	0.071	0.034	0.067	0.131	0.067	0.093
Err-Selection	0.156	0.093	0.111	0.031	0.086	0.063	0.064	0.149	0.124	0.096
Err-Best	0.125	0.075	0.039	0.015	0.044	0.034	0.039	0.103	0.056	0.070

Table 4. Selection Rules Test – Real Data

Just as for the simulated data, several projects (2, 4, 5, 6, 7, 8, and 10) showed that many of the SPI(t) and PF=1 forecasts are within a difference of five percent. As well, the review of tables 3 and 4 revealed another characteristic; in general, poor forecasts for the simulated data were made using PF=1 (projects 1, 2, 3, and 5), whereas for the real data it was observed for the SPI(t) method (projects 1, 3, and 9).

Another analysis of applying the selection rules is given in tables 5 and 6. These tables provide succinct evaluation for the following characteristics:

1) S & 1 within 5% – "yes" is shown when SPI(t) and PF=1 methods produce overall forecast results within five percent, otherwise "no"
2) S or 1 Better? – when the overall forecast using SPI(t) has less error, "S" is entered, otherwise "1"
3) Select Improve? – "yes" is entered when the value for Err-Selection is less than either Err-SPI(t) or Err-PF1 methods, otherwise "no"

In comparing the results tabulated for the two tables, two differences stand out. The "S & 1 within 5%" characteristic occurs only once for the simulated data, whereas for the real data it is seen for seven projects. For the "S or 1 Better?" evaluation, SPI(t) forecasting is better for the simulated data, while PF=1 is dominant for real data. However, it is recognized that among the eight projects having a better forecast from PF=1, six have forecast values within 5 percent from the SPI(t) values.

Simulated Data										
Project	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
S & 1 within 5%?	no	no	no	no	no	yes	no	no	no	no
S or 1 Better?	S	S	S	S	S	1	1	1	S	S
Select Improve?	yes	yes	yes	yes	yes	no	yes	no	yes	yes

Table 5. Compiled Results – Simulation Data

Real Data										
Project	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
S & 1 within 5%?	no	yes	no	yes	yes	yes	yes	yes	no	yes
S or 1 Better?	1	S	1	1	1	1	S	1	1	1
Select Improve?	yes	yes	yes	yes	no	yes	yes	no	yes	yes

Table 6. Compiled Results – Real Data

Perhaps, the most significant evaluation characteristic for the proposed selection rules is "Select Improve?" The idea of this measure is to answer the question: Does application of the selection rules provide forecasting improvement? For 8 of 10 projects, for both simulated and real data, the selection rules forecast had lower MAPE than, at least, one of the two methods. For the two projects in each set, where Err-Selection is not less than either Err-SPI(t) or Err-PF1, MAPE values are poorer by very small differences, less than 1.1 percent.

Summary/Conclusion

Two empirical studies reported that the performance factor equal to 1.0 provides better project duration forecasts than using the ES schedule performance index, SPI(t). However, for the examined projects, there are instances where SPI(t) was better. Thus, it was reasoned that there may be performance conditions which cause one method to forecast more accurately.

The focus of this study was to determine selection criteria for choosing between the two deterministic forecasting methods, PF=1 and SPI(t). Simulation of project execution, under various performance conditions, was a key element of the research approach.

The results from the simulation of 25 projects, applying 39 performance scenarios, were graphed to examine for patterns. The patterns observed for the paired values of lnSPI(t) and lnESp σ provided performance information, leading to criteria for selecting between the two methods. The proposed rules for method selection were tested using 10 projects each of simulated and real EVM project data. For both data sets, the selection rules for 8 of 10 projects yielded more accurate forecasts than at least one of the PF=1 and SPI(t) methods.

In final analysis, the two deterministic methods yield very comparable forecasts about 70 percent of the time. The risk of using the PF=1 method is there are instances when its forecast can be in error by greater than 10 percent. Whereas, the risk of exclusively using SPI(t) forecasting is it generally has larger error than PF=1, although the difference is small. The application of the selection rules moderates these risks, and thereby provides a more reliable forecast.

Suggested Research

Certainly, the duration forecasting selection rules proposed in this paper should be further examined before general adoption. It is suggested that those practitioners having real data apply the rules and report their findings. As well, application of the rules to simulated EVM data is welcomed, and may yield refinements or a better selection approach.

For those interested, the forecast method selection spreadsheet is available from the author upon request.

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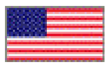

Walt Lipke retired in 2005 as deputy chief of the Software Division at Tinker Air Force Base, where he led the organization to the 1999 SEI/IEEE award for Software Process Achievement. He is the creator of the *Earned Schedule* technique, which extracts schedule information from earned value data.

Credentials & Honors:

- Master of Science Physics
- Licensed Professional Engineer
- Graduate of DOD Program Management Course
- Physics honor society - Sigma Pi Sigma (ΣΠΣ)
- Academic honors - Phi Kappa Phi (ΦΚΦ)
- PMI Metrics SIG Scholar Award (2007)
- PMI Eric Jenett Award (2007)
- Who's Who in the World (2010)
- EVM Europe Award (2013)
- CPM Driessnack Award (2014)
- Australian Project Governance and Control Symposium established the annual *Walt Lipke Project Governance and Control Excellence Award* (2017)
- Albert Nelson Marquis Lifetime Achievement Award 2018